Universidad Politécnica de Madrid
In cooperation with **Politecnico di Milano**

Analysing the complexity of the model-based decision making processes within the industrial management context

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- Politecnico de Milano, POLIMI, Milan, Italy.
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"If money is your hope for independence you will never have it.
The only real security that a man will have in this world is
a reserve of knowledge, experience, and ability."
Henry Ford

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ABSTRACT

Purpose

The decision-making process plays a key role in organizations. Every decision-making process produces a final choice that may or may not prompt action. Recurrently, decision makers find themselves in the dichotomous question of following a traditional sequence decision-making process where the output of a decision is used as the input of the next stage of the decision, or following a joint decision-making approach where several decisions are taken simultaneously. The implication of the decision-making process will impact different players of the organization. The choice of the decision-making approach becomes difficult to find, even with the current literature and practitioners' knowledge.

The pursuit of better ways for making decisions has been a common goal for academics and practitioners. Management scientists use different techniques and approaches to improve different types of decisions. The purpose of this decision is to use the available resources as well as possible (data and techniques) to achieve the objectives of the organization.

The developing and applying of models and concepts may be helpful to solve managerial problems faced every day in different companies.

As a result of this research different decision models are presented to contribute to the body of knowledge of management science. The first models are focused on the manufacturing industry and the second part of the models on the health care industry. Despite these models being case specific, they serve the purpose of exemplifying that different approaches to the problems and could provide interesting results.

Unfortunately, there is no universal recipe that could be applied to all the problems. Furthermore, the same model could deliver good results with certain data and bad results for other data. A framework to analyse the data before selecting the model to be used is presented and tested in the models developed to exemplify the ideas.

Methodology

As the first step of the research a systematic literature review on the joint decision is presented, as are the different opinions and suggestions of different scholars.

For the next stage of the thesis, the decision-making process of more than 50 companies was analysed in companies from different sectors in the production planning area at the Job Shop level. The data was obtained using surveys and face-to-face interviews.

The following part of the research into the decision-making process was held in two application fields that are highly relevant for our society; manufacturing and health care.

The first step was to study the interactions and develop a mathematical model for the replenishment of the car assembly where the problem of "Vehicle routing problem and Inventory" were combined. The next step was to add the scheduling or car production (car sequencing) decision and use some metaheuristics such as ant colony and genetic algorithms to measure if the behaviour is kept up with different case size problems.

A similar approach is presented in a production of semiconductors and aviation parts, where a hoist has to change from one station to another to deal with the work, and a jobs schedule has to be done. However, for this problem simulation was used for experimentation.

In parallel, the scheduling of operating rooms was studied. Surgeries were allocated to surgeons and the scheduling of operating rooms was analysed. The first part of the research was done in a Teaching hospital, and for the second part the interaction of uncertainty was added.

Once the previous problem had been analysed a general framework to characterize the instance was built. In the final chapter a general conclusion is presented.

Findings and practical implications

The first part of the contributions is an update of the decision-making literature review. Also an analysis of the possible savings resulting from a change in the decision process is made. Then, the results of the survey, which present a lack of consistency between what the managers believe and the reality of the integration of their decisions.

In the next stage of the thesis, a contribution to the body of knowledge of the operation research, with the joint solution of the replenishment, sequencing and inventory problem in the assembly line is made, together with a parallel work with the operating rooms scheduling where different solutions approaches are presented.

In addition to the contribution of the solving methods, with the use of different techniques, the main contribution is the framework that is proposed to pre-evaluate the problem before thinking of the techniques to solve it.

However, there is no straightforward answer as to whether it is better to have joint or sequential solutions. Following the proposed framework with the evaluation of factors such as the flexibility of the answer, the number of actors, and the tightness of the data, give us important hints as to the most suitable direction to take to tackle the problem.

Research limitations and avenues for future research

In the first part of the work it was really complicated to calculate the possible savings of different projects, since in many papers these quantities are not reported or the impact is based on non-quantifiable benefits. The other issue is the confidentiality of many projects where the data cannot be presented. For the car assembly line problem more computational power would allow us to solve bigger instances. For the operation research problem there was a lack of historical data to perform a parallel analysis in the teaching hospital.

In order to keep testing the decision framework it is necessary to keep applying more case studies in order to generalize the results and make them more evident and less ambiguous. The health care field offers great opportunities since despite the recent awareness of the need to improve the decision-making process there are many opportunities to improve. Another big difference with the automotive industry is that the last improvements are not spread among all the actors. Therefore, in the future this research will focus more on the collaboration between academia and the health care sector.

Keywords

Joint decision; scheduling; vehicle routing, decision-making, operating room scheduling.

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PREFACE

This document contains the results of four years of research in the Industrial Management Area. This work was developed at the Universidad Politecnica de Madrid (Home University) and Politecnico di Milano (Host University), with the addition of a short research stage in Argentina (INTEC).

The main supervisors of this thesis are:

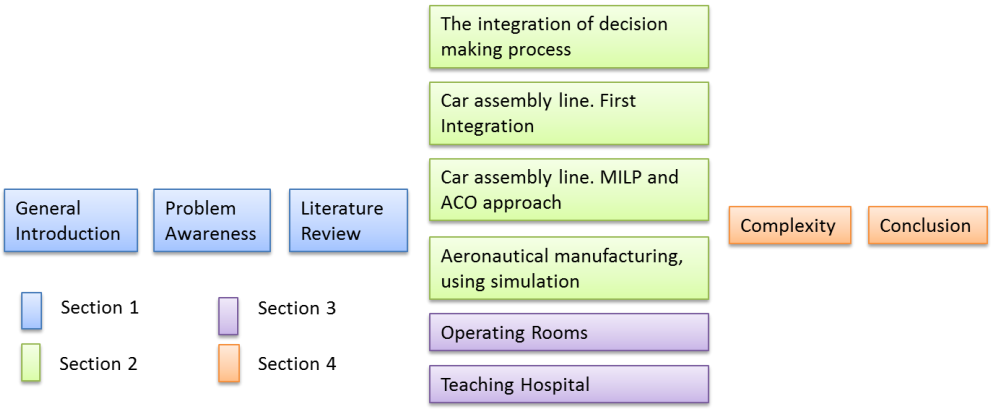
- Home university supervisor: **Álvaro García Sánchez.**
- Host university supervisor: **Alessandro Brun.**

Structure of this document

The following diagram (Fig. 0.1) shows the structure of this document. While the first section presents the problem, the solving approach, and the solving methods the second section presents the different application fields involved with industrial applications. The third section presents the health care application, and the forth section is the conclusion and appendix to the thesis.

This thesis could be read from beginning to end. However, should the reader wish to go to a specific section they can jump to the specific section or skip any section.

Figure 0.1: Structure of the document.



Outputs from this research

The latest improvements in computational power, solving techniques and algorithms could help to solve new types of problems. These extra capabilities could help us to face problems with different approaches with the purpose of obtaining a better solution.

These approaches were implemented in different application fields, such as assembly lines, and operating rooms. The different parts of this job were presented at various conferences and workshops. Some parts of this conference paper have evolved into a journal paper.

PROCEEDINGS OF INTERNATIONAL CONFERENCE:

Pulido, R., Garcia-Sanchez, A., Diego, J., Carlos, A. "A. collaborative Multi Ant Colony Optimization system for a Car Assembly Line", MAEB 2013, Madrid, Spain, 17-20 September, 2013.

Pulido, R., Garcia-Sanchez, A. "A. collaborative Multi Ant Colony Optimization system for a Car Assembly Line", ELAVIO 2013, Valencia, Spain, 8 -12 September, 2013.

Pulido, R. Ibañez, N. Aguirre, A. Mier. Ortega-Mier, M. "Operation Room under uncertainty" MOPTA 2013, Bethlehem, Pa, USA, 14 -16 August, 2013.

Pulido, R. Garcia-Sanchez, A. Ortega-Mier, M. "The inventory Routing Problem for the Mixed Car Assembly Line", CIO 2013, Valladolid, Spain. 10-12 July 2013.

Pulido, R. Garcia-Sanchez, A. Ortega-Mier, M. "The inventory Routing Problem for the Mixed Car Assembly Line", ICSO-Harosa 2013, Barcelona, Spain.

Pulido, R. Brun. A. Garcia-Sanchez, A., "Ant Colony Optimization algorithm and managerial insights for the Car Sequencing and Inventory Routing problem in a Car Assembly line" 18th International Working Seminar on Production Economics, Innsbruck, Austria 2014, 23-26 February 2014.

Pulido, R. Brun. A. Garcia-Sanchez, A. "Are companies taking advantage of joint decision in the production planning?" EurOMA 2014, Palermo, Italy, 20-25 June 2014.

Pulido, R. Brun. A. Garcia-Sanchez, A. "Is the decision making process of your company really integrated?" 1st EDIM Conference 2014, Milan, Italy, 11-12 June 2014.

Pulido, R. Garcia-Sanchez, A., Brun. A., Ortega-Mier, M. (2015). "The role of complexity and flexibility of the instance in the joint solution approach". XXI International Conference on Industrial Engineering and Operations Management. Aveiro, Portugal, July, 6th to 8th 2015.

Basán, N., Pulido R., Cocola M., Méndez C, "Aerospace Manufacturing Industry: A simulation-based Decision Support Framework for the Scheduling of Complex Hoist Lines" 44th JAIIO 2015, Rosario, Argentina, 31 August to 4th September 2015.

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Pulido, R. Garcia-Sanchez, A., Ortega-Mier, M., Brun. A. (2013) "MILP for the Inventory and Routing for Replenishment Problem in the Car Assembly Line." Journal of Production Management and Engineering (IJPME).

Pulido, R., Aguirre, A. M., Ibáñez-Herrero, N., Ortega-Mier, M., García-Sánchez, Á., & Méndez, C. A. (2014). "Optimization methods for the operating room management under uncertainty: stochastic programming vs. decomposition approach." Journal of Applied Operational Research, 6(3), 145-157.

Pulido, R., Aguirre, A. M., Ortega-Mier, M., García-Sánchez, Á., & Méndez, C. A. (2014). "Managing daily surgery schedules in a teaching hospital: a mixed-integer optimization approach." BMC health services research, 14(1), 464.

Pulido, R. Garcia-Sanchez, A., Brun. A., Ortega-Mier, M. (2016). "The role of complexity and flexibility of the instance in the joint solution approach. Lectures Notes in Management and Industrial Engineering." Engineering Systems and Networks: The Way Ahead for Industrial Engineering and Operation Management. Springer.

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This thesis represents the end of a stage in my life. For four years I had an amazing experience with exceptional people and I am still learning from my supervisors, professors, and colleagues. This is the continuation of the journey that I started with IMIM, which has provided me with one of the best experiences of my life.

Erasmus Mundus initiatives were a fantastic opportunity for me. This programme is the result of the efforts of the many people involved, whom I wish to thank for making this programme possible, a result of the sum of all the efforts of the scientific committee, office workers, directors, professors and the other people involved. Special thanks for helping to run this programme go to Antonio, Cali, Felipe, Matts and Paolo, and to those who faced and solved our everyday complications, Isabel, Kristin and Martina.

I highly appreciate the help of my supervisors Álvaro García Sánchez and Alessandro Brun who guided me during my PhD to this point. I also want to thank Alberto Portioli, Miguel Ortega Mier, and Carlos Mendez for their useful comments.

I am indebted to my many EDIM colleagues from the UPM, POLIMI, KTH, and INTEC for their support and for making these four years unforgettable.

Also, to all my friends, both new and old; together we have had ups and downs but I would not change any single moment that I spent with them.

I appreciate the encouragement, help and support during the PhD from Larissa who did not allow me to quit in the difficult moments.

Foremost, I am highly grateful to God for the blessings and opportunities that He continues to offer me.

Raul Pulido

DEDICATION

I would like to dedicate my thesis to my beloved family and extended family and to the loving memory of my Grandfather. I owe my deepest gratitude to my Mother and Father, who, despite the ten thousand kilometres or more of distance, have always encouraged me to keep trying and have always supported me in the good and the bad moments and have been close to me at every milestone of my life.

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SECTION 1. GENERAL INTRODUCTION

The first section of this thesis has three chapters. In the first chapter a general introduction of the thesis is presented. The second chapter is dedicated to the problem of awareness and in the third chapter a literature review of the decision theory is presented.

Chapter 1: Introduction

In this chapter a general introduction to the thesis is provided, followed by the motivation of the problem and which approach is used together with more detailed settings of the problems, and why these problems had been chosen.

MOTIVATION

Decision making plays a key role in the success or failure of a company, where virtually every job involves a certain type of decision-making. The ability to follow a proper decision-making process does not guarantee the success of the company, but it will increase the chance of succeeding. Numerous knowledge fields have research into this subject because of the direct impact on the organization's performance that the best decision-making process can have.

The possible benefits of good decision-making are a better use of resources, an increase in efficiency, business growth, and achievement of objectives, among others.

The decision-making process has been divided into different stages by different authors. Mintzberg et al. (1976) divided it into three phases: identification, development and selection. The identification phase is divided into recognition and diagnosis, the development phase into design and research and finally the selection phase into screen, evaluation-choice and authorization.

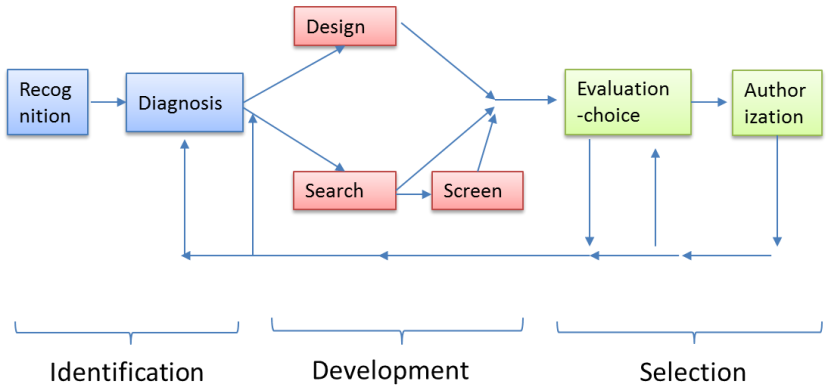

Figure 1.1: The relationship between the phases and routines of a decision-process (Mintzberg et al. 1976).

Academia has made great efforts for the second and third phase (Mintzberg et al. 1976). A quick literature review of the papers that appear in this field shows that the most common output of a paper is to highlight that one algorithm or solution method is x% faster that a previous algorithm, or that any technique could help to have a tighter boundary that helps to offer a better solution in less time than other methods.

It is necessary to keep researching into the development and selection stages, since the computational power now available offers us new possibilities of addressing problems that some years ago were impossible to solve. But the first stage of the decision should not be forgotten since interesting improvements could be achieved. The first stage to this achievement is to understand all the characteristics of a decision-making process, and the possible outputs of any changes in the approach.

Because several scholarly disciplines share an interest in the decision-making process these characteristics change depending on the fields. Some fields such as operation research and management science are concerned about how to improve the decision-making process. Others such as psychology are interested in the thinking behind the decision. Despite the models used, a common characteristic is the conception of decision-making as an information-processing activity taken by one or more actors. (Vroom, 1973).

Many operations management researchers assume that "integration is a must" and that cross-functional coordination and integration are necessary (Ketokivi, 2006). In later research Turkulainen et al. (2012) argued that the benefits are context-dependent and sometimes disaggregation is beneficial.

Following the idea of integration, joint decision-making is the one in which all the actors involved can participate in the decision-making process (Scharpf, 1998). However, joint decision-making process benefits could be attractive for some circumstances or unappealing in other situations. In this work, the

benefits of the decision-making process are explored, when it is advisable to use it, and examines when it is better to use another decision-making process.

The process of joint decision-making results in a paradox since the different actors may not achieve the optimal of their operation in order to achieve the optimal as a whole. A typical example of this situation is lean implementation. A reduction of the inventory reduces the inventory cost but increases the transportation cost. The global optimal is not the sum of the optimal of transportation plus the optimal of the inventory, but something in between. As more actors are taken into account, the difficulty or complexity of the problem increases.

Complexity

Complexity plays a crucial role in the decision-making process, but there is no generally accepted definition of complexity since different authors have proposed a definition that only captures a limited part of the phenomena. For dynamical systems theory, the complexity measures are usually computational complexities, which is a measure of the interactions. For example: "Kolmogorov complexity" (Kolmogorov, 1965) for information theory defines "the complexity of a string of characters as the length of the shortest program that can generate that string. This theory implies that random strings are maximally complex." (Adami, 2002).

Heylighen (2008) highlights that a fundamental part of a complex system is the connected parts via interactions. The components are both distinct and connected, autonomous and to some degree mutually dependent. The interdependence could create a conflict of goals since the improvement of one part could lead to the decrement of the other part.

Fig. 1.2 shows a diagram of some parts of the complexity in a decision. The higher the number of interactions the higher the complexity. The complexity could grow for different causes, such as taking into consideration a tactical and operational decision together. Also because the decision or many functional areas are addressed together, or a long term decision and a combination of the previous factors. As more blocks are taken into consideration the complexity of the decision increases up to the extreme of a holistic decision where everything is taken into account.

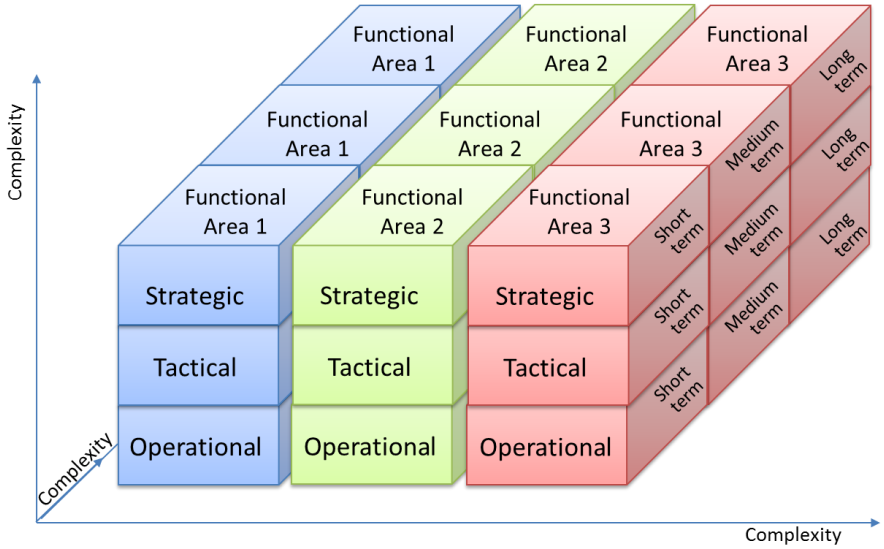

Figure 1.2: Complexity of the decisions. A higher number of "blocks" implies a higher complexity.

APPROACH

In the identification of the problem different approaches could be evaluated.

- The first option is to use the output of the first part of the problem and then to use it for the second part of the problem, and so on. We will refer to it as a sequential decision. This is common usually in industry and in every day decisions. The main advantage is that the complexity of the problems is lower than the complete problem. Each part of the problems is more likely to be solved up to optimality.
- The second option is to solve all the problems together. We will refer to this option as a joint decision. It consists in tackling the problems together, without any subdivision. Joint decisions have a high complexity.

The problems that could be divided into parts and solved independently, and where the output of each part does not affect the other parts are outside the scope of this research. In order to define what the entire problem is, it will be assumed to be one step higher that the way it is presented in the literature; e.g. in the case of the inventory and sequencing problem in a manufacturing plant, the entire problem will consist in solving both problems together. The holistic decision of the entire operation of the plant is out of the scope of this research because the available solution tools make it impossible to deal with this kind of problem.

INTEGRATED PLANNING IN INDUSTRY.

Industry outsiders may be surprised by how often a functional area overlooks or ignores the detailed activity planning of the other area, either because of more pressing problems or because it is less interesting. The level integration decision should be an output of a decision process and not determined by a side answer.

Leading companies take a more disciplined approach, recognizing that improving the level of integration is a critical step towards operational excellence. As stated before, it is difficult to integrate everything given the high degree of interdependence that exists. Determining the proper level of integration with the right level of complexity that could allow us to operate efficiently is a major step in the decision process, because an excess or deficiency of integration could have negative effects.

Integrated planning presents important challenges such as coordination across teams and functions, and a disciplined management of change to the new work structure.

The decision integration could be vertical, horizontal, or over time. For this work, the vertical decision integration is when the strategic, tactical and operational decisions are taken together. The horizontal decision integration is when the decisions of the different functional departments are taken together. The decision integration over time is when the short, medium, and long-term decisions are taken together.

This type of integration is common in industry. An example of the three different types of integration is presented in the literature. We have presented each paper as an example of only one type of integration, despite the fact that in some cases they could also be considered for two types of decision integration.

Vertical integration decision.

As an example, we could provide the type of decision that has to be made for a logistic network. The strategic level is that which designs the logistics network by prescribing facility locations, production technologies, and plant capacities. The tactical level prescribes the material flow management policy, including production levels at all plants, the assembly policy, inventory levels, and lot sizes. The operational level schedules operations to assure the in-time delivery of the final products to customers (Schmidt and Wilhelm, 2000). In Table 1.1, we present different papers that combine the vertical integration

decision. There is no example of tactical and strategic decisions since the operational decision is an intermediate step.

Table 1.1: Vertical integration decision.

Paper	Tactical	Operational	Strategic
Beaudoin et al. (2008)	X	X	
Bilgen and Ozkarahan (2004)	X	X	X
Brown, and Vassiliou, A. L. (1993).	X	X	
Ivanov, D. (2010).	X	X	X
Lackman et al. (2000)		X	X
Malhotra (1994)		X	X
Rozinat et al. (2010)	X	X	
Sagie and Koslowsky (1994).		X	X
Schmidt and Wilhelm (2000).	X	X	X

Horizontal integration decision.

As an example, this could be provided when two or more functional areas integrate their decisions. The vertical integration decision could be a success key for an organization since Frayret et al. (2003) highlight that the forest product industry has reached the point where profit cannot be reaped without the indolent coordination of their entire organization. In Table 1.2 we present different papers that combine horizontal integration decision.

Table 1.2: Horizontal integration decision

Paper	Number of Areas	Application
Caridi and Sianesi (2000)	3	Flow shop manufacturing, scheduling planning and scheduling
Eberts and Nof (1993)	2	Capacity allocation planning
Frayret et al. (2003)	4	Supply chain planning
Gyires and Muthuswamy (1996)	4	Multi-facility production and coordination
Kim et al. (2003)	2	Warehouse and inventory management
Miyashita (1998)	2	Integrated operations planning and scheduling
Tsukada and Shin (1998)	2	Tool management
Wooldridge et al. (1996)	2	Job shop manufacturing control

Decision integration over time.

Taking into consideration the planning horizon and depending on the availability of the data, a deterministic or stochastic model should be used. Forecasts are required for proper scheduling activities, such as generation scheduling, purchasing activities, production, maintenance, investment and so on.

Table 1.3: Decision integration over time.

Author (year)	Short Term	Medium Term	Long Term	Determin istic	Stochastic
Argoneto et al. (2008)	X	X		X	X
Campbell and Viceira M. (2002).		X	X	X	
Fleten and Kristoffersen (2008).	X				X
Gjelsvik et al. (2010)		X	X		X
Hanscom et al. (1980)		X	X	X	
Reneses et al. (2006)	X	X		X	
Xia et al. (2010)	X	X	X		

PROBLEM SETTING

Each problem deals with a different combination of a vertical integration decision, horizontal integration decision, and integration over time. In Figure 1.3 the type of decision of each chapter is presented. For example Chapter 9 deals with three functional areas (horizontal integration), and with two levels of vertical integration, and level 1 of integration over time. It is assumed that the more the decision is integrated, the higher its complexity.

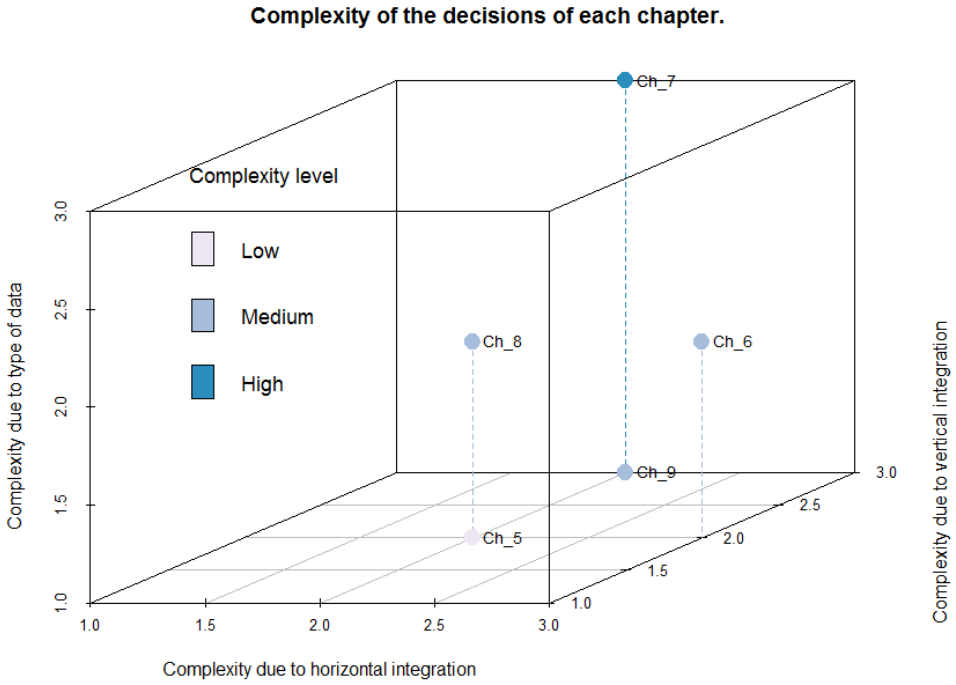

Figure 1.3: Complexity of the decisions of each chapter.

The selected research field will be the manufacturing and health care industry since both sectors play a key role in modern society. The focus for the manufacturing industry will be at the Job shop level and for health care at the scheduling and planning levels. One of the characteristics of the manufacturing industry, particularly the car industry, is the high speed at which the new techniques and best practices are spreading, one of the reasons being that in 2013, 72 million out of 86.9 million cars were produced by the top 10 car manufacturing groups (OICA, 2013).

In comparison, the health care sector is highly segmented, and the majority of the medical literature is about healing methods and not about the best use of resources or decision-making.

Manufacturing industry

The assembly line makes companies more efficient by dividing complicated tasks into simple tasks that are performed continually until the final product is achieved. It has been a long journey from the first use in the production of the T-Model by Henry Ford to modern assembly lines that can produce a huge diversity of complex products.

Sequencing problems are faced every day throughout the industry. The order in which the cars are produced is one of the most important decisions for the assembly line. As the assembly line has evolved to produce many models, scheduling the production has become a complex problem.

Automotive industry

The automotive industry has to produce hundreds of cars of different models every day so the production order of the vehicles needs to be decided. The schedule of this production is difficult since there are a lot of limitations in the production line. Some of the difficulties to sequence production are the different production times of each car in each workstation, the need for all the components to be on the production line before assembly and the shortage of extra workers.

One of the approaches presented to deal with this problem is the one described by Butaru et al. (2005) and (Solnon et al., 2008). The cars to be made are not identical because the options are different for each car. The workstations that install these options are designed to handle a maximum production percentage of each option. Therefore, the production manager needs to arrange the sequence to respect these percentages.

Each workstation has moved from installing one component to installing a variety of components, and it is also necessary to have an inventory of the different types of components in a compact space. The inbound logistic for feeding the workstation inside the factory is a critical issue in the car manufacturing industry. Replenishment is a critical issue since a lack of inventory could cause line stoppage or reworking. On the other hand, an excess of inventory increases the holding cost or even blocks the replenishment paths. The decision regarding the replenishment routes cannot be made without taking into consideration the inventory needed by each station during the production time, which will depend on the production sequence.

When we refer to replenishment we are refering to the Vehicle Routing Problem (VRP) + Inventory problem. The objective of VRP is to set the optimal routes for a fleet of vehicles to deliver to a given set of customers. The objective of the Inventory problem is to define the optimal amount of inventory that is delivered to each customer.

There are some extensions for the VRP such as Inventory Routing Problem (IRP) (Campbell et al., 1998), Multi-vehicle Routing Problem (MVRP) (Gambardella et al., 1999), Production Routing Problem (PRP) (Adulyasak et al., 2012), Capacited Vehicle Routing Problem (CVRP) (Ralphs et al., 2003) which have some things in common but differ in others. In order not to restrict

the research to an extension of the problem, a general definition of the problem was used.

The interaction of the concepts “Scheduling”, “Vehicle Routing Problem” + “Inventory Problem” on Assembly lines was studied. The first step was to get expertise in each concept separately, then research into the integration and add more complexity to the problem (see Figure 1.4).

Assembly lines are flow-oriented production systems, which are still typical for the production of high quantity standardized commodities and they are even gaining importance in the low volume production of customized products (Becker and Scholl, 2006). One of the most complex products that is built on the assembly lines are cars and trucks. The assembly lines are a way to mass-produce cars quickly and efficiently.

The focus of the research was the automotive industry as an example of all the complexities described above. The automotive industry is one of the most important European industries and the automotive sector is an essential reference for a broad spectrum of manufacturing industries. The improvement techniques in their assembly lines are often extended to other assembly lines.

A change in the production schedule affects the inventory and the replenishment of components. Sometimes improving one undermines the overall performance, thus, it is necessary to discuss when it is beneficial to take a joint decision and when it is not.

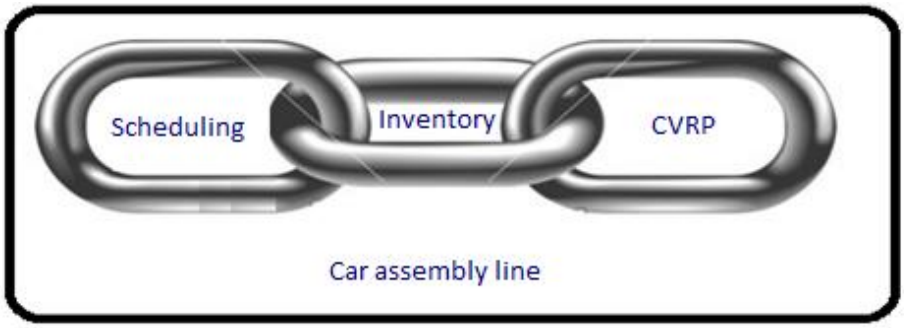

Figure 1.4: The interaction of scheduling, inventory and CVRP.

Aeronautical industry

Aeronautical manufacturing is a high technology industry that produces airplanes, spacecraft, satellites, missiles, and related parts. It is hard to imagine something more complex than a flying object, which requires thousands of man hours, complex manufacturing facilities and top class suppliers.

Among all the processes that raw materials have to follow to become finished products, the chemical anodized process was researched. The airplane

parts are exposed to extreme weather conditions, thus it is important that chemical treatments are properly applied to the parts to avoid any accident.

These parts have to take chemical baths in different tanks where they have to stay a minimum time to complete the chemical process, but lower than the maximum time that would damage the parts. Each part has to follow a recipe to be ready. The only way to move from one tank to another is using a crane that can carry one part from one tank to another.

Like the automotive industry, the scheduling of the production of aeronautical parts has many limitations. One of the main difficulties to plan the production scheduling is the different bathing time that each part has to be in each tank, which adds difficulty to having a smooth flow. In order to complete the chemical process each part has to follow a unique path. A path consists of the series of tanks that each part has to visit. This path is unique and different from the others. Usually these paths are not linear because the next tank of the recipe could require a jump forward or backward.

The other problem that is faced during the chemical treatment is that the movement between tanks can only be done by a crane / hoist. This hoist can only transport one part at a time, which could generate conflicts when more than one part needs transportation. As there is no intermediate buffer between tanks, it is necessary to assure that the destination tank is ready to receive the part. When the bathing time exceeds a limit the part becomes useless. During the time that a part is being transported another part may become flawed. This problem is often called the hoist scheduling problem (Bloch et al. 2010). Each part has to follow a different recipe through the chemical tanks.

The scheduling and the hoist problem could be solved with a sequential decision that implies deciding the schedule of the aeronautical parts to be processed and later finding the optimal/feasible path for the crane robot, separately solving one problem after the other. The other option is try to solve both problems simultaneously trying to synchronize the movement of the hoist with the scheduling of the aeronautical parts (see Figure 1.5).

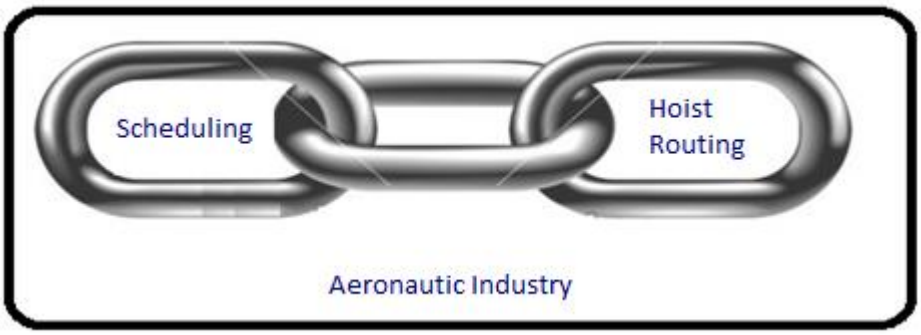

Figure 1.5: The interaction of scheduling, and Hoist Scheduling Problem.

Health care industry

The health care resources are insufficient in almost any country for the increasing demand of services to be met. This challenge has become greater with the growing and ageing of the population while governments are reducing the overall cost of the health care services. Health care providers must decide the most effective resource allocation and effective use of resources to provide these services.

Providing support for this complicated decision-making process could help to face these problems. Modern hospitals are complex organizations that have to deal with an increasing number of treatment options delivered by an increasing number of specialists. They usually serve as a research centre and for teaching.

In many hospitals the surgery department is one of the main cost contributors (Jebali et al. 2006). Moreover, the main cost of the surgery department is the operating rooms (ORs). The number of hospital admissions that will require surgery is increasing together with the demand for other services such as medical consultation. Therefore, the proper scheduling of the operating rooms and surgeries are important if the hospital is to operate properly. This is even more complicated in teaching hospitals that play a key role in the health care system by training the future doctors.

The scheduling of surgeries consists in deciding which surgical operation will be performed by each surgical doctor in a determined operating room during a time slot.

One of the limitations to scheduling the surgeries is that not all the surgeons perform surgery at the same time and not all the surgeries could be performed by the same surgeon. The ORs scheduling should target cost reduction and the efficient use of resources while maintaining the service level.

When the head of the surgical service draws up the schedule, they should take into consideration that a vacant OR produces a cost, also an idle surgeon has a cost, and the surgeons working extra time also have a cost.

The extra difficulty to create the scheduling of the ORs in a hospital includes the surgeon's expertise. The difference of expertise between surgeons in a teaching hospital is higher than in a non-teaching hospital. However, in all hospitals there are surgeons that have more experience than others and who can perform a surgery in less time. This is more evident in a teaching hospital where surgeries are performed by veteran surgeons and apprentices. Moreover, it is necessary that young surgeons perform a certain number of surgeries in order to complete their training.

Again, this decision could be made sequentially or jointly. In the sequential decision case, firstly, the time slots in the ORs are allocated to the different surgical services. Then the head of the surgical service decides which surgery will be performed in each time slot and which surgeon will perform the surgery (Blake and Carter, 1996). In the second case, the joint decision will be used to make all decisions simultaneously and the results will be compared with the sequential decision (see Figure 1.6)

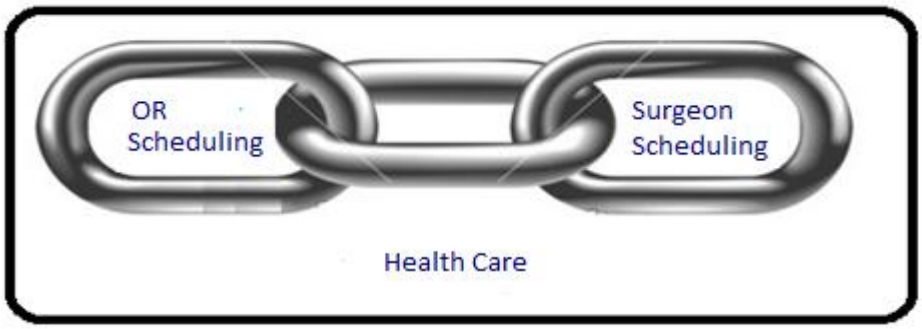

Figure 1.6: The interaction of OR Scheduling, and Surgeon Scheduling.

WHY IS THIS STUDY IMPORTANT?

There is no straight answer to what is better: to make a joint decision or to make a sequential decision. Both have their pros and cons. The joint decision consists in increasing the scope of the decision-making process; that is, adding decisions that could be made before or after.

This additional decision could come from other functional areas, or by adding tactical or strategic decisions to the operational ones, or taking short, medium, and long term decisions together. As shown in Fig 1.2, a joint decision consists in adding more "blocks" to the decision. The possible benefits of incorporating more "blocks" to the decision-making process (joint decision) are the saving of costs thanks to the better use of the resources due to the increased number of possible options that are evaluated. The decrease in the cost is accompanied by an improvement in the performance indicators.

However, despite the advantages of the joint decision, it is necessary to take into consideration the drawbacks of the use of a joint decision. The main drawback is the increase in complexity added to the problem.

Regardless, of the solution method that will be selected, solving a more complex problem will be more costly than a non-complex problem, since it will require more coordination among the parties involved, a higher amount of

resources and a longer solving time. Should the solving method selected be a mathematical model more computational power, time, and IT tools will be required to solve this big problem. When the solving times become excessive, other solution procedures such as non-exact methods should be evaluated but with the risk that the savings will be lower because the global optimum is not achieved.

THE NEXT STEPS

In the following chapters, a literature review of the possible achievement of this decision will be presented together with a survey on how the decisions are taken by different companies.

The survey will be used as a starting point for the research of the decision-making process, where the measure of the integration of the companies will be evaluated. The survey has answers from different professionals from many sectors, which will help us to understand the real decision-making process. This will be reinforced with some face-to-face interviews to better understand the decision-making process, and the decision support tools that are used.

From chapters 4 to 9 different models related to the manufacturing, aeronautical industry and health care that could represent typical problems will be developed, with different degrees of integration to research the impact of the integration of the decision-making process.

An additional complication for the decision-making process is that the level of integration that is good for one company may not be good for other company as their data are different from those of the original company.

For this reason, a pre-evaluation of the joint decision is advisable since there is a risk that the cost of implementation will be higher than the savings. A framework for a pre-evaluation of a decision will be designed for the sake of having more elements before deciding which type of decision to use. Thus it could help decision-makers of similar problems to pre-evaluate their problem.

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Chapter 2: Problem Awareness

In this second chapter, the problem will be presented together with the research design and the methodology.

PROBLEM STATEMENT

Decision-making is a vital part of the management world. Since decision-making is different from one company to another, the first step consists in understanding how these decisions are made in different companies. The next step of this research was to analyse and to compare when it is suitable to increase the scope of the decision, what the impact of the change of the decision type is, who the actors involved in the change are, which other application fields are suitable to those changes and when it is better to use the sequential decision-making process instead of the joint decision.

The main research question is: What is the impact of the complexity of the model-based decision-making process in the context of industrial management?

To help us to analyze and answer this research question, in Table, 2.1 four other secondary research questions and the goals of this thesis are presented. The first question is related to the opportunities offered by present-day computational power. This computational power opens the door to dealing with problems using techniques that some years ago were impossible to even think about. The second question deals with when the exact method is not powerful enough to deal with a real life-size problem, the dilemma of trying heuristic techniques or when a sequential approach appears. The third question deals with which characteristic of a problem makes it more likely that one approach or another will be used. Finally, the last question deals with the theory involved in this change of approach.

Table 2.1 Goals and secondary research questions.

Research Question	Goals

1	Using current knowledge and computational power, is it possible to develop models that deal with the increase in complexity for joint decision making in an efficient and effective manner?	To analyse and quantify the effectiveness of using a joint decision model for different functional areas in the different application fields and compare it with a separate decision process
2	When exact methods are not enough to deal with the increasing complexity of real size problems, is it better to try with heuristic methods or is it better to use sequential decision-making?	To increase the size of the problems up to real life-size problems and analyse the impact of the resultant complexity and the use of other solving techniques.
3	When is the use of complex decisions advisable and when is it not?	To determine the main characteristic of the instance that could provide promising results using one approach or another.
4	What is the managerial theory and implication behind the decision models that are currently being used?	To analyse the managerial insights and implications behind the current decision model with the analysis of their objective function and constraints.

RESEARCH DESIGN

The impact of the change in the decision process is analysed in the application fields of the manufacturing, aeronautical, and health care industry. With a deep analysis of the change in the decision-making process the research questions were answered. The analyses of these changes were supported by different techniques, such as simulation, mixed integer linear programming, interviews and heuristic techniques.

The basic design of this research was to select some cases from the application fields and modelled with different approaches. Once the models had been constructed, different experiments were run changing the conditions and analysing the behaviour of these changes in the output variables.

Despite the problems addressed in the literature, there are still a number of challenges and questions that can be solved by using the new techniques and computational power available. For the first research question, taking advantage of the increase in computational power, a model that increases the scope of the decision-making process will be used, and this will be compared

to traditional decision-making. These experiments were carried out for the car assembly line and the operating room scheduling.

In order to answer the research questions the application fields of manufacturing and health care were selected. The cases were modelled in a different way. In Fig 2.1 the scope of the model is presented for the car assembly line. We compared separately the production scheduling model, replenishment and the inventory level with the joint model. Similar work was done with the different parts of the operating room scheduling.

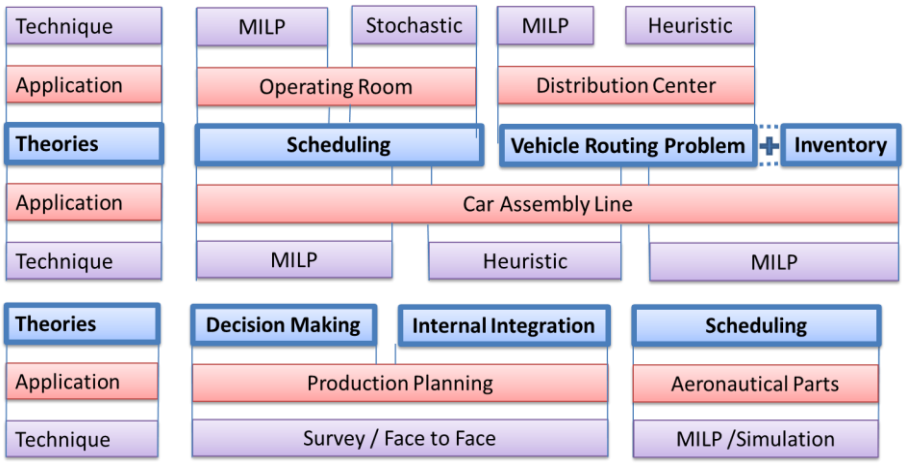

Figure 2.1: Layout of the Research.

The second research question was answered using a real life-size problem. This type of problem could not be solved using exact methods in a reasonable time, so we built a heuristic model to deal with the entire problem, with the disadvantage of non-optimal results which we compared with a sequential decision. As Afshin (2012) also reports that classical MIP and MILP tools are being used for the majority of the models and considering the computational complexity of real-life problems, it is necessary to develop efficient algorithms and metaheuristics for some cases.

The third research question is focused on creating a framework that could help managers to make a decision as to which decision approach should be taken. Monczka et al., (2008) highlighted that in a complex ecosystem, managers have to consider several important aspects of the movement of materials such as inbound logistics and their impact on the sequencing and the interaction between first-tier suppliers and the sequencing since tightening the supply chain impacts on the operation and on the cost of the supply-chain. In these cases it is not easy to decide whether to try to solve the different problems jointly or sequentially. The models constructed were analysed and experimentation carried out to try to identify the factors that make an instance more suitable to be solved with a sequential or joint decision.

Finally, business analysis requires understanding of the industry and the organization. Among other things, this comes from data analysis, and information, and the proper choice of analytical tools. For the last question the managerial insight acquired from all types of experimentation and interviews in all the application fields are presented.

RESEARCH METHODOLOGY

In order to describe the methodology we will follow the research onion of Saunders et al. (2009). We will start with the outer layers, and then go into the inner part of the research onion. We will start with the research philosophies, the approaches, and the strategies.

