A model for preventive maintenance planning by genetic algorithms based in cost and reliability

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Abstract

This work has two important goals. The first one is to present a novel methodology for preventive maintenance policy evaluation based upon a cost-reliability model, which allows the use of flexible intervals between maintenance interventions. Such innovative features represents an advantage over the traditional methodologies as it allows a continuous fitting of the schedules in order to better deal with the components failure rates. The second goal is to automatically optimize the preventive maintenance policies, considering the proposed methodology for systems evaluation.

Due to the great amount of parameters to be analyzed and their strong and non-linear interdependencies, the search for the optimum combination of these parameters is a very hard task when dealing with optimizations schedules. For these reasons, genetic algorithms (GA) may be an appropriate optimization technique to be used. The GA will search for the optimum maintenance policy considering several relevant features such as: (i) the probability of needing a repair (corrective maintenance), (ii) the cost of such repair, (iii) typical outage times, (iv) preventive maintenance costs, (v) the impact of the maintenance in the systems reliability as a whole, (vi) probability of imperfect maintenance, etc. In order to evaluate the proposed methodology, the High Pressure Injection System (HPIS) of a typical 4-loop PWR was used as a case study. The results obtained by this methodology outline its good performance, allowing specific analysis on the weighting factors of the objective function.

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1. Introduction

In a Nuclear Power Plant (NPP) Pressurized Water Reactor (PWR), the maintenance policy applied to the electrical-mechanical systems, due to the high level of reliability of these components, requires an optimized schedule. A high maintenance intervention frequency, as often recommended in factory specifications, however, it should sometimes represent unnecessary costs, which may not correspond to an increase on the components reliability. Besides, the factory recommendation for maintenance policies does not consider the aging of the component, which affect its operational condition.

On the other hand, according to Duffey [9], in a 4-loop PWR NPP, the maintenance costs during its lifetime represents about 30% of the total operation cost of the NPP. Hence, a little enhancement in the maintenance policy may proportionate a significant economical gain. Considering such arguments, this work is intended to develop a methodology to preventive maintenance policy optimization, which deals with operational, economical and safety aspects, providing an advanced methodology based upon a probabilistic cost-reliability model and a powerful optimization technique.

According to Duthie et al. [8], since the beginning of the last decade, researchers have been publishing papers addressing preventive maintenance optimization of nuclear power plant systems. This may be classified in three main groups. The first one has the focus on system’s reliability [12,32]. The second one focuses on probabilistic models and perform tests among some standard policies [8,24]. Finally, we can mention those, which apply expert
knowledge to determine good maintenance policies [31]. In order to avoid the optimization difficulties inherent to huge search spaces, many applications have considered systems with few components [2,11].

From the probabilistic point of view, Park et al. [26] contributed to the solution of the class of problem under discussion by including components with very small degradation degrees, Chiang and Yuan [6] have proposed approaches for maintenance optimization problems aiming at obtaining system’s availabilities by Markovian methods and Dijkhuizen and Heijen [7] have optimized the distribution of availability intervals instead of optimizing the preventive maintenance policy.

Unfortunately, all the mentioned references have a common feature: they all considered systems composed by a few components and even so they faced difficulties from the point of view of optimization. By the other side, it is well-known that safety-related nuclear systems have many redundancies and components with a great number of combination and alignment alternatives among them. So, in this case others approaches are necessary to deal with such complexity.

Muñoz et al. [23] were the first ones that have proposed the use of genetic algorithms (GA) [13] as an optimization tool for maintenance scheduling activities. Lapa et al. [14–16] applied GA in order to optimize inspection and maintenance intervals with a new approach. Instead of searching for an optimal intervention frequency, which means equally spaced interventions, they employed the optimization tool to search for the times in which preventive maintenance interventions should be performed (Flexible Interval Method—FIM). In this sense, it is understood that equally spaced intervention actions do not necessarily lead to the optimal policy.

Recently, Yang et al. [33] proposed a test surveillance policy optimization on the plant level. Test surveillance policy optimization has also been investigated by Lapa et al. (2001) [17,18]. This methodology has been successfully applied by Lapa et al. [20] in optimization problems that into account constraints in the search space. We need also to mention Bris et al. [3] research, in which they have developed a new approach to maintenance optimization based on cost. Recently, Lapa et al. [20] have proposed a new condition, in which it is considered that a maintenance intervention may sometimes not contribute to a given maintenance schedule.