The philosophy, positivism

The research philosophy adopted defines the way that our research is performed. Johnson and Clark (2006) argue that the important issue is “how well we are able to reflect upon our philosophical choices and defend them in relation to the alternatives that we could have adopted.". The choice of the philosophy is supported by other similar research in the field. Positivism adopts a clear quantitative approach for investigating quantitative phenomena in many sciences. Gill and Johnson (2002) advocate that a good positivist researcher has to create a structured methodology to facilitate the replication.

The approach, deductive

The next layer of the research onion is the approaches, which can be deductive or inductive. A deductive approach owes more to positivism. It involves the development of a theory that is rigorously tested. Robson (2002) lists five sequential stages: formulating a hypothesis; expressing the hypothesis in operational terms, testing this operational hypothesis, examining the specific outcome, and modifying the theory if needed. These five steps create a cycle. When necessary we should rebuild our hypothesis according to the findings.

The strategy, modelling

The philosophies and approaches are common to the different sciences, but for the strategy layer, the strategies division proposed by Kotzab et al. (2005) will be followed. Reviewing the characteristics of these strategies, and matching them with the research question, the background and the preference of the

authors, and reviewing similar works in the field of study, the modelling was selected.

Quantitative models generate models of causal relationships between control variables and performance variables. Then we can isolate the phenomenon and analyse and test. Mitroff et al. (1974) made an early contribution to the methodology discussion with their model.

In the conceptualization phase, the researcher creates a conceptual model of the parts of the subjects under investigation, in this case the assembly lines, aeronautical parts, and health care industry. Then, it is necessary to make a decision about the variables that need to be included in this model, and the scope of the model. In the next phase, the quantitative model is built, thus defining causal relationships between variables, such as cost, constraints, and requirements. Then, the model is solved using mathematical solving methods. Finally, the results of the model are implemented and a new cycle could begin (Mitroff et al., 1974).

The study of the supply chain from different approaches has been a constant in the field of Industrial Management research. The area that is of concern to this research is the integration of the supply chain, which has gained increasing attention in recent years, in the direction of gaining flexibility and cost efficiency. However, a high degree of integration is not necessarily desirable in all situations (Bagchi et al, 2003). To answer these types of problems, quantitative models have been used to solve operational management problems and develop scientific knowledge.

A major problem in solving real-life operational processes is that they are all different, depending on the work organization, information system used, flow lines, job shop characteristics, and so on. The majority of these processes are cluster processes based on the manufacturing technology used, and making general assumptions for theoretical models (Will and Fransoo, 2002).

The data collection is linked to the construction of the quantitative models, since the definition of variables and parameters can serve as a framework for the data collection (Mikkola, 2003). The simplification of the model plays a key role and is justified when a solution of the mathematical formulation describes the studied phenomena. (Wylie and Barrett, 1982).

The drawback of mathematical modelling is that the analysis is limited to the variables of the formulation, and when additional variables are added to the formulation the models can become extremely complex and cannot be solved with traditional solving tools.

The modelling of an assembly line could involve thousands of variables; the selection and estimation of the most important variables is extremely complex. The oversimplification makes the model unrealistic while

overstatement makes it almost impossible to solve. Therefore, it is necessary to create a model that can give us interesting information to apply to the operation of the assembly lines.

Implementation

The fourth phase of the model of Mitroff et al. (1974) is implementation. Strategies of empirical research should be used to test the implementation. This phase also tunes the parameters used to decrease many unrealistic assumptions in the previous stages due to the growing mathematical complexity (GroBler and Schieritz, 2005).

The main objectives of the thesis were obtained using quantitative models, such as linear programming methods, mixed integer programming, stochastic programming and heuristic techniques. Even though there is no doubt about the importance of qualitative models in decision-making science, such as participant observation or interviews, which can help to tune the models (Tayur et al., 1999), these qualitative models are used in the first part of section 2 to understand the complexity of the decision-making in companies.

Techniques and procedures

Mathematical mixed integer linear programming (MILP) will be used to model the car assembly lines and operating room scheduling; exact solution methods work better for small problems. Because they consume a high amount of memory and computational time, it is impossible to use these methods with larger data, so it is expected to use other solution techniques.

Heuristic techniques are usually explored when the exact methods cannot deal efficiently with the problem. These techniques trade optimality, completeness, accuracy and precision for a usually shorter solving time. These heuristic techniques do not guarantee the optimal, but the solution is still good enough to be used when the exact methods require excessive time and memory, or simply when they cannot achieve a solution. Heuristic techniques are designed for solving the MIP problems faster than the exact methods, but sometimes heuristics take more time to solve a problem than the exact methods.

Another commonly used technique used in quantitative research is discrete event simulation. One of the main advantages of simulation is the level of detail of the studied subject and the step-by-step visualization of the status of the system at any time. Discrete event simulation models the operation of a system as a sequence of events. The model of a complex system is a lab for researchers and managers in the different areas. It provides low cost

information-gathering for the decision-making. The dramatic increase in computing time and memory, and the development of more powerful simulation software allow us run highly detailed simulations where it is possible to evaluate several scenarios in a short time (Fishman, 2001). Discrete simulation was used to manufacture the aeronautical parts.

CONCLUSIONS

In this problem, a quick introduction to the problem was stated where the importance of the decision-making process was presented. Then the four research questions were presented, together with their goals. Different case studies based on manufacturing, aeronautical parts manufacturing and health care were developed. In these cases the sequential decision and the joint decision were performed using different techniques.

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Chapter 3: Literature Review

DECISION THEORY

Every day companies are faced with hundreds of decisions; some are irrelevant, and others can be determinant in the life of the company. Sometimes managers are so afraid to make a decision that they postpone it or make no decision at all, but this is also a decision.

The Cambridge Dictionary defines a decision as "a choice that you make about something after thinking about several possibilities" (Cambridge, 2015). Decision theory is concerned with the problem of making decisions. When statistical knowledge sheds light on some of the uncertainties involved in the decision, then it is called statistical decision theory (Berger, 2013).

A requirement to make a decision is that at least two possibilities exist. For example, if someone is travelling from point A to B, and there is only one possible road with no intersections or forks there is no decision about the direction that should be taken. The existence of alternatives is a requirement for a decision.

Interdisciplinary area

Decision-making has called the attention of researchers from different fields, such as psychologists, linguists, management scientists, and so on. There are different ways to theorize and, therefore, there are many research traditions with different (mathematical) technical aspects.

Contributions from different academic disciplines have helped create the actual body of knowledge. The main contributors are economists, statisticians, operation researchers, management scientists, psychologists, political and social scientists and philosophers. Even if Decision theory is a subject by itself, different disciplines have contributed to the body of knowledge of decision theory from a different perspective (Mitchell and Beach, 1990).

The perspective of political science sets the focus on the collective decision-making process, or the perspective of the philosopher is the rationality of decision while management science looks to improve the result of the decision. Each group of scientists has used their tools and methods to deal with similar problems, helping the development of decision theory (Hansson, 2005).

Types of decision theory

Most contributions to decision theories could be divided into two. Normative decision theory explains how the decision should be made. Descriptive decision theory explains how the decision is taken. Normative decision theory also takes rational thinking following procedures or methods as a prerequisite. However, the distinction between rational-normative and descriptive theories is fuzzy (Hansson, 2005).

Normative theory is based on the paradigms of expected utility theory and subjective expected utility theory. The expected utility theory is based on the act of choosing the option with the highest expected utility. The subjective expected utility theory adds the characteristic of the attractiveness of an option based on the decision-maker (Fishburn, 1983; Raiffa, 1968; Schoemaker, 1982; von Neumann and Morgenstern, 1953). Utility theories require the decision-maker to have all information describing the decision situation. Weber (1987) presented an interesting framework to deal with incomplete information, but in the rest of this research, it is assumed that all the information is complete.

CHARACTERISTICS OF A DECISION WITH COMPLETE INFORMATION

A traditional decision situation is characterized by a set of options, a set of objectives or attributes, a known probability distribution of the outcomes and decision-maker(s) with a stable preference structure and then they evaluate and decide. Within the framework of prescriptive decision theory, methods should help a decision-maker find an optimal or satisfying solution (Weber, 1987).

A set of options

The next task of a decision is the exploration of the set of options. Generating some different options may be complicated at first, but the wider the options that decision-makers explore, the better the final decision is likely to be (Samuelson and Zeckhauser, 1988).

How could all the options be explored? How many possibilities are enough? Which possibilities should be explored? Following the example of someone traveling from point A to B, should they explore only the highways, or also the toll roads, the expressway, the interstate, the boulevards, etc.? Alternatively, maybe they should also explore using an off-road vehicle and use the gravel roads or rural roads. The answer to this question depends on the scope of the problem, the solving time and the techniques selected.

Set of objectives

When options start to emerge, it is necessary to weigh the options according to the objectives. What are the good points or bad points of the options? The knowledge about the possible outcomes could be quantified in terms of losses or utilities (Berger, 2013).

Before assuming that something is better or worse, decision-makers have to select the decision objectives. In the example, the decision objective could be the price, the duration, the arrival time, the CO_2, and so on. Unfortunately, in decision-making there is often no single objective for a problem. Recently, there has been a growing interest in multi-objective decision techniques. The most important ones are Pareto optimality, desirability function, overlay plots and utility functions (Hendriks, et al. 1992)

A known distribution probability of the outcome

The rules describing the outcome could be deterministic or non-deterministic. The outcome is deterministic if the rules can be described univocally and are non-deterministic. The deterministic model could be analysed as a particular case of the non-deterministic model, where the outcome has a probability of 100%. When the outcomes of the options are unknown, at least it is necessary to know the distribution probability of the possible outcomes to consider it with complete information (Slowiński, 1993).

In our example to go from point A to point B, it is difficult to make the best decision if the duration of the trips depends on the traffic, which changes with a certain distribution probability. The decision as to which is the fastest route is not trivial.

Decision-makers with a stable preference structure

The decision-maker's preference could change over time. Decision objectives for a short time horizon could differ from the long-term horizon objectives. However, it is necessary to know how they will change. The proper decision horizon is crucial for a decision. The best-selected option according to one criterion could be the worst selected decision according to the selected criteria. Following the example, in order to go from point A to point B, if the path has to be travelled twice a day, we could buy a mountain bike or a car, but if it is one single time, maybe it is better to rent a bicycle or a car, or even pay for a ride. The long-term benefits may compensate the short term benefits or vice versa.

There are two polar schools of thought regarding the existence of preferences. Traditional thought based on the assumption of existing preferences and the emerging constructive processing approach that assumes preferences are constructed and based on the task and context factors present during choice (Hoeffler and Ariely, 1999). In this work, existing preferences will be assumed.

Deciding and valuing

Two methods are broadly used to construct preference models on favoured information from a decision-maker. The first one comes from the use of mathematical decision analysis. It consists in building relational models among the variables (Roubens and Vincle, 1985). The second one comes from artificial intelligence built up via learning from examples (Michalski, 1983).

In the evaluation phase, the different options are graded to try to obtain as much good as possible, in accordance with what has already been decided as good or bad (Kahneman and Tversky, 1979). The best option or the option that fulfills all the requirements is selected as the solution of the problem. Mathematical decision analysis will be used to study the relationship between the variables.

THE DECISION PROCESS

Different stages of decision models appear in the literature. Simon (1960) simplifies the decision process into three stages. “Finding occasions for making a decision; finding a possible course of action, and choosing the course of action,” Brim (1962) mentioned six stages: identification of the problem, obtaining necessary information, production of possible solutions, evaluation of such solutions and the selection of a strategy for performance.

Dewey (1978) divided the decision stages into five: the felt difficulty, the definition of the character of difficulty, suggestion of possible solutions, evaluation of the suggestion and further observation and experimentation leading to making the decision or not.

The next generation of authors claims that these phases of the decision process could come in a different order. One of the most influential authors of this idea is Mintzberg et al. (1976). The three stages of Simon (1960) are analogous to the Mintzberg et al. (1976) phases where the identification phase is also called the Intelligence, development phase and also called design, and the last phase also called choice.

In this new view, the decision process consists of phases but these phases do not come in a predetermined order (see fig 3.1). They subdivide each phase into different activities. The identification process phase is divided into recognition and diagnosis. The development phase is divided into design and search. Finally, the selection phase is divided into screen, evaluation-choice, and authorization. From all the activities, the decision-maker can go back to a previous phase or follow different paths to make a decision.

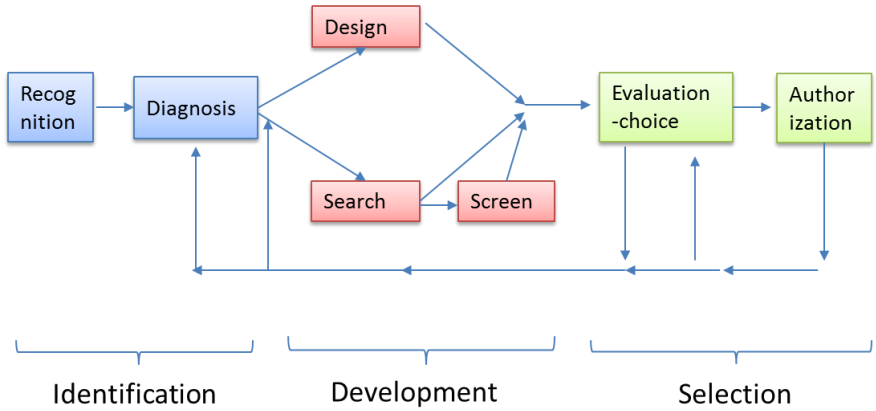

Figure 3.1: The relationship between the phases and routines of a decision process (Mintzberg et al. 1976).

Simon (1960) highlights a problem that companies spend the time and intelligence of their executives, from the longest to the shortest time and intelligence, on design, intelligence and choice. On the contrary, the decision theory has been exclusively concerned with the evaluation choice routine. Regardless of the fact that this was highlighted more than 50 years ago, a quick overview of the most important journals in the field such as the Journal of Operations Management, Management Science, Operation Research, Transportation Research, Computers and Operation Research, Manufacturing and Service Operation Management, etc. reveals that the trend of high focus on the evaluation choice routine continues.

Despite the fact that it is highly important, other phases should also be explored. In the following chapters, a framework that focuses on the first stages of the decision is presented.

DECISION-MAKING UNIT

More than one individual usually makes an industrial decision. Typically, one or a few decision-makers and several influencers. The precise mix of decision-makers' units change from one company to another, but several roles have

been identified (Stock and Zinszer, 1987). The decision-making unit could be defined as a group or teams who participate in a decision process. A single person could play more than one role, and there are many grey areas and intersections in these teams. (See Figure 3.2)

Webster and Wind (1972) came to the conclusion that only a subset of the organizational actors is involved in a decision-making situation. Furthermore, they proposed five roles. Bonoma (1982) added one role (initiator) to the five roles described previously, which results in the following list:

- Initiators: They are players who search for opportunities, unsatisfied needs or unsolved problems. They are more active at the beginning of the buying process than in the later phases.
- Deciders: They handle making the final deal of the decision. The deciders will review the information provided from the other parts of organizations, gatekeepers and initiators. They make the actual decisions and can do so due to their formal or informal authority within the organization.
- Influencers: They are those who may guide the deciders into a decision. They could be internal or external to the organization, such as consultants. They could be technical people who know the advantage or disadvantages.
- Gatekeepers: Their functions stop or allow the process to continue with their development of the process. During the decision-making there could be more than one gatekeeper along the process. They control the flux of information.
- Users: The ones who use the product, once everything is finished. Sometimes they initiate the process.
- Executor: They execute the decision made by the deciders, and sometimes they coincide as high-level officers. They have the formal responsibility for the implementation of the procedures involving the decision-making process.

Figure 3.2: Decision-Making Units source (Bayle, 2003).

MEASURING THE EXPECTED IMPACT

Once the decision-making unit has made the decision, it is necessary to measure the impact of that decision. As Peter Drucker said: "What gets measured gets managed." Then decision-makers can compare against similar decisions, or with similar companies. Unfortunately, it is difficult since severe financial measurements are confidential, and there are no standardized measuring methods, and diverse indicators are reported (Davies, 2002).

Most analyses of decision-making presume that two consequences with the same money outcome will be equally preferred. However, if a lower outcome were expected the team will be much happier that if a higher outcome were expected (Bell, 1985).

Although the expectation is an important element in the decision, they do not enter into the decision in quite the way anticipated by standard theories of business behaviour (Cyert, 1958). Then as a first step of this decision-making process, it is necessary to set boundaries to the expectation and take a look into the literature of one of the reference journals to implement improvements in decision-making using operation research techniques. A review of the recent issues of the Interfaces journal would provide a better overview of what we could expect. This journal was selected since it only presents industry cases verified by someone from the company.

The Interfaces journal's mission (Interfaces, 2015) is to publish manuscripts focusing on the practice of organizations in different areas such as operations management, information systems, strategy, and supply chain

management, and so on. It is important to highlight that one of the requirements for submission is a verification letter from the company where the work was developed.

The 18 issues of the Interfaces Journal that have been published in the last three years were reviewed. The papers that for any reason do not measure the impact achieved are omitted from this review. Such as non-quantifiable benefit or privacy issues. Tutorials, reviews or any other papers that do not measure the impact were excluded. Also, non-quantifiable savings papers were excluded. After the screening 56 papers were reviewed.

The analysed papers came from a diversity of the sectors that were reporting improvements in the decision-making process, despite Health Care followed by logistics being one of the most reported sectors with benefits from improvements from decision-making processes (see Table 3.3).

In Table 3.1 the different papers of the journal are presented. The table is divided into 4 sections, with the title, author, sector, and the measured impact reported. One of the limitations of this review is that the cost of the development and implementation is not reported in the papers reviewed.

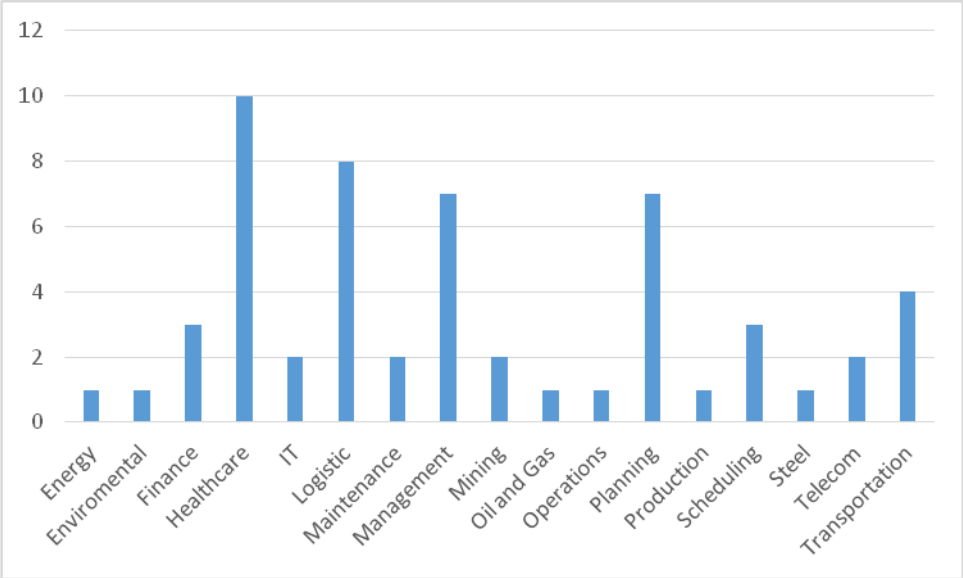

Figure 3.3: Number of papers in the different sectors of the last three years of Interfaces analysed.

It is not always easy to quantify and compare the impact of the decision-making. Some papers such as Guimaraes et al. (2014) or Sullivan & Newman, (2014 compare with the original plan. Others compare it with the previous year (Gershenfeld, 2015, Keskin et al., 2014, Diz et al., 2014) while others compare it with forecast savings (Álvarez-Socarrás et al., 2013, Mahadevan et al., 2013).

The comparison of a project impact also could be made in different companies (Humair et al., 2013) or using different types or financial indicators. Moreover, the quantification of non-monetary benefits, e.g. which is the impact on revenues of a higher services rate or increase of coverage from firefighter services (Akta et al., 2013) is always debatable and subjective.

Healthcare projects reported lives saved (Anderson et al., 2015), or monetary savings such as (Smalley et al., 2015). Despite that, both projects are from the same sector, a project that saves lives should not be compared with one that saves money. An interesting measure for which it is difficult to quantify the impact is presented in Thomas et al., (2013) where they reduce the time for bed assignment by 23 percent, and then cite a study from the American Advisory Board to estimate the contribution to the margin.

Table 3.1: Reported savings of Interfaces Journal.

Title	Author	Sector	Measured impact
Physician Scheduling for Continuity: An Application in Pediatric Intensive Care	Smalley et al., 2015	Healthcare	18.09% savings compared with hand decision.
Conjoint Analysis for Ticket Offerings at the Cleveland Indians	Gershenfeld, 2015	Operations	16% savings over the previous year.
Polio Eradicators Use Integrated Analytical Models to Make Better Decisions	Thompson et al., 2015	Healthcare	$40–$50 billion in net benefits for the countries covered.
Kidney Exchange and the Alliance for Paired Donation: Operations Research Changes the Way Kidneys Are Transplanted	Anderson et al. 2015	Healthcare	1,000 lives are already saved.
The Energy Authority Optimizes Water Routing and Hydroelectric Generation on the Columbia River	Hu et al., 2015	Energy	It is estimated that this project will reap benefits of $765–$952 million between 2011 and 2028.
Transforming Hospital Emergency Department Workflow and Patient Care	Lee et al., 2015	Healthcare	$190 million economic impact, which is a large amount of the hospital's $1.5 billion annual economic impacts.
Optimizing Network Designs for the World's Largest Broadband Project	Ferris et al., 2015	Telecom	$AUD 1.7 billion savings in unnecessary construction and design costs on this $AUD36 billion project. At the beginning of this 10-year project.
The Who-To-Follow System at Twitter: Strategy, Algorithms, and Revenue Impact	Goel et al., 2015	IT	500 million new connections. Also, more than 15% of Twitter's active users.
Decision Support System for PETROBRAS Ship Scheduling	Diz et al., 2014	Transportation	This led to a reduction of approximately 7.5 % in the company's operational costs for long-haul transport

Title	Author	Area	Improvement
Optimizing Transportation by Inventory Routing and Workload Balancing: Optimizing Daily Dray Operations Across an Intermodal Freight Network	Sun et al., 2014	Transportation	Loaded ratio and driver utilization have improved by 20% since the original implementation.
Multidepot Distribution Planning at Logistics Service Provider Nabuurs B.V	Demir et al., 2014	Transportation	The proactive planning approach reduces costs by 14.77 %.
Annual Distribution Budget in the Beverage Industry: A Case Study	Guimarães et al., 2014	Management	Making it 6.8 percent less than Unicer's original plan.
Matching Supply and Demand: Delayed Two-Phase Distribution at Yedioth Group—Models, Algorithms, and Information Technology	Avrahami et al., 2014	IT	Average cost savings of 7.55% from implementing the model.
SPRINT: Optimization of Staff Management for Desk Customer Relations Services at Hera	Vigo et al., 2014	Management	A reduction of 3% in FTE desk staff employees, in conjunction with a demand increase of more than 25%, maintained a better level of service than that of its competitors.
An Integrated Load-Planning Algorithm for Outbound Logistics at Webb Wheel	Keskin et al., 2014	Transportation	Since implementing the load-planning algorithm, WW has achieved cost savings of 4.4% over its previous load-planning process.
Relieving Pressure: Optimizing Water Distribution Pressure Management at Valley of the Moon Water District	Wasserkrug et al., 2014	Maintenance	Reduced the number of leaks and bursts by 16% compared to the previous year and by 19% compared to the average of the previous three years.

Title	Author	Area	Improvement
Analytics for Power Grid Distribution Reliability in New York City	Rudin et al., 2014	Maintenance	The reduction in risk for manholes with vented covers of 50 %, and a reduction of the risk of the surrounding structures by 20 %.
Business Analytics Assists Transitioning Traditional Medicine to Telemedicine at Virtual Radiologic	Körpeoğlu et al., 2014	Healthcare	System wide the operating costs after adjusting for demand growth has in the aggregate been reduced by 4% to 5%.
Scotsburn Dairy Group Uses a Hierarchical Production Scheduling and Inventory Management System to Control Its Ice Cream Production	Eldon et al., 2014	Scheduling	Convert production to units, they had a 3% increase in units/hr from 2010 to 2011.
Hierarchical Decomposition Approach for Crude Oil Scheduling: A SINOPEC Case	Chen et al., 2014	Scheduling	Comparison of schedules shows that the number of changeovers of pipelines, tanks, and CDUs was reduced by 19.05 % ($30 million cost savings).
Global Sourcing Approach to Improve Cash Flow of Agribusiness Companies in Brazil	Hamad & Gualda, 2014	Management	The methodology generated processes that helped one company reduce its logistic cash outflow by 49 % and its logistics costs by $10 million.
Cyclic Consumption and Replenishment Decisions for Vendor-Managed Inventory of Multisourced Parts in Dell's Supply Chain	Katariya et al., 2014	Management	Reduced the total error in meeting PSAs from 23% to 12%, improve fill rate from 77.3 % to 100 %, and reduced inventory by 6.4%.
Extraction and Backfill Scheduling in a Complex Underground Mine	Sullivan & Newman, 2014	Mining	This has resulted in c.120kt at 13 % ZnEq of extra ore now being included in the revised LOM Schedule.

Title	Author	Area	Improvement
Medium-Term Rail Scheduling for an Iron Ore Mining Company	Singh et al., 2014	Mining	89 kilotonnes more in five months of 2010, and 416 kilotonnes more than the manual plan for all of 2011. Therefore, 505 kilotonnes of additional iron ($114 million of additional income).
Economically Efficient Standards to Protect the Netherlands Against Flooding	Eijgenraam et al., 2014	Environmental	Approximately 7.8 billion euros in cost savings.
Operations Research Transforms Baosteel's Operations	Tang et al., 2014	Steel	Provided an annual economic profit of 20 million, which represents a 17% improvement.
Optimizing Chevron's Refineries	Kutz et al., 2014	Oil and Gas	The value that these efforts bring to Chevron now approaches $1 billion annually.
Dell's Channel Transformation: Leveraging Operations Research to Unleash Potential Across the Value Chain	Martin, et al., 2014	Management	The OR solutions have delivered an impact of $140 million by reducing markdown expenditures, improving online conversion rates, increasing ocean shipments, and enhancing customer satisfaction.
Kroger Uses Simulation-Optimization to Improve Pharmacy Inventory Management	Zhang et al., 2014	Management	An increase in revenue of $80 million per year, a reduction in inventory of $120 million, and a reduction in labour cost of $10 million per year.
Supply Chain Scenario Modeler: A Holistic Executive Decision Support Solution	Katircioglu et al., 2014	Management	Since this effort began in 2009, McKesson Pharmaceutical division has reduced its committed capital by more than $1 billion.

Title	Author	Area	Improvement
Redesigning Midday Meal Logistics for the Akshaya Patra Foundation: OR at Work in Feeding Hungry School Children	Mahadevan et al., 2013	Logistic	The annual cost savings are US$75,000, which would add 2,400 more children to the programme. When the program is implemented, it is estimated that the annual cost savings will be about US$1.96 million.
Optimization Models for Production Planning in LG Display	Chang & Chung, 2013	Planning	MRM optimization outperforms the MRM heuristic by an average of 31%. All the reductions were estimated as $50 million annually for the two sites.
A Specialty Steel Bar Company Uses Analytics to Determine Available-to-Promise Dates	Pajouh et al., 2013	Planning	A higher-margin sales generate over $300,000 per year. Moreover, it saves $200,000 per year by reducing yield loss throughout the company and its labour-cost savings to be $85,000 per year.
Incorporating Stochastic Lead Times Into the Guaranteed Service Model of Safety Stock Optimization	Humair et al., 2013	Planning	Savings of $100 million by P&G, $50 million by HP, and $20 million by Kraft Foods; a 26% inventory reduction by Boston Scientific; and a 25% finished goods inventory reduction by Black & Decker.
Automated Bed Assignments in a Complex and Dynamic Hospital Environment	Thomas et al., 2013	Healthcare	A 23% reduction in the average time from bed request to bed assigned. According to the American Advisory Board, an average 300-bed hospital with poor patient flow would add $10 million to the hospital's contribution margin if it increases its bed utilization by 27% (Luminosity Health 2012).

Title	Author	Area	Improvement
Practice Summary: Enhancing Forecasting and Capacity Planning Capabilities in a Telecommunications Company	Álvarez-Socarrás et al., 2013	Telecom	Avantel improved its demand forecasting and reduced its annual capital investment by almost 10%, while significantly reducing its operating expenses.
Automatic Dwelling Segmentation of the Buenos Aires Province for the 2010 Argentinian Census	Bonomo et al., 2013	Planning	A reduction of 25 employees working full time for 30 days.
A Decision-Making Tool for a Regional Network of Clinical Laboratories	Andrade-Pineda et al., 2013	Healthcare	Reducing outsourcing costs above 15% in the first six months.
Trane/Ingersoll Rand Combines Lean and Operations Research Tools to Redesign Feeder Manufacturing Operations	Jensen et al., 2013	Production	A 13% throughput improvement, 50% cycle-time reduction, and higher cell efficiency that led to recurring savings of more than $700,000 per year.
Medcenter Container Terminal SpA Uses Simulation in Housekeeping Operations	Legato et al., 2013	Healthcare	A reduction of in one week of the additional cost of housekeeping operations of about € 10,000.
Supply Chain Optimization and Planning in Heracles General Cement Company	Dikos & Spyropoulou, 2013	Logistic	There was a reduction of Heracles' total logistical costs by 37% between 2006 and 2009.
Optimizing Fire Station Locations for the Istanbul Metropolitan Municipality	Akta et al., 2013	Planning	27.3% of savings. The scenario implemented increases the city's fire station coverage from 58.6 % to 85.9 %, based on a five-minute response time, with an implementation plan that spans three years.

CPEL Redesigns Its Land Express Network	Zhang et al., 2013	Logistic	Savings of more than 20 % in annual operations costs.
Title	**Author**	**Area**	**Improvement**
Mathematical Programming Guides Air-Ambulance Routing at Orange	Carnes et al., 2013	Healthcare	It is projected that the optimized plans would yield savings of approximately 16.5 %.
Embotelladoras ARCA Uses Operations Research to Improve Territory Design Plans	López-Pérez & Ríos-Mercado, 2013	Logistic	A 15 % reduction from the number of routes. The investment savings for trucks was 8 % of the entire fleet. The company estimates a 3 % sales increase as a direct benefit of the new territory alignment.
Evaluation of Transportation Practices in the California Cut Flower Industry	Nguyen et al., 2013	Logistic	A 35 % system-wide transportation cost decrease of $20 million per year is estimated if all California cut flower growers participate in the consolidation centre.
Optimal Routing and Assignment of Consultants for Energy Education, Inc.	Yu & Hoff, 2013	Logistic	In a recent 12-week period, the results of the research reduced EEI costs by 24 % and provided several qualitative benefits.
HP Enterprise Services Uses Optimization for Resource Planning	Santos et al., 2013	Planning	Since its deployment in the Bangalore operation, the RP tool has enabled resource utilization rates of 90–95 %, compared with utilization rates of 75–80% before its implementation.
Routing and Scheduling of Cross-Town Drayage Operations at J.B. Hunt Transport	Pazour et al., 2013	Scheduling	Hunt has documented the annualized cost savings of the cross-town heuristic implementation at $581,000.

IBM Blends Heuristics and Optimization to Plan Its Semiconductor Supply Chain	Degbotse et al., 2013	Planning	On-time deliveries to commit date increased by 15%. Asset utilization is increased by 2–4% of costs. Inventory decreased by 25–30 %.
Title	**Author**	**Area**	**Improvement**
Optimizing Capital Investment Decisions at Intel Corporation	Kempf et al., 2013	Finance	The velocity program and the framework provided Intel with hundreds of millions of dollars in cost savings and at least $2 billion in revenue upside during a recent period of global economic crisis.
Hewlett-Packard: Delivering Profitable Growth for HPDirect.com Using Operations Research	Tandon et al., 2013	Finance	The integration of these solutions into HP's marketing planning and warehouse operations processes has helped to generate an additional $117 million in revenue for HPDirect.com.
Carlson Rezidor Hotel Group Maximizes Revenue Through Improved Demand Management and Price Optimization	Pekgün et al., 2013	Finance	To date, compliant hotels have increased revenue by more than $16 million annually. CRHG anticipates that the worldwide incremental revenue from this solution will exceed $30 million annually.
Optimizing Ship Routing to Maximize Fleet Revenue at Danaos	Varelas et al., 2013	Logistic	Danaos Corporation concluded that its 2011 incremental revenues from using ORISMA were $1.3 million from timesaving and $3.2 million from fuel savings. Danaos' profitability increased by 7–10 % annually.
Advancing Public Health and Medical Preparedness with Operations Research	Lee et al., 2013	Healthcare	The rapid dispensing achieved by improved throughput can translate to as many as 40 % fewer casualties (deaths and hospitalizations) and hundreds of millions of dollars in potential savings.

Supply Chain–Wide Optimization at TNT Express	Fleuren et al., 2013	Logistic	Total net accumulated savings were 132 million euros and the CO2 emissions reduction was 228 million kilograms.

The savings of governmental actions presented a bigger impact than the companies' papers. For example, the environmental project (Eijgenraam et al., 2014) reported the highest savings of 7.8 billion euros. Some projects are implemented in multiple companies (Humair et al., 2013) or multiple years (Hu et al., 2015), meanwhile others are single shots projects (Ferris et al. 2015, Bunomo et al. 2013).

A project could have a significant impact on the increase in production of 3% (Eldon et al., 2014), two digit savings in the already optimized company are difficult to find. The average of the projects that report savings are 15.95% with a standard deviation of 9.06, a maximum of 37% and a minimum of 3%.

The main purpose of this review is for it to be used as a boundary of the expected impact of the good decision and avoid disappointment in the decision-makers caused by unrealistic expectations.

THE BENEFITS COST ANALYSIS

This is one of the techniques used for evaluating an option by comparing the benefits with the cost of the option. One of the objectives of benefit-cost analysis (BCA) is to make business decisions evaluating the merit of the options.

Benefits

The estimation of the benefits is an extremely important element of the decision-making process. Benefits are obtained after costs are incurred. Then they always have to forecast or be intuited, and many times too optimistically since the benefits could be severely affected by implementation problems.

As discussed previously, it is complicated to assign monetary values to lives saved, or firefighters' coverage, or ecological and social impact. It is important to review similar projects of the sector, or projects that used similar techniques to get an idea of the benefits, to set appropriate boundaries to the expectation of the benefits. The results of the benefits of review could be used to get an idea of what is likely to be achievable and what is not.

Costs

The cost of a decision could be divided into implementation cost and recurrent cost. The main costs to take into consideration are the cost of developing new decision tools (hardware, software development, software licences, integration with existing software organizational change cost, migration from previous version and initial training).

Turney (2000) emphasises that there are a large number of costs that are usually ignored and could affect the result. For example, the cost of intervention where the manufacturing process is affected by its normal process, the cost of unwanted achievements, the cost of computation, the cost of testing several cases, human-computer interaction cost, and the cost of program instability. Recurrent costs such as operation expenses, maintenance and security cost, should be taken into consideration. Other indirect costs such as the cost of resilience to change from the organization are difficult to quantify (Posnett and Jan, 1996).

Evaluation

The general acceptance criteria are when benefits outweigh the costs; the decision is accepted. Despite BCA being a valuable tool for decision-making, it forces decision makers to provide quantitative data to support their arguments, assigning monetary values to all benefits and costs. Discounting BCA is an advanced version of BCA that converts all benefits and costs into their value in the present. However, the results are very sensitive to the choice of the discount rate. (Boardman, 2010)

As all these costs should have been covered by the benefits of a new decision system, when the scope of the decision-making process was decided, bounding the expectations regarding the benefits should be done to avoid the acceptance of options where costs are bigger than benefits. Moreover, keep exploring other alternatives, and the also the alternative of not doing anything.

Sometimes savings of around 3 % (Eldon et al., 2014) are enough to cover all the expenses. However, if savings higher than 50% are necessary maybe other options should be explored since the average of the savings reported (15.9%) is far from the savings needed to cover the costs, even though some exceptional cases are reported. The decision- maker should proceed with caution, explore more options and not rely too much on luck.

CONCLUSION

This chapter has been dedicated to the decision theory. It started with the basic decision theory, and the different points of views from the different disciplines, and the two types of decision theory: normative and descriptive

All the characteristics of a decision with complete information have been enumerated. After the characteristics, the decision process has been described, followed by the decision-making unit. Then, it is suggested knowing the expected impact of a decision compared with the literature. Finally, the benefits cost analysis has been analysed.

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SECTION 2. SURVEY AND MANUFACTURING CASE STUDIES.

Having presented a general introduction to the thesis in section 1, section 2 starts with an exploration of the integration of the decision-making process. After that a car assembly line is analysed, in chapter 5, where a tactical and operational decision model based on MILP is presented and in the next chapter the functional area of sequencing is added to the model. Then a bigger problem is solved using heuristic ant colony optimization. Finally, an aeronautical manufacturer using simulation will be analysed.

Chapter 4: The integration of the decision making process.

MOTIVATION

After a discussion of the decision theory, and which are the steps of a decision making process, the next step of this research was to learn about the decision making in companies. This chapter investigate the decision making process of a production planning at shop level in different companies.

In order to answer the fourth research question: Answering the fourth research question of this thesis: *What is the managerial theory and implication behind the decision models that are currently being used?* It is necessary to start with the understanding of the industry and organization. As it was anticipated in the previous chapter, a survey and interviews were used in this part of the research.

The internal and the external integration of the supply chain have become essential for many industries. However, according to a global survey of the supply chain: companies have put so much attention about supply chain integration that they have forgotten about the internal integration. The literature about internal integration defines it as a key element in the performance of the company and the entire supply chain. Besides there is a problem of misconception of their own level of internal integration. Companies could trust to be integrated based in misconceptions or incomplete information. This could lead to miss valuable synergies that could reduce the overall cost.

Companies have put a lot of attention to integrate the supply chain, companies are using their resources to persuade the integration with their supplier and client but they have forgotten the internal integration.

Using a survey among production planning practitioners, it was investigated the decision-making process of the internal planning, operation scheduling and inventory control at the shop level. The degree of integration was analysed using the decision-making process and other drivers suggested in other studies. One of the findings was that many companies have a misalignment in the implementation of their philosophies. Consequently, the possibility of enhance was lost by silo decisions and managers should implement the internal integration practices in the different areas of the production planning.

INTRODUCTION

There is substantial scientific and non-scientific literature on supply chain collaboration and management and supply chain integration. The literature highlights the advantages of this integration; successful cases are reported in the different industries, such as manufacturing and automotive (Landry, 1998; Akintoye et al., 2009). Some researchers, such as de Souza and Ledur (2011), have empirically confirmed a positive relationship between supply chain management and operational performance; they assume that creating alliances with members of the same chain improves its competitive advantage, reflected by a superior performance of all members.

Unexpectedly, the results obtained in the global supply chain survey highlight that "supply chain managers often perceive that their companies are more accomplished in external integration efforts than they are in internal efforts" (Poirier et al., 2008).

Integration is a term used in several fields and one of the general meanings is "Process of attaining close and seamless coordination between several departments, groups, organizations, systems, etc. although they are not compounded into an entity"

Integration could be achieved through interaction or communication activities with the functional departments. Other literature characterizes it as an act that stimulates teamwork, the share of resources and collective goals.

Topolsek et al. (2009) highlights the importance of internal integration as a prerequisite for successful external integration. Each company must first make sure it achieves a high level of internal integration and then integrate itself into a competitive company of the supply chain.

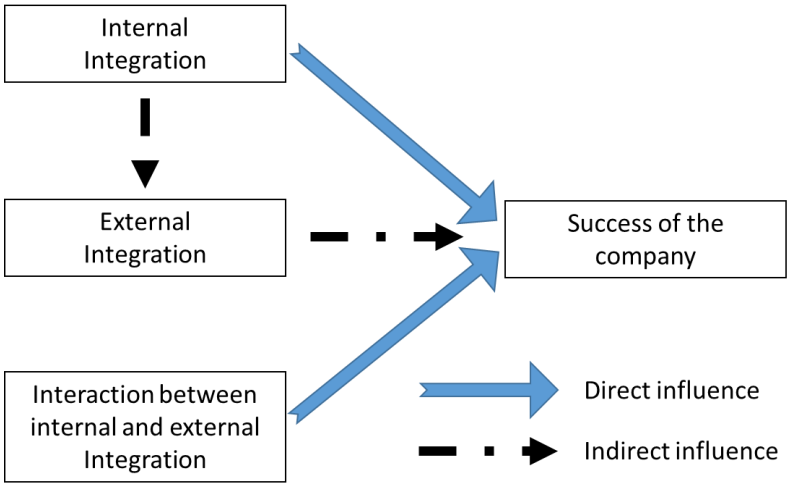

Figure 4.1: Influences of the internal and external integration adapted from (Topolsek et al 2009).

Lee (2002) emphasises that information shared through the use of IT and tight coordination allow us to control the supply chain efficiently. All this is facilitated by the use of the Internet. Despite the news and scientific papers about the use of IT decision systems in enterprise that control each area of companies and all the integration theories, we wish to investigate the current degree of integration of the different departments at shop level.

Since there is a lack of information about specific types of integration in the production planning area (Williams et al., 2013), we wish to research into the integration of production planning through a survey in order to know the current degree of integration in the industry. An increase in the awareness of key structural decisions in internal integration facilitates external integration with customers and suppliers (Langowitz, 1988; Millson et al., 1992)

The aim of this study is to measure the internal integration in the production planning area. Using a survey among production planning professionals from different industrial sectors, we evaluate the degree of internal integration and information-sharing in the different parts of the company. Later, we evaluate the effect of the performance of an integrated decision-making process.

Internal integration

Internal integration is the core competence derived from linking internal activities to best support the (internal or external) client at the lowest cost. This total cost concept requires that all the components be managed holistically, and they be taken into consideration (Bowersox, 2002). One example is an increase in the logistic cost by using air transportation, justified by the decrease in the inventory cost, resulting in an overall lower cost.

Souder and Sherman (1993) defined the goal of integration as “a state of high-level values, common objectives, and collaborative values.” and that

traditional silo departments should be eliminated to enhance the coordination among the areas.

Internal integration is the missing link in establishing how visibility affects the responsiveness of the supply chain. Accurate, timely, and complete information is not enough if there is a lack of internal integration (Williams et al., 2013).

Narasimhan and Kim (2001) place great emphasis on the use of strategies for information system utilization to persuade integration. Zailani and Premkumar (2005) found that traditional managers are concerned about their functions inside their departments and about bureaucratic tasks with a prejudice against integration.

Information sharing

Information sharing refers to the exchange of information among the interested users of this information. There is a discussion on the use of IT in different areas such as inventory, where Mishra et al. (2013) found evidence that firms' IT capabilities have significant positive effects on their inventory efficiency. Lee (1992) warns us regarding the use of inefficient information systems, which could cause more losses than benefits. For example, when the retrieval and input of information is tedious, laborious, and many manual processes exist. Also, when the information is not accurate or is outdated.

Another problem is data integration and communication among the systems. For example, a company using various types of software, and programs that do not understand each other highlights the importance of the IT system in integration (Lee, 2002)

Heeks (2002) analyses several failures of information technology implementations, giving the design gap as one of the reasons for failure (the mismatch between IS and current local user needs).

Main integration drivers and measurements

Pagell (2004) developed a model of the drivers for internal integration; he claims that a better integration fosters the strength and competencies of the firm. He highlights the business structure and the measurements, and rewards cross-functional teams, job rotations, top management support, information technology, and communications as drivers for performance.

Frohlich and Westbrook (2001) measure the integration of the supply chain using arcs of integration, and eleven years later (Schoenherr and Swink, 2012),

continue this study recognizing internal integration as the strength of the relationship between outward arcs and other performance indicators.

OBJECTIVE

As mentioned in the introduction, proper internal and external integration are beneficial for the performance of the company and the entire supply chain. However, despite the literature emphasising internal integration for a successful external integration, companies have decreased their focus on internal integration (Poirier et al., 2008).

Integration should occur between internal and external functions. Inside the organization, the different departments should work together. The focus is on the internal planning process. In particular, the survey investigated the decision-making processes related to internal planning, operations scheduling, and production activity control at shop floor level (be it a job shop/parts manufacturing or assembly department).

Several studies have revealed that some companies fail, despite the fact that the different departments are achieving their objectives, because of a "silo view" and make decisions in complete isolation without considering other departments' opinions (Capasso and Dagnino, 2012). We want to know if the decision-makers in the different stages, share the same department or person.

A study of the complexity of the organizations performed by Malhotra and Mackelprang (2012) warns us that the complexity of organization is continually increasing. The issue that obtains an advantage from an integrated supply chain is more complex than the research expected.

One of the keystones of this article is the misalignment between *perceived* integration and *real* integration. For example, the decision-making process of a functional department should take into consideration variables and constraints of another functional department to be integrated.

The objective of this paper is to measure the degree of integration of the company through an analysis of the decision-making process, the business structure, the information sharing, and the company's own perception of integration. Moreover, we will analyse their impact on the performance.

Proposition 1. Higher perceived performance should be the result of the perceived integration.

Proposition 2. It is possible to measure the misalignment between the perception of the integration of the supply chain and the level of integration calculated using the drivers proposed by Pagell (2004).

Proposition 3. A higher level system of information sharing increases the internal integration of the company.

Proposition 4: Group orientation could better explain the relationship with the production planning performance process.

METHODOLOGY

The methodology used to address the hypothesis presented in this research was a survey, following the steps proposed by Forza (2002), which could be summarized as follows: link to the theoretical level, design, pilot-test, collect data for theory testing, analyse the data, and conclude.

One definition of *internal integration* is proposed by Zhao (2011) as "the degree to which a firm can structure its organizational practices, procedures and behaviours into a collaborative, synchronized and manageable process." Also, it includes the use of data and information systems, real-time data, integration of the different activities, and cross-functional cooperation. Finally, internal integration identifies that the company should not act as a functional silo but as an integrated process.

From the main drivers that are proposed by Pagell (2004), we focus on the structure, the measurements and rewards, job rotations, information technology, and communications as drivers for performance in order to measure the degree of integration of production planning and to get further knowledge of the integration of the production, inventory and replenishment schedule.

Past studies (Swamidass and Newell, 1987) have described the difficulty to obtain financial measurement, despite the additional difficulty to isolate the plant from the other departments and business units. Although it is preferable to obtain objective measurements, these are difficult to compare in different sectors, and production structures, so we decided to ask for perceptual measurements of managerial performance.

To study the level of internal integration, we decided to give questionnaires to production planning specialists regarding their perception of the production planning process and its level of integration.

Questionnaire design

For data collection, a semi-structured questionnaire was developed that contained open-ended and closed-ended questions. The questionnaire survey looks at the production planning specialists in different plants (we define *production plant* as the unit of analysis in order to make a better comparison for different-size plants) and, in some cases, compares the results among plants of the same company.

We ran a pre-test using a company with several plants; the comments received from the pre-tester helped us modify the scales and questions.

The questionnaire, accompanied by a cover letter, was sent by two methods: e-mail and LinkedIn. In the first method, we emailed different companies and then asked them to be forwarded to the head of production planning. The second and most successful method was through LinkedIn where we looked for groups of professional production planning practitioners and found mainly two groups, APICS and POMS. We sent a small personal message that invited them to participate in the study. We obtained 72 responses, 56 valid entries, and 16 invalid entries since they did not complete the questionnaire.

This research was considered exploratory. The questionnaire was designed to be answered in 15 to 20 minutes. It consisted of 23 questions, with a majority of multiple-choice questions and Likert scales, and with 4 long open questions.

Three versions of the questionnaire (English, Italian, and Spanish) were produced to facilitate the answers of the respondents, especially for the open questions. The web-based survey tool Typeform© was used. Some scales are inspired from Koste et al. (2004) to capture some flexibility attributes. To avoid problems with confidentiality issues, and increase the response rate, we did not ask for any personal data or financial information of the company and all the data was treated anonymously.

Respondents were asked to describe their decision-making and planning algorithms or software that they use, with respect to the following:

- Characteristics of their production facility (size, workers, products, and clients)
- Degree of perceived integration and performance
- Decision drivers
- Business structure (job rotation, goals, philosophy)
- Information sharing (IT, software, inventory tracking)
- Decision-making process at shop level (input, variables and constraints taken into account)

DATA ANALYSIS

Before starting with the analysis, a data cleaning was performed. We eliminated 16 incomplete answers and an open question since the majority of the answers were extremely basic. Data analyses were undertaken using functional language and environment to statistics STATA© and R© 3.0.2. with RStudio v0.98.

Characteristics of their production facility

In this part, the sample is characterized. Multiple questions are used and the descriptive statistics are presented in Table 4.1. Table 4.1 contains the

composition of the sample based on the size of the production capacity, sectors, and the production structure.

The sample is made up of different sectors with an emphasis on the Automotive and car component sector; companies with more than 50 employees in the production facility represent more than 50% of the sampling. Finally, the production structure is more represented by the Job shop but all the production structure are represented with at least 17%.

Table 4.1: Sample statistics.

Employees	Frequency	Percent	ValidPercent	CumulativePercent
< 010 employees	14	25,0	25,0	25,0
< 050 employees	11	19,0	19,0	44,0
< 250 employees	20	35,0	35,0	80,0
> 250 employees	11	19,0	19,0	100,0
Total	56	100,0	100,0	
Sector				
	Frequency	Percent	Valid Percent	Cumulative Percent
Automotive / Components	18	32,0	32,0	32,0
Defence	5	8,0	8,0	41,1
Electric	3	5,0	5,0	46,0
Electronics	8	14,0	14,0	60,0
Energy	3	5,0	5,0	66,1
Food and Beverage	7	12,0	12,0	78,0
Manufacturing	3	5,0	5,0	83,0
Personal Care	5	8,0	8,0	92,0
Telecom	4	7,0	7,0	100,0
Total	56	100,0	100,0	
Structure				
	Frequency	Percent	Valid Percent	Cumulative Percent
Assembly line / Repetitive (semi continuous, high volume)	14	25,0	25,0	25,0
Batch processing (moderate volume and variety)	15	26,0	26,0	51,0
Job shop (small lots, low volume, general equipment)	17	30,0	30,0	82,0
Projects (Non routine jobs)	10	17,0	17,0	100,0
Total	56	100,0	100,0	

Degree of perceived integration and performance

We use a Likert scale, to measure the perceived degree of internal integration, and performance of the production planning (see Table 4.2), where 1 means non-integrated or poor performance and 5 is fully integrated or good performance respectively. Where nobody perceives their performance as a poor performance, and in general performs highly, the perceived integration has a larger standard deviation and range.

Table 4.2: Perceived integration and performance.

	Mean	Std Dev	Min	Max
Perceived integration	3.23	1.24	1	5
Perceived performance	3.63	0.84	2	5

To test our first proposition that higher perceived performance should be the result of the perceived integration, we made a regression analysis to explain the behaviour of the performance due to the integration (see Table 4.3). The perceived integration in not statistically significant at the 0.05 level, although the coefficient is positive, which indicates that higher integration is related to higher performance. For our proposition 1, we could assume that they are correlated, but the integration is not enough to explain the performance.

Table 4.3: Regression analysis.

Perceived performance	Coefficients	Std. Err.	t	P>|t|
Perceived integration	0.08	0.09	0.89	0.38
Constants	3.36	0.32	10.54	0.00

Decision drivers

Business structure. We coded the multiple option questions scale in line with the following equivalences- Job rotation was assigned a zero and allowed up to 5 points if it was strongly advised. It is interesting to note that only two respondents answered that it was strongly recommended. Despite many rotation ideas, it is not widely implemented in the companies. For the structure, we assigned 5 to the assembly line and 1 to the project base. For the number of variants, 5 was for a single product and 1 when each product was different.

For the philosophy, we assigned 0, 1, or 2 Since LEAN, JIT, TOC persuades the integration, we assigned two points if they mentioned it. 1 point was awarded for any other and if there was no philosophy or they did not know it, 0 points.

For Goals, if they were based on a single performance we assigned the minimum of 1, and if they included more areas we rated the entire company up to 5. For the decision-making, we assigned two points if the decision of the three areas was performed by the same department but only one if only 2 shared the department, and zero otherwise.

Information sharing. For the use of IT/Optimization software, we assigned 0, 1 or 2 points according to the given software, to measure how efficient one of the most common used IT softwares is in production planning. We measured the level of integration of the inventory management system by assigning 5 points, if it was done automatically, 3 points if it was done manually, 2 points if it was done for some products and 1 point if it was not done.

Decision-making process. The most difficult part to incorporate into the integration index was the open question because the transformation from text to a numeric value is always subjective. The open question asked about the schedule, replenishment, inventory, and exception management. We assigned one point to the index for each part of the description of the decision-making process that took into consideration something that was not from this area (e.g., for replenishment, if they provided responses on the constraints related to scheduling or production, they were given an integration point.

The maximum points assigned were 5. We limited the assignment to 5 mentions per type of answer, since a long answer has more chances of mentioning other items as the size of the answers varies a lot. Answers shorter that 100 characters were discarded (10 were eliminated). The rest of the scales were rated on a five-point Likert scale.

In Figure 4.2, the scree plot of the factor analysis is displayed. To underline the factors that explain these results, and start to test our second proposition, we performed an exploratory factor analysis. The eigenvalues of the first 4 factors were 4.17, 1.49, 0.62 and 0.52. We decided to accept the first two components using the typical threshold of 1. The Cronbach alpha test resulted in an average inter-item covariance of 0.30 and a reliability coefficient of 0.76.

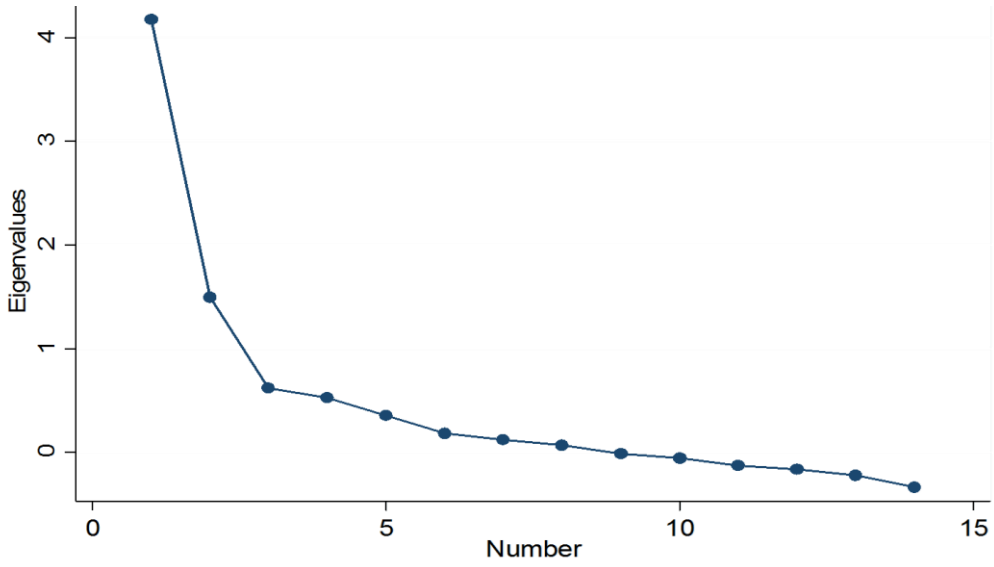

Figure 4.2: Screen plot of eigenvalues after factor.

To maximize the square of the variance of the two factors that we will retain, we will use a Varimax rotation. We will rename Factor 1 as an integration factor, and Factor 2 as a complexity factor.

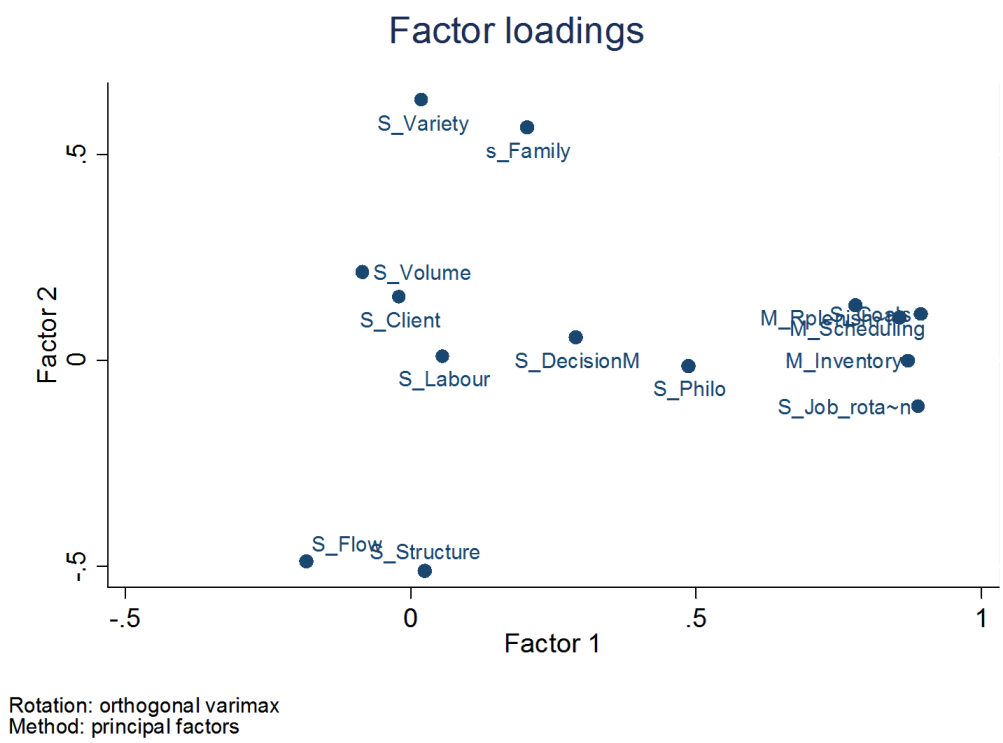

Figure 4.3:The plot of the factor loadings after Varimax rotation.

Using the two factors obtained in the previous step (complexity and integration), the normalized value of the IT score, and the inventory integration of the IT, we explain the perceived integration (see Table 4.4). Let us focus on the only predictors that are statistically significant at 95% level, which are the ones related to IT. Also, the other predictor related to information sharing is important for the result. It is interesting that the IT and the inventory integration explain the perceived integration instead of the indirect measurement of integration and the complexity. The use of an information sharing system makes the companies believe that they are integrated without evaluating the others factors. For the second proposition, we could measure the perceived integration using the different drivers described by Pagell (2004).

Table 4.4: Perceived integration factors.

Perceived integration	Coefficients	Std. Err.	t	P>|t|
Integration	0.13	0.12	1.12	0.27
Complexity	0.06	0.13	0.45	0.65
Score of IT	0.35	0.12	5.24	0.00
Inventory Integration	0.19	0.10	1.92	0.07
Constants	0.00	0.10	0.03	0.98

For the third proposition, we want to know if a higher level shared information system could increase the internal integration. We assume that one of the main influencers in perception of integration was the use of information systems (IS) or information technologies (IT). We ran a correlation analysis between these two variables and found a strong correlation between the use of the information sharing and the IT system (See Table 5). However, many authors such as (Gunasekaran and Ngai, 2004) have stated that IS by itself it is not enough to guarantee the integral integration of the supply chain. However, it is impossible to have it without an IS system. We could therefore say that IT is necessary but not sufficient.

Table 4.5: Correlation between Integration and IT.

	Perceived integration	Information Sharing	System Inventory Int
Perceived integration	1.00		
System InvInt	0.27	1.00	
Information Sharing	0.71	0.13	1.00

Clusters use multiple predictors to explain the relationship between variables. To test our fourth proposition, which according to Kaufmann and Carter (2006) is related to performance, the data were cluster-analysed using principal component analysis. We used the k-mean clustering technique using

a Euclidean distance and the number of groups selected was 4, despite the proposed limit by Lehman (1979) of between n/30 and n/60, since 2 groups oversimplify the explanation and a bigger group gives us few elements in each group.

The clusters were first tested using ANOVA to test the differences in the defining variables among the cluster. Secondly, a Scheffe pairwise comparison of the mean was performed to determine which pairs were significantly different. The results are presented in Table 4.6. which presents the cluster means and the standard deviation and the relative ranking of the emphasis of the characteristic among the group. The numbers in the parentheses show the group number from which this group was significantly different to the other groups.

Table 4.6: ANOVA post hoc test.

		Cluster			F=Value
	1	**2**	**3**	**4**	(p=probability)
Perceived Performance	0.89	-0.56	-1.10	0.50	15 (0)
Pairwise	(2,3)	(1,4)	(1,4)	(2,3)	
Std. Dev.	0.31	0.79	0.61	0.79	
Rank	1	3	5	3	
Perceived integration	-0.39	-0.75	-0.08	0.81	16.09 (0)
Pairwise	(4)	(4)	(-)	(1,2)	
Std. Dev.	0.94	0.83	0.41	0.62	
Rank	4	5	3	2	
System InventoryInt	-0.40	-0.88	-0.04	-0.94	34.42 (0)
Pairwise	(4)	(3,4)	(2,4)	(1,2,3)	
Std. Dev.	0.52	0.48	0.76	0.64	
Rank	5	6	2	6	
System Sharing	-1.03	0.33	-1.16	0.44	12.3 (0)
Pairwise	(2,4)	(1,3)	(2,4)	(1,3)	
Std. Dev.	0.74	0.81	0.82	0.77	
Rank	6	1	6	4	
Measure complexity	-0.22	-0.65	-0.52	0.85	17.7 (0)
Pairwise	(4)	(4)	(4)	(1,2,3)	
Std. Dev.	0.82	0.22	0.23	0.97	
Rank	3	4	4	1	
Measure integration	0.75	-0.28	0.24	-0.91	3.96 (0.013)
Pairwise	(2,4)	(1)	(-)	(1)	
Std. Dev.	0.72	0.85	0.55	0.68	
Rank	2	2	1	5	
No. Firms	8	20	6	21	
Percent	15%	36%	11%	38%	

RESULTS AND DISCUSSION

The four clusters are named according to their characteristic:

Cluster 1: Highly integrated

The first cluster accounts for the remaining 15% with 8 units. They perceived themselves as high-performance companies. The reason for that is that they also achieve a high measure of integration and a medium complexity. They do not claim to have a super integrated information sharing system, or everything automated, but they manage to overcome these difficulties with other practices such as staff rotation, or the philosophies used.

Cluster 2: High IT

The second cluster accounts for 36% of the firms, with 20 units. They use complex IT systems to result in a highly integrated firm. However, they perceived themselves with a low-medium performance, and one of the explanations is that they lack communication among their IT systems. Also, they recognize this problem because they do not perceive themselves as very integrated.

Cluster 3: Bad performers

This cluster of 6 units is the least numerous of the three clusters with 11% of the population. They are highly integrated but are not performing well since they have the lowest information sharing. They only use some inventory tracking but the information systems are not spread among the company and the decision-makers take the decision in isolation, and in the analysis of the open questions they hardly mention any item that is not typical for this area.

Cluster 4: Misaligned

This cluster of 21 units is the most numerous of the three clusters with 38% of the population. This is the most interesting cluster since they have a high complexity, and the majority claim a high degree of integration, but they achieve a low score for integration. They do not encourage the main drivers of the integration, such as staff rotation. They give incentives mainly in personal performance and in the open questions do not mention any concept of other areas. They perceive a medium performance of the production planning process. This opens an interesting question about if there is also a misperception of the performance or they are achieving averagely.

Unfortunately, with the information collected we cannot triangulate the information to answer this question.

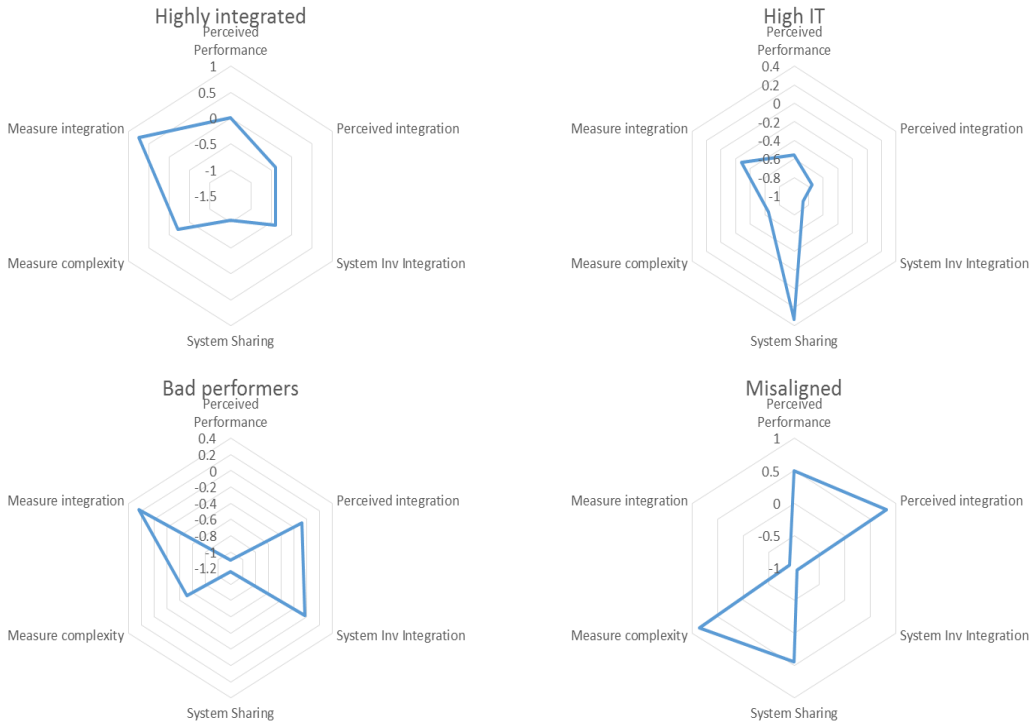

Figure 4.4: Graphs of the four clusters.

OpCos under the same company.

From our sample, we have six companies that belong to two groups (similar IP address or mail affiliation). Despite being unable to obtain any statistical analysis for the number of respondents, we were able to obtain some interesting insights that will be analysed in the next part of this research. The first interesting part, which was our initial assumption, was that the Operational Companies (OpCos) from the same group will behave in the same way.

The only question that was answered fairly similarly was how the goals are defined, which at least for all the OpCos of the company are common. For the philosophies that they claim to implement, they answer with different theories, which despite being similar to Lean or JIT, are not the same. After a detailed analysis of the open question, we realize that the answer is as far from each other as any other company of the same cluster.

There are potential synergies that may be realized by combining or standardizing activities such as R&D, manufacturing, purchasing or distribution. (Dessein et al., 2010).

Other possible problems caused by loose synergies is the lack of knowledge-sharing since the best practices are not spread around the group. Alternatively, if it is wished to spread the knowledge, it is difficult to do so because of the lack of standardization.

SUMMARIZING

For Proposition 1, we used a linear regression to analyse the interaction of the perceived integration and perceived performance, which was not enough to explain the performance.

For Proposition 2, we used the drivers proposed by Pagell (2004) to measure the internal integration and we used a Factor analysis to make a reduction of the variables used. We keep two factors that we named as Integration and Complexity. Also, we realized that the perception of integration is different to the one that is measured, mainly explained as a problem of misperception.

For Proposition 3, we used a correlation matrix to measure the degree of correlation between the perceived performance and the use of an Information system, which was very high.

For Proposition 4, we used a clustering technique to identify the different firms. We obtained 4 clusters: a highly integrated one, high IT, Bad performers and a misaligned one. We ran a pairwise analysis to measure the difference among the groups.

Implications

There is a general agreement that competitive supply chains employ the internal integrated process, which is frequently misconceived as just the use of software. Choosing and integrating the software is a major task that should be carried out carefully. However, there are other opportunity areas where we could improve the internal integration.

One that should be highlighted is taking more parties into consideration in the decision-making process by inviting the other stakeholders of the other process to explain and understand the cost and implication of the changes that can help the other functional areas (remember the example of a higher transportation cost).

We were surprised at the results for Job rotation, which apparently is a policy that is easy to implement. It was only strongly advised by 12% of the companies. The majority of the firms have it but they do not encourage it or it is difficult to achieve it. On the other hand, we were pleased to find that the

performance of the whole company is part of the goal performance of more than 55% of the firms.

CONCLUSIONS

The analysis of the open question gave us interesting results that went beyond the scope that we assigned. We got a better knowledge of the integration level through the accounting of mentions of other variables and constraints of other functional areas. Some plants claim a higher integration, but they do not take into consideration other decision factors outside their area, in other words, they continue with the silo view.

To get a better understanding of the results obtained through the survey, we performed some face-to-face interviews to enrich the perception and get a deeper vision than what we got from tables and matrices.

With one of the plants further interviewed, we realized that they reported that they have IT software, lean philosophy, and claimed to be integrated, but the interesting fact was that when they explained their decision-making, they only reported the constraints and variables of the department; they are still pursuing the excellence of their operating silos, not overall performance. The biggest problem is that they have the perception of integration.

It is very interesting when we have multiple answers from the same company that there is a misalignment in the internal planning process and decision-making activities in all the operational companies (OpCos) of the group. We expected the same decision pattern to be kept among the group. However, we realized that at a group level, there is no clear and unifying vision of how the internal planning process should be taken. We suggest that the contribution of all internal companies could help devise a similar map that would help the sharing of knowledge and good practices.

A great opportunity area is to try to obtain more information from the IT / Optimizer used and what information it contains. Unfortunately, many answers are proprietary system, or even the ones that use specific software like SAS© do not detail which modules they use, and so it was impossible to give a better score for the use of IT. Only the use of IT in industry is the subject of many researches.

Another opportunity area is the open question, which gives us really valuable information for a deeper analysis of the decision-making process of the different companies, where a content analysis or data mining techniques could help us extract more information.

The main limitation is sample size, which does not allow examining if this behaviour depends on the geographic location of the plant, since we do not have enough data for each subgroup to make a proper analysis.

In the next stage of this research, we are planning to launch a second wave of the survey request to obtain a larger sample in order to generalize this conclusion to different sectors, and countries. Another interesting step of this research is to conduct a study inside big companies and to gain an insight into the behaviour and integration of the different Operational Companies. Creating a bigger database of the differences will enable many managerial insights to be obtained. An immediate feedback tool based on other results will increase the response rate.

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Chapter 5: Car assembly lines, first integration step

MOTIVATION

In the previous chapter, using a survey and interviews, it was found that many companies believe they are integrated, but they are not. As the second step of this research, the first research question was studied: *Using current knowledge and computational power, is it possible to develop models that deal with the increase in complexity for joint decision-making in an efficient and effective manner?*

Usually as part of the diagnosis, the matching phenomenon is found. The decision-maker may be reluctant to act on a problem for which he sees no apparent solution, similarity he may hesitate to use an idea that does not deal with a difficulty, but when there is a matching with the problem he is more willing to initiate the decision-making action (Mintzberg et al. 1976). Then there is a trend to define the scope of the problem in the same way that others have defined it. An additional phase after the diagnosis, called the definition of the scope, is added to identify the different size of the scope.

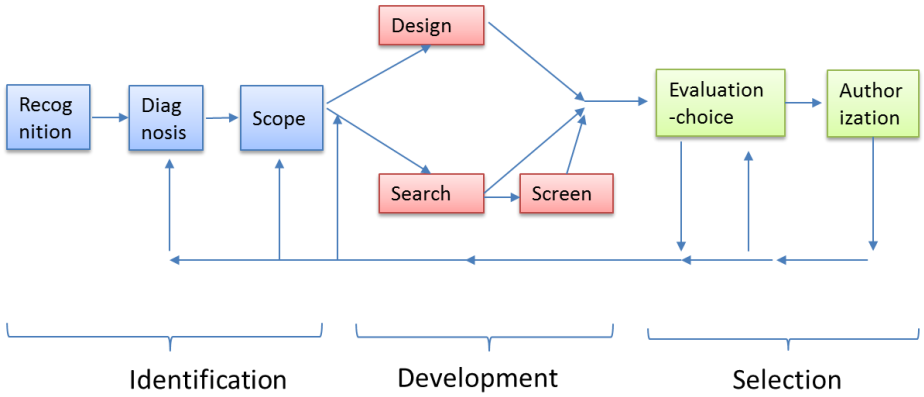

Figure 5.1: The relationship between the phases and routines of a decision process adapted from Mintzberg et al. (1976).

To evaluate the impact of the change of scope, it must be decided if it is better to integrate or keep it separate. A model that combines operational and tactical decisions in the replenishment of a car assembly line was developed. This model compares the results of joint decisions with sequential decisions The joint model has a higher complexity than the sequential model (see Figure 5.2).

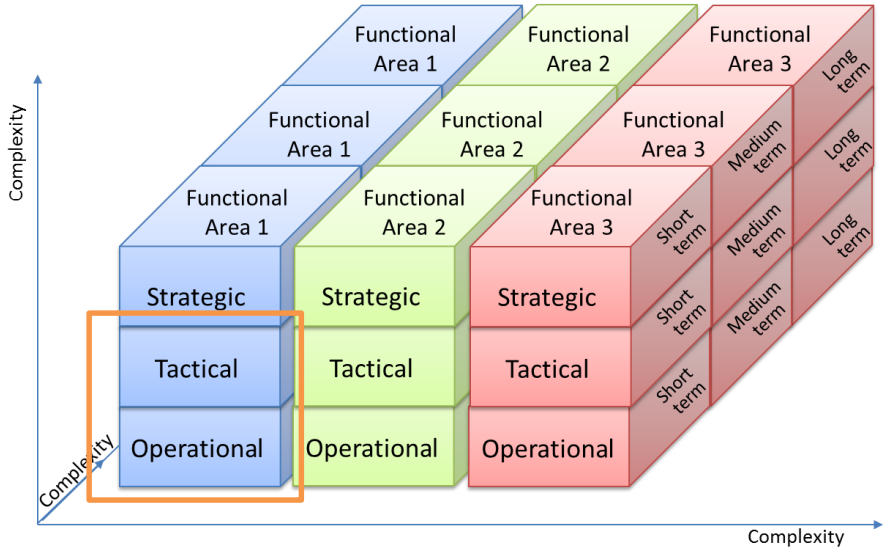

Figure 5.2: Complexity of the decisions. A higher number of blocks implies a higher complexity.

A car assembly line usually produces hundreds of cars every day and each workstation in the assembly line needs car components to perform its task. The replenishment of components is a critical issue for the assembly line to operate properly. In a multi-model assembly line, this task becomes more complicated than in a single model assembly line. A lack of inventory could cause some problems in the production line but excess inventory could also create it.

The inbound logistics for feeding the workstation inside the factory represent a critical issue in the car manufacturing industry. Nowadays, this issue is even more critical than in the past since more types of cars are being produced on the assembly lines. Consequently, as workstations have to install many types of components, they also need to have an inventory of the different types of components in a usually compact space. The replenishment of the inventory is a critical issue since a lack of it could cause line stoppage or reprocessing. On the other hand, an excess of inventory could increase the holding cost or even block the replenishment paths. The decision of the replenishment routes cannot be made without taking into consideration the inventory needed at each station during the production time, which will depend on the production sequence plan sent by the central office. This problem deals with medium-sized instances, and is solved using online solvers.

INTRODUCTION

Today's customer looks for a specific configuration of cars, which has encouraged car manufacturers to offer a wide range of options for each item of the cars. Car manufacturers have changed from offering a single model to offering a huge number of model configurations. These car manufacturers

have evolved from selling one model of one car as Ford did, with his Model-T, to offering many options (Ghosh and Roger, 1989).

For instance a single visit to a car manufacturer's web page, such as Mercedes Benz, allows us to customize a car by choosing each component, such as rims, engine, tyres, the design of the interior and exterior, steering, radio, safety, colour, the engine size, seats, and so on. This creates more theoretical configurations than the actual ones that could be produced in one year.

Today's factories use car assembly lines in which the setup times between models can be ignored, and so the mixed model line approach is used.

This flexibility is provided by the development of the interactions between humans, machines, equipment, robots, transportation systems, and so on. In this paper, we focus on the interaction of routing and the replenishment of components. However, this flexibility increases the complexity of the replenishment of components.

Assembly lines are flow-oriented production systems, which are still typical for the production of high quantity standardized commodities and they are even gaining importance in the low volume production of a customized product (Becker and Scholl, 2006). One of the most complex products that are built on assembly lines is cars and trucks. The assembly lines are a way to mass-produce cars quickly and efficiently. Mass production relies on the ability to assign easy tasks to humans and robots and move parts from one worker to another until the car is finished. Different tasks require certain machine equipment, worker skills and components to be utilized. For the single model line (see Figure 5.3), this was easy to solve because the requirements were periodic and homogeneous.

The place used to store the components next to the assembly line is limited. An increased use of space necessitates reconfiguring the assembly line while keeping the components in a different place implies that someone or something should do that additional task.

Providing the components as soon as they are needed creates many transportation problems and a high cost for the factory.

The Oxford Dictionary defines "replenishment" as "restore (a stock or supply) to a former level or condition." The core issue is determining what the proper level is and in which order the station will be replenished. This creates two problems; the inventory problem, and the routing problem.

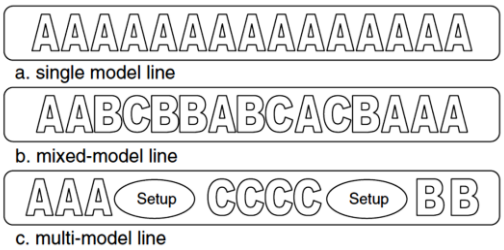

Figure 5.3: Different types of assembly lines source (Kazemi, 2011).

The vehicle routing problem.

Delivering the components to the workstations involves several transportation vehicles whose use and purchase have a direct affect on the cost. Therefore, it is necessary to try to minimize the number of vehicles used and the distance they travel. The vehicle routing problem was described by Laporte (1992) as the problem of designing optimal delivery or collection routes from one or several depots to some customers.

Campbell (1998) presents an extension called the Inventory Routing Problem (IRP), which is based on the usage of products instead of orders. IRP deals with the repeated distribution of products to a set of customers, taking into consideration the capacity of the vehicles and a penalty for a stock out. There is a different version of this problem with added features and adjustment for different types of industry, such as oil and gas (Gronhaug, 2010), or the use of genetic algorithms for a distribution network (Moin, 2011 and Archetti, 2012).

The IRP is the starting point for studying the integration of different components of the logistics value chain, i.e. inventory management and transportation (Campbell, 1998).

Nevertheless, those approaches do not take into consideration the deterministic consumption over time (since the production sequence is known), nor the cost of storage close to the assembly line.

The inventory problem (line-side storage)

Inventory policies where the number of components that should be replenished for each customer (workstation) is one of the most studied questions in Operations.

The traditional inventory policies, such as Reorder Point, Min/Max, Lot for Lot or demand flow, or item location, are not suitable for this kind of problem since many types of the same components are installed at the same workstation, so storage space is limited. Carrying zero inventory and stocking less production (Hall, 1983) is not possible because the replenishment time is

constrained by the routes. In this problem, it is assumed that the number of vehicles is lower than the number of workstations.

The replenishment of the car production line also presents some singularities since the size of some of the components is large, and many items depend on the type of car that is being assembled.

An excess of inventory induces an increase in the cost of interest on working capital, space cost, and the risk of material obsolescence. A high inventory level on the assembly line is a big cost contributor. Some of the car manufacturer's objectives are keeping low stock levels, performing the replenishment of the production line, and providing the required components at the right time (Monden, 1983). On the other hand, if there is a lack of components, there is a risk of incurring rework costs or even the stoppage of the line.

Two methods of components replenishment are used in the industry. The first and widely extended is the line-side storage next to the workstation, where the workers take the components that they will install for the current vehicle. The transportation (material handling) vehicle replenishes all the components before they are needed.

The other system used in the car-manufacturing environment for the replenishment of components is the Set pallet system (SPS) that is used in some Toyota plants, which consists of changing the line-side storage or flow racks for a moving pallet or for dollies traveling with the cars being assembled. Given that the size of the dolly is not enough to carry all the components needed to assemble one car, the dolly needs to be changed in different parts of the assembly line, and the transport of the dollies from the warehouse to the connection points also requires routing techniques. Albeit being conceived to work in plants adopting traditional material handling systems, the model presented in this paper could be adapted to deal with this material handling approach.

Integration of production and logistics

There are several papers in the literature that deal with the integration between production and logistics decisions at the strategic level, but almost nothing has been done to integrate production and logistics problems at the operational level for daily decisions (Jin, 2008). Kaminsky (2003) proposed a two-stage model of the manufacturing supply chain, called the "2 Stage Production Distribution Problem" (2SPDP). Eskigun (2005) considers the outbound supply chain as the solution to minimize the fixed costs of facility location and transportation costs using a Lagrangian heuristic. The two key flows in such relationships are material and information. Prajogo (2012) addresses the

integration of the relationship between material and information while Volling (2013) focuses on the planning of capacities and orders.

Traditionally, these two problems have been dealt with separately. It is expected that improvements may be obtained by coordinating inventory policies and transportation, but it is less obvious how to make these improvements. The replenishment of the production line is critical for the proper operation of the assembly line. An excess of inventory creates an increase in the cost of interest on working capital, space cost, and the risk of material obsolescence. On the other hand, a lack of components will probably result in rework costs or even result in the stoppage of the line.

MODELLING ASSUMPTIONS

In the car assembly line being investigated, the production sequence has been decided for a planning period. The car has to go through N stations to be assembled. Each station installs a different type of component that needs to be close to the assembly line before it is needed. All the components required for the production day are in one single warehouse. The transportation vehicles carry these components from the warehouse to the Stations (see Figure 5.4).

A "route" is defined as the course taken by a homogenous transportation vehicle and its arrival time at the workstations to get from the warehouse to the stations and back again. A transportation vehicle could have an empty route.

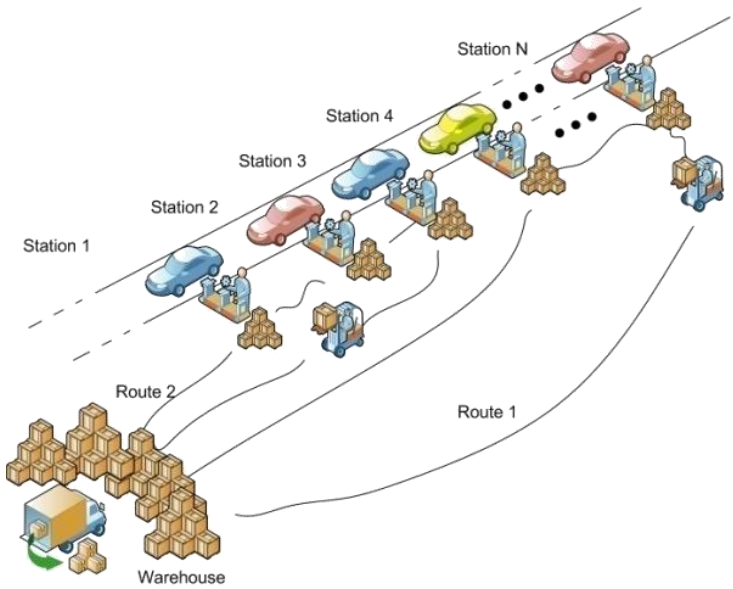

Figure 5.4: Description of the vehicle routing problem and inventory problem.

The assembly line already exists, and no changes to the production capacity or number of stations can be made.

Each model has a set of characteristics, such as engine, rims, tyres, steering, an so on. These components could have different trims (Low or High). All the models are different from other models in at least one type of component (see Table 5.1).

Table 5.1. Type of different models

Model	Rims	Engine	…	Component n
A	Low	Low	…	Low
B	Low	Low	…	High
…	…	…	…	…
N	High	Low	…	High

The components required to assemble the products are stored next to the workstation. This storage space is capacitated. A holding cost will be imputed for every component that is stored in this area. As Grave (1987) suggests for nondeterministic displacement times and the high cost of the line stoppage, a safety stock is kept to deal with a possible delay in the replenishment of the components.

The transportation vehicles that bring the components to the stations are capacitated and homogeneous. An early arrival of the component causes space problems with the buffers of the production lines while a late arrival can cause several problems on the production line. The components needed for the operation of a station are delivered as a kit. Dispatching only with a just-in-time policy increases the transportation cost and the green impact of the production line. It is necessary to select the route and the number of required components to get the lowest cost.

The final solution consists in designing routes for the transportation vehicles and the number of each component that needs to be transported to replenish the components, thus minimizing the total cost.

The model contemplates safety stock to mitigate the risk due to any uncertainty; the level of the safety stock is determined by company policy and can be set to zero.

PROBLEM FORMULATION

In this section, we begin by introducing the sets, parameters and decision variables (see Table 5.2). Later, we present the objective variables and the requirements.

Table 5.2: Sets, parameters and decision variables.

Index Set	
R	all homogenous transportation vehicles that could perform a route
L	all locations (workstations and warehouse)
M	all car model configurations
C	all car components
A	trim levels
J	characteristic J ⊆all car components × trim levels
τ	discretized production time
Parameters	
R_{mj}	1 if the model m ∈ M requires characteristic j∈ J
$Y_{m\tau l}$	1 if model m ∈ M is processed during cycle τ ∈ T in location l ∈ L
ST_{jl}	safety stock corresponding to characteristic j ∈J in location l ∈ L
STo_{jl}	initial stock corresponding to characteristic j ∈J in location l ∈ L
A	amortization per transportation vehicle; it has to be paid if the transportation vehicle is used at least once
TC	traveling cost per distance unit
HC_j	unitary holding cost of component corresponding to characteristic j ∈J per time unit
MC	unitary moving cost of component
T	number of cycles to be planned T=|τ|
CAP	maximum capacity of kits in a transportation vehicle
$TDIS_{ll'}$	displacement time from l ∈ L to l'∈L
M	a large scalar value
Variables	
w_{rl}	1 if route r ∈ R attends l ∈ L; 0 otherwise
$x_{rll'}$	1 if l ∈ L immediately precedes l' ∈ L, on route r ∈ R; 0 otherwise
t_{rl}	discrete time in which the route$r$ ∈ R arrives to the location l ∈L
$dem_{j\tau l}$	demand for component corresponding to characteristic j ∈J in cycle τ ∈τ, in location l ∈ L
$dem^{ac}_{j\tau l}$	accumulated demand for the component corresponding to characteristic j ∈J at the beginning of cycle τ ∈τ in location l ∈ L
$c_{jlr\tau}$	amount of component replenished with characteristic j ∈J required in location l ∈ L, in route r∈R in cycle τ ∈τ.
$c^{ac}_{jsr\tau}$	Accumulated amount of component replenished with characteristic j ∈J required in location l ∈ L, in route r∈R in cycle τ ∈τ.
$st_{j\tau l}$	Stock of component corresponding to characteristic j ∈J in location l ∈ L at the beginning of cycle τ ∈ T
α_r	1 if the route$r$ ∈ R is used for the replenishment; 0 otherwise

$\beta_{\tau rl}$	1 if $t_{rl} = ord(\tau)$, 0 otherwise
$q_{jl'r}$	amount of component required with characteristic $j \in J$ in station l'∈ Lin route$r \in$ R
$f_{jll'r}$	The flow of component corresponding to characteristic $j \in J$ between l and l'' ∈ L in route$r \in$ R

The MIP problem minimizes the total cost of replenishment and inventory.

$$min. \sum_{rll'} TC \times TDIS_{ll'} \times x_{ll'} + \mathrm{MC} \sum_{jll'r} f_{jll'r} + A \times \sum_r \alpha_r + \sum_j HC_j \times st_{j\tau l} \quad (1)$$

The model is subject to the constraints equations (2) to (26). Equation (1) is the objective functions. Equations (2, 3, 4) ensure that each location is served by one route. Equation (5) ensures that the route has a predecessor except for the warehouse. Equation (6) forces that if a route reaches a location, the route departs from that location. Equations (7, 8) set the number of routes equal to the number of vehicles. Equation (9) accounts a route if the vehicle visits at least one location. Equation (10) assigns first vehicle number 1. Equation (11) limits the number of vehicles used to the available ones. Equations (12, 13) define the arrival time for each location. Equation (14) has the constraint that a number of materials should be lower than the capacity. Equation (15) sets the demand for certain characteristic only when the car requires this characteristic.