2. Probabilistic modeling

In this section, we present models that calculate both the reliability of a component and the individual cost per component while submitted to a given maintenance schedule.

2.1. The reliability model for preventive maintenance scheduling at component level

In this work, we use the approach proposed by Lapa et al. [15] for calculating the reliability of a component undergoing a given maintenance policy. This model consists on a generalization of a traditional model proposed by Lewis [22] propitiating reliability calculation for any proposed schedule and not only periodical ones.

We will consider mixed systems comprised by components which alternate among on-line (on operation) and hot-standby condition and, from the failure’s point of view, hot-standby components are considered operationally activates. Hence, mixed systems are considered to be integrally and permanently operating during the considered time interval (system’s mission).

Consider \( R(t) \) the reliability of a component which is susceptible to suffer corrective maintenance or is subjected to a preventive maintenance policy but did not already undergo any maintenance intervention at a time \( t \), where \( t \) is the operating time or the time the component is ready to start in a hot-standby condition.

Let \( T_m(i) \) be the date scheduled for the \( i \)th maintenance intervention of component \( m \) and \( T_m(\text{ult}) \) be the date of the last maintenance intervention realized until time \( t \). So, ult is exactly the number of maintenance interventions undergone until time \( t \). Therefore, Eq. (1) includes such hypothesis in the traditional model:

\[
R_m[t, T_m(i), T_m(\text{ult})] = R[t - T_m(\text{ult})] \prod_{i=1}^{\text{ult}} R[T_m(i) - T_m(i - 1)], \quad T_m(\text{ult}) \leq t < T_{\text{mis}} \quad (1)
\]

As we intend to consider the influence of the maintenance suffered by one component over whole system’s operation, we assume that the component is out of operation during its maintenance time period (outage time) \( \Delta_m(i) \). We also consider a probability \( p \) of doing a bad (non-satisfactory) maintenance:

\[
R_m[t, T_m(i), T_m(\text{ult})] = \begin{cases} R[t - T_m(\text{ult})](1 - p)^{\text{ult}} \prod_{i=1}^{\text{ult}} R[T_m(i) - T_m(i - 1)], & T_m(\text{ult}) \leq t < T_{\text{mis}} \\ 0, & T_m(i) \leq t \leq T_m(i) + \Delta_m(i) \end{cases} \quad (2)
\]

Note that Eq. (2) is not exactly the component’s reliability, once it is a cumulative distribution function and could not return values smaller than those already obtained. Hence, Eq. (2) represents both the reliability during the operational and the non-operational state during the outage time.

The factor \( p \) (probability of unsatisfactory maintenance) introduces a new condition, in which it is considered that a maintenance intervention may sometimes not contribute
or even prejudice the systems reliability. In order to allow the evaluation of the limits and constraints that may be generated by this condition over the maintenance policies of a component, the consideration of this condition is analyzed considering the Flexible Interval Method (FIM), using Eq. (2) during the times the component is operating:

\[
R_m[t, T_m(i), T_m(ult)] = R[t - T_m(ult)](1 - p)^{ult} \prod_{i=1}^{ult} R[T_m(i) - T_m(i - 1)]
\]  

(3)

Considering that the component’s reliability under aging effects can be represented by a Weibull distribution and admitting \( p << 1 \), and consequently \( (1 - p)^{ult} \approx e^{-p^{ult}} \), we get

\[
R_m[t, T_m(i), T_m(ult)] = \exp \left[ -(t - T_m(ult))/\theta_j \right]^{\gamma_j} \exp[-p(ult)]
\]

\[
\times \left[ \prod_{i=1}^{ult} \exp \left[ -((T_m(i) - T_m(i - 1))/\theta_j \right]^{\gamma_j} \right] \quad (4)
\]

where: \( m \) and \( \theta \) are the aging factor and the characteristic life of the component.