Equation (16) defines a number of components that are left at the station. Equation (17) sets the accumulated demand. Equations (18, 19) set the accumulated components required. Equation (20) defines the stock. Equation (21) establishes the safety stock. Equations (22, 23, 24) establish that the required amount of components will be equal only to the replenished components when the replenishment occurs. Finally, equations (25, 26) define the time of the replenishment.

$$\sum_{rl|l \neq l'} x_{rll'} = 1 \ \ \forall\, l' \in L \setminus \{WH\} \quad (2)$$
$$\sum_{rl'|l' \neq l} x_{rll'} = 1 \ \ \forall\, l \in L \ \setminus \{WH\} \quad (3)$$
$$\sum_r w_{rl} = 1 \ \ \forall\, l \in L \setminus \{WH\} \quad (4)$$
$$w_{rl} = \sum_{l'|l' \neq l} x_{rll'} \ \ \forall\, r \in R, \forall\, l \in L \setminus \{WH\} \quad (5)$$
$$\sum_l x_{rll'} = \sum_l x_{rl'l} \ \ \forall\, l' \in L, \ \forall\, r \in R \quad (6)$$
$$\sum_{rl} x_{r\,l\,wh} = \sum_r \alpha_r \quad (7)$$
$$\sum_{rl'} x_{r\,wh\,l'} = \sum_r \alpha_r \quad (8)$$
$$\sum_{ll'} x_{rll'} \leq M \times \alpha_r \ \ \forall\, r \in R \quad (9)$$
$$\alpha_r \geq \alpha_{r+1} \ \ \forall\, r \in R \quad (10)$$
$$\sum_r \alpha_r \leq |R| \quad (11)$$
$$\boldsymbol{if\ l = wh} \ \ t_{rl'} \geq TDIS_{ll'} - M(1 - x_{rll'}) - M\left(2 - w_{rl-w_{rl'}}\right) \ \ \forall\, r \in R, \forall\, l, l' \in L \quad (12)$$
$$\boldsymbol{else} \ \ t_{rl'} \geq t_{rl} + TDIS_{ll'} - M(1 - x_{rll'}) - M\left(2 - w_{rl-w_{rl'}}\right) \ \ \forall\, r \in R, \forall\, l, l' \in L \quad (13)$$
$$\sum_{jl} f_{j\,wh\,lr} = CAP \ \ \forall\, r \in R \quad (14)$$

$$dem_{j\tau l} = \sum_m R_{mj} Y_{m\tau l} \quad \forall j \in J, \forall \tau \in T, \forall\, l \in L \tag{15}$$

$$f_{jll'r} - f_{jl'l''r} \geq q_{jl'r} - M(1 - x_{rll'}) - M(1 - x_{rl'l''}) - M(3 - w_{rl} - w_{rl'} - w_{rll''}) \quad \forall j \in J,\ \forall\, l, l', l'' \in L, \forall\, r \in R \tag{16}$$

$$dem^{ac}_{j\tau l} = dem^{ac}_{j\tau-1l} - dem_{j\tau l} \quad \forall\, j \in J,\ \forall l \in L,\ \forall\, \tau \in T\backslash\{1\} \tag{17}$$

$$\boldsymbol{if\ \tau = 1}\ \ c^{ac}_{jl'r\tau} = c_{jl'r\tau} \quad \forall\, j \in J, \forall l' \in L, \forall\, r \in R, \forall\, \tau \in T = \{1\} \tag{18}$$

$$\boldsymbol{else}\ c^{ac}_{jl'r\tau} = c^{ac}_{jl'r\tau-1} + c_{jl'r\tau} \quad \forall\, j \in J, \forall l' \in L, \forall\, r \in R, \forall\, \tau \in T\backslash\{1\} \tag{19}$$

$$st_{j\tau l} = STo_{jl} - dem^{ac}_{j\tau l} + \sum_r c^{ac}_{jlr\tau} \quad \forall\, j \in J, \forall\, \tau \in T\backslash\{1\}, \forall l \in L \tag{20}$$

$$st_{j\tau l} \geq ST_{jl}\ \forall\, j \in J, \forall\, \tau \in T, \forall l \in L \tag{21}$$

$$c_{jl'r\tau} \geq q_{jl'r} - M(1 - \beta_{\tau rl}) - M(1 - \textstyle\sum_l x_{rll'})\ \forall\, j \in J, \forall l' \in L, \forall r \in R, \forall\, \tau \in T \tag{22}$$

$$c_{jl'r\tau} \leq q_{jl'r}\ \forall\, j \in J, \forall l' \in L, \forall r \in R, \forall\, \tau \in T \tag{23}$$

$$c_{jl'r\tau} \leq M \times \beta_{\tau rl}\ \forall\, j \in J, \forall l' \in L, \forall r \in R, \forall\, \tau \in T \tag{24}$$

$$t_{rl} \leq \tau + M(1 - \beta_{\tau rl}) + M(1 - \textstyle\sum_l x_{rll'})\ \forall r \in R, \forall l' \in L, \forall\, \tau \in T \tag{25}$$

$$t_{rl} \geq \tau - M(1 - \beta_{\tau rl}) - M(1 - \textstyle\sum_l x_{rll'})\ \forall r \in R, \forall l' \in L, \forall\, \tau \in T \tag{26}$$

COMPUTATIONAL STUDY

The *AIMMS 3.13* modelling software was used and the *Gurobi 5.5* standard solver was used to obtain the solution to the problem. To deal with a bigger instance, the *Gurobi* was used at the *NEOS* server (Czyzyk, 1998, Gropp, 1997, and Dolan, 2001).

The specification of the neos-2 and neos-4 are Dell PowerEdge R410 servers with the following configuration:

• CPU - 2x Intel Xeon X5660 @ 2.8GHz (12 cores total), HT Enabled, 64 GB RAM.

For neos-3 and neos-5 are Dell PowerEdge R420 servers with the following configuration:

• CPU - 2x Intel Xeon E5-2430 @ 2.2GHz (12 cores total), HT Enabled, and 64 GB RAM.

There are no public instances in the literature. The data for the experimentation was based on Car Sequencing instances from Regin & Puget (1997) instance #1, #2, and #3. The instances are public at Car Sequencing Problem Lib (www.csplib.org). From this sequence, we made up the missing data. First we tested the current instances; then we duplicated the number of stations (extended instances) keeping the same production ratio. Each instance had 100 cars. A stopping criterion of 3600 sec was set for all the instances (see Table 6.3).

The holding cost, as was stated before, represents the cost of the opportunity to have the space used to keep inventory instead of production activities.

Table 5.3: Instances to be tested.

Instances	NCar	Mod	Stations
Regin & Puget #1	100	22	5
Regin & Puget #2	100	22	5
Regin & Puget #3	100	25	5
Regin & Puget #1(ext)	100	22	10
Regin & Puget #2(ext)	100	22	10
Regin & Puget #3(ext)	100	25	10

In Table 5.4 the displacement time between stations is displayed. The acceleration, travelling time, deceleration, and the unloading of the components make up the displacement time. The travelling time is only relevant when the distance is greater than 5 stations.

The algorithm was compared with a traditional constraint vehicle routing problem (CVRP) with optimal routes, keeping in consideration the production and capacity of the vehicle. Once the route is obtained, the intrinsic cost of the inventory is calculated. A fixed cost of €266 for the use of the transportation vehicle, plus a holding and moving cost of components.

Table 5.4: Displacement time between stations.

Station	WH	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
WH		2	2	2	2	2	3	3	3	3	3
S1	2		2	2	2	2	2	3	3	3	3
S2	2	2		2	2	2	2	2	3	3	3
S3	2	2	2		2	2	2	2	2	3	3
S4	2	2	2	2		2	2	2	2	2	3
S5	3	2	2	2	2		2	2	2	2	2
S6	3	3	2	2	2	2		2	2	2	2
S7	3	3	2	2	2	2	2		2	2	2
S8	3	3	3	2	2	2	2	2		2	2
S9	3	3	3	3	2	2	2	2	2		2
S10	3	3	3	3	3	2	2	2	2	2	

The algorithm was compared with a traditional constraint vehicle routing problem (CVRP) with optimal routes, keeping in consideration the production and capacity of the vehicle. Once the route is obtained, the intrinsic cost of the inventory is calculated. A fixed cost of €266for the use of the transportation vehicle, plus a holding and moving cost of components.

We will present the results from the six instances in section 4.3. For comparison details, we will examine the instance of Regin & Puget #1(ext). This instance has 100 cars, with 22 types of cars, and will be produced in 10 stations. The experimentation will run with a different travelling cost and holding cost ratio.

Routing Analysis

In Tables 5.5 and 5.6 we show the arrival time of the transportation vehicles at the stations. Table 5.5 uses the compound approach, and Table 5.6 uses a classical CVRP.

Table 5.5: Arrival time of the transportation vehicles (instance Regin & Puget #1).

Station	WH	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
V1	15			13	11			3	5	8	
V2	23	15	21			2	13				10
V32											

Table 5.6: Arrival time of the transportation vehicles of a classical CVRP (instance Regin & Puget #1).

Station	WH	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
V1	25	12	19	21	23	14					16
V2	28						15	25	19	23	
V3											

Both routes use only two vehicles; the joint approach uses the first vehicle to deliver the urgent components and dispatches the second vehicles later, thereby reducing the cost.

Inventory Analysis

In Figures 6.5 and 6.6, the inventory levels of station 3 are displayed. The holding cost of the instances displayed for high trim is 20 cents per minute and 10 cents per minute for the low trim. The model adjusts the replenishment to minimize the area below the line.

The replenishment is done as soon as the station reaches the safety stock, e.g. the arrival at Station 3 happens at minute 21 instead of minute 13. This delay of 8-time units represents 15% savings in the holding cost (see Table 7). The safety stock plays an important role in the cost; it is space and money that we have dedicated to avoiding logistic problems.

The maximum stock on the assembly line also decreases from 61 to 56 for low trim and from 25 to 22 units for high trim; this decrease of 8 units represents 10% of savings in space that can be allocated to other production activities. The inventory level is always above the safety stock.

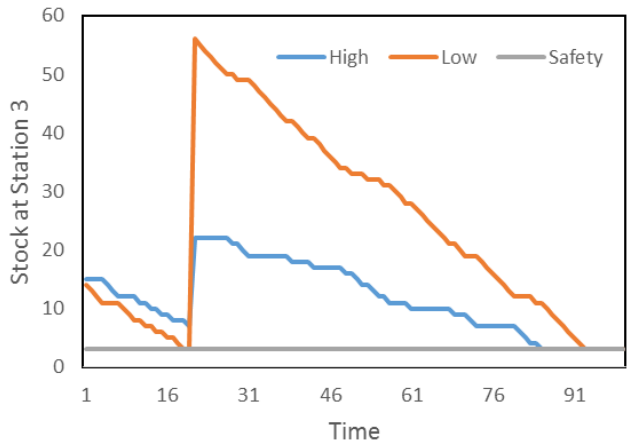

Figure 5.5: Stock and Safety Stock at Station 3 of the instance joint model (instance Regin & Puget #1(ext)).

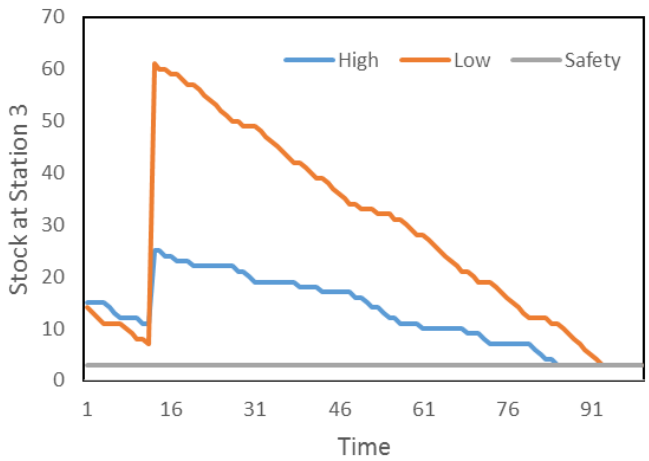

Figure 5.6: Stock and Safety Stock at Station 3 of the instance (instance Regin & Puget #1(ext)) of CVRP

Table 5.7: Cost of the stock in the Station 3 (instance Regin & Puget #1(ext)).

	Join Model	CVRP	Diff (%)
High trim	172.4	196.4	13.9
Safety Stock	60	60.0	0.0
sub total	232.4	256.48	10.3
Low trim	203.6	246.8	21.2
Safety Stock	30.0	30.0	0.0
sub total	233.6	276.8	18.5
Total	466	533.2	14.4

Cost Analysis

Table 5.9 shows a comparison between the costs of the 3 instances. In all the instances, we obtain savings due to the joint decision, taking into consideration the most suitable time to replenish, instead of only the shortest path which could provide interesting savings only by changing the route.

The model of this system has 4 costs (see Eq.1); the fixed cost for the use of a transportation vehicle (A), the cost of the distance travelled (TC), the cost of carrying the load (MC) and the holding cost (HC). Changing the cost of any of the parameters will reflect the routing and replenishment routes of the company.

Table 5.8: Comparison of total cost (instance Regin & Puget #1(ext)).

	Join Model	CVRP	Diff(%)
Route	203.6	246.8	-3.24%
Inventory Cost	30.0	30.0	11.42%
Total	7111	7676	7.99%

Table 5.9: Comparison of the results of the two approaches.

Instance	MC/ HC	N Mod	N Car	N Loc	N Var cont	N Int Var	Obj Joint	CVRP	HC	Total CVRP +HC	Diff (%)
Regin & Puget #1	0.5	22	100	5	4500	1611	29364	828	32403	33231	13.2
Regin & Puget #2	0.5	22	100	5	4500	1611	28966	828	30843	31671	9.3
Regin & Puget #3	0.5	25	100	5	4554	1611	28721	828	31722	32550	13.3
Regin & Puget #1(ext)	0.5	22	100	10	13548	3366	56151	1611	60687	62298	10.9
Regin & Puget #2(ext)	0.5	22	100	10	13548	3366	55457	1611	56624	58235	5.0
Regin & Puget #3(ext)	0.5	25	100	10	13575	3366	57311	1611	65297	66908	16.7
Regin & Puget #1	5	22	100	5	4500	1611	3678	828	3337	4165	13.24%
Regin & Puget #2	5	22	100	5	4500	1611	3657	828	3240	4068	11.24%
Regin & Puget #3	5	25	100	5	4554	1611	3615	828	3084	3912	8.22%
Regin & Puget #1(ext)	5	22	100	10	13548	3366	7111	1611	6068	7679	7.99%
Regin & Puget #2(ext)	5	22	100	10	13548	3366	6874	1611	5662	7273	5.80%
Regin & Puget #3(ext)	5	25	100	10	13575	3366	7047	1611	6134	7745	9.90%
Regin & Puget #1	50	22	100	5	4500	1611	1117	828	334	1162	4.0
Regin & Puget #2	50	22	100	5	4500	1611	1111	828	324	1152	3.7
Regin & Puget #3	50	25	100	5	4554	1611	1110	828	309	1137	2.4
Regin & Puget #1(ext)	50	22	100	10	13548	3366	2149	1611	607	2218	3.2
Regin & Puget #2(ext)	50	22	100	10	13548	3366	2133	1611	567	2178	2.1
Regin & Puget #3(ext)	50	25	100	10	13575	3366	2161	1611	652	2263	4.7

A good example of the problem (see Table 5.8) of considering the problem separately is that CVRP selects the best route for all the instances of the same number of stations for the same total demand of components. However, the demand over the time is different, and consequently the stocks are different.

When the moving cost is more representative for the model (MC>HC), savings decrease since the CVRP achieves the optimal, and the impact on the holding cost is not so important. On the other hand, when the holding cost becomes more important (MC<HC) this model presents bigger savings than the separate decision. For all the instances, we obtain a better result with the joint decision than with the separate approach.

All the CVRP and HC problems were solved up to optimality. For the joint model only the small instance and the instance that got a ratio of HC/MC of 50 was solved to optimality. The extended instances required the stopping criterion of one hour.

In Table 5.10 the result of the ANOVA analysis is displayed. We set the type of instance and the different results and obtain a p=0.950. Then we assume that the results are the same for the different instances, since the moving cost of the components is the same for high or low trim, and the only difference is the difference of the holding cost of the components.

Table 5.10: ANOVA comparison among different mix of demands.

Source	DF	SSC	MS	F	P
Instance	2	408247	204124	0.00	0.999
Error	15	3.23E+9	2.16E+E8		
Total	17	3.23 E+9			
s=14688	r-sq=0.01%		r-sq(adj)=0.00%		

CONCLUSIONS

In this work, the inventory and the routing problems have been solved jointly. The routing model should consider more factors than just the transportation cost; also, the inventory should consider more factors than replenishment when a level is reached. The main factor in the delivery of material should not only be the decrease of the transportation costs but also the decrease of the holding cost of the components.

The selection of the routes and the inventory levels should consider the specific requirement of materials over time to decrease the cost.

The cost of space is an amplifier of the savings of the model. When there are restrictions in the space closest to the assembly line, the model tries to keep the lowest inventory along the planning period. The replenishment is made before the inventory level reaches the safety stock. Following the Lean idea, it is possible to decrease the safety stock until it reaches zero safety stock, always keeping in mind the risk of any delays, which could lead to the stoppage of the assembly line.

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Chapter 6: Car assembly lines, using MILP and ACO approach

MOTIVATION

In the previous chapter, the operational area and tactical area of a car assembly line were combined. Interesting results were found, but the complexity of the problems increases. In this chapter, another functional area is added to the scope of the problem (see Figure 6.1) increasing the possible options but also the complexity increases. The decision-making units also have to change. In this example the scheduling, replenishment and inventory of the car assembly line will be combined. In a separate approach, the decision-maker is the manager of each department, and the users are the workers of that department. In the joint approach, there are more decision- makers, influencers and gatekeepers that could have a conflict of interest. As the complexity increases the solving time of the MILP also increases, therefore it is necessary to use heuristics as ant colony optimization (ACO) to solve bigger instances.

In this chapter, a comparative of the ACO system and MILP to deal jointly with sequencing, routing, and line-side storage problems in a mixed model car assembly line is presented.

In today's market, customers demand an even wider range of car models. Consequently, the majority of car manufacturers have changed from having a single model assembly line to mixed-model assembly lines, generating enormous challenges for the operation of the assembly line. Taking a holistic look at car production (i.e. considering sequencing, routing, and line-side storage) allows us to study the performance optimization of the production process.

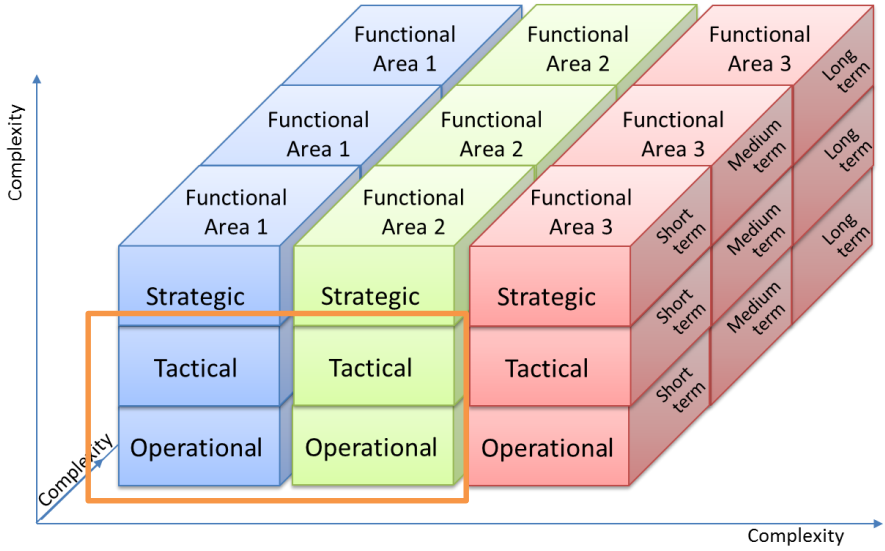

Figure 6.1: Complexity of the decisions. A higher number of blocks implies a higher complexity.

We started with a review of the existing algorithms. We could not find any papers addressing this problem jointly so a MILP formulation was developed. We developed an ACO to deal with bigger instances. The mathematical model for the operation of the assembly line was based on the approach of sequence rules, whereby an assembly line can handle a pre-determined production rate for each option. The approach to the inventory and sequence part was an extension of the Inventory Routing Problem, whereby the inventory and transportation costs are minimized. In our tests, we prove that the benefits of the joint decision are larger when the value of space is higher than in a low-cost facility. The main thrust of this work consists in the development of the MILP and ACO systems and a discussion of the managerial insights into production and replenishment. Additionally, the change of the modelling approach from single problems to a joint approach is suggested.

INTRODUCTION

The increase in car manufacturing complexity due to the globalization of business and the immense variety of models being produced makes it necessary to take the time to consider more than one part of the production process at a time. Car manufacturers have evolved from selling only one model of one car, as Ford did with his Model-T. Nowadays, a representative case is BMW, which theoretically offers 10^{32} configurations of their cars, out of which tens of thousands have been demanded (Meyr 2009).

Effective scheduling of the assembly line could allow good control of the entire system. A mixed-model manufacturing facility is done by setting the production schedule (Miltenburg et al. 1990). The assembly line is the drum that sets the rhythm for this orchestra, and the suppliers and all of their related activities should follow them. Some parameters, such as production capacity and production ratio, are "almost" fixed, but the scheduling, the inventory, and ways to replenish are not fixed.

The scheduling should persuade the smoothing of the requirements for components to facilitate the entire operation of the supply chain (Drexl and Kimms 2001). A related problem is an inventory necessary for this operation. A high inventory level on the assembly line is a big cost contributor. The car manufacturer's objective is to keep low stock levels, performing the replenishment of the production line and providing the required components at the right time (Monden 1983). If the shipment arrives too early, there may be no place to store it; if the shipment arrives too late, the car assembly line has to be stopped.

The problem with the scheduling of the car assembly line is not new, although using a holistic view of car production (i.e. considering sequencing, replenishment, and routing) allows us to study the performance optimization of the production process. There is growing interest in solving multi-objective problems, which has led the researcher to combine algorithms and create an extension of the classical algorithms to achieve their objectives (López-Ibáñez and Stützle 2010).

The novel contribution of this chapter consists in the proposal and testing of a joint model to decide the sequencing of the assembly line and obtain routes that optimize the replenishment and the line-side storage of the automotive assembly line. We developed a Mixed Linear Integer Programming (MILP) formulation and Ant Colony Optimization (ACO) to deal with the bigger instances. The idea behind those algorithms is that instead of addressing the scheduling, routing, and inventory problems separately, we could obtain a better solution with a joint approach.

After a preliminary analysis that involved factory tours of as many as a dozen car assembly manufacturing plants around Europe and Japan, we believe that the problem presented in this paper is still relevant in today's manufacturing environment. The material handling to provide components to the workstations is done using forklifts, towing train (trailer) or any other transportation vehicles, but the proper routing for the replenishment vehicles is still necessary.

The present work is a continuation of an earlier study on car assembly lines meant to explore the advantage of the joint decision in planning and scheduling. In the previous chapter, we developed an MILP for the routing and inventory problem. In this work, we deal jointly with the sequencing, routing, and inventory problems. Since only very small instances can be solved using MILP, we developed an Ant Colony Optimization algorithm to deal with larger instances.

The vehicle routing problem and inventory problem reviewed in the last chapter will be combined with the car sequencing problem.

Car sequencing problem

Dincbas et al. (1998) define the sequencing problem as the selection of the appropriate order in which cars are produced. Sequencing problems have been discussed in the literature for many years. As they are NP problems with high complexity, it is necessary to find proper sequences because it is unreasonable to require an assembly line to move slowly enough to allow every option to be put on every car. A set of consecutive cars is subject to sequencing rules that restrict the maximum number of occurrences of certain characteristics in a sequence. The line can handle a predetermined quota of cars for each option. The algorithm searches for a sequence of models that meets the demand without violating any rules (Boysen et al. 2009). The sequencing rules are typically of type $H_0 : N_0$, which means that out of N_0 successive models, only H_0 may contain the option $\boldsymbol{O}$ (Drexl and Kimms 2001). An interesting model is presented by Giard and Jeunet (2010), who offer the option of hiring utility workers to avoid any infeasibility of the solution, which results in more colour grouping.

ACO literature review

From the literature review, we found that the majority of algorithms for the CSP have a single objective of minimizing the violations, while the CSPLib and Roadef are the reference instances. Recently the use of multiple pheromones has given good results. For the inventory routing problem (IRP) or vehicle routing problem, (VRP) with extensions, more approaches that are multi-objective appear and multiple ant colonies.

The multiple ant colonies present promising results. The test instances for the VRP problem is out of our context because they use a test instance of tens of thousands of visited cities, and no car-manufacturing plan has this number of workstations (see Table 6.1).

Table 6.3: Review of the CSP and IRP problems using ACO.

Paper	Type of problem	Data	ACO Type	Multiple Objective	Multiple Pheromone
Gottlieb et al. 2003	CSP	CSPLib	classic	No	No
Gravel et al. 2005	CSP	CSPLib	classic	No	No
Gagné et al. 2006	CSP	Roadef	classic	No	No
Solnon 2008	CSP	Roadef	classic	No	Yes
Morin et al. 2009	CSP	CSPLib	ACS-3D	No	Yes
Solomon 1987	VRP	Own	ACS	No	No
Gambardella et al. 1990	VRP	Solomon	ACS	No	No
Barán and Schaerer 2003	VRP	Solomon	multiple	Yes	Yes
Bell et al. 2004	VRP	Christofides	multiple	Yes	No
Huang and Lin 2010	IRP	Solomon	modified	Yes	No

Following a classical approach, we started with the MILP, and we followed with a heuristic approach. The choice of the heuristic was Ant Colony Optimization introduced by Dorigo et al. (1996) since it has offered good results for these kinds of problems (Gottlieb et al. 2006; Silvia et al. 2008).

PROBLEM DESCRIPTION

Based on the characteristic defined in the introduction, we will define the assembly process, the Car Sequencing Problem (CSP) approach, and then the travelling to replenish the components. The present problem is an extension of the CSO proposed for the Roadef challenge in 2005, where we also considered the inventory level and the replenishment of these components.
The assembly process of a car requires the car's chassis (body in white) to pass through several workstations. We define a car as being assembled when it has passed through all the workstations that install the different components.

The takt time is the amount of time that must elapse between two consecutive cars. Since some car configurations require more than one takt time at the workstation to carry out the tasks assigned to that workstation. Other car configurations require less time to assemble. Since the assembly line cannot slow down to meet the longer takt time, we use the CSP approach of interspersing cars with a longer takt time with cars with a lower takt time. The different production rates are defined for the trim level of the components that will be installed. To make the trim level clearer, in the workstation where the radio is installed, high trim could mean a hi-fi radio/MP3/DVD and a low trim could mean an FM radio. To find sequences that maintain the production rate

in each workstation, each time the production rate is above this number, it is considered a rule violation.

Each model has a set of unique characteristics, such as types of wheels and tyres, radio, sunroof, car seat, and so on. As detailed above these components can have different trim levels. The combination of components and trims gives us the characteristics. In every workstation, a specific kit of components is installed. All the components required for the workstation have to be replenished from a warehouse before that they are required.

The holding cost is a figurative cost or penalty for having an excess of line-side storage for the following reason: the probability of damage or loss of a component increases with the time that the component itself remains in line-side storage. The holding cost of high trim components will be higher than that of low trim components. The second reason for this cost is the limited space of the line-side storage, but an excess of inventory could obstruct the proper operation of the line. When there is an excess of components, the operator spends more time searching and selecting among them.

When considering the forklift or the towing train (trailer), we have to consider the so-called displacement time. The displacement time is the sum of the acceleration time, the travel distance, the breakage time, and the time to unload the components. The displacement times between stations are similar since the only time that is distance dependent is the travelling time, and then it only influences the result if the distance is considerable.

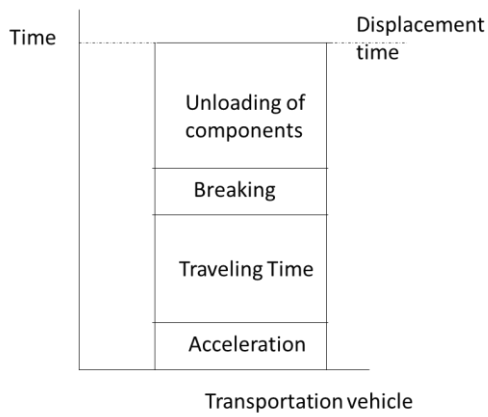

Figure 6.2: Displacement time of transportation vehicle.

JOINT FORMULATION

The engine of a car supply chain is the assembly line; it keeps the rhythm of the orchestra. Using the traditional car assembly line approach, the production planning department obtains the best car sequence. From the best sequence, the best routing is calculated, and from the best routing the best inventory is calculated (see Figure 6.3). The joint approach searches among all possible combinations to obtain better solutions. This is possible since we can have many similar costing car sequences, replenishment routes, and inventory levels. If we play with the combination, we can obtain a better solution. We will follow this approach in the MILP and ACO formulation.

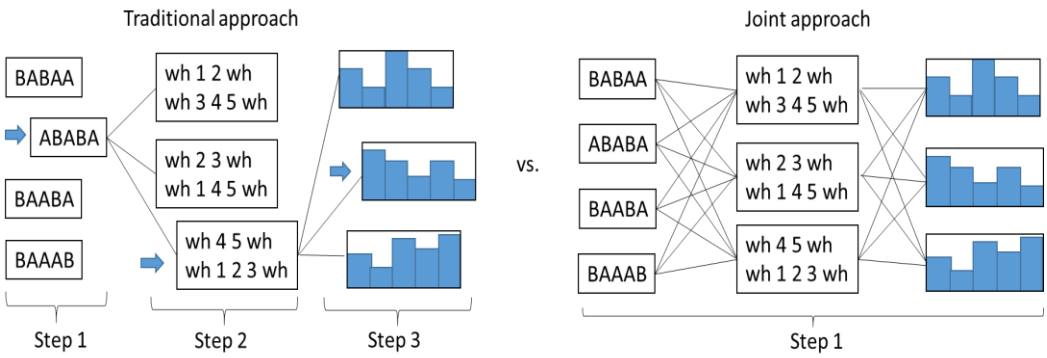

Figure 6.3: Instead of solve the scheduling, then the replenishment and after the inventory, a joint model solves it together using an MILP or an ACO.

MILP FORMULATION

In this section, we begin by introducing the notation needed to formulate the problem. Afterwards, we present the mixed integer linear programme for the joint solution of the problem.

Table 6.4: Set, parameters, and variables.

Name	Description
	Sets
R	homogenous transportation vehicles that could perform a route
L	locations (workstations and warehouse);
M	car model configurations;
C	car components;
A	trim levels;
J	characteristic J ⊆ all car components × trim levels;
τ	discretized production time;

	Parameters
D_m	total demand of model m ∈ M;
R_{mj}	1 if the model m ∈ M requires characteristic j ∈ J;
AVH	amortization cost (per period) per transportation vehicle;
$TDIS_{ll'}$	displacement time from l ∈ L to l' ∈ L;
TC	traveling cost per distance unit;
MC	moving cost of component;
CAP	maximum capacity of kits in a transportation vehicle;
LEN	maximum length of the route;
HC_j	holding cost of component corresponding to characteristic j ∈ J per time unit;
ST_{jl}	safety stock with characteristic j ∈ J in location l ∈ L;
STo_{jl}	initial stock for characteristic j ∈ J in location l ∈ L;
$H_j : N_j$	at most H_j of N_j successively sequenced cars may have characteristic j ∈ J;
VC_j	violation rule cost per characteristic j ∈ J;
M	a large scalar value;
	Variables
w_{rl}	1 if route r ∈ R attends l ∈ L; 0 otherwise;
$x_{rll'}$	1 if l ∈ L immediately precedes l' ∈ L, on route r ∈ R; 0 otherwise;
$y_{m\tau l}$	1 if model m ∈ M is processed on cycle τ ∈ T in location l ∈ L, 0 otherwise;
t_{rl}	discrete time in which the route r ∈ R arrives to the location l ∈ L;
$dem_{j\tau l}$	demand for component of characteristic j ∈ J in cycle τ ∈ T, in location l ∈ L;
$dem^{ac}_{j\tau l}$	accumulated demand for the component with j ∈ J at cycle τ ∈ T in l ∈ L;
$c_{jlr\tau}$	amount of component replenished with j ∈ J required in l ∈ L, in ∈ R in τ ∈ T;
$c^{ac}_{jsr\tau}$	accumulated amount of component with j ∈ J in l ∈ L, in r ∈ R in cycle τ ∈ T;
$q_{jl'r}$	amount of component required with characteristic j ∈ J in l'∈ L in route r ∈ R;
$st_{j\tau l}$	Stock of component to characteristic j ∈ J in l ∈ L at cycle τ ∈ T;
α_r	1 if the route r ∈ R is used for the replenishment; 0 otherwise;
$\beta_{\tau rl}$	1 if $t_{rl} = ord(\tau)$, 0 otherwise;
$f_{jll'r}$	flow of component with characteristic j ∈ J between l and l'' ∈ L in r ∈ R;

The objective function

$$min. \sum_{rll'} TC \times TDIS_{ll'} \times x_{ll'} + \mathrm{MC} \sum_{jll'r} f_{jll'r} + AVH \times \sum_r \alpha_r + \sum_j HC_j \times st_{j\tau l} + \sum_{j\tau} VC_j \times z_{j\tau} \quad (1)$$

The objective function minimizes the cost of the displacement of the transportation vehicles, the cost of moving each component, the amortization of the transportation vehicles, the holding cost and the cost of violating a production rule (see Equation 1), which is subject to the following restrictions:

subject to

$$\sum_{\tau} y_{m\tau l} = D_m \ \ \forall\, m \in M, \forall\, l \in L \tag{2}$$

$$\sum_{m} y_{m\tau l} \leq 1 \ \ \forall\, \tau \in T, \forall\, l \in L \setminus \{WH\} \tag{3}$$

$$y_{m\tau l} = y_{m\,\tau-1\,l-1} \ \ \forall\, m \in M, \forall\, \tau \in T, \forall\, l \in L \setminus \{WH\} \tag{4}$$

$$\sum_{m} \sum_{\tau'-\tau}^{\tau+N_{j-1}} R_{mj}\, y_{m\tau' l} \leq H_j + M z_{j\tau} \ \ \forall\, j \in J, \forall\, \tau \in T, \forall\, l \in L \setminus \{WH\} \tag{5}$$

$$\sum_{rl\,|\,l \neq l'} x_{rll'} = 1 \ \ \forall\, l' \in L \ \{WH\} \tag{6}$$

$$\sum_{rl'|l' \neq l} x_{rll'} = 1 \ \ \forall\, l \in L \ \setminus \{WH\} \tag{7}$$

$$\sum_{r} w_{rl} = 1 \ \ \forall\, l \in L \setminus \{WH\} \tag{8}$$

$$w_{rl} = \sum_{l'|l' \neq l} x_{rll'} \ \ \forall\, r \in R, \forall\, l \in L \setminus \{WH\} \tag{9}$$

$$\sum_{l} x_{rll'} = \sum_{l} x_{rl'l} \ \ \forall\, l' \in L, \ \forall\, r \in R \tag{10}$$

$$\sum_{rl} x_{r\,l\,wh} = \sum_{r} \alpha_r \tag{11}$$

$$\sum_{rl'} x_{r\,wh\,l'} = \sum_{r} \alpha_r \tag{12}$$

$$\sum_{ll'} x_{rll'} \leq M \times \alpha_r \ \ \forall\, r \in R \tag{13}$$

$$\sum_{ll'} x_{rll'} = LEN \ \forall\, r \in R \tag{14}$$

$$\sum_{r} \alpha_r \leq |R| \tag{15}$$

$$\boldsymbol{if\ l = wh}\ \ t_{rl'} \geq TDIS_{ll'} - M(1 - x_{rll'}) - M(2 - w_{rl} - w_{rl'}) \ \ \forall\, r \in R, \forall\, l, l' \in L \tag{16}$$

$$\boldsymbol{else}\ \ t_{rl'} \geq t_{rl} + TDIS_{ll'} - M(1 - x_{rll'}) - M(2 - w_{rl} - w_{rl'}) \ \ \forall\, r \in R, \forall\, l, l' \in L \tag{17}$$

$$\sum_{jl} f_{j\,wh\,lr} = CAP \ \ \forall\, r \in R \tag{18}$$

$$dem_{j\tau l} = \sum_{m} R_{mj} y_{m\tau l} \quad \forall j \in J, \forall \tau \in T, \forall\, l \in L \tag{19}$$

$$f_{jll'r} - f_{jl'l''r} \geq q_{jl'r} - M(1 - x_{rll'}) - M(1 - x_{rl'l''}) - M(3 - w_{rl} - w_{rl'} - w_{rll''}) \quad \forall j \in J, \ \forall\, l, l', l'' \in L, \forall\, r \in R \tag{20}$$

$$dem^{ac}_{j\tau l} = dem^{ac}_{j\tau-1l} - dem_{j\tau l} \ \ \forall\, j \in J, \forall l \in L, \forall\, \tau \in T \setminus \{1\} \tag{21}$$

$$\boldsymbol{if\ \tau = 1}\ \ c^{ac}_{jl'r\tau} = c_{jl'r\tau} \ \ \forall\, j \in J, \forall l' \in L, \forall\, r \in R, \forall\, \tau \in T = \{1\} \tag{22}$$

$$\boldsymbol{else}\ c^{ac}_{jl'r\tau} = c^{ac}_{jl'r\tau-1} + c_{jl'r\tau} \ \ \forall\, j \in J, \forall l' \in L, \forall\, r \in R, \forall\, \tau \in T \setminus \{1\} \tag{23}$$

$$st_{j\tau l} = STo_{jl} - dem^{ac}_{j\tau l} + \sum_{r} c^{ac}_{jlr\tau} \ \ \forall\, j \in J, \forall\, \tau \in T \setminus \{1\}, \forall l \in L \tag{24}$$

$$st_{j\tau l} \geq ST_{jl} \ \forall\, j \in J, \forall\, \tau \in T, \forall l \in L \tag{25}$$

$$c_{jl'r\tau} \geq q_{jl'r} - M(1 - \beta_{\tau rl}) - M(1 - \sum_{l} x_{rll'}) \ \forall\, j \in J, \forall l' \in L, \forall r \in R, \forall\, \tau \in T \tag{26}$$

$$c_{jl'r\tau} \leq q_{jl'r} \ \forall\, j \in J, \forall l' \in L, \forall r \in R, \forall\, \tau \in T \tag{27}$$

$$c_{jl'r\tau} \leq M \times \beta_{\tau rl} \ \forall\, j \in J, \forall l' \in L, \forall r \in R, \forall\, \tau \in T \tag{28}$$

$$t_{rl'} \leq \tau + M(1 - \beta_{\tau rl}) + M(1 - \sum_l x_{rll'}) \ \forall r \in R, \forall l' \in L, \forall \tau \in T \quad (29)$$

$$t_{rl'} \geq \tau - M(1 - \beta_{\tau rl}) - M(1 - \sum_l x_{rll'}) \ \forall r \in R, \forall l' \in L, \forall \tau \in T \quad (30)$$

Eq. (2) warrants that the demand is satisfied. Eq. (3) allows only one car at one station. Eq. (4) makes sure that the car passes to the next station. Eq. (5) is the production ratio rule. Eq. (6), Eq. (7), and Eq. (8) ensure that each location is served by one route. Eq. (9) obeys the route to have a predecessor except for the warehouse. Eq. (10) forces the situation where if a route reaches a location, the route departs from that location. Eqs. (11, 12) set the number of routes equal to the number of vehicles. Eq. (13) accounts for a route if the vehicle visits at least one location. Eq. (14) sets the maximum length of the route. Eq. (15) limits the number of vehicles used to the available ones. Eqs. (16, 17) define the arrival time for each location. Equation (18) sets the maximum capacity of the route. Eq. (19) sets the demand for certain characteristics only when a car requires this characteristic. Eq. (20) defines the number of components that are left at the station. Eq. (21) sets the accumulated demand. Eqs. (22, 23) set the accumulated components required. Eq. (24) defines the stock. Eq. (25) establishes the safety stock. Eqs. (26, 27, and 28) establish that the required amount of components will be equal only to the replenished components when the replenishment occurs. Finally, equations (29, 30) define the time of the replenishment.

ANT COLONY OPTIMIZATION

In this subsection, we describe the ACO algorithm that we developed to deal with the joint problem describe above. We use the following notation. The problem is defined by a 10-tuple (C , Class, O, A, J, S, H_j:N_j, r_{ij} ,V, $TDIS'_{ss}$) that is explained in Table 6.3.

Table 6.5: 10-tuple parameters explanation for the ACO formulation.

Name	Description
C	$= \{c_1, \dots, c_m\}$ is the set of cars to be produced;
Class	the set of all different cars sharing the trim level for all components;
O	$= \{o_1, \dots, o_m\}$ is the set of different components;
A	trim levels;
J	characteristic $J \subseteq O \times A$;
S	$= \{s_1, \dots, s_m\}$ is the set of stations to install the different components;

$H_j : N_j$	at most H_j of N_j, where N_j successive cars may have characteristic j;
r_{ij}	C × O →{0, 1}, r_{ij} =1 if in station s_i the component with the characteristic H_j is installed, $r_{ij} = 0$ otherwise;
V	defines a maximum number of transportation vehicles;
$TDIS_{ss'}$	defines displacement times from station S_i to station S_j.

The following notation is used to denote the change of sequences:

- a sequence is noted $\pi = \{c_{i1}, c_{i2}, \dots, c_{ik}\}$;
- the unique set of options required by a car is a class $class\ Of(c_i) = \{h_j \epsilon H | r_{ij} = 1\}$;
- a route is defined as a nonempty subset of stations attended by each vehicle, $R_{v_i} = \{s_0, s_{1,} \dots, s_{m+1}\}$ where $s_0 = s_{m+1}$ denotes the depot;
- the set of all sequences that may be built is π_c;
- the concatenation $\oplus$ of two sequences is the first followed by the second;
- a sequence π1 is a subsequence of another π2 , π1 ⊆ π2, if there are another two sequences that can be concatenated to π1 to create π2;
- τ cycle (takt) time; and
- the cost of the sequence π and the route R depend on the number of violated constraints, the vehicles used, the distance traveled by each vehicle, and the amount of stock in the assembly line (see equation 32).

The problem is solved when a production plan is found that minimizes the total cost of violating the sequence rules, the cost of the routes for replenishing all the components, and the holding cost of line-side inventory meeting all the constraints.

Each route will be attended by only one transportation vehicle. A production plan will be defined as the set of production sequences and the routes for the vehicles that permit replenishment of the components for the given production requirements. The solution is driven by four main costs: the cost of using utility workers to overload the station due to a violation of the sequence rule (33), the use of transportation vehicles (34), the distance travelled by the transportation vehicles (35), and the inventory cost of the components (36).

$$cost(\pi, R) = \sum_{o_i \in o} \sum_{\pi_{k \subseteq} \pi} \text{violation}(\pi_k, O_i) \times \text{vioCost} + \sum_n (\text{travelCost(Vn)} + vehicles\ Used(V_n) \times Cost) + \sum_m \text{holdingCost}(s_m) \quad (32)$$

where

$$\text{violation}(\pi_k, O_i) = 0\ if \sum_{cl \subseteq \pi_k} r_{lj} \leq H_j\ , 0 \text{ otherwise} \quad (33)$$

$$vehicles\ Used(V_n) = 0\ of\ distanceTraveled(V_n) = 0, 1 \text{ otherwise} \quad (34)$$

$$\text{travelCost(Vn)} = \sum_{l \in R} \text{TDIS}_{ll'} \times unitCOstKm \quad (35)$$

$$\text{holdingCost}(s_m) = \sum_{j\tau} \text{stock}_{j\tau} \times unitCostStock \quad (36)$$

ACO Algorithm

Following the ACO scheme, each part of the problem is modelled as the search for a best Hamiltonian path (each vertex is visited exactly once) in the graph. We will give a brief outline of how the algorithm works and in the appendix we give a detailed formulation of the construction algorithm following the ideas of Dorigo et al. (1996). The Ants cooperate using pheromones that ants deposit on when they select the edge of the graph. The levels of pheromones determine the attractiveness of the path increasing the probability of it being used by other ants.

Solutions are constructed probabilistically using a pheromone model, and then the solutions are used to update the pheromone values. As we use utility workers for the sequence part, all the sequences are feasible by definition. Nevertheless, sequences not respecting the takt time or workload balancing will have to bear the extra cost. A big enough set of transportation vehicles is defined to ensure that all the routes are feasible and capable of delivering the components when needed.

The transportation vehicles depart from the depot with a load of components that (on average) equal the number of vehicles, v, divided by the

number of stations, s, times the number of cars produced, n, always respecting vehicle capacity (see Eq. 37).

$$\frac{\mathrm{v} \times \mathrm{n}}{\mathrm{s}} \leq capacity\ Of\ Vehicles \tag{37}$$

Each vehicle from the replenishment route departs from the warehouse $(s_i = 0)$, visits the stations, and goes back to the warehouse again at the end of the route. The transportation time includes travelling from station s_i to station s_i and unloading the components. In order to promote the exploration of different solutions, each routing ant starts the exploration from a different point; we multiply the probability matrix for Eq. 38 as a factor of the selection of the $candS$ in ACO algorithm.

$$\frac{(\mathrm{ord(ant)} + 1)}{\mathrm{total\ N\ number\ Of\ Ants}} \tag{38}$$

The algorithm uses two types of ants: sequencing ants and routing ants. The sequencing ant will be complete when the ant contains a full production sequence of cars. A routing ant will have terminated its path when all the stations are visited.

First, pheromone trails are initialized, and then at each cycle, sequence ants construct a full sequence and a full route from an empty sequence and an empty route. Cars are iteratively added until the sequence is completed. At every step, car candidates are restricted to the ones that generate the minimum cost, which means that the choice is restricted only to cars that create minimum extra cost. With this set of candidates $(cand)$, the next car is chosen using transition probability Eq. (39 or 40). The sequencing ants keep doing this until all the cars are sequenced. Then the demand over the time is calculated and, the routing ant replenishment route is built. In order to build the route, we start from an empty route. The depot is duplicated a number of times to equal the number of transportation vehicles. We start to add stations from the non-attended locations $(candS)$ among the ones that generate the minimum cost and for each vehicle we choose the one that adds the minimum cost. The probability Eq. (41) will depend on τ_{ij} and η values. Once all stations have been attended, we decrease the number of vehicles and repeat the creation of routes unless that number of vehicles cannot attend all the stations on time. We should keep the best solution to lay pheromones. Finally, we repeat the entire process. The algorithm stops iterating after a maximum number of cycles has been performed.

The method of building the car sequence, taking into consideration the classes of the cars is inspired by the one described by Solnon (2006), in section 6, for combining two pheromones. The vehicle routing is inspired by the approach of Baran and Schaerer (2003). The first colony minimizes the number of vehicles while the second colony minimizes the inventory cost. Both colonies use independent pheromones and collaborate in sharing a global best solution. This solution is used to update the pheromones.

$$\mathrm{p}(\mathrm{c}_i, \mathrm{candCar}, \pi) = \frac{[\tau_1(c_j,c_i)]^{\alpha_1}[\tau_2 classOf(c_i)]^{\alpha_2}}{\sum_{c_k \in cand}[\tau_1(c_j,c_i)]^{\alpha 1}[\tau_2 classOf(c_i)]^{\alpha 2}} \text{ if the last car of } \pi \text{ is } \mathrm{c_j} \tag{39}$$

$$\mathrm{p}(\mathrm{c}_i, \mathrm{candCar}, \pi) = \frac{[\tau_2 classOf(c_i)]^{\alpha_2}}{\sum_{c_k \in cand}[\tau_2 classOf(c_i)]^{\alpha 2}} \text{ if } \pi \text{ is empty} \tag{40}$$

$$\mathrm{p}(\mathrm{s}_i, \mathrm{candS}, R_{v_i}) = \frac{[\tau_3(s_i,s_j)]^{\alpha_3}[\eta(s_i,s_j)]^{\beta}}{\sum_{s_k \in candS}\left[[\tau_3(s_i,s_j)]^{\alpha 3}[\eta(s_i,s_j)]^{\beta}\right]} \text{ if } \mathrm{s_j} \subseteq \mathrm{candS}, 0 \text{ otherwise} \tag{41}$$

Where $\alpha_1, \alpha_2, \alpha_3$ and β are respectively the relative weights for the pheromone and heuristic values. A full solution is defined as the sequence and the route of vehicles to replenish the components. After each iteration, we obtain a full feasible solution to the problem that is improved after each iteration. A decrease in the use of the vehicle is given after several iterations where vehicles could select the "nil" route (stay at the warehouse).

Pheromones.

The three proposed pheromone structures achieve complementary goals; the first aims to identify a good sequence, the second aims to identify critical cars, and the third aims to identify vehicle routes that can deliver the components on time.

- *pheromone* τ_1. Ants lay an amount of pheromone $\tau_1(\mathrm{c_i},\mathrm{c_j})$ on a couple of cars $(\mathrm{c_i},\mathrm{c_j}) \in C \times C$, which represents the past experience of sequence car $\mathrm{c_j}$ after $\mathrm{c_i}$. This pheromone is bounded with [Tmin, Tmax] and is initialized at Tmax for every couple.
- *pheromone* τ_2. Ants lay pheromones on car classes cc ∈ Classes(C) and the amount of pheromone τ_2(cc) represents the past experience with the car sequence of this class without violating any constraints. This pheromone is bounded with [Tmin, Tmax] and is initialized at Tmin.

- *pheromone* τ_3. Ants lay pheromones on the path between the current location and the possible location $(s_i,s_j) \in S$ and the amount of pheromone levels of $\tau_3(s_i,s_j)$, indicating how proficient it has been in visiting station j after i. This pheromone is bounded with [Tmin, Tmax] and is initialized at Tmin.
- *heuristic* $\eta(s_i\ s_j)$. The dynamic attractiveness of the arc (i,j) will be: $\eta(s_i\ s_j) = 1/stock_j$. It will be computed dynamically depending on the inverse of the stock level in each station at each time.

Pheromones Update.

Each pheromone will be laid and updated according to its characteristics.

Updating Pheromone τ_1 Once every sequence ant has constructed a sequence, the quantity of pheromone in all pheromone trails is decreased in order to simulate evaporation, multiplying every arc by $(1-\rho 1)$. Then the best ant deposits along its path a trail of pheromones inversely proportional to the total cost generated by the violated constraints. If the resulting pheromone value is lower or higher than the range, it will be adjusted to the closest boundary.

Updating Pheromone τ_2 Ants lay pheromones on car classes during the construction; when no more cars can be scheduled without breaking any production rule, some pheromone is laid on the classes of the cars that have not been scheduled. The pheromone update occurs during the construction step. Every ant adds pheromones, not just the best ant. In order to simulate evaporation, each class is multiplied by $(1 - \rho 2)$.

Updating Pheromone τ_3 First, local updating is conducted by reducing the amount of pheromones on all visited arcs by multiplying current pheromone levels by $(1 - \rho 3)$. Global trail updating is performed for all the arcs included in the best route found by one of the ants.

ACO parameters tuning

In this stage, we identified and controlled the correct combination of values for the algorithm. The ACO was tuned, using as starting values those suggested by Dorigo et al. (1996) and Solnon (2008) but taking into consideration that there are no universal values that can solve each ACO problem (Eiben et al. 1999). We tested the different values of the parameter with all small instances solved with MILP. We fixed the rest of the parameters and fluctuated the examined parameter, and then we repeated this process with the rest of the

parameters. Table 6.4 presents the values of the parameters that performed better.

Table 6.6: ACO Parameter settings.

	β	α_n	ρ_n	τ_{min}	τ_{max}	Note
Pheromone 1		3	1%	0.01	4	the experience of car_j after car_i
Pheromone 2		6	2%	1	10	critical models
Pheromone 3		2	0.5	0.1	5	the experience of loc_2 after loc_1
Heuristic η	5					heuristic info

COMPUTATIONAL STUDY

The MILP was modeled in *AIMMS* 3.13, and the standard solver Gurobi 5.5 was used to obtain the solution to the problem. The ACO was programmed in C++ using *Code::Blocks*. The computational experience was performed on a machine with an Intel Core i3-2350 processor M 2.30 GHz 6 Gb RAM running under Windows 7.

As there are no public instances in the literature for the joint problem, we based all the experimentation on the instances used in Regin & Puget (1997); these amounted to instances #1, #2, #3, and #4, which have been widely used in other articles. These instances are public at car sequencing problem lib (www.csplib.org). From those production sequences, we made up the missing data to obtain some small, medium and large instances. We created a reduced instance (R#No.r) that contains the first 50 cars of the instances. Furthermore, an extended instance was created, duplicating the number of stations (R#No.e) and keeping the same production ratio. For the instances of 200 or more cars found in the literature, the MILP is not able to build the model. As no comparison point for this problem exists, no experimentation was performed with bigger instances. A terminating criterion of 3,600 seconds was set for all the instances.

There are two typical ownership options for the transportation vehicles that were experimented. The first one is when the car manufacturer is the owner of the fleet and each transportation vehicle generates an amortization, travelling, and moving cost. The second one is used as a material handling company, in this case only where travelling and moving costs exist.

In Table 6.5 the computational results are presented. The first four columns present the instances and their characteristics. The following columns present the solution for the car sequencing (a), vehicle routing problem (b), and the holding cost (c). Column (d) presents the sum of these costs. Column (e) presents the total cost of the Joint Approach solved with the MILP. The next column, (f), is the difference between the MILP joint approach and the separate

approach. Column (f) shows the mean of the 50 ACO runs; the next column is the standard deviation of 50 ACO runs. The last column presents the difference between the ACO and the separate approach. The solutions of the car sequencing R#1, R#2, and R#4 are the same as the best known in literature; however, in the case of R#3 our algorithm could not achieve the best known solution in the given time. Despite the fact that the ACO could not achieve the optimal solution, with the exception of the small instances, better results were obtained within all the instances than with the MILP using the one-hour stop criterion; in all cases, the results were seen in less than two minutes, especially for the extended instance where the gap is bigger.

Table 6.7: Computational results of car manufacturing ownership of transportation vehicles.

Instance	No mod	No car	No loc	Car seq (a)	VRP (b)	HC (c)	Total (d)= a+b+c	Obj Joint (e)	Δ % d-e	aco μ (f)	aco σ	Δf % d-f	Δf % e-f
R#1.r	9	50	5	500	458	910	1868	1740	6.8	1803	37.8	3.5	-3.6
R#2.r	7	50	5	0	458	912	1370	1235	9.8	1307	43	4.6	-5.8
R#3.r	8	50	5	300	458	1001	1759	1564	11.1	1565	58.1	11	-0.1
R#4.r	10	50	5	600	458	893	1951	1841	5.6	1899	29.4	2.6	-3.2
R#1	22	100	5	0	828	3192	4020	3632	9.6	3625	125	9.8	0.2
R#2	22	100	5	600	828	2887	4315	4050	6.14	3954	42.3	8.4	2.4
R#3	25	100	5	400	828	3324	4552	4072	10.5	4099	154	9.9	-0.7
R#4	23	100	5	200	828	3213	4241	3963	6.5	3876	76.2	8.6	2.2
R#1.e	22	100	10	0	1650	6214	7864	7759	1.34	7464	194	5.0	3.8
R#2.e	22	100	10	1200	1650	6332	9182	9038	1.57	8785	179	4.3	2.8
R#3.e	25	100	10	800	1783	6427	9010	8810	2.22	8442	139	6.3	4.18
R#4.e	23	100	10	400	1650	6174	8224	8113	1.35	7808	168	5.1	3.8

Table 8.6: Computational results from using a material handling company.

Instance	No mod	No car	No loc	Car seq (a)	VRP (b)	HC (c)	Total (d)= a+b+c	Obj Joint (e)	Δ % d-e	aco μ (f)	aco σ	Δf % d-f	Δf % e-f
R#1.r	9	50	5	500	510	866	1876	1781	5.06	1812	43.8	3.4	-1.7
R#2.r	7	50	5	0	514	926	1440	1295	10.07	1342	62.7	6.8	-3.6
R#3.r	8	50	5	300	522	961	1783	1613	9.53	1708	75.1	4.2	-5.9
R#4.r	10	50	5	600	505	995	2100	1855	11.67	1955	61.5	6.9	-5.4
R#1	22	100	5	0	1189	2918	4107	3887	5.36	3932	89.6	4.3	-1.2
R#2	22	100	5	600	1192	3002	4794	4399	8.24	4410	102.5	8.0	-0.3
R#3	25	100	5	400	1194	3153	4747	4460	6.05	4443	80.7	6.4	0.4
R#4	23	100	5	200	1194	3134	4528	4339	4.17	4278	55.3	5.5	1.4
R#1.e	22	100	10	0	5120	6373	11493	11491	0.02	11074	126.1	3.6	3.6
R#2.e	22	100	10	1200	4530	5836	11566	11485	0.70	11135	138.2	3.7	3.0
R#3.e	25	100	10	800	4522	6642	11964	11841	-0.65	11381	107.5	3.3	3.9
R#4.e	23	100	10	400	3992	6170	10562	10489	0.69	10148	149.2	3.9	3.3

In Table 6.6, the computational results of using a material handling company are presented. The joint approach obtains better results or in the bigger instances similar results. When the bigger instances are solved, the size of the model does not allow the solver to explore all the branches of the tree. In one instance (R#3.e), the joint approach was 0.6% below the traditional approach, but in the rest of the cases, it achieves at least the same results, and the majority of the results are better. In this approach, the routing cost in the big instances becomes more relevant than in the first approach because of its intense use of material handling and no discount for intensive use is modelled.

The aim of this paper is not to discuss whether to outsource material handling, but to discuss the benefits of the joint approach and ACO in the two cases. The outsourcing decision will depend on the strategy of the company. The purpose of experimentation with the two approaches is to highlight what makes sense with a joint approach in both cases. Therefore, the resultant costs of Table 5 and Table 6 are not comparable since the transportation cost is highly dependent on the negotiation of the contractual terms with suppliers and workers.

Finally, we analysed the stock. It can be noticed that the stock level decreases until it reaches the level of the safety stock before replenishment, which opens the opportunity to manage the risk of working without safety stock in order to realize the possible saving, and also manages the possibility of incurring a cost if there is any delay in the transportation.

MANAGERIAL INSIGHTS

According to our expectations, the integration of the decision has resulted in the achievement of better results. The fact that one part of the organization achieves the best possible performance might not be beneficial for the entire organization, so the decision-making process should be done in conjunction with the other stakeholders in the process. Unfortunately, this is not always possible since real-life problems are far more complicated than this model. However, as can be seen in Table 4, the goal of the decision-maker with regard to scheduling, routing, and inventory should be to reduce the total cost, not only the cost associated with the process they are responsible for, and this cannot be achieved without a compound approach.

When we model with a Joint approach, we allow the decision model to choose from among several options, which increases the possibility of achieving a better solution. Unfortunately, as we expect from the MILP, the computational cost in some cases is excessive with regard to the savings and

then the only possibility is to use the ACO, which, despite not achieving the optimal, gives us good quality results.

Comparing the Afshin et al. (2012) review of the paper that deals with more than one part of the supply chain against the number of papers for each echelon of the supply chain, there is a lack of compound approaches from the researchers. On the other hand, the industry is using decision systems such as Oracle E-Business SCM, SAP SCM, i2, IBM, or LogicTools, which, despite their inability to give the global optimal since they give solutions in seconds or minutes, give solutions that pursue an integrated optimization.

The last but not least of these managerial insights. After a literature review the majority of the papers still focus on one of the specific problems that face a production plant, such as scheduling or routing. They integrate new solving methods, techniques or cuts and find the optimum for many isolated problems. In parallel, the IT industries have developed fast solvers and great computational power. In the vision of the authors the next natural step incorporates more problems together to achieve a better solution.

In the heuristic arena, the different algorithms are concerned with avoiding being trapped in a local optimum, but as we continue modeling specific parts of the problem with a "silo view", the majority of the solutions are a local optimum of the entire solutions, since we do not model the entire problem. With the actual modelling techniques and solvers, we should try to follow a holistic view of the modelling not only on the assembly line with the sequencing, routing, and line-side storage problem, but as a goal of the majority of our models.

The advantage of joint decision-making becomes more important when the cost of space is higher than in a low-cost facility. The production space is a limited resource; it has to be used in an activity that adds value to the product and decreases the holding space. This becomes a key factor in factories where the inventory is limited, and there is no possibility to store more than one or two hours' inventory.

CONCLUSIONS

The first contribution of this paper is the development of a mixed integer programming model for solving an inventory routing problem to satisfy the sequence requirements, since this kind of model is not reported in the literature and the authors believe that this could be an interesting research area.

This paper uses the natural cooperative behaviour of ants to obtain a solution to combined problems. The second contribution of this work consists

in the development of a collaborative ant colony optimization system to obtain a high-quality solution for problems that cannot be solved to optimality, and the joint solution to the problem using ACO, to the best of the authors' knowledge, has not been described throughout the literature.

The results yield savings of around 7% on all costs in the instance tested with respect to the solution obtained using a separated approach. It is expected that larger instances will maintain the same performance (or better) in terms of savings since the decisions are taken independently. Factories with a reduced production space should be more interested in this kind of approach. This would justify the investment in more computational power or the design of other solution methods.

We believe that the results tested in the small- and medium-sized cases are promising. The decrease in the number and use of transportation vehicles, reduction in inventory next to the assembly line, and minimization of the number of utility workers to handle violations of the sequencing rules could be interesting for future research. Therefore, making an industry-sized model could be justified.

The limits to this approach are that the instances from which we can compare the results are too small and the incorrect balance between costs that could depend on the specific real case, but the solution is sensitive to this balance of costs. Finally, the inabilities to suggest structural changes in management policies (e.g. Outsourcing the material handling) since the costs are also case dependent.

For future research, given that this is an NP-hard problem and since the subproblem of routing is NP-hard, the overall problem is NP-hard. From this point, many research paths could be followed. The first one is to try to add cutting planes or decomposition methods to handle real-life problems. The other option is to implement other metaheuristics different to ACO that could provide a good solution in a short period with average computational power. In the ACO line, the focus could be placed on larger problems, combining different techniques, like additional types of pheromones, ranking methods, and different construction strategies for the route, such as a local exchange or candidate list. For the modelling part, we could also add some "ad-hoc" features to customize the model to better represent a client reality, with discounts for excess use or nonlinear holding costs.

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Chapter 7: Aeronautical manufacturing plant, using simulation

MOTIVATION

Several manufacturing processes rely on the use of hoist, crane or some material handling device to change the work in progress from one workstation (tank) to another. Two main decisions have to be made. The first one is the proper sequence of the parts that are manufactured and the second one is the route of the material handling device to move this work in progress.

Hoist scheduling is a typical problem in the operation of different processes arising in the aerospace and electroplating industries. This problem includes several hard constraints that should be considered: single shared hoist, heterogeneous recipes, eventual recycle flows, and no buffers between workstations.

This problem is an example of a problem where obtaining an optimal solution to one part of the problem does not lead to an optimal overall solution, in some cases not even to a feasible solution. If the optimal schedule is obtained to minimize the processing time of the orders that will be produced, maybe the hoist will not be able to find any path that could make the movements when they are required by the production sequence. The other option is to solve everything together as Aguirre et al., (2011) did, but it requires a lot of time and assumptions. For this reason, we implemented a simulation that used heuristics to take everything into consideration, and despite the optimal not being found, good and feasible solutions were obtained.

Two operational decisions were made jointly (see Figure 7.1). The use of discrete simulation using heuristics lets us obtain a feasible solution in a reasonable amount of time, in addition to being able to easily model breakdowns that are difficult to simulate with exact methods, and visualize the change in the interest variables over time.

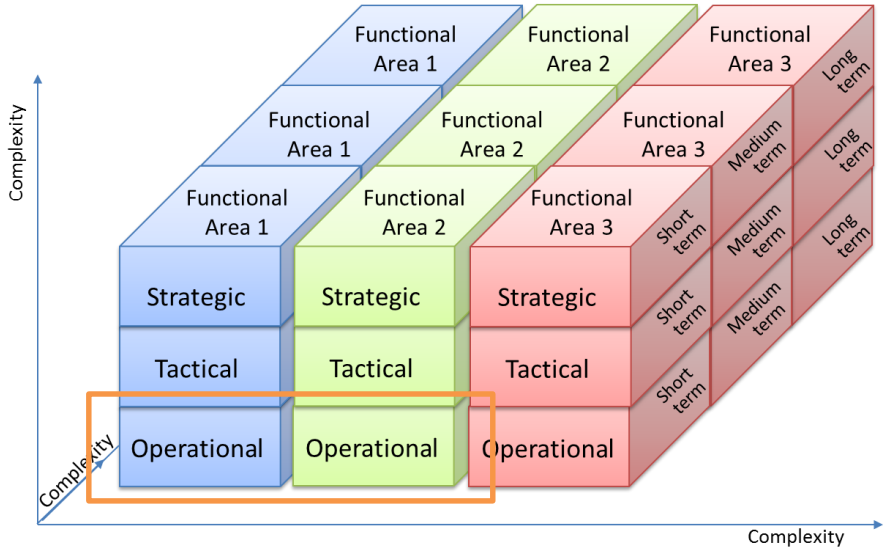

Figure 7.1: Complexity of the decisions. A higher number of blocks implies a higher complexity.

The aim of this chapter is to simulate and optimize the design and operation of a complex manufacturing system with a reasonable computational effort. The simulation model is able to consider heterogeneous recipes, possible recycle flows and no buffers between workstations simultaneously.

In addition, we present heuristic–based strategies to find interactively and improve the solution generated over time. Due to the nature of the chemical process, the residence time in each tank is bounded by strict limits. All the transfer activities in the system are executed by a single hoist that can carry a single unit at a time. The product will be defective if any of these constraints are violated. Different heuristics were tested by using real-world data taken from the surface-treatment process of metal components of an aerospace industry to minimize the total production cost.

INTRODUCTION

The solution of complex real-world scheduling problems has attracted the attention of researchers and practitioners for many years. Flow shop scheduling considers that a set of jobs has to be transferred through several stages, by using a shared automated transfer device (hoist). Each job is processed in a sequence of units, with a flexible processing time, where every machine can only perform one job at a time and cannot be interrupted. Flow-shop problems are usually focused on finding the best processing job sequence that minimizes the completion time of the last job in the system, which is widely known as the makespan (MK) criterion.

The new market conditions for products have led to a flexible design of the production line that can produce many job types. Each product type differs from the sequence of stages that are visited and in the time spent in each one (Aguirre et al. 2008; Aguirre et al. 2011). The analogy to that in chemical processing is the order in which the components visit the different tanks and the duration of the chemical treatment, which should be between a minimum and a maximum of time for quality reasons (Kujawski and Swiatek 2011). Scheduling the jobs and controlling the handling device (hoist) is crucial for the system performance. Often the plating process is a major bottleneck, and the hoist scheduling problems are very complex.

These kinds of problems are commonly found in electroplating lines that are used to cover parts with a metal coating. These machines can be found in many types of industries such as the manufacture of printed circuits boards, in the automated wet-etch station in the semiconductor industry, in the chemical treatment of aeronautical parts, and in household electrical appliances, etc. (Manier and Block 2003).

The current work is focused on the critical surface treatment process of large metal components in the manufacturing industry (Paul and Chanev 1998). The scheduling of heavy aircraft parts is characterized by a higher complexity than a typical flow-shop problem. This process involves a flow through a series of chemical tanks, in which a material-handling tool is in charge of the transfer movements between the different tanks, including the input and output of the system. Not reaching the minimum processing time, or exceeding the maximum allowed time may cause not only material waste but also loss of the critical resource of production time. It is important to remark that transfer times are directly related to the initial position of the hoist, the actual position of the component and the next stage of the component. Thus, the handling device has to transfer heavy parts at low speed through the production line. The tanks can only contain one part, and so it is necessary for the next tank to be idle before the movement is made. This problem has been addressed in the literature, which gives priority to the most advanced item in the production line. However, there are cycles in the sequences that the parts should follow, making the scheduling for the decision- maker even more complex.

The hoist works during the entire shift moving from one tank to another, loading and unloading heavy and big parts in an aggressive chemical environment. This can cause the hoist to become stuck until an operator unblocks it. This may happen several times per day and after a few minutes the hoist is working again. This is an important issue, especially when the optimal work in process (WIP) needs to be determined. If only one part is

allowed to be in the system, the scheduling of the hoist is very simple since the hoist only has to wait for the part outside the tank and transport it to the next stage. In this case, the resulting throughput is unacceptable. In the event that the hoist becomes stuck, it could be easily repaired without any damage to production. On the contrary, if something goes wrong a high WIP may cause several pieces to be damaged. Furthermore, generating a scheduling with a high WIP without defective parts is extremely complex and will probably take more time than the shift where it is to be performed.

The main objective of this work is to develop a discrete simulation model to evaluate, analyse and design the operation of electroplating for the aerospace industry based on the hoist scheduling problem. Also, a sensitivity analysis is performed to assess how different input parameters affect the variable response of the decision model. In this way, it seeks to find different proposals to minimize the makespan and increase the productivity levels of the line and the efficiency of the overall system by minimizing the defective parts (waste).

The model is developed in *SIMIO* (Thiesing et al. 1990), which is a modern simulation software belonging to the category of discrete simulation languages. This type of software is widely used to simulate systems of high complexity. The proposed model provides a 3D user-friendly graphical interface that easily allows evaluating the operation of the system over time. The methodology used in this simulation is described in Figure 7.2.

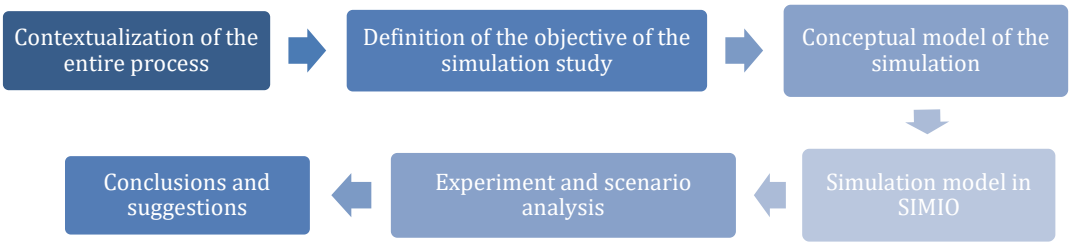

Figure 7.2: Methodology of discrete simulation.

PROBLEM STATEMENT

The electroplating process consists of jobs that are chemically processed in different chemical tanks for a range of time. The jobs are transported from one tank to another by a single automated hoist. The electroplating line can process different jobs, which should follow different recipes. A recipe is defined as the combination of the different stages that an item must follow and the specific time window that the job should be in the tank.

In practice, jobs vary in size or other properties and require different sequences or processing times. Each produced item type has its sequence of visiting workstations, processing intervals, and so on. In the case of the electroplating industry, usually metal elements are coated with noble metals e.g. nickel, chrome.

The Hoist Scheduling Problem also occurs in other industries, such as the production of printed circuit boards and food processing (Aguirre et al. 2014). In practice, production lines manufacture multiple item types because either a line was designed to perform multiple technological processes or within a single technological process (e.g. chroming), jobs vary in size or other properties and require different sequences or processing times.

The hoist is capable of transferring only one item at a time from one chemical tank to another. The transfer time of the hoist consists of the travelling time from the actual position of the tank, the loading time, the travelling time to the destination tank, and the unloading time. The loading and unloading times are constant and known in advance. The travelling time depends on the distance between the tanks. The processing time starts when the hoist unloads the item in the tank and finishes when the hoist picks up the item. If the duration of the processing time is below or above the time window, the item becomes defective.

Each tank operates independently and has a unary capacity. Also, there is no buffer between adjacent workstations. That is to say, the item has to be moved to its next tank after the processing time is finished but before the upper bound of the time window. Some critical tanks have a null time window, which implies that as soon as the processing time is finished, the item should be moved immediately.

An example (MxN=4x3) which represents the main features of this problem is shown in Figure 7.3.

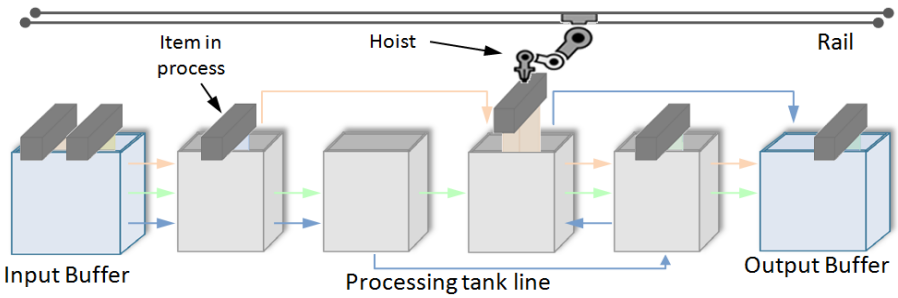

Figure 7.3: Automated job-shop system with heterogeneous recipes.

Different conflicts

When the hoist problem is solved, it needs to be assured that feasible schedules are generated. When the work-in-progress (WIP) of the system is higher than 1, three types of conflicts can arise (Yih, 1994).

1. *Conflict by tank availability:* a conflict may occur when a job finishes its processing in one stage and the next tank in the recipe is busy. In this case, the hoist must first serve the job that is in the destination tank before moving the first job. Unfortunately, this is not always possible because when the second tank is released the job in the first tank may be defective. The worst version of this conflict is when the destination tank of job A is the current location of job B, and destination tank of job B is the current location of job A (see Fig. 7.4).
2. *Conflict by hoist availability:* a conflict may occur when a job is ready to be transported, and the hoist is being used by another job. The job should wait until the hoist is idle but sometimes it is too late. This becomes more critical when the minimum and maximum processing times are equal because there is no extra time to wait for the hoist. For this reason, it was needed to develop an algorithm to verify the status of both the robot and the jobs waiting for it.
3. *Conflict by hoist location:* a conflict may occur when a job needs to be transported but the hoist is too far and when the hoist arrives it is too late. This conflict is more common when the hoist is unloading at one end of the transportation line.

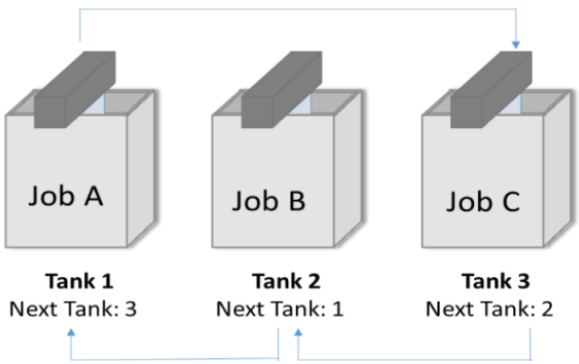

Figure. 7.4: Conflict by tank availability.

PROPOSED SIMULATION MODEL

Most of the real-world systems are highly complex and virtually impossible to solve by using purely mathematical approaches. The increasing availability of simulation language, the increase of computational power, and the development of simulation techniques have made simulation an appropriate tool to deal with this kind of problem (Banks et al. 2004). In contrast to optimization methods, simulation models are "run" rather than solved, allowing the model to be observed.

Simulation allows organizations from different sectors to experiment and analyse the different operation areas of their organization. They can model their process in virtual settings, reducing the time and cost requirements associated with physical testing. Therefore, complex systems operations can be assessed by developing a discrete event simulation.

Moreover, the proposed simulation model provides a 3D user-friendly graphical interface that allows obtaining a better visual experience of the world of simulation models. It provides rich 3D objects to make the simulation look more realistic than 2D simulations. Also, simulation models can be easily tweaked and adjusted, providing rapid responses to even the most abstract situations. Therefore, to represent the operation of the electroplating line, a computational model was developed by using the SIMIO modelling environment. The following components are considered in the model:

- Tanks / workstation: where different chemical processes are performed, e.g. anodized sulphuric aluminium, chromic anodized, passivation, chroming by immersion, cleaning and so on.
- Jobs: multiple item types are produced in this process.
- Input / Output of the line
- Hoist: device materials are handling charge transfer items between workstations.

Model in SIMIO

In the proposed SIMIO-based simulation model, each physical component of the real process, such as jobs or workstations, is represented by an object with a predefined behaviour. As shown in Figure 7.5 source, server, and sink objects, connected by multiple time path objects, have been used to build the whole simulation, model. The objects used belong to the Standard Library. In Figure 7.5, 2D and 3D animation views of the developed model are given. A

detailed description of how the electroplating line has been modelled is explained below.

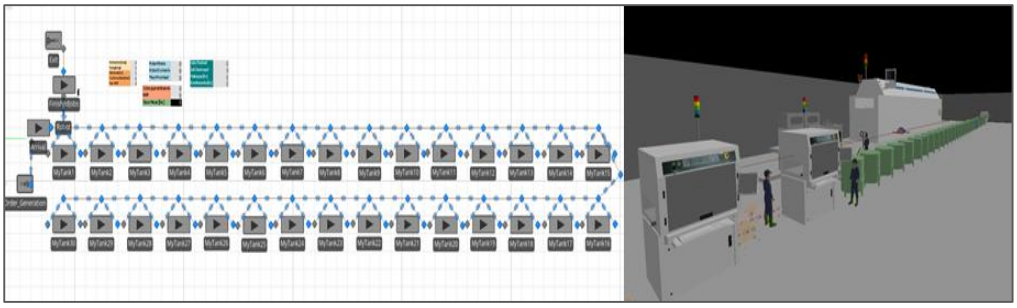

Figure 7.5: 2D and 3D SIMIO model of the electroplating line.

Jobs

All the aeronautical parts that are to be produced are called Jobs. As shown in Figure 7.6, they are the dynamic entities processed on the line. The model entities are the types of jobs that are processed in the tanks. Each job has a unique recipe associated with it, which is specified in *ModelJob* properties and a sequence table. Each recipe establishes the path to be followed through the different tanks, and the minimum and maximum residence time that is allowed in each tank. Different labels are assigned during the process to allow the Jobs to follow their paths and to track them to obtain useful output data.

In Table 7.1 an example of anodized sulphuric Titanium is presented. The different recipes could vary in the path or in the processing times of each tank. A tank could be visited more than once (tank 6 is visited in stages 5 and 8). A job could move backwards in the line (tank 22 is followed by tank 16), and not all tanks are visited for all recipes. The difference between the maximum and minimum times could be zero, i.e. fixed and exact processing time (stage 10).

Figure 7.6: Dynamic entities, their properties and sequence table.

Table 7.1: The recipe for anodized sulphuric Titanium.

Stage	**Tank**	Minimum Time (min)	Maximum Time (min)
1	**5**	10	15
2	**6**	5	6
3	**13**	1	2
4	**12**	5	5.5
5	**16**	3	10
6	**21**	10	15
7	**22**	10	15
8	**16**	3	10
9	**20**	5	20
10	**3**	20	20

All jobs are generated by a Source Object called "*OrderGenerator*"(see Figure 7.7). In this step, the scheduling is done because the jobs are created according to a recipe table ("*Recipes.JobType*") and an Arrival Time Property ("*ArrivalTimeProperty*"). The different arrival times are created using different heuristics that will be explained later. The jobs enter the line by a "*Server Object*" which is constantly evaluating the work in process (WIP), the availability of the first tank of the recipe, and the availability of the hoist to enter the system.

Finished jobs are moved to the output of the line by the hoist. A sink object is used to model the behaviour of the output of the planting system (Figure 7.7). The response variables are updated in this module.

Chemical Tank

A Server Object is used to represent the chemical tanks (see Figure 7.8). Tanks operate independently, they do not have buffers (No intermediate Storage), and they never have faults. The processing time of the tank is determined by the minimum processing time of each job (Table 7.1); after this period the job could stay until it reaches its maximum processing time. After this time, the job will become defective.

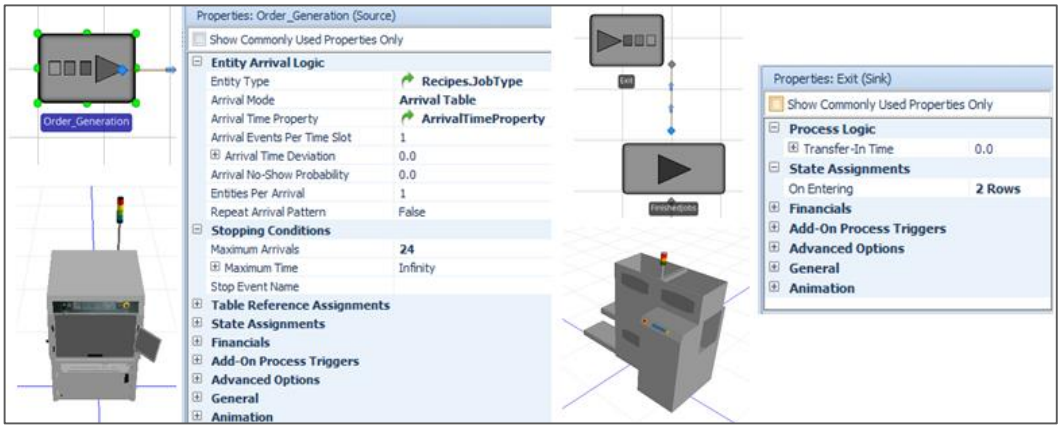

Figure 7.7: 2D and 3D SIMIO model (Input / Outputs of the line).

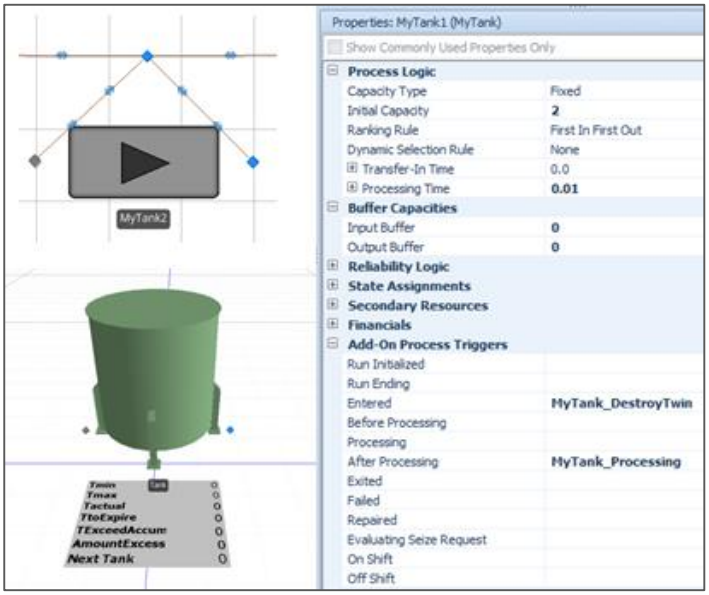

Figure 7.8: 2D and 3D SIMIO model (chemical tanks).

When a job is processed in the tank, this job transmits all its properties (minimum and maximum processing time and next tank) to the workstation and the *MyTank_DestroyTwin* process is performed. Then, the "*MyTank_Processing*" process is carried out. Also, the jobs could be in four states according to the current processing time and the job properties. As shown in Figure 7, the jobs do not have to pass through all the states.

- State 1: job has not yet reached its minimum processing time in the tank, and has not reached the minimum time required for the hoist to pick it up. Then, the job does not request the hoist.
- State 2: job has not yet completed its minimum processing time in the tank but it has reached the minimum time required for the robot to pick it up. So, job requests the robot with a high priority.
- State 3: job has reached its minimum processing time but is in its tolerance range (between the minimum and maximum processing time). Also, it has not yet reached the threshold time required to be considered urgent. Job requests the robot with a medium priority to avoid becoming defective.
- State 4: the job is in the most critical state because it has completed its processing and has reached the threshold time to be considered urgent. In this way, it has the highest priority to request the hoist.

Note that if the Job is not serviced by the hoist before reaching its maximum processing time, it must be discarded because of the high-quality standards for aeronautical components. In the diagram (see Figure 7.9) the parameter "*WarningT*" is a threshold that the hoist needs to move from any point of the line to the other end of the tank. "*Tmin*" is the minimum processing time and "*Tmax*" is the maximum time before becoming defective. "Wait" and "Job processing" make references to record the time passing. When the model requests this, the hoist idles and also checks if the next tank is available.

The request from the hoist is made with the creation of a twin job that goes to the loading part of the tank, and when the hoist arrives and the original parts complete its processing time, both parts are loaded on the hoist, and the twin job is destroyed when the hoist arrives at the next tank.

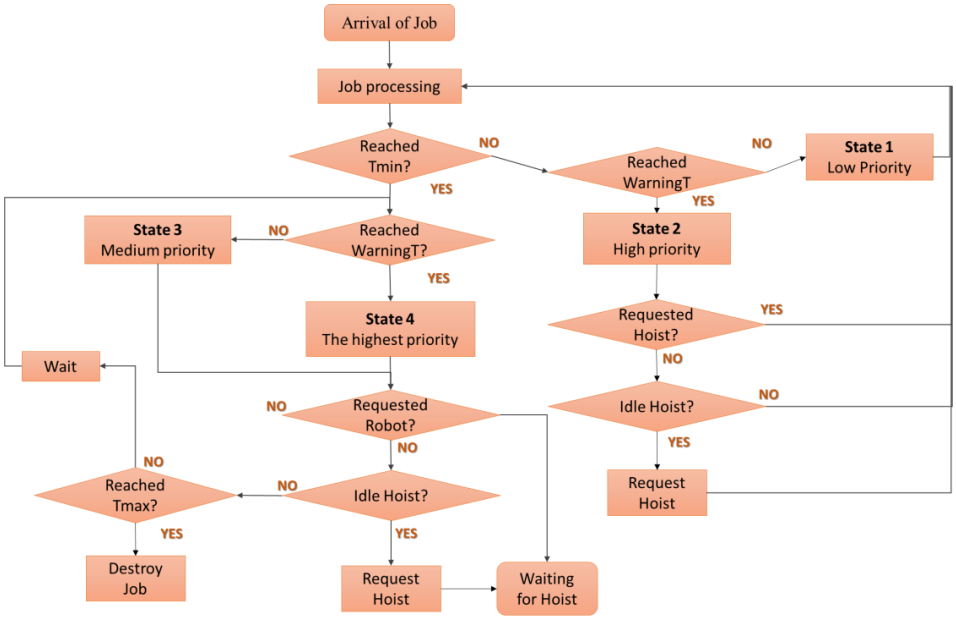

Figure 7.9: Flow chart of the states of the chemical tanks.

Automated material-handling device / hoist

Controlling and optimizing the hoist is crucial for the system performance since a wrong order to move the different jobs among the stages could significantly change the throughput and the number of defective parts. The behaviour of the automated material-handling device / hoist is modelled as a Vehicle Object. The hoist attends any job that requires transportation. Also, the robot travels along a rail that is modelled as a *TimePath* Object, the loading and unloading time of the jobs being constant. When the hoist is idle it should park in the middle of the line at an intermediate node called "*Home*."

Moreover, several processes are performed, within the tanks and the line input, to verify the status of the robot (idle or available) and order requests waiting to seize it. In Figure 7.10, a diagram of the process to evaluate the maximum priority is displayed. This is a crucial part of the logic of the model. It consists in only allowing one job in the entire system to request the hoist. Only when the hoist is idle, will the job with the highest priority and with the destination tank available be able to make the request. The interval between hoists could fail if modelled as an exponential distribution with mean (4 hours), with a recovery time of a uniform distribution of 1 to 2 minutes.

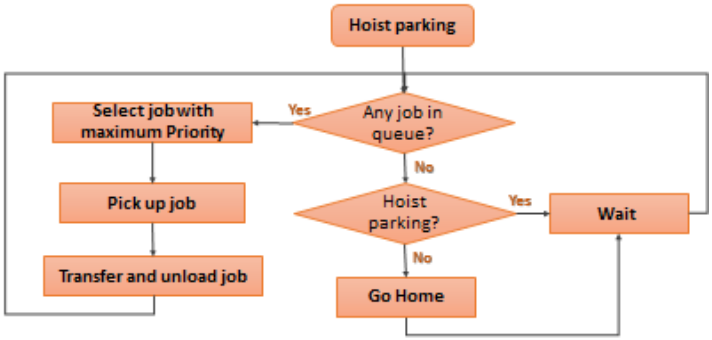

Figure 7.10: Hoist decision diagram.

Model assumptions

The major assumptions for constructing the simulation model were:

- There are N types of jobs following a given production sequence (recipe). They have to be processed by a sequence of chemical tanks from the input buffer to the output buffer (some tanks may be skipped in the process). There are re-entrant and possible recycle flows to the same unit. Each stage has specific time windows of processing time in each tank. Products will become spoiled if the processing time falls outside the time window.
- There are M workstations (chemical tanks), each of which has a specific functionality, has a single production unit per stage, never breaks down and there is no intermediate storage between stages.
- There is a single automated material-handling device (hoist), which transports jobs between the tanks. Its loading / unloading speeds are constants. Its capacity is one. The travelling speed is constant. The hoist can experience breakdowns.

Heuristics

After many experimentations and suggestions from the operator of the real-world system, the following heuristics were implemented in the simulation model to define the input sequence. The sequence that follows the jobs will be created by using the following heuristics:

- •Heuristic 1: Order the jobs according to the total production time, starting with the smaller total processing time.
- •Heuristic 2: Order the jobs according to the total production time. Sequence a short job followed by a long job, and repeat.