Operating the exponential, we have:

\[
R_m[t, T_m(i), T_m(ult)] = \exp \left[ -((t - T_m(ult))/\theta_j)^{\gamma_j} + (-p(ult)) \right]
\]

\[
\quad + \sum_{i=1}^{ult} \left[-((T_m(i) - T_m(i - 1))/\theta_j)^{\gamma_j} \right] \quad (5)
\]

In order to evaluate the gains due to the practice of preventive maintenance, once for components under aging effect \( m \) is greater than 1, it is necessary to calculate the relation between the reliability of a component undergoing a periodical maintenance interventions \( (R_m[t, T_m(i), T_m(ult)]) \) and those related to a component which does not undergo any maintenance \( (R(t)) \):

\[
\frac{R_m[t, T_m(i), T_m(ult)]}{R(t)} = \frac{\exp \left[ -((t - T_m(ult))/\theta_j)^{\gamma_j} + (-[p(ult)] + \sum_{i=1}^{ult} \left[-((T_m(i) - T_m(i - 1))/\theta_j)^{\gamma_j} \right] - (T_m(ult)/\theta_j)^{\gamma_j} \right]}{\exp[-(t/\theta_j)^{\gamma_j}]} \quad (6)
\]

At time exactly after the last maintenance intervention, we obtain:

\[
\frac{R_m[T_m(ult)]}{R[T_m(ult)]} = \exp \left[ -[p(ult)] + [T_m(ult)/\theta_j]^{\gamma_j} \right]
\]

\[
+ \sum_{i=1}^{ult} \left[ -((T_m(i) - T_m(i - 1))/\theta_j)^{\gamma_j} \right] \quad (7)
\]

In order to have effective maintenance, the relation must be greater than one. Then, the exponent of the right side term in Eq. (7) must be positive:

\[-[p(ult)] + [T_m(ult)/\theta_j]^{\gamma_j} + \sum_{i=1}^{ult} \left[ -((T_m(i) - T_m(i - 1))/\theta_j)^{\gamma_j} \right] > 1 \quad (8)
\]

Hence:

\[ p < \frac{\sum_{i=1}^{ult} \left[-((T_m(i) - T_m(i - 1))/\theta_j)^{\gamma_j} \right] - [T_m(ult)/\theta_j]^{\gamma_j}}{ult} \quad (9)
\]

Note that inequality nine does not depend only on the Weibull distribution parameters and the number of maintenance interventions [22]. In this case, this inequality depends functionally on variable ult and, consequently, may assume different values along the maintenance policy. Until now, the maintenance policy planning have been done regarding this a priori condition. In this work, we aim that the optimization methodology will automatically handle this condition for a given value of \( p \).

2.2. Global maintenance policy evaluation at system level

The model introduced above (Eq. (4)) describes the behavior of a single component submitted to a given maintenance test policy. However, the aim of this work is to estimate the availability of multi components systems. To estimate the system’s failure probability for any given combination among the component’s state (operating or testing), some global evaluation technique (fault trees, minimum cut sets or Markovian chains) should be used in order to represent the overall system’s reliability (Eq. (10)) as a function of each component reliability (Eq. (4)):

\[ R_{sis} = \text{fun}\{R_m^1[t, T_m(ult), T_m(i)]; R_m^2[t, T_m(ult), T_m(i)]; \ldots R_m^x[t, T_m(ult), T_m(i)]; \} \quad (10)
\]

where \( x \) is the number of components of the system.

2.3. The cost model

Initially, a cost estimation model for a given maintenance policy onto a single component is developed. Fig. 1 shows

Fig. 1. Maintenance interventions over a component.
the time axis in which the maintenance intervention dates for a given mission with duration $T_{\text{mis}}$.

The non-failure probability along the interval between the operation start and the first maintenance date $T_m(1)$ can be expressed by

$$R[T_m(1)] = P[t_{\text{fail}} \geq T_m(1)]$$

(11)

where $t_{\text{fail}}$ is the time period until the component’s failure.