- •Heuristic3: Identify the tank that is visited most times and disperse the jobs that use that "critical" tank for all orders.
- •Heuristic 4: Identify the two most common ending tanks (A and B), and intercalate one of A, followed by one of B, and then any other, and repeat until all the jobs have been sequenced.
- •Heuristic 5: Use *OptQuest* to identify which is the best sequence of the system. *OptQuest* could select which order will be taken by each job.

EXPERIMENTAL CASE ANALYSIS

A key stage of a simulation project is the verification and validation of the model. The verification process was done to assure that it was properly codified, and then it was validated with the available data. Banks et al. (2004) highlights that the goal of validation is double: firstly to produce a model that represents the real behaviour as accurately as possible, and increase the model's level of credibility so the model could be used by the decision-makers. The next step is to perform a sensitivity analysis.

The electroplating line of the aeronautical manufacturing system comprises 30 chemical tanks and one hoist. There are 24 types of jobs; each one with its specific sequence. The input and the output of the line are in the front part of the production line. The jobs might require visiting the same tank more than once.

Sensitivity Analysis

Once the model is verified and validated, decision variables are identified to make a design of the experiments (see Figure 7.11). The Experiment Mode in *SIMIO* defines a set of scenarios and performs a sensitivity analysis. The major goal is to evaluate more variables of the control variables and their impact on the response variables.

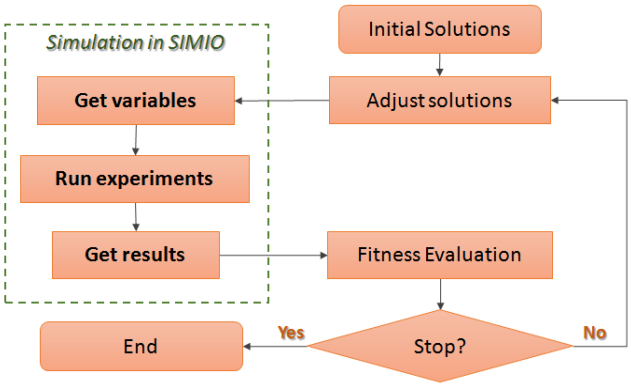

Figure 7.11: Optimization by simulation for the electroplating line.

Control variables

The following input variables are used in this simulation of the case study:

- Max_WIP: Maximum number of jobs that could simultaneously be in the system.
- Input_Order: It is the order in which the jobs enter the system; it is defined by the different proposed heuristics.
- Interarrival_Time: Minimum period between the inputs of two orders.
- Priority: Three different methods were used to assign the priority to request the hoist. The first takes into consideration the time to become defective, assigning highest priority to the jobs about to expire. It is similar to the first method, but it assigns the highest priority to the jobs that are more advanced. The third method takes into consideration the time that the job has exceeded the minimum processing time.

Output variables

Moreover, performance indicators are defined to evaluate the different experiments:

- Makespan: The time in which the last job is completed.
- Job Finished / Defective: The number of non-defective jobs that are completed and the defective jobs.
- Cost: It is the total cost to produce all the orders. It is computed as the sum of the operation cost of the line plus the cost of the defective units.

RESULTS AND ANALYSIS

The control variables were combined to create all the possible scenarios. Each scenario was run 5 times. Table 7.2 presents the best results obtained. There are no significant differences in the behaviour of the different Input orders when the Max WIP is 3, but when it is increased to 4, the only sequence that does not present a defective job is Heuristic 4.

A maximum WIP below 3 jobs, increases the cost since the system is too slow. Maximum WIP above 5 increases the cost since the defective units increase. Finding a feasible sequence with a WIP of 3 is not so complicated; however, with a WIP of 4 it is difficult (only one was found) but presents the best performance. The second priority rule gives the highest priority to the job that is closest to becoming defective.

Table 7.2: Results obtained for different scenarios from simulation model.

	Control Variables				Results		
Scenario	Input Order	Max WIP	Interarrival Time	Priority	Cost	Makespan	Defective Jobs
1	4	4	12	2	189.176	18.9176	0
2	4	3	13	2	195.042	19.5042	0
3	1	3	13	2	195.209	19.5209	0
4	2	3	13	2	195.209	19.5209	0
5	3	3	13	2	195.209	19.5209	0
6	1	3	12	2	195.237	19.5237	0
7	2	3	12	2	195.237	19.5237	0
8	3	3	12	2	195.237	19.5237	0
9	4	3	12	2	195.309	19.5309	0
10	4	3	14	2	195.376	19.5376	0

The simulation was also used to obtain the best range of the inter-arrival times between jobs. Since the system behaves similarly to the first 3 heuristics only heuristic 1 will be compared with heuristic 4 (see Figure 7.12).

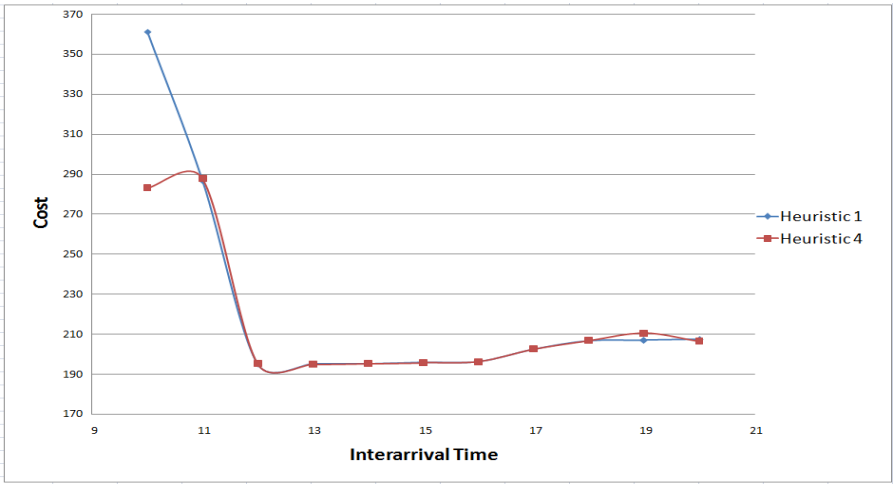

Figure 7.12: Inter-arrival time.

A type "2" priority and a max WIP of 3 is used in this experimentation. It can be seen that as we increase the inter-arrival time, the performance of the line improves because fewer defective units appear, until there is a dip of 12 to 13 minutes, and then the cost starts to increase again because of the cost associated with a longer use of the production line.

After evaluating all the results, the best configuration that minimizes both the makespan and the number of defective products is shown in Figures 7.13 and 7.14. The jobs schedule is given in Figure 7.13 while the hoist schedule is depicted in Figure 7.14.

Note that the results reported by simulation runs are represented graphically by using a user graphical interface. This interface is integrated with the simulation model for quickly evaluating simulation results and helping the decision-making process.

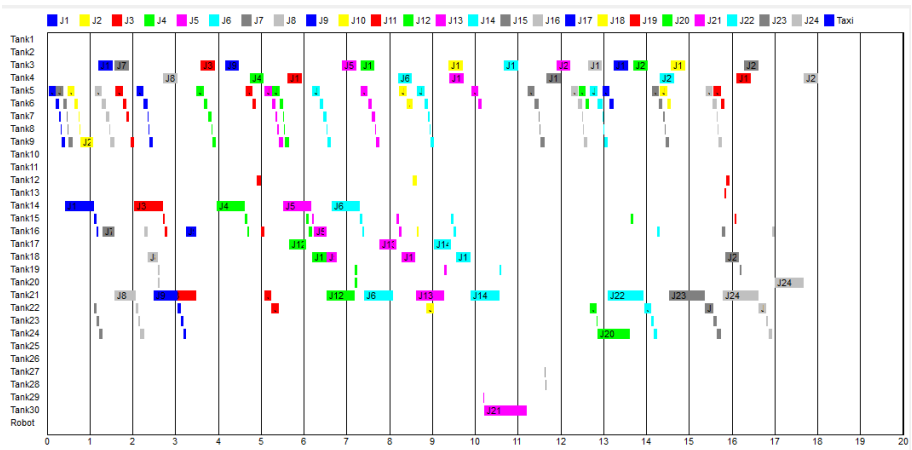

Figure 7.13: Jobs Schedule.

Figure 7.14: Hoist Schedule.

CONCLUSIONS

An innovative discrete event simulation modelling tool has been used to evaluate different parameters and priority-based heuristic policies for a hoist scheduling problem.

These types of systems are used commonly in the manufacture of printed circuit boards (PCBs) in electroplating plants and also in the automated wet-etch stations (AWS) in semiconductor manufacturing systems. Simulation is a proper approach to solving this challenging scheduling problem. Despite not finding the optimal solution, this strategy was capable of offering a good solution in a short period. The aim is to find the best jobs sequence that allows minimizing the total makespan while the number of defective products is reduced. Different heuristics were integrated into the simulation model to test the different jobs sequences to be processed on the line.

A flexible simulation framework plays a key role in this complex system. The schedule of 24 jobs, with an average of 15 chemical stages each one, implies more than 360 movements of big heavy parts by using a shared hoist across the production line. Moreover, hoist failures are explicitly represented in the simulation tool.

We observed that the capacity of the built-in optimizer OptQuest was fairly limited for dealing with this complex system. When apart from the control variables, the optimizer must deal with the schedule of the parts, the solution takes several hours, generating a poor solution when the time limit is reached. For this reason, we embedded heuristics based on the knowledge of the operators and several numbers of experimentations.

Another of the advantages when solving these kinds of problems by simulation is that the decision-maker may easily evaluate the impact of increasing the WIP in terms of the number and cost of the defective parts. Interesting ideas coming from the decision-makers such as changing the chemical for the non-used tanks to the highly used tanks could be easily tested knowing the cost of the change and the improvement of the performance.

According to the simulation results, the line performance is mainly affected by the initial order of the jobs. For this reason, other methods to build sequences should be evaluated. However, the line performance is also affected

by WIP, interval time and priority. The proper selection of these parameters could be done by using simulation.

The proposed simulation model allows the decision-makers to evaluate future improvements in the system design, such as a second hoist, faster hoists and more tanks. This work can also be extended to be connected with Excel, to the proprietary system of the company or with a meta-heuristic to help the model build a better initial processing sequence.

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SECTION 3. HEALTH CARE INDUSTRY

In the last section, the integration of the decision-making process was analysed, and then we integrated tactical and operational decisions, after which we added other functional areas. As the size of the problem increased some heuristics were used, while in the last chapter of the section, we simulate an aeronautical manufacturing process. In section 3, we move the research to the health care sector, which also faces multiple decision-making problems, but with different names. In Chapter 8, we analyse the decision-making process in a hospital, for the assignation of operating rooms, and the surgeries that should be performed and by who. Then, in chapter 9, we work with a teaching hospital, which in addition to the normal considerations for assigning operating rooms, should prepare the surgeons of the future, and deal with the pressure of delivering a quality service.

Chapter 8: Operating Rooms Optimization

MOTIVATION

Despite manufacturing facilities and hospitals looking like two different worlds, managers have to make decisions that impact the overall performance of the hospital. The solutions require good coordination, the same priorities, good decision-making, and expertise. One example is the operating rooms, which are the engine of the hospitals. The proper management of the operating rooms and its staff represents a great challenge for managers and its results impact directly on the budget of the hospital since management is one of the major costs of a hospital.

To solve this problem the hospital also has its decision-making units (see Figure 8.1), where the initiators are the doctors that detect the problem, the influencers are doctors from other hospitals and suppliers that tell them their experience, the surgeons are the users, the gatekeepers are the heads of the operating rooms that ensure that the requirements are fulfilled, the service heads are the deciders and the executors the ones that implement the solution.

Figure 8.1: Decision-Making Units for the operating room assignment base on (Bayle, 2003).

In the decision-making process at the moment the scope of the decision is changed, the decision making unit grows. Instead of having only one head of medical services in charge to decide about a surgery that will be performed in a time slot assigned to them, the decision is made together to persuade the best overall decision for the hospital. In the first part of the chapter, a deterministic approach is used and later a stochastic approach.

This chapter presents a MILP model for the efficient scheduling of multiple surgeries in Operating Rooms (ORs) during a working day. This model considers multiple surgeons and ORs and different types of surgeries. Stochastic strategies are also implemented for taking into account the uncertain in surgery duration (pre-incision, incision, post-incision times). Also, heuristic-based methods and a MILP decomposition approach is proposed for solving large-scale OR scheduling problems in a computationally efficient way. All these computer-aided strategies have been implemented in AIMMS, as an advanced modelling and optimization software, developing a user-friendly solution tool for operating room management under uncertainty.

INTRODUCTION

Nowadays, hospitals managers are focusing on providing a greater use of their resources with the reduction of operating costs. In this context, operating theatres represent a critical area due to the direct impact of any improvement on the hospital budget (Souki, 2011). Operating theatres usually contain a set of surgical and recovery rooms with a limited number of beds and personnel, such as nurses, surgeons and anaesthetists. Therefore, the best way to improve

the performance of operating theatres is by trying to synchronize surgery in a better way, as planning and scheduling surgery seems to be the most useful and efficient strategy for this purpose.

Many contributions to operating theatre planning and scheduling have been developed in the literature. A few contributions break down the problem of planning and scheduling decisions into two levels. In the first one, surgical cases are first assigned to a particular time-block in a week (date) whereas in the second level daily surgical cases are scheduled (see Augusto et al., 2010; Cardeon et al., 2010; Fei et al., 2010).

Similarly, we could compare the block scheduling strategy where surgeries are pre-assigned to surgeons according to the surgical service and have to be scheduled in blocks prior to the working day, to the open scheduling strategy where surgeries submit a request for OR time and a detailed schedule is generated during the day of surgery. The latter strategy is common, for example, in Neurosurgery operations where a patient list is only known 24h before a surgical day. This flexible scheme avoids unfilled blocks in a working day. Also, urgent/emergent surgeries should not be delayed until an available surgeon is free. This strategy eliminates the OR idle times when surgeons have already finished (Denton et al., 2007).

A real application problem appears in Batun et al. (2011) where they study the impact of different operating costs in the ORs. They suggested accounting a negative operating cost of an operating room when not in use by the staff and accounting the overtime as a penalty cost. Also considered is the operating cost of the surgeons when they are idle or waiting for another surgery.

This problem has attracted the attention of numerous researchers and practitioners in recent years. In 2013, the optimization modelling competition MOPTA selected this problem as a relevant one for study in the operational research community (MOPTA, 2013). According to the participants and organizers, this kind of problem commonly appears in many hospitals in different countries where the scheduling process is carried out without any support system.

In this paper, we consider the scheduling problem of daily surgical cases in the operating theatre presented in MOPTA 2013. Thus, we will study the situation where a hospital is already working, and the number of ORs and surgeons are given. Due to the hospital administration having decided to use their ORs more efficiently, the manager needs to allocate and sequence a set of already planned surgeries in a given number of available ORs and surgeons in each particular surgical day. Therefore, we have to find the best sequence of surgeries that minimize the total surgical cost made up of OR idle time and

OR overtime and surgeons' waiting times. To do this, let us assume that the set of surgeries to be scheduled is known 24h in advance of the surgical day, and the number of available ORs and surgeons are fixed. Then, all planned surgeries will have been done during the surgical day. Also, we must consider that all the surgeries can be performed in any of the ORs and surgeries could be performed by any of the surgeons. In our case the surgical operation durations (pre-incision, incision and post-incision times) are also imprecise and have to be modelled as a random distribution. Finally, surgeons move between ORs performing surgeries until all are finished.

Then, based on the principal ideas of global precedence (Méndez and Cerdá, 2003), we formulated a MILP model for the scheduling of multiple surgeries in homogeneous ORs with several available surgeons. This problem can be tackled as a generalized scheduling problem with multiple resources, as was presented in Capónet al. (2007). Other formulations have been developed previously for a similar problem by Batun et al. (2011) but they do not exploit the real strengths of precedence concepts (Méndez et al., 2006) and also take a priori decisions as surgeries are pre-assigned to surgeons.

Thus, the main contribution of this work is the development of a tightened model in terms of integer and continuous variables that allow us to take into account all the features of this problem without considering predefined decisions. This model is formulated taking into account a single surgeon or multiple surgeons working in several ORs and can also consider different types of surgeries during a normal working day. Also, based on this model, a stochastic strategy and a decomposition approach were proposed to solve the problem considering the uncertainty in the duration of surgical operations.

Finally, all these approaches were implemented in the AIMMS advanced modelling and optimization software widely used for industrial and educational applications. Therefore, we created a user-friendly interface for hospital managers, where they can easily configure the basic parameters and obtain a reliable solution in a short computational time.

Daily Surgical Scheduling problem in Operating Theatres

This work studies the scheduling problem of surgical cases arising in operating theatres. This problem assumes that multiple homogeneous ORs and surgeons are available to perform surgical activities, like pre-incision, incision and post-incision operations. According to this, surgeries must be scheduled in order to minimize the total surgical cost formed by OR vacant cost, surgeon waiting cost and OR overtime (see Table 8.1).

Table 8.1: Hourly Cost.

OR Vacant Cost	Surgeon Waiting Cost	OR Overtime Cost
CV	CW	CO
$1,209.60	$1,048.80	$806.40

The set of planned surgeries to be scheduled is known in advance on the surgical day, the number of available ORs, and the surgeons are given. Thus, different types of surgeries (A-J) must be performed during the surgery time horizon defined by T between 4-12 hours. Each surgery type is characterized by its preparation time (TP), surgery time (TS) and cleaning time (TC). The complete set of data related to the preparation, surgery and cleaning times of different types of surgeries can be found in MOPTA 2013. Then, according to the number of surgeries to be performed, the type of surgeries and the time horizon, a set of problem instances are defined (see Table 8.2).

Table 8.2: Sequencing Instances.

Instance	T (in hours)	No. Surgeries	Surgeries to be Sequenced (by Type)										
			I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11
1	4	4	A	A	C	J							
2	4	5	A	A	G	H	J						
3	4	5	A	D	G	G	J						
4	8	6	A	B	F	G	G	H					
5	8	7	C	D	F	H	J	J	J				
6	8	10	A	A	A	C	D	G	I	J	J	J	
7	8	11	A	A	F	F	G	H	H	I	I	J	J
8	12	7	A	B	D	E	G	G	J				
9	12	10	A	A	B	D	G	G	I	I	J	J	
10	12	11	A	A	C	E	E	F	G	H	I	I	J

General MILP Formulation

In this section, we present a general MILP continuous time formulation for the daily surgical scheduling problem in operating theatres with the uncertainty in the surgery durations. This model takes into account the surgeries *s, s'*, of each type *i,* to be scheduled during a surgical day and also, considers the set of available surgeons and operating rooms denoted by *k, k'* and *r*. The set of scenarios to be solved is presented by the *w* index. The following Table 8.3 provides the full notation about sets, parameters and variables used by the model.

Table 8.3: Notation of sets, parameters and variables.

Index Set	
S	surgeries to be scheduled in a surgical day (s, s')
I	type of surgery (i)
I_s	subset of surgeries s of type $i(i_s)$
K	surgeons(k, k')
R	operation rooms (r)
W	scenarios(w)
Parameters	
TP_{iw}	preparation time of type of surgery $i \in$ I in scenario w $\in W$
TS_{iw}	surgery time of type of surgery $i \in$ I in scenario w $\in W$
TC_{iw}	clean-up time of type of surgery $i \in$ I in scenario w $\in W$
CV	cost per minute of having an OR vacant
CW	cost per minute of having the surgeon waiting
CO	cost per minute of using an OR beyond the normal shift length
T	normal shift length
M	large scalar value much more longer than the normal shift length
Variables	
x_{sr}	binary variable, 1 if surgery s ∈ S is done in room r ∈R; 0 otherwise
$y_{ss'k}$	binary variable, 1 if s∈ S precedes s'∈ S in surgeon k ∈ K, 0 otherwise
$z_{ss'kk'}$	binary variable, 1 if s precedes s'∈ S and it is done by different surgeon k and k'∈ K, 0 otherwise
q_{sk}	binary variable, 1 if surgery s ∈ S is done by surgeon k ∈ K, 0 otherwise
ts_{sw}	start time of the surgery s ∈ S in scenario w ∈ W
tsS_{kw}	start time of the surgeon k ∈ K in scenario w ∈ W
msR_{rw}	makespan of room r ∈ R in scenario w ∈ W
msS_{kw}	makespan of surgeon k ∈ K in scenario w ∈ W
vt_{rw}	vacant time of room r ∈ R in scenario w ∈ W
ot_{rw}	overtime of room r ∈ R in scenario w ∈ W
wt_{kw}	waiting time of surgeon k∈ K in scenario w ∈ W
tc	total surgical cost

The principal aim of this MILP model is to minimize the expected total surgical cost represented by *tc* for a set of selected scenarios *w*. According to this, two sets of decision variables need to be evaluated. First, the assignment binary variable x_{sr} that determines the allocation of surgery *s* in operation unit *r* while q_{sk} provides information about if surgery *s* in done by surgeon *k*, both adopting value 1. And then, sequencing binary variables, using precedence-based ideas are proposed to determine if surgery *s* is done after or before *s'* by the same surgeon *k* or by different surgeons *k,k'* by $y_{ss'k}$ or $z_{ss'kk'}$ respectively.

Note that all continuous variables associated to the start times of surgeries ts_{sw} and surgeons tsS_{kw}, completion time of rooms msR_{rw} and surgeons msS_{kw} and operating times, such as operation room vacant time vt_{rw} and overtime ot_{rw}, and surgeon waiting time wt_{kw}, depends on w and so take a specific value for each scenario.

The main equations of this model are explained as follows. Equation (1) represents the mean total surgical cost *(tc)*, formed by the overtime cost, vacant time cost and waiting time cost to be minimized by the model for the considered scenarios W. Equation (2) shows that each surgery must be performed in only one OR r by $x_{sr}=1$. Equation (3) ensures that each surgery is supported by a single surgeon k by adopting $q_{sk}=1$. Sequencing and timing constraints in the same OR and also by the same surgeon are presented by equations (4-5) and equations (8-9) by using binary variables $y_{ss'k}$. Also binary variable $z_{ss'kk'}$ is introduced in order to consider the sequencing and timing decisions of surgeries performed by different surgeons but in the same OR, as shown in equations (6-7). Equation (10) defines the completion time of the operating rooms msR_{rw} while equation (11) estimates the completion time by the surgeons msS_{kw}. After that, equations (12-13), it is proposed to determine the initial time of each surgery $ts_{s\ w}$and surgeon tsS_{kw} in the system, respectively. In addition, the overtime ot_{rw}, vacant time vt_{rw}, and waiting time wt_{kw} variables are calculated in equations (14-16) by using the information of the initial and the completion time of surgeries and surgeons in the system.

$$min.tc = \frac{CO}{||W||}\sum_{rw} ot_{rw} + \frac{CV}{||W||}\sum_{rw} vt_{rw} + \frac{CW}{||W||}\sum_{kw} wt_{kw} \quad (1)$$

$$\sum_r x_{sr} = 1 \quad : \forall s \in S \quad (2)$$

$$\sum_k q_{sk} = 1 \quad : \forall s \in S \quad (3)$$

$$ts_{sw} + TS_{i_s w} + TC_{i_s w} \leq ts_{s'w} - TP_{i_{s'}w} + M(1 - y_{ss'k}) + M(2 - x_{sr} - x_{s'r}) + M(2 - q_{sk} - q_{s'k}) \quad : \forall s, s', r, k, w | (s' < s) \quad (4)$$

$$ts_{s'w} + TS_{i_{s'}w} + TC_{i_{s'}w} \leq ts_{sw} - TP_{i_s w} + M(y_{ss'k}) + M(2 - x_{sr} - x_{s'r}) + M(2 - q_{sk} - q_{s'k}) \quad : \forall s, s', r, k, w | (s' < s) \quad (5)$$

$$ts_{sw} + TS_{i_s w} + TC_{i_s w} \leq ts_{s'w} - TP_{i_{s'}w} + M(1 - z_{ss'kk'}) + M(2 - x_{sr} - x_{s'r}) + M(2 - q_{sk} - q_{s'k}) \quad : \forall r, s, s', k, k' | (s' < s), (s'k') \wedge (sk) \quad (6)$$

$$ts_{s'w} + TS_{i_{s'}w} + TC_{i_{s'}w} \leq ts_{sw} - TP_{i_s w} + M(z_{ss'kk'}) + M(2 - x_{sr} - x_{s'r}) + M(2 - q_{sk} - q_{s'k}) \quad : \forall r, s, s', k, k' | (s' < s), (s'k') \wedge (sk) \quad (7)$$

$$ts_{sw} + TS_{i_s w} \leq ts_{s'w} + M(1 - y_{ss'}) + +M(2 - q_{sk} - q_{s'k}) : \forall s, s', k, w | (s' < s) \quad (8)$$

$$ts_{s'w} + TS_{i_{s'}w} \leq ts_{s'w} + M(1 - y_{ss'}) + M(2 - q_{sk} - q_{s'k}) : \forall s, s', k, w | (s' < s) \quad (9)$$

$$msR_{rw} \geq ts_{sw} + TS_{i_s w} + TC_{i_s w} - M(1 - x_{sr}) : \forall s, r, w \quad (10)$$

$$msS_{kw} \geq ts_{sw} + TS_{i_s w} - M(1 - q_{sk}) : \forall s, k, w \quad (11)$$

$$ts_{sw} \leq TP_{i_s w} \ : \forall s, w \quad (12)$$

$$tsS_{kw} \leq ts_{sw} + M(1 - q_{sk}) : \forall s, k, w \quad (13)$$

$$ot_{rw} \geq msR_{rw} - T \ : \forall r, w \quad (14)$$

$$vt_{rw} \geq msR_{rw} - \sum_s \left(\left(TP_{i_s w} + TS_{i_s w} + TC_{i_s w} \right) \times q_{sk} \right) : \ \forall r, w \quad (15)$$

$$wt_{kw} \geq msS_{kw} - tss_{kw} - \sum_s \left(TS_{i_s w} \times q_{sk} \right) : \ \forall k, w \quad (16)$$

DETERMINISTIC PROBLEM

In this section different approaches are tested using deterministic data for surgical activities. First, we present some heuristic approaches to obtain an initial solution of this problem by considering two operating rooms Ors ($|r|$=2) and a single surgeon ($|k|$=1) with the information of the average scenario ($|w|$=w). Then, we will compare the solutions of these heuristic approaches with the ones provided by the full-space MILP model presented above.

Dispatching rules-based heuristic algorithms

In this section, five dispatching rules are evaluated in order to provide the hospital manager with a fast and reliable solution to be implemented. These heuristics are inspired by Iser et al. (2008) and Souki (2011). The principal aim of these quick heuristics is to evaluate the solution of the system without using an optimization tool. The first four heuristics, in Algorithms 1-4, are based on a simple sorting criterion ordering the surgeries according to their preparation times (TP) and/or surgery times (TS). The heuristics have been named as "parameter to sort" / type of sorting (A for ascending or D for descending). Finally, we have developed a more accurate heuristic specially proposed for this problem structure. This heuristic named as "Ad-Hoc Heuristic" is described as follows in Algorithm 5.

Algorithm 1: Heuristic TS/A

Step 1: Surgeries I of the instance is ordered in ascending order of incision time TS_{iw}.

Step 2: The surgeon in which every surgery is realized is decided by taking into account the sequence previously obtained in the Step 1.

Algorithm 2: Heuristic TS/D

Step 1: Surgeries *I* of the instance is ordered in descending order of incision time TS_{iw}.

Step 2: The surgeon in which every surgery is realized is decided by taking into account the sequence previously obtained in the Step 1.

Algorithm 3: Heuristic (TS+TP)/A

Step 1: Surgeries *I* of the instance is ordered in ascending order of the addition of the incision time $TS_{iw}$and the preparation time TP_{iw}.

Step 2: The surgeon in which every surgery is realized is decided by taking into account the sequence previously obtained in the Step 1.

Algorithm 4: Heuristic (TS-TP)/A

Step 1: Surgeries *I* of the instance is ordered in ascending order of the subtraction of the incision time TS_{iw}minus the preparation time TP_{iw}.

Step 2: The surgeon in which every surgery is realized is decided by taking into account the sequence previously obtained in the Step 1.

Algorithm 5: Ad Hoc Heuristic

Create two ascending ordered lists using the $TS_{iw}$and TP_{iw}

repeat

in the first OR, the surgery with the longest $TS_{iw}$is selected

if the surgery has been sequenced before, **then**

it is eliminated from the TS_{iw}list.

else

the surgery is assigned and eliminated from the TS_{iw}list

end if

in the second OR, the surgery with the longest TP_{iw} that has not been sequenced is assigned and that surgery is eliminated from the list

if the surgery has been sequenced before, **then**

it is eliminated from the TP_{iw} list

else

the surgery is assigned and eliminated from the TP_{iw} list

end if

until no more than one surgery is left in the lists

if both lists are empty **then**

finish

else

this surgery is assigned in the OR which will be available first

end if

finish

Results

The heuristics and the MILP model presented above were modelled using AIMMS 3.13 (Bisschop and Roelofs, 2011). The solver used was Gurobi 5.0 Optimization (2012) in a PC with Intel Core i3-2350M 2.30 GHz with 6 Gb RAM under Windows 7. The termination criterion was imposed in 3600 sec. in order to provide good-quality results in reasonable CPU time for the hospital manager.

Solutions obtained in Table 4, demonstrate that in all instances our model solves up to optimality in only a few seconds or minutes. For eight of the ten cases analysed the CPU time was less than 1 minute and only for the most complex instances (7 and 10) our model takes more time (3 min. and 6 min.). Model size is reported in this table by the number of variables and constraints while the complexity of the solution is demonstrated by the number of nodes and iterations explored. The performance of the model is measured by the relative gap between the initial and final solution and also by the CPU time consumed. The initial solution was reported in all cases in less than 5 seconds. And the relative gap between the initial and final solution was less than 7.0 percent for all cases analysed.

Table 8.4: Results of the deterministic problem using (2R,1k).

Instance	Total Cost	CPU Time	Binary Var	Cont. Var	Equations	Nodes	Iterations	Initial sol
1	480	0.02	14	34	68	193	893	480
2	449	0.03	20	41	98	524	2123	449
3	261	0.03	20	41	98	493	2238	261
4	630	0.06	27	49	134	2378	8845	630
5	943	3.61	35	58	176	98451	376165	943
6	2,165	17.65	65	91	338	547572	2162232	2,299
7	6,186	82.3	77	104	404	2688876	10712959	6,583
8	983	0.87	35	58	176	21767	90654	983
9	1,915	18.34	65	91	338	466586	2098862	2,007
10	4,363	359.2	77	104	404	11043003	44030805	4,701

Our formulation provides a reduced number of binary sequencing variables in comparison to other MILP formulations reported in the literature up to now, e.g., Batun et al., (2011). Our model is much more tightened due to the fact that it associates a single general precedence variable to the surgeon when in other formulations the sequencing variables are proposed for each OR using the concepts of unit-specific precedence-based representation. So, the number of sequencing variables grows with the number of ORs and the number of ORs is always greater than or equal to the number of surgeons. In addition, the unit-specific precedence formulation has to consider all the combinations between two different surgeries s,s' where $s \neq s'$ and the number of alternative sequencing decisions for each OR should be $|S|^{*}|S|-1$. In our model, the number of sequencing decisions for each surgeon is reduced by half.

Figure 8.2 shows the model behaviour for the most complex instance 10 (2R,1k) of the deterministic problem, drawing the lower bound and the upper bound solutions over time. As we can see in Figure 1, the lower bound was initialized at zero. This is a critical point in the solution performance since our model was able to find good-quality initial feasible results in only a few seconds but required a lot of time to assure the optimality of the solution found. Then based on the behaviour of our model, we were able to offer optimal solutions within a few minutes, or if the instance is small or there is not enough

time, you can select an upper time limit. A detailed schedule and costs of this particular instance 10 using (2R, 1K) is reported in Figure 8.3.

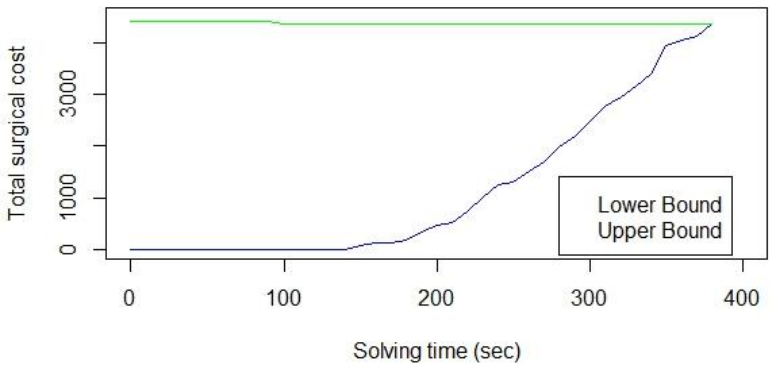

Figure 8.2: Solution behaviour of the MILP for instance 10 using (2R, 1k).

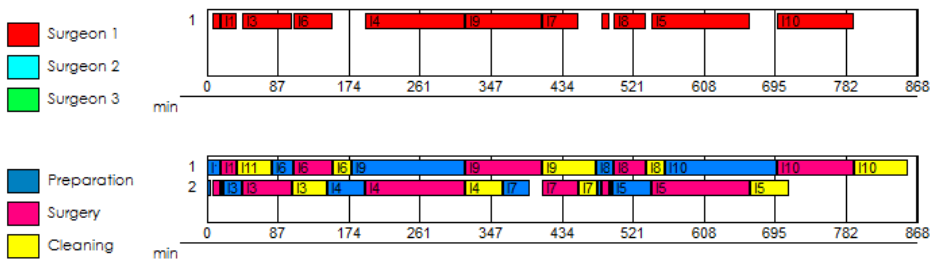

Figure 8.3: Solution Schedule of instance 10 using (2R,1k).

Table 8.5 shows the results of the heuristics by using the mean scenario. Both, “Heuristic TS/A” and “Heuristic (TS+TP)/A”, present better solutions than the others (“Heuristic TS/D” and “Heuristic (TS-TP)/A”) while our “Ad-Hoc Heuristic” provides the best result for each instance. Despite this, the solutions reported by heuristics are still far from the optimal ones obtained for each particular problem instance (see Table 5). In conclusion, heuristic methods based on a simple sorting criterion have poor performance but are fast and can be implemented even by hand.

Table 8.5. Result comparison for problem (2R,1k).

Instance	TS/A	TS/D	(TS+TP)/A	(TS-TP)/A	Ad Hoc	MILP
1	2,222	3,710	2,222	3,028	1,569	480
2	3,236	3,538	3,236	4,095	1,098	449
3	4,116	3,836	4,116	4,348	1,059	261
4	5,408	7,531	5,440	5,432	2,359	630
5	6,456	6,853	6,456	5,772	1,470	943
6	9,759	14,440	9,759	15,391	9,362	2,165
7	16,832	18,303	16,760	19,654	9,018	6,186
8	8,615	10,168	8,615	9,302	3,362	983
9	10,918	11,870	10,918	13,866	2,495	1,915
10	18,730	20,809	17,877	20,484	7,930	4,363

Our MILP model could be used to address multiple surgeons and ORs simultaneously but in this work we only present the case of a single surgeon and multiple OR problems.

STOCHASTIC PROBLEM

In this section we will study the problem in which the duration of surgical activities, closely linked to the type of surgery, is uncertain. All the input data provided by MOPTA 2013 Competition represents historical information which is assumed to be independent and can be modelled by a standard probabilistic distribution with its own parameters. So, no correlations exist among the duration of the pre-incision, the incision, and the post-incision times for each surgery type. According to this, a good solution for a stochastic model will be the one that minimizes the expected total cost for all scenarios together. Other approaches that consider only a certain type of cost or use the most likely scenario for the evaluation can be easily implemented.

An extra index for the w scenarios is considered by the MILP model in this problem. Here, binary variables do not depend on w assuring the same sequencing and assignment decisions for all the scenarios evaluated. Only the timing decisions of surgical activities differ in each scenario. The model is solved considering two operating rooms ORs ($|r|=2$) and a single surgeon ($|k|=1$) minimizing the expected value of the total cost assuming that all proposed scenarios ($|w|=100$) have the same probability of occurrence.

Scenario reduction

In stochastic programming the number of scenarios plays a key role in obtaining a reliable solution. For this problem we emulate 100 scenarios using Monte Carlo simulation. We assume that the use of the entire set of 100 scenarios gives us the "Optimal value". Then, a suitable reduction of scenarios decreases the solution time but increases the result error. This error will be calculated with the following expression according to the best solution found.

$$Result\ Error = \frac{ObtainedValue - OptimalValue}{OptimalValue} * 100$$

On the other hand, exploring all the scenarios increases the solution time in some cases beyond the threshold. Only the first five instances will be evaluated with the MILP model since it can be solved up to optimality (see Table 6).

Figure 8.4 shows the percentage of error between the values obtained using a specific number of scenarios from 0-100. When the number of scenarios is below 20, the error in some cases is above 30%. Then, the error decreases gradually with the number of scenarios. After analysing that, we conclude that in over 50 scenarios the error remains under 10%, it being unnecessary to consider many more numbers of scenarios for the resolution of the stochastic problem.

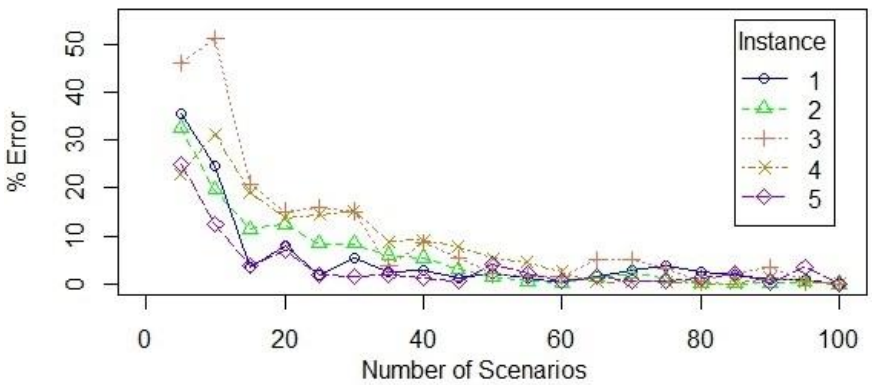

Figure 8.4: Analysis of Error vs. Number of scenarios.

Decomposition approach: Constructive-Improvement methods

The MILP-based decomposition approach was developed "ad-hoc" for the specific structure and features of this problem. The constructive-improvement

methods were proposed using MILP models, as the one presented above, taking the advantages of General-Precedence (GP) concepts and also the strengths of exchanging information between them. This iterative solution allows decomposing the problem into small sub-problems that can be solved separately, in a sequential way, consuming moderate computational effort. Each algorithm consists of five sequential steps: initialization, selection procedure, setting binary variables, model resolution and updating parameters.

In the constructive algorithm, a reduced MILP model is solved in each iteration obtaining an aggregated schedule with minimum Mean Total Cost (z). When all surgeries are inserted into the system, this phase finishes reporting an Initial Solution (see Algorithm 6).

Then, starting from this solution, the improvement algorithm determines the surgeries to be released per iteration by choosing the first N consecutive surgeries on the Surgery List. Released surgeries are re-scheduled in the system by optimizing q_{sk}, x_{sr}, $y_{ss'k}$, $z_{ss'kk'}$ while binary variables of non-released surgeries remain fixed. After solving, the result of the MILP model is compared with the Best solution obtained up to this iteration. The Best solution is reported and its schedule is updated. This improvement phase finishes when no released surgery can enhance the best solution found (see Algorithm 7).

Algorithm 6: Constructive Method

Step 1: Initialize parameters iter, N and variables $ts_{sw}, q_{sk}, x_{sr}, y_{ss'k}, z_{ss'kk'}$

Step 2: Select N consecutive surgeries to be scheduled in each iteration *iter* by following their lexicographic order from the Surgery List $(s_1, s_2, \dots, s_s)$

Step 3: Set fixed all binary variables $q_{sk}, x_{sr}, y_{ss'k}, z_{ss'kk'}$ of inserted surgeries.

Step 4: Solve the MILP model for selected surgeries and optimize $ts_{s,w}$ variables of all inserted surgeries.

Step 5: Update parameters and report aggregate schedule. (Back to Step 2)

Algorithm 7: Improvement Method

Step 1: Initialize parameters *iter, N* and start from the initial solution found (Schedule list).

Step 2: Select N consecutive surgeries to be re-scheduled in each iteration *iter* by following their lexicographic order from the Surgery List $(s_1, s_2, \dots, s_s)$.

Step 3: Set fixed all binary variables $q_{sk}, x_{sr}, y_{ss'k}, z_{ss'kk'}$ of non-released surgeries.

Step 4: Solve the MILP model for released surgeries and optimize $ts_{s,w}$ variables of all inserted surgeries.

Step 5: Update parameters and report improvement schedule (Back to Step 2).

The solution obtained by the "ad-hoc" decomposition approach can be also enhanced by exploiting the strength of the proposed General Precedence MILP formulation, releasing and optimizing a greater number of binary variables of non-released surgeries per iteration. According to this, we can play with the assignment variables q_{sk}, x_{sr} improving the model behaviour without significantly increasing the number of released variables.

Finally, in both constructive and improvement methods we have decided to use a lexicographic order for the selection procedure since incorporating randomness makes the reproducibility of the results impossible. The analysis of different selection rules to improve the solution performance of the algorithm needs to be studied in detail in future works. The algorithm ends when no other released surgery could improve the best solution found or after 3600 sec. of CPU time. We adopt this termination criterion in order to make a fair comparison with the full-space MILP model presented above.

Results

Increasing the number of scenarios will improve the quality of the solution at the expense of the experiment lasting longer. The solution for the 100 scenarios is presented in Table 8.7 considering all scenarios together and the solution for the mean case using the average scenario. Here, it can be seen that the relative difference between the full case and the mean case is very high. According to this, using the full case is much better than using the mean case.

Table 8.8 shows the principal results and analysis among stochastic, constructive and improvement methods. For the first 4 instances analysed, both stochastic and decomposition methods provide optimal solutions in a short CPU time (< 5min). But, for the biggest instances 5 to 10, the stochastic model could not ensure optimal results in 1 hour of CPU time. According to this, the decomposition approach (constructive method + improvement method) emerges as an efficient solution tool for solving large scale problems with reasonable computational effort.

Table 8.7: Result of the stochastic problem using 100 scenarios.

Instance	Total Cost	CPU Time	Bin Var	Cont Var	Eqs.	Nodes	Iterations	Mean Cost	Diff	CPU Time
1	676	27	18	1319	6109	171	40730	739	9.3	1.5
2	1173	36	25	1426	9011	3002	461512	1220	4.1	4.2
3	1613	37	25	1426	9011	1912	322763	1612	0	2.9
4	1670	354	33	1534	12513	5201	881252	2046	22.5	6.7
5	2045	3600	42	1643	16615	160652	29823967	2299	12.5	12.7
6	45326	3600	75	1976	32521	53526	17994882	5364	22.5	47.6
7	10465	3600	88	2089	39023	46982	14530619	10084	7.8	132
8	2512	3600	42	1643	16615	33409	4708673	2921	16.3	9.3
9	5511	3600	75	1976	32521	83891	20361739	5238	2.5	43.3
10	10406	3600	88	2089	39023	37142	15621953	9549	10.1	411

Thus, our constructive algorithm was able to provide initial good-quality solutions for all these cases in less than 5 min. For the biggest instances, in some cases the constructive algorithm obtains a better solution in 5 minutes than the stochastic result in one hour.

The improvement method increases the quality of the solution in less than half an hour. In almost all cases the decomposition approach obtains the same or a best solution in half the time of the stochastic method and an average improvement of 3.22%.

Table 8.8: Comparative using Constructive Method N=1, Improvement Method N=1.

	Stochastic Model		Constructive Method			Improvement Method			Total
Instance	Total Cost	CPU Time	Total Cost	CPU Time	% Imp	Total Cost	CPU Time	% Imp	% Imp
1	676	27	676	5	0	676	24	0	0
2	1173	36	1173	17	0	1173	52	0	0
3	1613	37	1613	15	0	1613	77	0	0
4	1670	354	1671	29	0	1670	85	0	0
5	2045	3600	2135	51	-4.36	2135	126	0	-4.36
6	4532	3600	4979	192	-9.87	4419	1856	12.32	2.50
7	10465	3600	9659	277	7.71	9089	2049	5.44	13.15
8	2512	3600	2512	48	0	2512	121	0	0
9	5511	3600	4939	156	3.36	4939	1324	0	3.36
10	10405	3600	8704.83	281	16.34	8580	1500	1.20	17.55
Mean	4060	2205		107.1	1.32		721.4	1.90	3.22

The parameter *N* plays a key role in these algorithms. In the constructive algorithm, it is the number of surgeries inserted at each iteration while in the

improvement algorithm it represents the number of release surgeries to be re-scheduled. A small number of *N* narrows the search space with the possibility of eliminating the global optimal but decreasing CPU time.

Table 8.9 shows the results of giving more degrees of freedom to the algorithm by inserting and releasing two surgeries instead of one in both the constructive and improvement steps. The constructive method improves the results for only two of the ten instances analysed, since it has more flexibility to construct a better solution, but regrettably, it takes much more time to solve the problem. For the improvement part, when *N=2*, the algorithm takes much more time and no significant improvement can be seen after 3600 sec.

Table 8.9: Comparative using Constructive Method N=2, Improvement Method N=2.

	Stochastic Model		Constructive Method			Improvement Method			Total
Instance	Total Cost	CPU Time	Total Cost	CPU Time	% Imp	Total Cost	CPU Time	% Imp	% Imp
1	676	27	676	9	0	676	24	0	0
2	1173	36	1173	34	0	1173	112	0	0
3	1613	37	1613	31	0	1613	130	0	0
4	1670	354	1671	63	0	1670	153	0	0
5	2045	3600	2135	121	-4.36	2135	375	0	-4.36
6	4532	3600	4480	658	1.13	4381	3600	2.22	3.32
7	10465	3600	9574	1174	8.52	9574	3600	0	8.52
8	2512	3600	2512	116	0	2512	383	0	0
9	5111	3600	4939	598	3.36	4939	2780	0	3.36
10	10405	3600	8705	1223	16.34	8580	3600	1.44	17.55
Mean	4020	2205	3748	402.7	2.50	3725	1475.7	0.36	2.83

Table 8.10 presents the experimentation of the constructive phase, *N=2*, and the improvement phase, *N=1*. The constructive phase obtained better results, but took a longer time since more possibilities are being evaluated at each iteration. The improvement phase makes some improvements to the results of the other options using some extra time.

More experimentation was done using $N > 2$, but the performance was poor. The time stop criterion was applied for the majority of the instances with almost no improvement. As *N* became the Total number of surgeries, the problem transformed into the stochastic model, which had to be solved several times, offering poor performance. As was discussed, small values of *N* should be used.

Table 8.10: Comparative using Constructive Method N=2, Improvement Method N=1.

	Stochastic Model		Constructive Method			Improvement Method			Total
Instance	Total Cost	CPU Time	Total Cost	CPU Time	% Imp	Mean Total Cost	CPU Time	% Imp	% Imp
1	676	27	676	9	0	676	36	0	0
2	1173	36	1173	34	0	1173	61	0	0
3	1613	37	1613	31	0	16138	162	0	0
4	1670	354	1671	63	0	1670	88	0	0
5	2045	3600	2135	121	-4.36	2135	1200	0	-4.36
6	4532	3600	4480	658	1.13	4381	2891	2.2	3.32
7	10466	3600	9574	1174	8.52	9089	3600	5.06	13.15
8	2512	3600	2512	116	0	2512	176	0	0
9	5111	3600	4939	598	3.36	4939	743	0	3.36
10	10406	3600	8705	1223	16.34	8580	1476	1.4	17.55
Mean	4020	2205	3748	403	2.50	3711	1043	0.88	3.30

As a conclusion, our decomposition method, by using only the constructive phase, was able to provide even better results than the stochastic model for large problem instances with a significant reduction in CPU time. Also, our algorithm was able to solve these problems using many more scenarios without any significant decrement in the efficiency of the solution found. Finally, possible enhancements can be tested in the algorithm by using different *NxN* parameters and selection rules according to the case study analysed.

CONCLUSION

This work presents the main contributions and results obtained for the daily scheduling problem of surgical cases in operating theatres under uncertainty. An efficient and also tightened MILP model was developed taking into account all the features of this challenge problem. In addition, stochastic strategies were implemented in order to deal with the uncertainty in surgery durations. Results show that our MILP-based model represents an efficient solution approach for solving deterministic cases, in which timing information is known, providing optimal results in short computational time (< 5min). Also, in stochastic cases, when the prior information is unknown, our stochastic model provides good-quality results but does not assure optimality in a time limit imposed of 1 hour for the largest cases.

In order to improve the solution found and also reduce the CPU time consumed by the stochastic model, a decomposition approach based on constructive and improvement methods was developed. This approach allows

decomposing the problem and finding an initial good-quality result in less than 5 minutes even for the most complex case in comparison with the full-space stochastic model. Then, an improvement method was applied to enhance the solution by 3.22% (on avg.) in less than 3600 seconds. For example, for the most complex case, our approach was able to improve the solution reported by the full-space model by more than 17% using only 1500 sec. which is quite acceptable for this offline solution purpose.

All these solution strategies were implemented in AIMMS® using the principal strength of this modelling and optimization based software. Thus, an end user application was developed with a friendly interface for the hospital manager to introduce and remove data and solve deterministic and stochastic cases without needing any previous information about the result of the problem.

The feedback received from surgeons about the tool was useful to simplify our tool, since the majority of them do not understand operational research terminology, and they want a user-friendly tool with their own terminology that offers reliable and quick results. Unfortunately, many of the surgical scheduling operations in public hospitals are done by hand, which represents a lack between data and IT systems. This becomes a challenging opportunity for our application to be implemented at any hospital, reducing total surgical costs and at the same time improving resource utilization.

As a conclusion, we can realize now how much money hospitals are loosing by not using the proper scheduling system. If we compare with traditional heuristic rules, the ones probably used in real life, our MILP model could provide a total saving of between 25-75%.

In the stochastic problem, the difference between using a decomposition method against the traditional full-space method gives savings of 5% on average for the largest instances analysed and reduces CPU time by more than 50%. Using these kinds of tools represents a high reduction in total surgical cost and its utilization is really important to everyday scheduling. The specific requirements of the hospital manager will be added in a future step so as to represent real life conditions more accurately.

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Chapter 9: Operation Rooms Optimization in a Teaching Hospital

MOTIVATION

An interesting application of operating room scheduling can be found in Spanish hospitals, which provide an an interesting study case since the country's population is markedly older than most nations in Europe: 17.5% of the Spanish population is 65 years old, and the median age is 42.6 years (CIA, 2014). Spain has one of the highest life expectancies in the European Union, where the average is 81.8 years; at 84.7 years, the country also has the highest female life expectancy in Europe. The implication of this aging population is that more elderly patients will need to undergo surgery and have to be placed on a surgery waiting list.

The Spanish health-care system is both public and private: according to the last report in 2013 there are 452 public hospitals and 311 private hospitals. The system incorporates 4,201 ORs for the country's around 47 million inhabitants. Every year, 24,342 surgeons perform 4.74 million operations (1,129 surgeries per OR per year) (SGISEI, 2013).

The last official Spanish statistics from 2013 state that there are 20,721 residents doctors, from which 5,698 are working and studying to become surgical specialists in Spanish hospitals, and many of them perform surgeries every day (SGISEI, 2013).

These resident doctors are trained in teaching hospitals, which beside their normal task need to assure that these future surgeons have performed enough surgeries to be in charge of the health care system of the future years. This objective is contrary to other performance indicators, since resident doctors require more time to perform a surgery than an experienced surgeon, thereby causing more delays to the already saturated public health system. In this example more players such as residents, and heads of teaching are added to the decision units.

This chapter examines the daily surgical scheduling problem in a teaching hospital. This problem relates to the use of multiple operating rooms and different types of surgeons in a typical surgical day with deterministic operation durations (preincision, incision, and postincision times). Teaching hospitals play a key role in the health-care system; however, existing models assume that the duration of surgery is independent of the surgeon's skills. This problem has not been properly addressed in other studies. We analyse the case

of a Spanish public hospital, in which continuous pressures and budgeting reductions entail the most efficient use of resources.

To obtain an optimal solution to this problem, we developed a mixed-integer programming model and user-friendly interface that facilitates the scheduling of planned operations for the following surgical day. We also implemented a simulation model to assist the evaluation of different dispatching policies for surgeries and surgeons. The typical aspects we took into account were the type of surgeon, potential overtime, idling time of surgeons, and the use of operating rooms.

It is necessary to consider the expertise of a given surgeon when formulating a schedule: such skill can decrease the probability of delays that might affect subsequent surgeries or cause cancellation of the final surgery. We obtained optimal solutions for a set of given instances, which we obtained through surgical information related to acceptable times collected from a Spanish public hospital.

We developed a computer-aided framework with a user-friendly interface for use by a surgical manager that presents a 3-D simulation of the problem. Additionally, we obtained an efficient formulation for this complex problem. However, the spread of this kind of operational research in Spanish public health hospitals will take a long time since there is a lack of knowledge of the beneficial techniques and possibilities that operational research can offer for the health-care system

BACKGROUND

Teaching hospitals play a key role in the majority of health-care systems as these institutions provide medical attention to the community and train future health professionals. Several studies have identified operating rooms (ORs) as a hospital's largest cost area (Macario et al., 1995, Fei et al., 2009). Optimizing ORs is difficult since many constraints need to be considered, and solving this issue within a reasonable time is difficult (Meskens et al., 2012). Improvements made in the scheduling of an OR lead to enhanced cost efficiency and better patient service (Gupta and Denton, 2008).

In this situation, the objective is to determine the optimal assignment of ORs and surgeons to each operation on a daily basis; consequently, it is necessary to find the best sequence of operations for each surgeon with the goal of minimizing the total surgical cost resulting from an OR's underuse or overuse and from surgeons' waiting times. Here, we will assume that a set of

surgeries is known 24 hours in advance of the operations and that the number of available ORs and surgeons is also known. All the planned operations have to be performed on the surgical day. The tasks that have to be performed in the surgery are divided into the following:

- TP: preparation time (preincision),
- TS: surgery time (incision), and
- TC: clean-up time (postincision).

The OR staff has to support a surgery during the preparation, the operation itself, and in the clean-up. However, surgeons are required to be present only during the operation itself until the completion of the incision. Thus, surgeons can perform an operation in a different OR immediately after finishing the previous surgery. One example of this type of decision-making process is found in a Teaching hospital in Toledo, where we started describing the actual decision-making process and then a computer aided decision would be introduced.

Conventional decision-making process

This description of the conventional decision-making process is based on interviews conducted at a teaching hospital in Toledo, Spain. After a negotiation among the head of physicians and the head of the different medical sections, ORs are assigned to each section.

For example, two ORs may be available for urology from Monday to Friday, though an additional OR is available on Wednesday. Despite most of its ORs being able to handle all medical services, in order to avoid unnecessary changes of specific instruments required for particular medical services, the medical services use the same ORs on a weekly basis.

Every day the service head decides which patients on the waiting list will undergo surgery and in what order and which surgeons will perform the operations. At the Toledo hospital, the head of each medical service takes this difficult decision by hand. Finally, a secretary puts all these details into the hospital's computer system and the information is sent to the hospital's reception office so that all the necessary procedures and preparations for surgery may begin. If for any reason, the patient is unable to undergo the operation, it has to be rescheduled.

Teaching hospitals

Health care systems rely on teaching hospitals to train future health professionals, conduct medical research, fulfil part of the patient-care needs, and sometimes offer services not available in other facilities (AHA, 2009). Various studies have found that resident doctors take longer to perform a surgical operation than experienced doctors. Becoming a properly trained surgeon requires resident doctors to work and study for 4–5 years, depending on their intended medical specialty, and during this time they carry out different types of surgery. The scheduling of surgery being performed in teaching hospitals has not been properly addressed in the literature (Bridges and Diamond, 1999).

Two typical differences between a normal hospital and a teaching hospital is that in a normal hospital the surgery is pre-assigned to a surgeon according to some decision criteria such as the one that diagnoses the problem or the one chosen by the patients. Then, it is just necessary to coordinate the use of the operating rooms. The second main difference is that the surgery duration depends on the surgical team assigned and added to this is the decision to evaluate which surgeon it is better to assign to each surgery and where to perform the surgery.

A teaching hospital may be considered as a particular case of a normal hospital where the different resources (surgeons) may take different times, according to their experience, and there is no pre-assignment of surgeons to surgeries.

Some normal hospital algorithms have to make some assumption and preassign surgeries to surgeons to deal with teaching hospital problems. An example of this is Fei et al. (2010) that pre-assigns the surgical case to be treated for different surgeons (or, more generally, surgery groups) and the duration of the surgery is independent of the surgeon. Jebali et al., (2006) allow the model to assign a surgeon to perform an operation but do not make any distinction between surgeons. Other algorithms like Kharraja et al., (2006) define a block scheduling where each surgeon requests a block of time to perform surgeries.

Literature review

A literature review can make different classifications according to patient characteristics (elective or non-elective), performance measures, decision delineation (date, time, room, or capacity), research methodology, and considerations of uncertainty and applicability (Cardoen et al., 2010). The

schedule for ORs is usually done in an intuitive manner by the OR actors, thus, introducing optimization techniques will require a cultural change because it may restrict the authority of some of those individuals (Jebali et al., 2006).

Many studies have addressed different aspects of the topic of optimization techniques from various points of view with regard to the decision-making process in OR scheduling. There are different classifications of the problems in this area. One of the most important issues is decision delineation. No agreement has been reached about classifying the decisions made regarding surgery and its scheduling. Since the boundaries are unclear, various papers have addressed different parts of the decision-making process (Cayirli and Veral, 2003).

A literature review conducted by Guerreiro and Guido (2011) made an interesting classification of hierarchical decision levels. *Strategic* is when OR times are assigned among different surgical services. This is also known as the "case mix planning problem". *Tactical* involves the development of a master surgical schedule (MSS). An MSS is a schedule that defines the number and type of available ORs. There is also the *operational* type, which is concerned with the scheduling of elective patients on a daily basis after an MSS has been developed.

The strategic level of decision-making is generally performed following annual negotiations between the hospital manager and the head of surgical services. This part of the decision-making process is beyond the scope of the present study. Accordingly, in terms of the hierarchical decision-level classification, this study tackles a combination of tactical and operational problems.

Another important literature review—one by Cardoen et al. (2010) — deliberately avoids these classification levels since they lack clear definitions. Cardoen et al. (2010) suggest creating a classification according to the type (date, time, room, and capacity) and level (discipline, surgeon, and patient) of decision being made. The type of decision in question could be the assignment date on which surgery will be performed, the time indications, the operating surgeon, the OR, and the allocation capacity. In this study, we will take all these elements into consideration—except the date.

With an open scheduling strategy, surgeons submit a request for OR time, and a detailed schedule is generated prior to the day of surgery. This procedure is common, for example, in neurosurgical operations, where the patient list is known only 24 hours before the day of surgery. This flexible scheme avoids unfilled blocks in the working day (Denton et al., 2007). In the present study, we will focus on the deterministic daily scheduling problem in ORs under an open scheduling strategy.

The performance measures examined in the literature are the following: waiting time (patient, surgeon, and throughput); utilization, under-utilization/undertime (OR, ward, and intensive care unit); over-utilization or overtime (OR and ward); general (OR and ward); levelling (OR, ward, post anaesthesia care unit, holding area, and patient volume); makespan; patient deferral; financial measurements; and surgeons' preference (Cardoen et al., 2009).

The aim of the present study was to develop a generic deterministic model for dealing with the daily scheduling of a set of surgeries in a teaching hospital in a reasonable time. The surgeries can be performed in a given number of ORs by different types of surgeons. We consider most of the problems encountered in the OR's daily operations. We evaluated the proposed approach using real data from a Spanish hospital, a friendly and efficient computer-aided tool and a simulation software.

METHODS

Operational research techniques have helped health-care managers optimize their operations. We will address this issue using a mixed-integer programming model (MILP) and a user-friendly interface; these will allow the scheduling for surgeries planned the following day. Additionally, we will implement a simulation model to facilitate the evaluation of different dispatching policies related to surgical operations and surgeons. A MILP solution has previously been developed for a similar problem (Batun et al., 2011); however, that did not exploit the real strength of general-precedence concepts and did not preassignan operations to a surgeon or use different types of surgeons.

The MILP model was created using *AIMMS 3.14* (Bisschop and Roelofs, 2011) and was solved with the standard solver Gurobi Optimization 5.5; it was simulated with *Enterprise Dynamics 8.01* by *In control*. As noted above, the model presented is a generic one as applied to one Spanish teaching hospital. In the remainder of this chapter, we present a 3D simulation of the different dispatching policies, which will be followed by the MILP formulation.

Objective function

Some studies have found that OR performance measures, such as utilization, overtime, and on-time performance, may be used as achievable targets at most hospitals (CAB, 2001). Denton and Gupta (2013) highlight how, despite the tightness of surgical schedules, it is possible to achieve a balance among the

three competing criteria of surgeon waiting, OR staff idling, and overtime costs. The objective function minimizes the sum of these three costs.

- *Surgeon waiting cost.* Since the surgeon is a very expensive resource, decreasing the surgeon's waiting time has been the subject of many papers (Denton et al., 2007, Denton and Gupta, 2003, Gupta, 2007, and Lebowitz, 2003). This factor has to take into consideration the minimum waiting time a surgeon needs between operations (Pause Time).
- *OR waiting cost* (under-utilization). OR idling is the direct cost associated with having an OR vacant, with no surgical activity being performed (Cardoen et al., 2010, Lebowitz, 2003, Dexter, 2003, Dexter and Traub, 2002, Ozkarahan, 2000, Fei et al., 2008, and Adan and Vissers, 2002).
- *Overtime cost*. Late starts result in direct costs associated with overtime staffing when the surgery finishes later than the end of the appropriate shift (Kharraja et al., 2006, Denton et al., 2007. Gupta, 2007, Fei et al., 2008 and Adan and Visser 2002.

The OR staff works in a normal shift of 7 hours (T = 420 minutes). Accordingly, overtime needs to be considered if the OR staff has to work beyond the normal shift length, T. For simplicity, all the patients are ready to start the surgical procedure when the OR is ready. Three main costs are taken into account (see Table 9.1): (a) the cost per hour of OR idling time (vacant time cost); (b) the cost per hour of OR overtime (overtime cost); and (c) the cost per hour of surgeon waiting time (waiting time cost).

Table 9.1: Estimated hourly cost.

OR vacant cost	Surgeons' waiting cost	OR overtime cost
CV	CW	CO
€ 900	€ 700	€ 1500

Assumptions

We assume that a set of ORs and surgeons are available each day. Additionally, we stipulate that only surgeon 1 in OR 1 can perform surgery D, which is an extremely complex operation, and that surgery A should be performed by a resident (surgeon k = 2). The remaining surgeries can be

performed in any OR by any surgeon. The ORs can operate in parallel. Figure 9.1 presents a simple example of seven surgeries scheduled in three ORs with two surgeons. The first idle time cost (a) is incurred when the patient has to wait for surgeon 2. OR1 and OR2 generate extra time cost (b). Surgeon 1 generates waiting cost when the surgeon finishes surgery 1 and has to wait to start surgery 4. The vacant time is the time between surgeries where the surgeon cannot perform other activities since the surgeon is wearing surgical uniform.

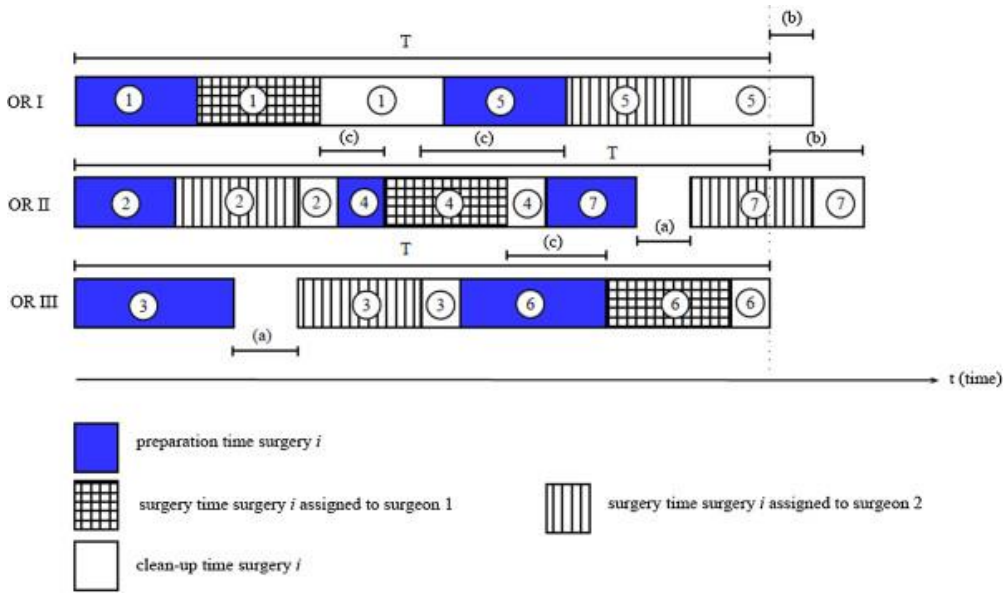

Figure 9.1: **Scheduling of a given surgical day.** Where (1–7) are the surgeries performed in three ORs with two surgeons. And (a) is the OR idle time, (b) is the over time, and (c) is the waiting time of the surgeons.

Data accessibility

We looked for available public data to test our model, but the majority of the papers dealing with OR scheduling do not present a complete dataset. We used data from the waiting list of the urology department of the general hospital in Toledo, mentioned above, to test the model. That information included an estimate of the duration of the surgery.

We experimented with six instances, each consisting of five to nine surgeries. Table 9.2 contains the preparation time, the incision time for each surgeon, and the clean-up time. Each surgeon had different surgical times according to their expertise, which allowed them to perform an operation faster or slower. Surgeon (k = 1) was the fastest surgeon, surgeon 2 the slowest, and surgeon 3 intermediate. Each instance represents different types of working days, with two ORs and three surgeons being available. For example, instance

1 represents the smallest instance, in which only five surgeries have to be performed, and instance 6 represents the largest instance, in which nine surgeries have to be performed (see Table 9.3). To test the model, we ran it on a day with the following availability: three ORs and two groups of surgeons—one without residents ($k = 1$) and the other with residents ($k = 2$).

Table 9.2: Surgery Durations (min.).

Surgery type (i)	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**
TP	15	20	15	20	25	30	35	40
$TS_{k=1}$	20	35	40	45	85	130	190	220
$TS_{k=2}$	30	53	60	n.a.	128	195	285	330
$TS_{k=3}$	25	44	50	n.a.	106	163	238	275
TC	10	20	35	40	40	50	50	60

Table 9.3: Surgical day instances with several ORs and surgeons (k).

#Instance	**#ORs**	**#*k***	**#Surgeries**	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	2	1	6	A	B	C	D	E	E			
2	3	2	5	E	E	D	F	G				
3	3	2	6	C	D	D	E	F	H			
4	3	2	7	B	B	C	D	E	G	G		
5	3	2	8	A	B	B	C	D	E	F	G	
6	4	3	9	A	B	C	D	E	E	F	G	H

Spanish hospitals usually operate from 8:00 a.m. to 3:00 p.m. ($T = 420$ minutes). Extra time is possible only if a request is made for this during the day. Thus, it is important to know when additional time will be required, which cannot exceed 2 hours. If any delays occur apart from the approved extra time, the surgeon and other staff need to finish the surgery without additional payment. Therefore, if the anaesthesiologist or surgeon realizes that a surgery will not be completed on time, they usually prefer to cancel the surgery and reschedule it before it begins.

Simulation model

We used a simulation to evaluate different solutions without any disturbance to the hospital's operations (Ballard, Kuh, 2006). We built the simulation model using the Enterprise Dynamics discrete-event simulation tool, which emulates different dispatching policies of surgeries and surgeons.

We set different strategies for the dispatch of surgeries such as ordering (ascending or descending) them according to the duration of a given surgery time (TS). When two surgeons were idle, we selected either the faster or slower surgeon to perform the surgery (Lebowitz, 2003).

MILP problem formulation

In this section, we begin by introducing the notation needed to formulate the problem (see Table 9.4). Thereafter, we present the MILP for the OR scheduling.

Table 9.4: Indexes, Parameters, and Variable Sets.

Index Set	
S	Set of surgeries s to be scheduled in a surgical day
S_k	Subset of surgeries *(S)* that can be performed by surgeon k
S_r	Subset of surgeries *(S)* that can be performed in room r
R	Set of operating rooms r
K	Set of surgeons k
Parameters	
TP_s	Preparation time (preincision time) of the surgery s
TS_{sk}	Surgery time (incision time) of the surgery s by surgeon k
TC_s	Clean-up time (postincision time) of the surgery s
CV	Cost per minute of having an OR vacant
CW	Cost per minute of having the surgeon waiting
CO	Cost per minute of using an OR beyond the normal shift length T
T	Shift length
PT	Pause between surgeries done by the same surgeon
MOT	Maximum overtime
$MaxS$	Maximum number of surgeries performed by a surgeon
M	A large scalar value
Variables	
x_{sr}	Binary variable; 1 if surgery $s \in S$ is done in room $r \in R$, 0 otherwise
$y_{ss'k}$	Binary variable; 1 if $s \in S$ precedes $s' \in S$ and is done by the same surgeon $k \in K$, 0 otherwise
$z_{ss'kk'}$	Binary variable; 1 if s precede $s' \in S$ and it is done by different surgeon k and $k' \in K$, 0 otherwise
q_{sk}	Binary variable; 1 if surgery $s \in S$ is done by surgeon $k \in K$, 0 otherwise
msR_r	Non negative variable equal to the make span of room $r \in R$
msS_k	Non negative variable equal to the make span of surgeon $k \in K$
ts_s	Non negative variable equal to the start time of the surgery $s \in S$
tsS_k	Non negative variable equal to the start time of the surgeon $k \in K$
vt	Non negative variable equal to the vacant time

ot_r	Non negative variable equal to the overtime of room $r \in R$
wt_k	Non negative variable equal to the waiting time of a surgeon $k \in K$
vt_r	Vacant time of room $r \in R$
ot_r	Overtime of room $r \in R$
wt	Waiting time of a surgeon
tc	Total cost

Most studies (Fei et al., 2009, Denton, 2007 and Gupta, 2007) on this topic make the assumption that the surgeons for each patient are already known. However, the problem of assigning surgeons, residents for each operation in several ORs, does not appear to have been addressed in OR planning and scheduling (Ghazalbash et al., 2012). To the best of our knowledge, no models have involved different types of operations in multiple ORs with different types of surgeons. This study presents a detailed scheduling scheme for different surgery cases in multipurpose ORs with multiple types of surgeons. Based on the principal ideas of general-precedence concepts (Méndez et al., 2006), we formulated a MILP model for the scheduling of multiple surgery types in multiple ORs with several available surgeons.

We present a MILP model for this particular problem with the aim of minimizing the total surgical cost denoted by the overtime cost (*CO*), vacant time cost (*CV*), and waiting time cost (*CW*) in equation (1). Equations (2) and (3) guarantee that all surgeries are performed in only one OR by just one surgeon. The sequencing and timing constraints in the same OR and also by the same surgeon are presented in equations (4) and (5) and equations (6) and (7), respectively.

The binary variable $z_{ss'kk'}$ is introduced to consider the sequencing and timing decisions of operations performed by different surgeons but in the same OR, as shown in equations (8) and (9). Equations (10) and (11) are provided to estimate the completion time both in the ORs (makespan of the rooms) and by the surgeons (makespan of the surgeons). Equations (12) and (13) determine the initial time of each operation and surgeon in the system. Additionally, overtime (*ot*) is calculated in equation (14) while equation (15) limits the amount of overtime and equation (16) limits the number of operations performed by the same surgeon. Vacant time (*vt*) and waiting time (*wt*) variables are calculated in equations (17) and (18), respectively.

$$min.\ \ tc = CO\sum_r ot_r + CV \times vt + CW\sum_k wt_k \qquad 1$$

$$\sum_r x_{sr} = 1 \quad \forall s \in S_r \qquad 2$$

$$\sum_k q_{sk} = 1 \quad \forall s \in S_k \qquad 3$$

$$ts_s + TS_{sk} + TC_s \le ts_{s'} - TP_{s'} + M(1 - y_{ss'k}) + M(2 - x_{sr} - x_{s'} + M(2 - q_{sk} - q_{s'k}) \quad \forall s, s', r, k \mid (s' < s) \tag{4}$$

$$ts_{s'} + TS_{s'k} + TC_{s'} \le ts_s - TP_s + M(y_{ss'k}) + M(2 - x_{sr} - x_{s'} + M(2 - q_{sk} - q_{s'k}) \quad \forall s, s', r, k \mid (s' < s) \tag{5}$$

$$ts_s + TS_{sk} + PT \le ts_{s'} + M(1 - y_{ss'k}) + M(2 - q_{sk} - q_{s'k}) \quad \forall s, s', k \mid (s' < s) \tag{6}$$

$$ts_{s'} + TS_{s'k} + PT \le ts_s + M(y_{ss'k}) + M(2 - q_{sk} - q_{s'k}) \quad \forall s, s', k \mid (s' < s) \tag{7}$$

$$ts_s + TS_{sk} + TC_s \le ts_{s'} - TP_{s'} + M(1 - z_{ss'kk'}) + M(2 - x_{sr} - x_{s'r}) + M(2 - q_{sk} - q_{s'k}) \quad \forall r, s, s', k, k' \mid (s' < s \tag{8}$$

$$ts_{s'} + TS_{s'k'} + TC_{s'} \le ts_s - TP_{l_s} + M(z_{ss'kk'}) + M(2 - x_{sr} - x_{s'} + M(2 - q_{sk} - q_{s'k}) \forall r, s, s', k, k' \mid (s' < s) \tag{9}$$

$$msR_r \ge ts_s + \sum_k (TS_{sk} \times q_{sk}) + TC_s - M(1 - x_{sr}) \ \forall s, \tag{10}$$

$$msS_k \ge ts_s + TS_{sk} - M(1 - q_{sk}) \quad \forall s, k \tag{11}$$

$$ts_s \ge TP_s \quad \forall s \tag{12}$$

$$tsS_k \le ts_s + M(1 - q_{sk}) \quad \forall s, k \tag{13}$$

$$ot_r \ge msR_r - T \quad \forall r \tag{14}$$

$$ot_r \le MOT \quad \forall r \tag{15}$$

$$\sum_s q_{sk} \le MaxS \quad \forall k \tag{16}$$

$$vt \ge \sum_r (msR_r) - \sum_s (TP_s + TC_s) - \sum_{sk} (TS_{sk} \times q_{sk} \tag{17}$$

$$wt_k \ge msS_k - tsS_k - \sum_s (TS_{sk} \times q_{sk}) \ \forall k \tag{18}$$

Where

$$x_{sr} \in \{0,1\}, y_{ss'k} \in \{0,1\}, \ z_{ss'kk'} \in \{0,1\}, q_{sk} \in \{0,1\},$$
$$msR_r > 0, \quad msS_k > 0 \qquad ts_s > 0, \quad tsS_k > 0, \ vt >$$
$$ot_r > 0, \ \ wt_k > 0.$$

RESULTS

We evaluated the performance of our approach using part of the waiting list from the urology department of the teaching hospital in Toledo. We defined six instances with different numbers and types of surgeries. The computational experiences were performed on an ASUS PC with Intel Core i3-2350 M 2.30 GHz with 6 GB RAM running the solver in parallel mode with two threads under Windows 7.

Simulation results

The results of the different strategies for various surgeries and surgeons are presented in Table 9.5. In the last column, the results from running 100 replications are displayed.

Table 9.5: Costs of the different strategies for the dispatch of surgeries (euros).

Instance	Optimal (MILP)	Faster *k*, ascending TS	Faster *k*, descending TS	Slower *k*, ascending TS	Slower *k*, descending TS	Results of 100 scenarios	
						Mean (std)	Min-Max
1	3,400	3,850	4,325	3,850	4,325	3,812 (53)	3775-3850
2	2,850	3,579	4.320	6,966	4,850	4,914 (1,277)	3,579-6,966
3	3,258	8,541	6,616	9,141	7,204	7,162 (1,337)	5,591-9,475
4	5,100	7,291	10,300	5,900	9,662	7,848 (1,104)	5,900-10,562
5	3,650	9,600	7,783	8,800	6,729	7,073(960)	5175-10,329
6	4,183	15,668	13,539	13,637	15,456	13,563 (933)	11,066-16,568

It is evident from those results that no dispatching policy was able to outperform the others. For some instances, using the faster surgeon first was better; in other instances, using the slower surgeon was advantageous. We made the same observation with the ascending or descending order. Another option was to try many random combinations to obtain a good solution. In some instances, that worked to an acceptable degree; however, with a larger number of ORs and surgeons, there was a greater difference from the optimal situation. It should be noted, though, that all of the results were far from optimal.

MILP results

Table 9.6 presents the computational performance of each instance; Table 9.7 shows the detailed costs and Figure 9.2 displays the solution schedule in a Gantt chart. In that chart, we observed that the waiting time of the surgeons was minimized and that changing the ORs would avoid delays with the postincision time and the clean-up time for the next patient. The overtime was

minimized, but it was inevitable in some situations. OR occupation also increased since in the majority of the cases as soon as one patient left, the preincision procedure began for the next.

Table 9.6: Results of the instances.

Instance	CPU time (s)	Total cost (€)	Integer variables	Continuous variables	Constraints	Nodes	Iterations
1	3.8	3,400	33	15	140	10,552	36,167
2	3.5	2,850	65	19	357	5,812	26,076
3	4.7	3,258	90	20	510	4,734	21,390
4	140	5,100	119	21	691	224,573	948,271
5	456	3,650	152	22	900	558,804	2,984,012
6	1,720	4,183	387	28	3,013	1213370	5,627,758

Table 9.7: Detailed cost of the instances.

Instance	**1**	**2**	**3**	**4**	**5**	**6**
Waiting time (min)	75	45	65	75	90	95
Waiting time cost (euro)	875	525	758	875	1050	1,108
Overtime (min)	20	30	55	115	20	63
Overtime cost (euro)	500	750	1,375	2,875	500	1,575
Vacant time (min)	135	105	75	90	140	100
Vacant time cost (euro)	2,025	1,575	1,125	1,350	2100	1,500
Total cost (euro)	3,400	2,850	3,258	5,100	3650	4,183

We did not experiment with any operations bigger than surgery type *H* (320 minutes' duration) as they would require a full day in the OR and would result in a trivial answer (one OR, one long surgery), which was not relevant to this study.

Our model was able to deal with multiple surgeons in multiple ORs. The solutions are presented in Table 9.6. Some of the tested instances are solved up to optimality within a few minutes—in some cases, in less than 1 minute. The model takes more time to solve the most complex instances.

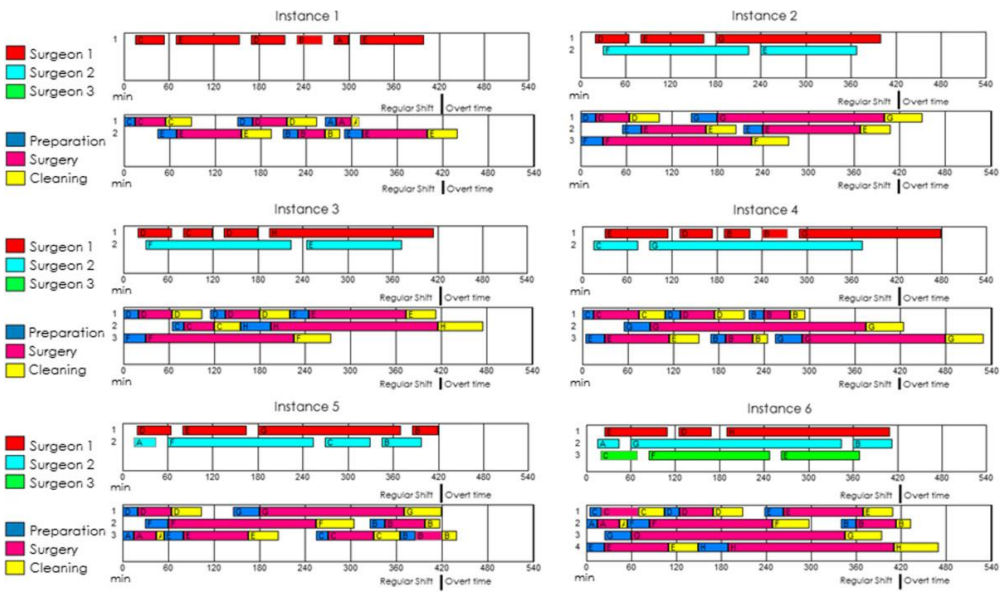

Figure 9.2: **Gantt diagram of instances 1–6.** Each panel refers to one instance. Every panel has a pair of Gantt diagrams, the upper Gantt diagram is the schedule of the surgeons and the lower Gantt diagram is the schedule of each operation room.

The model size is also reported in Table 9.6 according to the number of variables and constraints while the complexity of the solution is demonstrated by the number of nodes and iterations explored. As with other similar models, the solution time for an instance with the same number of surgeries varies considerably depending on the data. This is a critical point in the solution performance: our model was able to obtain high-quality initial feasible results in only a few minutes, but it needed much more time to ensure the optimality of the solution found. With the general-precedence formulation, a reduced number of binary sequencing variables has been reported compared with other MILP formulations, e.g., that presented in Batun et al., (2011).

Our model was refined through using pairs of constraints associated with the general-precedence formulation and appears to be much more efficient than that since it uses a unique general-precedence variable for sequencing surgeries simultaneously for both ORs and surgeons. In other formulations, the sequencing variables are proposed for each OR using surgery-specific precedence-based representation. Since the number of binary variables increases with the number of surgeries and the number of ORs is greater than the number of surgeons, our representation can significantly reduce the size of the problem (Méndez et al., 2006). As an example, using a unit-specific representation, the number of sequencing variables will be $|S|*|S-1|$ in each OR as a result of $s \neq s'$; in our formulation, the number of combinations is reduced to $(|S|*|S-1|)/2$ for each surgeon, since $s > s'$ under general-

precedence concepts. This is because if the sequence exists in one tuple of the constraints, it does not exist in the other.

The combinatorial sequencing problem size increases with the number of surgeries considered, as noted above. That is why it is so important to reduce the number of binary sequencing variables when solving large problems with reduced computer effort.

Variation of the number of surgeons and ORs

This problem can be solved by varying the number of ORs and surgeons and by minimizing the total surgical cost (OR idling, surgeon waiting, and overtime). If the number of surgeons and ORs is constant, the idling time of the ORs is zero since they are never vacant. Then, the waiting time for the surgeon increases since the surgeon has to wait for both the clean-up and preparation of an OR to be completed before starting the next operation.

The final configuration will depend on the resources available on a surgical day, and the manager must decide on and evaluate the best possible option. The manager may choose to perform the surgeries with fewer surgeons or staff or use the same number of surgeons and ORs if they are available that day. In Figure 9.3, we present instance 5 using one extra surgeon (3 Surgeons and 3 ORs). Having the same number of surgeons as ORs meant that the cost increased from €3,650 to €4,083 (€1,800 for overtime and €2,283 for vacant time). There is no single answer as to whether it is better to have more ORs than surgeons on a given day: this situation should be evaluated for each instance with the use of the mathematical model.

Figure 9.3: **Gantt diagram of the instance 5 using the same number of surgeons and rooms.** The upper Gantt diagram is the schedule of the surgeons and the lower Gantt diagram is the schedule of each operation room.

Importance of differentiated surgery times in a teaching hospital

Not all surgeons are the same. In the context of a teaching hospital, this matter becomes very important. According to Bridges et al., (1999), who compared 14,452 cases in terms of operating time, that time was longer in 10,787 procedures when a resident performed the surgery rather than it being done by an experienced surgeon. As with any other process, an experienced surgeon usually works faster than a student. Some faculty surgeons have performed operations for many years, and the residents are still learning. We incorporate this feature into our model by trying to represent actual behaviour at teaching hospitals. In Table 9.3, we assign different operation durations to different surgeons, assuming that each surgeon may perform each operation faster or slower than the projected time.

The misguided assumption that all surgeons perform equally can create significant scheduling problems. This is especially important in a teaching hospital, where residents perform many operations during the surgical day. In the next example, we planned the surgical day under the false assumption that surgeon 1 and surgeon 2 (the resident) perform their operations in the same amount of time. When we reviewed the results (see Figure 9.4), we found that there would be no overtime: all the staff would finish early at a total cost of €1,725. In this situation, the planner could even consider including additional surgeries. However, when the surgeons followed the sequence obtained, the residents took more time, and the result was completely different: there was considerable overtime, and an increase in the total cost of up to €6,048. In the previous section (Table 9.6), we solved instance 5 by considering from the outset the difference among surgeons in terms of skill: the resulting cost was €3,650, which is significantly lower than €6,048.

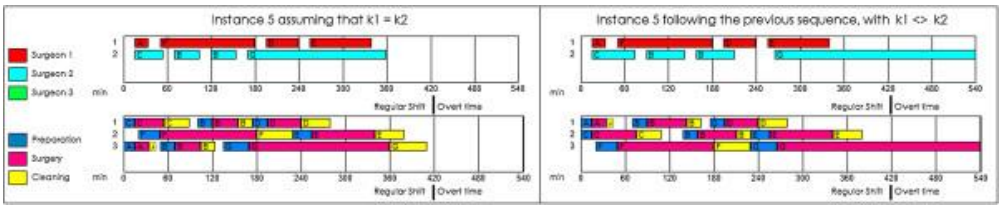

Figure 9.4: **Problems of assuming that the surgeons perform the surgeries in the same time.** On the left part are the Gantt diagram (surgeons and operation rooms) of the instance 5 assuming that all the surgeons perform the surgeries in the same time. On the right part are the results of follow the previous sequence, with surgeons that perform the surgeries in different times.

The objective with the above example is to highlight the problem with a commonly accepted assumption when scheduling, whereby the duration of a surgery is independent of the surgeon's skill. This could result in additional

costs owing to unforeseen delays or cancellations of surgery through limitations with the extra time. For this reason, it is important to differentiate between surgeons.

Rescheduling

Many changes can occur in the course of a day at a hospital, such as the duration of surgeries and the starting time of those procedures. A rescheduling procedure based on fixed variables x_{sr}, q_{sr}, and ts_s relates to the completed surgeries and surgeries that have already begun. The start time and duration of surgeries are modified according to new information, and scheduling can be solved up to optimality in only a few seconds using a deterministic approach.

With our model, we can handle uncertainties in surgery duration and modify the schedule immediately after the occurrence of unexpected events during the surgical day. The values of the fixed variables allow the determination of other values related to the general precedence for the same surgeon, for different surgeons, for different ORs, and for the same OR, thereby decreasing the overall solution time.

Figure 9.5 presents the rescheduling in instance 6. When surgery G has a delay of 25 minutes, the algorithm fixes the variables associated with surgeries E, A, and C, and determines the new start of surgery G. It then optimizes the remaining surgeries. The optimal situation with this example was achieved in 15 seconds. A smaller instance could be solved faster, and rescheduling based on the first surgery would take the same amount of time as normal scheduling. If we recall the optimal outcome for instance 6, presented in Figure 9.3, surgeon 2 should perform surgery B in OR 2 after that surgeon completes surgery G, though surgery B now becomes assigned to surgeon 3.

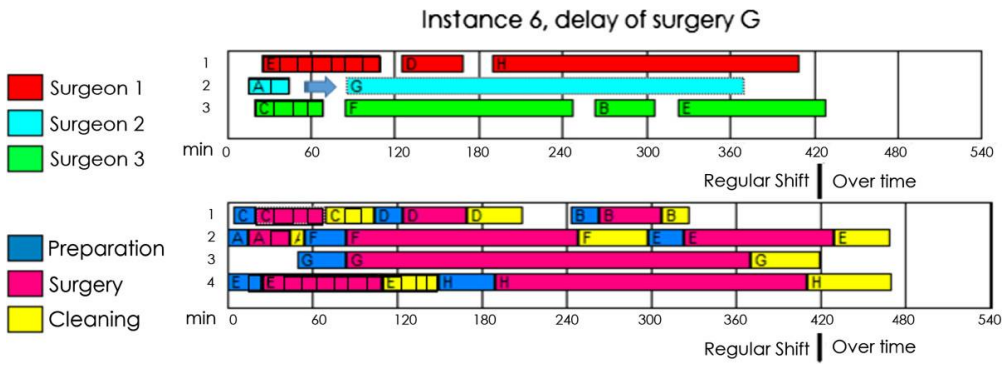

Figure 9.5: **Gantt diagrams of the rescheduling of instance 6.** The hatched surgeries (A, E, C) are fixed, and the surgery G is delayed 25 minutes. The upper Gantt diagram is the schedule of the surgeons and the lower Gantt diagram is the schedule of each operation room.

The rescheduling tool allows the OR planner to deal with new conditions that arise during the surgical day, implementing the required modifications to the schedule, thereby decreasing the cost impact and avoiding surgery cancellation.

Software interface

We developed a user-friendly interface in AIMMS (Bisschop and Roelofs, 2011) to deal with this complex optimization problem (see Figure 9.6). We included a guide to help users become familiar with the process. Additionally, we added a rescheduling capability, and we facilitated the changes to the experimental data. Our solution tool provides the manager with the possibility of easily changing parameters and obtaining high-quality results faster. The video presents a brief overview of the interface and its rescheduling capabilities in real time.

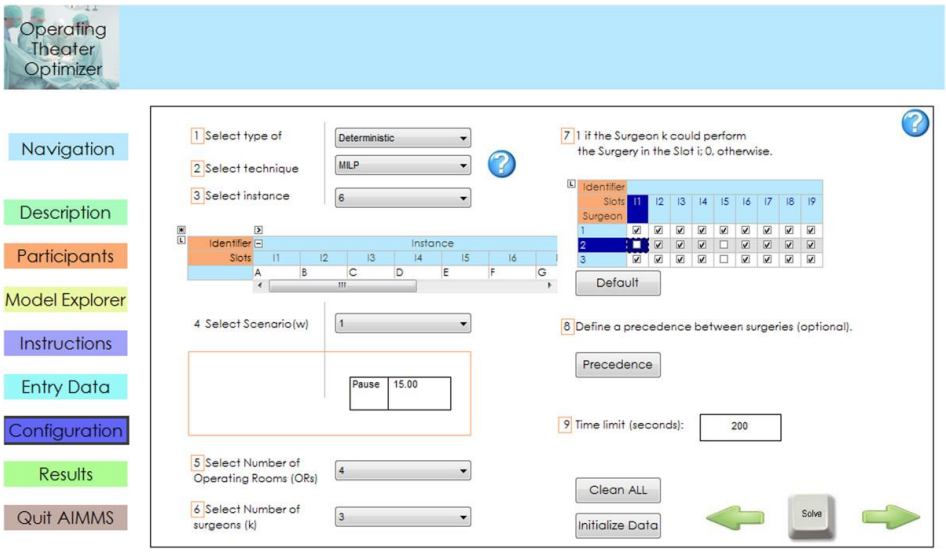

Figure 9.6: **Screenshot of the configuration page of the software interface.**

We used Enterprise Dynamics simulation software to facilitate the evaluation of the different schedules performed by various surgeons. The interface allows the planner to visualize any schedule in 3-D (see Figure 9.7) and to evaluate different dispatching policies for surgeons and surgeries, as indicated in Table 9.4. The simulation model aims to mimic the behaviour of the OR, allowing the planner to easily change the parameters of the simulation and to set a predefined schedule; alternatively, the planner may introduce dispatching rules and see their effects in the accrued costs at the end of the simulation.

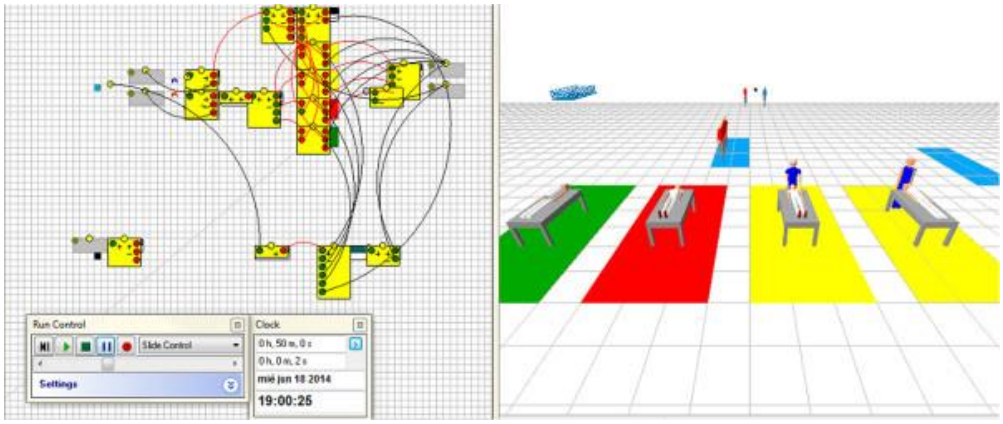

Figure 9.7: **Screenshot of the 3D simulation.** The left part is the diagram of the simulation and the right part is the 3D display.

DISCUSSION

We presented the model we developed to physicians, who provided useful feedback. We took their suggestions into consideration and made some improvements to the model, such as limiting the amount of overtime available and the maximum number of operations that could be performed by a surgeon in a day. In addition, the physicians noted that it was unrealistic to perform one surgery and then immediately begin the next one. Accordingly, we added some pause time (PT) to the model; in some of the results, this time was the only waiting time cost present.

The main problem with our model arises from the fact that a surgeon sometimes moves from one OR to another OR. This procedure is currently only done in special cases at the Toledo teaching hospital, such as when the surgeons are in a hurry as the surgeons themselves prefer to perform all their scheduled operations in the same OR.

The problem with using a single surgeon for surgical operations in parallel ORs has already been examined (Batun et al., 2011, Mancilla and Storer, 2013). Mancilla and Storer (2013) presented an interesting discussion on this topic, arriving at the conclusion that the use of parallel ORs depends on ratios: the cost ratio (cost of waiting/cost of idling) and the "setup to surgery time ratio". The problem in limiting the mobility of surgeons is that during the clean-up time and preparation time for the next patient, the surgeon is not occupied. Therefore, there is a significant time saving if surgeons move from one OR to another, avoiding idling costs. If all the operations by one surgeon are scheduled in the same OR, a major benefit of the scheduling is lost.

Uncertainty with times

If our model is used to develop OR schedules, having an accurate estimate of the operating time required for each surgery type is a prerequisite to its effective use. However, assessing an operation's execution time is not easy because it depends on the patient's pathology, which may be known only partially, and on the surgeon's expertise (Wright et al., 1996, Dexter and Macario, 1996).

Since there are no historical data—either on the probabilities or distribution of the surgery duration for each patient—we followed the strategy of finding a fast, accurate solution using the time estimated by the head of surgery. Asking the head of surgical services to provide a forecast concerning the three times (preparation, surgery, and clean-up) for each operation increases the complexity of using the system; it also increases the complexity of the model without obtaining a better solution since all the data are used for the estimate. Having an information system that stores all records relating to surgeons and patients would help increase the accuracy of such estimates.

Interesting approaches have been made in the stochastic field such as Batun et al., (2011), however, obtaining a more robust solution usually has the requirement of a high computational cost. Since the aim of this paper is to deal with the daily scheduling, using a deterministic approach to generate a good solution in a reasonable time was preferred.

Despite the use of a stochastic or deterministic model approach it is advisable to periodically update the solution with the most recent data.

In the event that the actual time of the surgery differs from the predicted model, the solution will be affected and it will be necessary to run the scheduling again with the new information. In order to take the best decision, for example, changing the beginning of the next surgery, or the surgeon that will perform the surgery, in the event that is needed in the rescheduling phase, the minimum pause time constraint could be relaxed to minimize the impacts of the delays.

Limitation of the model

The main limitation with our model is that we first need to define the set of surgeries that should be sequenced each day. A future developmental step would be to select from the entire waiting list which surgeries should be performed according to their urgency (time on the waiting list).

Using historical data to feed the model could help the decision-maker to obtain accurate predictions of the duration of the surgeries performed by each surgeon. However, the same operation can have different times even when

performed by the same surgeon because every patient is different: according to the head of the medical service, "Nobody knows what they might find when they enter the operating room". Although we developed a general model for a teaching hospital, there are still many specific considerations that need to be studied and implemented in the final program for it to be used on a daily basis.

CONCLUSIONS

The principal contribution of this paper is the development of an effective computer-aided framework based on mixed integer lineal programming and a simulation model for the daily schedule of the ORs of a teaching hospital managing multiple surgeries performed by different surgeons.

The MILP model is able to deal with scheduling different types of surgeries in parallel ORs and with multiple surgeons. Using this model, decisions are made on an operational level because the capacity of the resources (ORs and surgeons) and the operations that need to be performed are known 24 hours in advance.

Our model provides high-quality results within a reasonable time for the decision-maker, and allows a new schedule to be created if any circumstances change. By incorporating the advantages of model formulation, we can easily allow surgeons to specialize in only certain types of operations and deal with real-world problems without incurring additional computational costs.

The daily surgical scheduling in ORs with multiple surgeons is still a complex issue for the managing director of a hospital. Our tool was specifically designed to help managers analyse and evaluate possible profitable results within a reasonable time frame. There are several specific requirements that are significant to a manager-director that could be examined in future research towards more accurately representing real situations. Some future considerations could be the stochastic duration of the surgeries themselves, different operating times depending on the surgeon, and the upstream and downstream resources necessary to support surgical activities, such as preoperative and postoperative actions.

These and other practical considerations provide an opportunity to continue research in this area: the promising results in terms of savings and publications represent more opportunities for operational research in health management. In addition, it is necessary to convince the decision-makers of the advantage of health-care operation research; they need to know that it is worth investing their time and money in further studies of this nature even in the face of current ongoing cuts in the public health-care system.

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SECTION 4. FINAL THOUGHTS

In section 3, the integration of the health care sector was analysed, and then the scheduling in a teaching hospital was implemented. In the last section we identify the factors that make an instance likely to use a joint approach, summarize the thesis and present the final conclusion of this thesis. In chapter 10, we highlight the fact that some instances are more suitable for a joint approach while others are not. We then identify the factors that could make an instance more suitable to be used with an overall approach, and when it is more suitable to make the decision separately. Finally, in the last chapter we present the overall conclusion and future research directions of this work, followed by the appendices of the thesis.

Chapter 10: The role of complexity and flexibility of the instance in the joint solution approach

MOTIVATION

Many pieces of research address the development of new algorithms and new solution techniques for decision-making; however, most of them do not consider the characteristics of instance in their analysis, such as the complexity and flexibility of the instance. Building a complex model, such as a joint model, requires a huge amount of time and effort while the resulting solution of such joint models may or may not be the best solution for all the actors involved in the process. Therefore, it is important to make an in-depth analysis of the instance before investing the time and effort to build a joint model. In this regard, this paper provides an instance evaluation procedure to help decision-makers decide whether to use a joint decision or not for a particular instance.

INTRODUCTION

The traditional decision-making process is usually sequential where the best decision is taken for the first stage of the process and then this output of the first stage is used as a basis for the next stage decisions and so on. However, by using a sequential decision-making process it is difficult to reach an overall optimal solution as the final decisions completely depend on the first-stage decision. To overcome this limitation a joint decision approach offers a great opportunity to reach an overall optimal solution by enlarging the search space. Joint decision-making can have many implications since, besides the intrinsic

cost and time of developing the joint model, it may involve a possible change in the organizations in order to allow different actors to share information and to persuade global goals instead of local goals. This requires a close collaboration and coordination among the different actors involved in the overall process. Interestingly, many operational management researchers assume that "integration is a must" and that cross-functional coordination and integration are necessary (Ketokivi, 2006). However, in later research, Turkulainen et al. (2012) argued that the benefits of integration and cross-functional coordination are context-dependent and sometimes disaggregation is beneficial.

Joint decisions usually result in a paradox since the different actors may not achieve the optimal solution for their sub-operations in order to achieve an overall optimal solution. Therefore, a joint decision-making process could be attractive for some circumstances and unappealing in other situations. Considering this paradoxical nature of joint decisions, this research attempts to explore "When is it advisable to use a joint decision-making process and when is it better not to use it? The contribution of this paper is to create an "instance evaluation procedure" based on the complexity and flexibility of the instance to help the decision-makers to decide before investing their time and effort in the preparation of a joint decision model. To this end, the authors argue that it is highly important to consider instance characteristics before setting out on a joint decision model.

Characteristics of the Instance

The instance is the complete set of data that defines the problem space e.g. in the case of a scheduling problem the number of days, workers, job shops, production lines, units to produce and so on. One of the most important characteristics of an instance is the size of the problem, which is determined by the number of continuous and binary variables that represent all the relationships among variables and parameters. The problem size is considered as a major contributor to the complexity of the instance. However, there are many other factors that need to be considered when analysing the instance complexity. The complexity and flexibility of the instance plays a crucial role in the decision-making process. For dynamical systems theory the complexity measures are usually computational complexities that are a measure of the interactions (Adami, 2002). Similarly, Heylighen (2008) highlighted that a fundamental part of any complex system is the parts connected via interactions. These parts can be distinct and/or connected as well as autonomous and/or to some degree mutually dependent. This interdependence can create conflicting goals since the improvement of one part could lead to the decrement of the other part. Therefore, just considering the total number

of variables present in a problem space as the only parameter/measure of complexity is not the right approach. Many other factors need to be considered when analysing the complexity of an instance. An important work in this regard is by Vanhoucke and Maenhout (2009) where they characterize the Nurse scheduling problem. In their work, they highlight four factors to analyse the complexity of the indicators: a) problem size, b) the preference distribution measures, c) the coverage distribution measures, and d) the time related constraints.

Similarly, flexibility of an instance is another key characteristic that needs to be considered when analysing a joint decision. Flexibility is "the ability to change or react with little penalty in time, effort, cost, or performance" (Upton, 1994). Thus, a flexible instance of workers means the extent to which the employees can perform different tasks. In this research, we propose considering three new factors while analysing the instance characteristics. These factors include preference distribution, coverage distribution and cost dispersion.

FACTORS FOR INSTANCE ANALYSIS

In this section we propose and define three indices that need to be considered when analysing an instance for a joint decision. These factors are discussed briefly.

Preference distribution (PD)

The preference distribution measures the dispersion among the needs or requirements of resources by the different entities over the scheduling horizon. If all the requirements are similar the preference of distribution will be low, but on the other hand if all the requirements are different this index will be high. It can be measured using equation 1. Where $Entity_i$ is the requirement of resources of the entity.

$$PD = \frac{\sqrt{\frac{\sum_{i=1}^{N}(Entity_i - \overline{Entity})^2}{NumberOfEntities}}}{\overline{Entity}} \quad (1)$$

Extra coverage constrainedness (ECC) Rigidity / Flexibility

The coverage requirements are expressed by the average of the extra capacity (availability) of all machines (resources). When this number is close to 0, we could say that it is a rigid instance that there is no extra resource; when it is close to 1 its means that it is a flexible instance meaning we have some extra resources. This factor can be measured with the help of equation 2.

$$ECC = \frac{\sum_{Machine}\left(1-\frac{requirement_{machine}}{capacity_{machine}}\right)}{number\ of\ resources} \quad (2)$$

Cost dispersion (CD)

The cost dispersion is a measure that is used to quantify the variation of cost among the different areas, in which the decision will be made together. We will refer to the total cost of each part, which, for example, in the case of the inventory, will be the total cost of the inventory not the cost of each unit of inventory. It can be measured using equation 3.

$$CD = \frac{\sqrt{\frac{\sum_{i=1}^{N}(Cost_i-\overline{Cost})^2}{NumberOfCosts}}}{\overline{Cost}} \quad (3)$$

In the next section, these factors are studied using 2 case studies where different combinations of the preference distribution, extra coverage constrainedness and cost dispersion are tested. The size of the instance is constant and the amount of resources available helps to characterize the instance. The three indexes vary between low (close to 0) and high (close to 1).

CASE STUDIES AND RESULTS

The computational experience was performed in a Windows-PC with an Intel Core 7, 8 GB of RAM, running Windows 7, with the AIMMS 3.14 mathematical modeller and Gurobi 6.0. A maximum stop criterion of 3600 sec was set for all instances.

Case study 1

In a car assembly line, the production sequence has to be decided for the planning period. Each workstation could deal with a production rate, which means that a workstation could install X high trim components each Y cars. In the event that the number of high trim components is higher, an extra utility worker has to come to help, with a penalty cost. Each station installs a different type of component that needs to be next to the assembly line before it is needed. The transportation vehicles carry these components from the warehouse to the workstations where it is assumed that all the components exist. Each model has a set of characteristics, such as engine, rims, tyres, steering, etc. These components could have different trims (Low or High). All the models are different from the other models in at least one type of component. The components required at each workstation are delivered as a kit. The model was implemented using mixed integer linear programming. A

detailed description can be found in (Pulido et al. 2014a). There are 3 main decisions that have to be taken and are usually taken sequentially.

1. The production sequence that minimizes the use of extra utility workers.
2. The distribution cost of components that minimizes transportation cost.
3. The inventory level that minimizes the inventory cost.

The first index will be calculated as the deviation of the number of high trim elements that each car requires, and the average entity will be the one for which the assembly line was designed. For the second index, the machines will be the workstation and transportation vehicle. The requirement of workstations of the car assembly line will be the requirement of each car model for this workstation, while between the production ratios and for the transportation vehicles, the requirement will be the demand for the use of a vehicle, and its capacity will be the transportation capacity.

The results of the experimentation are presented in Table 10.1, where the first column of the instance defines the instance with respect to three indexes, and the left part of the table is the result of the traditional sequential approach while in the right part is the result of the joint approach. Promising results appear when the preference distribution is high, and there is diversity among the tasks that have to be done and also when there is extra coverage of resources since there is flexibility of the allocation. And finally when there is diversity of the cost there are promising results, especially when the biggest cost contributor is the last of the sequential model.

Table 10.1: Result of Case Study 1.

PD,ECC,CD	Sch	Transp	Invent	SeqD	Sch	Transp	Invent	JointD	Savings
L,L,L	594	1432	928	2954	638	1424	796	2858	3%
L,L,H	594	716	9283	10593	638	715	7921	9274	14%
L,H,L	0	1439	902	2341	0	1426	813	2239	5%
L,H,H	0	720	9023	9743	22	716	7979	8717	12%
H,L,L	308	1435	944	2687	308	1434	834	2576	4%
H,L,H	308	718	9436	10462	396	714	8124	9234	13%
H,H,L	0	1436	947	2383	0	1424	795	2219	7%
H,H,H	0	718	9469	10187	0	712	7952	8664	18%

Case study 2

The teaching hospital plays a key role in the health care system. Inside the hospital, the main part of this structure is the operating rooms, since the majority of the patients go through the operating room

The scheduling of the surgeries is important since the vacant time of the operating room, the idle time of a surgeon, and the extra time cost of the

operating room impact directly on how the hospital functions. A detailed explanation of the model can be found in (Pulido et al. 2014b). There are 2 main decisions that have to be taken and are usually taken sequentially.

1. The doctor who performs the surgery that minimizes the extra time. Each surgeon has a different expertise and could perform a surgery faster or slower.
2. The operating room schedule that minimizes the vacant time of the surgeons and idle operating rooms.

The first index will be calculated as the deviation of the length of the surgery against the average surgery duration. In order to calculate the second index the machine will be the surgeons and operating rooms. The requirement of surgeons will be the total length of the duration of the surgeries that could be performed by a surgeon between the shift length (capacity) while the requirement of the operating room will be the total length of surgeries that can be performed in this operating room between the shift lengths.

Table 10.2 presents the results. First the indexes used, then the overtime, vacant OR time and surgeon waiting time cost for the sequential decision and the same three costs for the joint decision, and the savings. The Joint Decision is advisable with promising results when the preference dispersion is high, because when it is low the results are negligible. The role of the ECC is minor, since it plays a complicated role, as there is a penalty for the extra resources (vacant time cost). The dispersion of the cost is also important, especially when the cost of vacant time is high.

Table 10.2: Result of Case Study 2.

PD,ECC,CD	OverT	VacT	WaitT	SeqD	OverT	VacT	WaitT	JointD	Savings
L,L,L	1307	885	362	2554	1387	885	210	2482	3%
L,L,H	980	885	620	2485	1040	905	360	2305	8%
L,H,L	0	1020	350	1370	13	885	210	1108	24%
L,H,H	0	1020	600	1620	0	1135	120	1255	29%
H,L,L	1027	1545	58	2630	1307	1065	58	2430	8%
H,L,H	770	1545	100	2415	980	1065	100	2145	13%
H,H,L	40	990	362	1392	40	1065	58	1163	20%
H,H,H	0	1050	540	1590	0	1035	100	1135	40%

Prescriptive framework

A prescriptive framework is developed based on results, and acquired experience is presented. With a more detailed analysis of the input data, we can assess the preference distribution of the instance, the extra coverage (flexibility/ rigidity) of instance, and the homogeneity of the cost. If the results

of this pre-processing of the data are promising, we can decide to take the next step and start to build a joint model.

When the preference distribution is low, which means similar products or tasks need to be produced/performed, the benefits of the Joint Decision decrease. On the other hand, if we have bigger diversity the results could be promising.

The extra coverage constrainedness plays a key role and will depend on whether there is a penalty or not for having extra resources. However, if there is no extra coverage the possible savings will decrease.

The major influence that we found is cost dispersion, since when it is low the results are not so promising, but when there is a high dispersion then it is necessary to know the position of the most expensive cost as this plays a key role. When the highest cost is the final decision, the possible savings increase considerably.

However, for choosing the right type of model, it is important to take into consideration the number of actors or the size of the problem, since this will determine if we use exact or non-exact methods. The goal ambiguity, frequency of decision and uncertainty should be taken into consideration in advance in order to decide on exact or non-exact methods.

For the reason mentioned previously, we suggest analysing the likelihood of savings based on the preference of distribution, coverage of the instance and homogeneity of cost. Figure 10.1 shows the proposed evaluation process/ procedure.

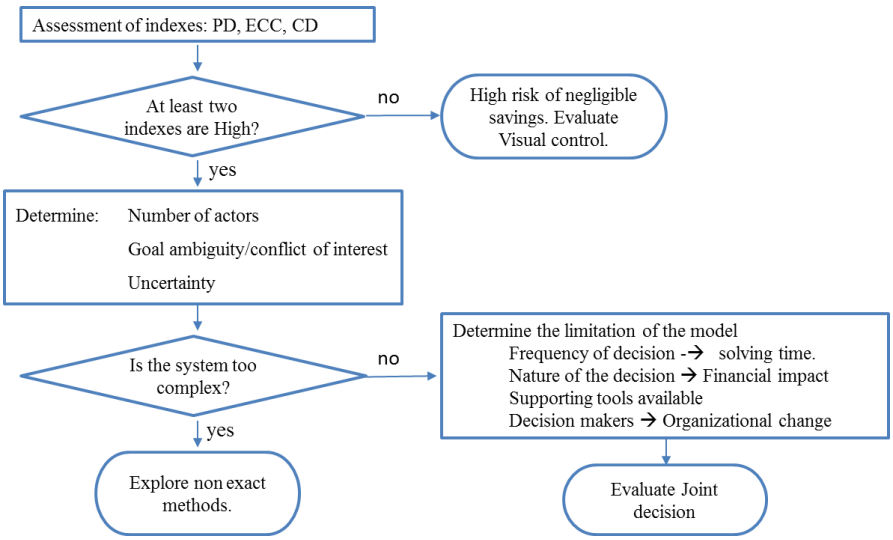

Figure 10.1: Instance Evaluation process.

Conclusion

The major benefit of a joint decision is the possible cost savings, thanks to the better utilization of key resources. The decrease in the cost is accompanied by an improvement in the key performance indicator such as the use of resources or the decrease in overtime. As expected, the use of a joint model increases the size of the model, the complexity and the solving time. When the computational time is high other non-exact solution methods should be evaluated with the risk of a decrease in savings for non-achievement of the global optimum.

The range of possible savings for the same problems using a joint model depends on the data being quite large, but the bottom line is close to zero. Therefore, before deciding the type of model, we suggest pre-evaluating the instance as in some cases the implementation cost can be higher than the savings. Therefore, in some cases it is better to use the traditional sequential approach since the preparation of a complex model does not guarantee enough savings to justify the development of the joint model. Hence, this research concludes that any possible savings of a joint decision are case-dependent and every case should be evaluated before investing time and effort in a joint decision approach. The case/instance should be evaluated from its complexity and flexibility perspective.

As a further work we intend to test the proposed framework using more case studies, which can be generalized to other areas to try to help other researchers and practitioners to decide when or not it is better to use a joint decision.

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Chapter 11: Conclusion and future directions

INTRODUCTION

During the past chapters, we have discussed several topics with the common denominator of the model-based decision-making process. In this chapter we started with a recap of the entire work, followed by a recap of the research question, and finalize with the overall conclusion and future direction of this work.

A RECAP OF THE WORK REALIZED

In the first section of the thesis we present an overall introduction of the thesis, the second section deals with a survey and manufacturing cases, the third section with health care sector cases, and finally in the fourth section are the final thoughts.

This research area will keep being relevant as long as almost every managerial position requires decision-making. Researchers have a look at tools and techniques that help to make a decision that helps decision makers to increase the possibilities of making a decision that leads to successful results.

Mintzberg et al. (1976) present their relationship between phases of the decision process, highlighting that the identification phase (first phase) had been unattended. Adding a phase after the diagnosis phase, where the identification of the scope is determinate, we analyse the changes caused by the change of scope in various cases of the manufacturing industry and health care sector.

Changing the scope of a decision has a direct impact on the complexity from all points of view of a decision. These changes have impacts on the organization of the decision-making unit, since as we add more players with different interests the decisions increase their complexity. This increment of complexity could be caused by different factors such as adding more functional areas, or mixing operational decisions with tactical and strategic decisions, or by increasing the term of a decision from only short term to medium or long term or by a combination of those factors.

This leads to two possibilities; the first is to take a sequential decision using the output of one decision as the input to the other decision, while the second is to take a joint decision, taking all the decision together. Then the different combinations of the problems are presented for the manufacturing and health care sector. After the introduction, the four research questions were presented

followed by the research design and the layout of the research where the different techniques and the research methodology were introduced.

In the third chapter, a literature review was conducted on the different decision theories and the characteristics of a decision with complete information, the decision process and the decision-making unit. A deep literature review of a journal specialised in presenting successful decision model real life stories was undertaken, where the different savings were analysed. It is important to highlight that some cases are not comparable; for example, the savings of human lives cannot be compared with monetary savings. Finally, it is suggested the expected impact of a decision compared with the literature should be known together with a benefits cost analysis.

The second section presents a survey and manufacturing cases. Starting with the fourth chapter a survey and face-to-face interviews were performed to understand the decision-making process in different companies from different sectors, and their perception of integration. There is a general agreement that competitive supply chains employ the internal integrated process, which is frequently misconceived as just the use of the software. Also, we obtained many misalignments between their beliefs and what they do, for example, job rotation, which is considered as an integration factor that is apparently easy to implement, was only strongly advised by 12% of the companies.

In Chapter 5, a model-based decision for the car assembly line was implemented. The inventory routing problem and the inventory problem were combined in a MILP model and implemented separately. The integration of production and logistics is a common goal of an integrated company. Therefore, the routing model should consider more factors than just the transportation cost, such as the specific requirements of materials over time to decrease the cost. The cost of space is an amplifier of the savings of the model.

In the next chapter, the complexity of this model was increased by adding the car scheduling problem to the inventory routing problem and the vehicle routing problem. A MILP model was developed, but it requires a lot of computation time to solve mid-size instances. After that, an Ant Colony Optimization heuristic was used. The ACO model obtains a good quality solution in a fraction of the time. Two ownership policies of the transportation vehicles were tested, the first one where the car manufacturing company has the ownership of the transportation vehicles and when they use a material handling company. As there are no public instances to compare, we could not compare the results of the ACO for bigger instances. However, we believe that the results tested in the small and medium-sized case are promising and will remain valid for bigger instances.

In chapter 7 a simulation for an aeronautical manufacturing plant was performed. The problem presented is not exclusive to aeronautical manufacturing plants since several manufacturing processes such as printed circuit boards and automated wet-etch stations in semiconductors rely on the use of hoists, cranes or some material handling device to change the work in progress from one workstation to another. This problem is an example of a problem where obtaining an optimal solution to one part of the problem does not lead to an optimal overall solution, in some cases not even to a feasible solution. Two operational decisions were made jointly, and the use of heuristics and simulation let us obtain a feasible solution in a reasonable amount of time and simulate breakdowns that are difficult to model with exact methods. One of the advantages when solving these kinds of problems by simulation is that the decision-maker may easily evaluate the impact of a WIP variation and its impact on production time and the cost of defective parts. Interesting ideas coming from the decision-makers, such as changing the chemical from non-used tanks to the highly used tanks, could be easily tested knowing the cost of the change and the improvement in the performance. The proposed simulation allows the decision-makers to evaluate future improvements in the system design such as a second hoist, faster hoists and more tanks.

Section 3 refers to the health care sector. In chapter 8 an operating room optimization is presented. Despite manufacturing facilities and hospitals looking like two different worlds, the decision of a hospital manager does not differ a lot from a manufacturing manager. Both are evaluated by the key performance indicators of the usage of the production facilities (machines or operating rooms), overtime, workers', outputs, and so on. One of their goals is the proper management of the operating rooms which are the engines of a hospital. A model to decrease the three main costs of the operating rooms (OR vacant cost, surgeon waiting cost and OR overtime cost) is presented. We started with a MILP model where the times are deterministic and we compared it with some heuristic models. In the second part of the chapter, we deal with stochastic duration times of the surgeries. We compared the stochastic MILP model with a decomposition method that is a hybrid between an exact and a heuristic method. We can now realize how much money the hospital is losing not using a proper scheduling system. If we compare with traditional heuristic rules, the ones probably used in real life, the MILP model could provide an average saving of 25%.

In the next chapter, we presented an operating room optimization in a teaching hospital. This case was performed in a hospital in Toledo, Spain. The Spanish population is one of the most aging populations in Europe, which is increasing the pressure on the health care system. Part of the health care system

is based in teaching hospitals, which besides the normal hospital activities, these hospitals have to train the doctors of the future. To achieve that, it is necessary for resident surgeons to perform some surgeries even though they take longer to perform them. This creates conflicts in the decision-making units since the objectives of the decision-makers persuade contrary objectives. A MILP model was compared with a simulation to quantify the improvements. The daily surgical scheduling in ORs with multiple surgeons is still a complex issue for the managing director of a hospital. Our tool was specifically designed to help managers analyse and evaluate possible profitable results within a reasonable time frame.

Finally, in section 4 we present the final thoughts of this thesis. In Chapter 10, we analyse the role of complexity and flexibility of the instance in the joint solution approach. What is good for one company might not be good for another company even though they deal with the same problem. The range of possible savings for the same problems using a joint model depends on the data being quite large, but the bottom line is close to zero. Then before deciding the type of model, we suggest pre-evaluating the instance, as in some cases the implementation cost can be higher than the savings. Then we identify the factors that could make an instance offer promising results. We found that the preference distribution, the extra coverage constrainedness and the cost dispersion could make an instance more suitable to use a joint approach. Therefore, in some cases it is better to use the traditional sequential approach since the preparation of a complex model does not guarantee enough savings to justify the development of the joint model.

RESEARCH QUESTION SUMMARY

The four research questions were solved throughout the different chapters. In the next paragraphs a brief summary of the answer to the research questions is presented.

The main research question regarding the impact of the complexity of the model-based decision-making process in the context of industrial management has been answered through all the chapters. Each chapter has represented a part of the integration in different industries, to generalize the results. Also, each chapter could be taken as an initial step for a further integration process.

There is a correlation between the level of integration and the complexity. An excessive degree of integration could lead to too many resources being spent to reach a decision that is not justified by the savings. On the other hand, a lack of integration could be a missed opportunity to save resources or improve performance.

Despite the fact that three indices were identified to decrease the chance of failure in the integration, defining a general threshold for all the problems is

almost impossible. For example, maybe it is less complex to integrate three small functional areas rather than two big functional areas. Defining what is bigger and smaller for all the cases depends on the type of problem and the cases. The best approach is to make this comparison with the actual state-of-the-art of the problems, which also evolves with the growth of computational power, solving techniques, and also the size and requirements of the problems.

Also this blurry threshold to decide what the level of integration is changes with the time, supporting tools and the needs of the company. In some points, more than one solution could exist, and then it is necessary to spend more time exploring the options in the initial stage of the decision-making process.

The first sub-research question was*: Using current knowledge and computational power, is it possible to develop models that deal with the increase in complexity for joint decision making in an efficient and effective manner?*

Current knowledge and computational power allow us to deal with the bigger problem as we did in Chapters 5, 6, 8 and 9. This computational power opens up new possibilities for exploring different decision-making scopes. This new model could offer us interesting savings and cost reductions. There was a decrease in transportation vehicles, extra workers, defective parts, overtime and waiting time. For example in Chapter 6, savings of around 7% were obtained with respect to the solution obtained using a separate approach. The impact of these types of models is directly influenced by other factors such as the cost of space. As presented in Chapter 5, factories with a reduced production space should be more interested in this kind of approach.

Unfortunately, despite the increase in computational power there is also an increase of industry-size problems that even high computational servers cannot solve in a reasonable time. It was only possible to solve small and medium cases with promising results, which led to seeking other alternatives to keep solving the problem with a joint approach using constructive methods, simulation or heuristics, or to carry on using the sequential approach.

This leads us to the second sub research question*: When exact methods are not enough to deal with the increasing complexity of real size problems, is it better to try with heuristic methods or is it better to use sequential decision-making?*

The use of exact methods guarantees the optimal solution but only when the solver is capable of solving it in a reasonable period. Here it is important to explain the concept of reasonable period, which is case dependant. If we are dealing with a tactical solution to create the daily replenishment schedule of car components, a solution that requires some hours is not reasonable at all, on the other hand if we are planning the yearly oil drilling schedule, a solution that requires some days is perfectly reasonable.

In the smallest solution, the MILP-based approach performs better that the heuristic solution but as the instance increases the ACO performs better than the MILP. Unfortunately, the percentage of improvement with respect to the sequential decision decreases with the ACO since the heuristic approach does not obtain the optimal.

When we deal with a stochastic model such as in the operating room in Chapter 8, where the complexity added due to the stochastic nature of the problem makes it necessary to explore options like hybrid methods, such as constructive methods and improvement methods, where we obtain similar results in a fraction of the solving time of the exact method. An average improvement of 4.2% was achieved with 1/6 of solving time in the instance that requires more than one hour to be solved.

When the optimal solution of one part of the problem causes infeasibilities for the second part of the problems, such as in Chapter 7, there is no option and a joint approach should be used, in this case, based on simulation, but other options could have been used.

In almost all the instances of all the case studies, the joint approach is better than the sequential approach, or at least obtains the same solution. However, these savings hardly reach two digit savings. Therefore, it is necessary make a benefit-cost analysis, to quantify if the possible savings justify all the drawbacks caused by the joint solution, such as an increase in complexity, more computational time, organizational challenges and so on.

In the third sub-research question we analyse the complexity*: When is the use of a complex decision advisable and when is it not?*

As obtained in Chapter 10, the possible savings of increasing the complexity of a problem are data dependent. For the same problems, some instances could provide good savings and for other instances almost zero savings. The lower bound could be as low as 3 (or even zero) percent, and the upper could reach up to 40 per cent.

Despite the fact that we are dealing with the same problem as the vehicle routing problem or operation room scheduling, for some companies that deal with this problem the joint approach maybe a good approach for a company while for another it may not be. Then three factors were identified that could characterize an instance to evaluate if that instance should be considered for a joint approach or not before the model is developed. This could save valuable time and money in the construction of a model that will deliver poor results.

The first factor was preference distribution, which measures the dispersion among the needs for resources by the different entities. The second factor was the extra coverage constrainedness, which is the average of the extra capacity of all machines, and the third factor is the cost dispersion that is a measure that quantifies the variation of the cost of the different areas. Once that that factor

has been calculated it is possible to decrease the uncertainty regarding the possible output. When the instance presents at least two factors with a high certainty, the chances of higher savings are higher. When the majority of the factors are low the chances of obtaining negligible savings are high.

The fourth and last sub research question is related to managerial insights: *What is the managerial theory and implication behind the decision models that are currently being used?*

Starting from the framework of Mintzberg et al. (1976) where they present the relationship between the phases of a decision process, we proposed adding a definition of the scope phase after the diagnosis phase to evaluate the most promising scope for the decision-making process.

Besides the three factors explained in the last answer, other limitations exist such as the frequency of the decision, which is related to solving time, the nature of the decision and its financial impact, the supporting tools available, the decision-makers and the organizational changes implied in the solution. All this generates an increase in the complexity of the decision.

Increasing the number of players in the decision-making unit generates many organizational challenges. As we have more people involved in the decision with different interests and sometimes with conflicts of interest, the achievement of a joint solution also requires soft skills from the managers, as, for example, in the case of the operating room scheduling in a teaching hospital in Chapter 9. At the moment we persuade a joint solution, the conflict of interests appear, the head of the operating rooms looks for a decrease in the overtime in the operating room, the head of medical services persuades that more of the surgeries required by their services are done, and the head of teaching encourages the residents to perform more surgeries to have better and more prepared surgeons in the future. Then the implementation of decision support tools is only one stage of the solution; a change is also needed in the organization to achieve an overall best solution.

The other highly important part of the decision criteria is the benefit-cost analysis that was analysed in Chapter 3, which highlighted that all the cost incurred by the new decision-making process should be covered by the benefits of a new decision system when the scope of the decision-making process was decided. The expectations regarding the benefits should be bound to the acceptance of options where costs are higher than benefits. Success stories in papers report savings of around 15.9%, therefore, if the savings required to cover all the expenses is higher than 50%, maybe it is better to look for another option.

FINAL CONCLUSION

The contribution of this thesis could be divided into different parts. The first contribution is to investigate the benefit and implications of a joint decision. The main benefit is the possible savings thanks to the better utilization of key resources. Unfortunately, this creates important implications and organizational challenges, generating costs that have to be fulfilled with the savings of the joint approach.

A careful benefit-cost analysis should be performed and the savings needed to justify the implementation of the new decision-making process evaluated. The literature review of the success cases presents average savings of 16 % with a standard deviation of 9, a maximum of 37% and a minimum of 3%. This implies that if a cost reduction of more than 50 % is necessary to cover all the costs, it is better to look for alternatives; although it is possible to obtain bigger savings, it is not very likely.

For the managerial theory, we research into the decision-making process starting with a literature review of the different theories, and analyse the misalignment between the beliefs of integration and the real integration. We also propose a framework to evaluate the instance, in order to analyse when it is advisable to follow a joint approach for an instance and when it is not.

It is important to highlight the need to add an extra phase to the definition of the scope to decide if a traditional sequential approach is better or a joint solution approach is possible, since a shift in the scope of the problems creates new possibilities that could achieve a better global solution. We recommend spending more time on the first phase of the decision-making process, evaluating the alternatives and defining the scope since this has a huge impact on the decision. Then the utilization of either solving method will not affect the solution so much since many of the different techniques offer a similar solution.

The last contribution is the development of different decision models to contribute to the decision-based model body of knowledge. To develop the algorithm model we presented a MILP model to deal with the vehicle routing problem plus the inventory problem and another version to also deal with the car scheduling problem. We accompanied this model with its heuristic version. We created two simulation models; one for the aeronautical manufacturing plant and another for the operating room scheduling at teaching hospitals. For the teaching hospital, we also presented a MILP, model. For the operating room scheduling we presented a different heuristic model and a MILP model to deal with the deterministic and stochastic version of the problem. For the stochastic version of the problem a hybrid method was also developed. These hybrid algorithms (constructive and improvement method) are a combination of exact and heuristic methods.

FUTURE RESEARCH

There are three future research lines that we have to consider. The first one is the evaluation of the frameworks comparing them with other case studies from other sectors to try to make them more general, and identify other important factors that help to decrease the uncertainty.

The second research line is in the health care sector, which presents great opportunities for researchers since the majority of the knowledge disseminated among the health sector is related with medical issues, which provide many opportunities for the management of the hospital, unlike the automotive industry where there are only a few players controlling all the market, causing a fast spread of the latest state-of-the-art techniques. Hospital control is split among federal and local goverments, private organizations, and non-profit organizations, causing the organizational changes to be split slowly among the hundreds of thousands of hospital and health care facilities. This offers opportunities for researchers to help to create change in the health care sector.

If the scope of the problems is changed the complexity offers unlimited combinations to explore. There are so many problems that shifting the scope to combine it with other related problems could offer interesting results, thereby moving one step closer to holistic integration.

RESEARCH LIMITATIONS AND AVENUES FOR FUTURE RESEARCH

In the first part of the work it was really complicated to calculate the possible savings of different projects, since in many papers these quantities are not reported or the impact is based on non-quantifiable benefits. The other issue is the confidentiality of many projects where the data cannot be presented. For the car assembly line problem more computational power would allow us to solve bigger instances. For the operation research problem there was a lack of historical data to perform a parallel analysis in the teaching hospital.

In order to keep testing the decision framework it is necessary to keep applying more case studies in order to generalize the results and make them more evident and less ambiguous. The health care field offers great opportunities since despite the recent awareness of the need to improve the decision-making process there are many opportunities to improve. Another big difference with the automotive industry is that the last improvements are not spread among all the actors. Therefore, in the future this research will focus more on the collaboration between academia and the health care sector.

Appendices

QUESTION OF THE SURVEY

1. In which sector are you?
2. Number of employees working in the manufacturing facility(es) on which you planning activities are focused (shop floor / warehouse / assembling lines / …)
3. Which process structure do you use for manufacturing or assembling? In case that in your facilities have many process, select the one that it is more related to your job position.
4. How do you consider the performance of your production planning process? Ranging from poor performance [1] to good performance [5].
5. What is the degree of integration of the production planning process? Ranging from non-integrated [1] to fully integrated [5].
6. How is the flow of materials through production process? Ranging from no flow [1] to continuous flow [5].
7. Which is the amount of labour spent on produce a unit form the beginning to the end of the process? Ranging from low labour content [1] to high labour content [5].
8. Which level of labour skill or expertise do you need in your production process? Ranging from a low labour skill [1] to a high labour skill [5].
9. What is your production volume? Ranging from a quantity of one [1] to large scale mass production [5].
10. How many types of products family do you produce? E.g. for the car industry product family is a Civic, Accord, etc.
11. How many variants of this products family do you produce? E.g. for the car industry model is each type of Civic that is produced.
12. Who is the decision maker of the production sequence? Name of the position / department (e.g. chief production / manufacturing) please do not write any personal name.

13. Who is the decision maker of the replenishment policies? Name of the position / department (e.g. chief of inventory / manufacturing) please do not write any personal name.
14. Who is the decision maker of the inventory management? Name of the position / department (e.g. chief of inventory / manufacturing) please do not write any personal name.
15. Do you know which production method (philosophy) do you use to plan the production ? JIT, Lean, Total Quality Management, theory of constraints (TOC), etc.
16. Do you keep track of the inventory next to the production system?
17. Do you use any IT system / optimizer to communicate / optimize the production? SAP, Cplex, AIMMS, proprietary system, EPR or similar. Please specify as many as you want.
18. Explain briefly how do you schedule your production. Resources constraints, inputs, outputs and goals.
19. Explains briefly how do you make the replenishment of materials. Resources, constraints, inputs, outputs and goals.
20. Explain briefly how do you manage your inventory. Resources, constraints, inputs, outputs and goals.
21. How do you deal with the exceptions? Such as special orders or urgent orders.
22. Does your company has job rotation through the different departments?
23. The performance indicators of your job position are based on:
24. In case that you want to receive the report of the survey please provide us an email to send you the report. We will not share any email with any one.

ACO PSEUDO CODE

Algorithm 1

Initialize pheromones
Repeat
  $\pi \leftarrow$ empty {Start to sequence the cars}
  while $|\pi| \leq |C|$ do let $C - \pi$ denote the set of cars of C that are not sequenced

```
cand←the minimum cost generated by {ck∈C−π}|∀cj∈C−π,
cost(π<ck>)≤cost(π<cj>)
if ∀ci∈cand, cost(π<ck>)≤cost(π<cj>) then
   for every car class cc ∈{classOf(ci)}∈ C − π do
      T2(cc) ←T2(cc)+ cost(π<cj >) − cost(π)
   end for
end if
Choose ci ∈ cand with the probability p(ci, candCar, π)
π ←<ci >
end while
keep the best sequence
calculates the instant demand for the best sequence
repeat
   R← empty {Routes for transportation vehicles}
   for vn = maxVehicles to vn =1 do
      while |R|≤|S| do
         let (R–S) denote the set of non-attended stations
         duplicate the depot a number=Vn
         the ants select a candS←the min cost generated by {sk ∈ R − S}
with p(si, candS, R)
      end while
      if stock at station ≤ safety stock then
         break
      end if
      decrease one replenishment vehicle vn = vn − 1
      keep the best route for the transportation vehicles
   end for
until stop criteria
calculate the cost
keep the best solution and update the pheromones
until stop criteria
```