Considering $C_m$ and $C_r$, respectively as costs regarding preventive maintenance and repair (if it is the case), the total cost, $C_T$, referred to the component’s operation during the interval from the beginning of its operation and the time it suffers the first maintenance $T_m(1)$, indicated by the superscript index (0→1), is given by:

$$C_T^{0\to 1} = C_m - R[T_m(1)] + C_r \{1 - R[T_m(1)]\}$$

(12)

Generalizing such concept to the other intervals, we must define a conditional probability. Then, $R[t|T_m(1)]$ represents the probability of the system to fail until time $t$, considering that it did not fail until $T_m(1)$:

$$R[t|T_m(1)] = P[t_{\text{fail}} > T_m(1) + t|t_{\text{fail}} > T_m(1)]$$

(13)

Applying some properties of the probability space over Eq. (13), we have:

$$R[t|T_m(1)] = R[T_m(1) + t]/R[T_m(1)]$$

(14)

Using $t=T_m(2)-T_m(1)$, in Eq. (14), we can extend Eq. (12) to the interval between the first and the second maintenance interventions (interval 1→2) as follow:

$$C_T^{1\to 2} = C_m^{1\to 2} \{R[T_m(2)]/R[T_m(1)]\} + C_r^{1\to 2} \{1 - \{R[T_m(2)]/R[T_m(1)]\}\}$$

(15)

Generalizing Eq. (15) for the ‘ult + 1’ intervals between maintenance, being the last one between the last maintenance intervention and the end of the mission, we get

$$C_T^{0\to T_{\text{mis}}} = \sum_{j=1}^{ult} C_m^{(j-1)\to j}[R[T_m(j)]/R[T_m(j-1)]] + C_r^{(j-1)\to j} \{1 - \{R[T_m(j)]/R[T_m(j-1)]\}\}$$

$$+ C_r^{\text{ult}\to T_{\text{mis}}} \{1 - [R[T_{\text{mis}}]/R[T_m(ult)]]\}$$

(16)

where $T_m(0)$ is the date of beginning of the mission.

Considering that, for the last interval ‘$T_m(ult)\to T_{\text{mis}}$’, a potential cost of a corrective maintenance (repair) is added, and Eq. (16) evaluates the total cost referred to a component, which undergoes an ult preventive maintenance in times $T_m(j)$ where $j=1\cdots ult$, along a mission of duration $T_{\text{mis}}$.

To consider several aspects, such as the repair and maintenance duration interval in the cost model, it is necessary to analyze it coupled with the reliability model (Eq. (10)), which also deals with such features. More details about such interconnection between two models are described later, together with the definition of the objective function.

Note that such coupling is desirable considering that the cost model considers the mission as a sum of intervals between maintenance interventions. The impact of outages in the whole system is neglected.

In a system comprised by $X$ components, the total cost for the system’s operation is the sum of the total costs for each component; hence, integrating in $X$, we have

$$C_T^{0\to T_{\text{mis}}} = \sum_{Q=1}^{X} C_T^{0\to T_{\text{mis}}}$$

$$= \sum_{Q=1}^{X} \left\{ \sum_{j=1}^{ult} C_m^{Q(j-1)\to j}[R_Q[T_m(Q)(j)]/R_Q[T_m(Q)(j-1)]] + C_r^{Q(j-1)\to j} \{1 - [R_Q[T_m(Q)(j)]/R_Q[T_m(Q)(j-1)]]\} + C_r^{Q\text{ult}\to T_{\text{mis}}} \{1 - [R_Q[T_{\text{mis}}]/R_Q[T_m(Q(ult))]]\} \right\}$$

(17)

where $Q$ is the component index and $j$ is the maintenance intervention index.

3. Genetic modeling

Genetic algorithms (GAs) [10,13] are powerful optimization techniques, inspired by the principles of natural selection and species evolution. Due to their robustness and easy customization, GAs have been successfully applied to a wide range of problems, including several complex optimization problems found in nuclear engineering, such as: reactor core design [27,29] and core reload [5], transient identification [1,28,30] and reduced scale experiments design [19,21].

Generally, modeling an optimization problem by a GA consists on two main features: (i) defining a genotype, that is the data structure which encodes a solution candidate and (ii) provide an objective function, which evaluates a solution candidate.

3.1. Genotype structure

In this new problem, the genotype must encode all possible scheduling combinations for all system components. Traditionally, the problem is basically a numerical optimization problem, where the search variable is the test or maintenance frequency. But now we need to know when and how many interventions must be performed in all system components. In this sense, an alternative binary discretization approach, where the time axis is discretized considering a time-step of 15 days, has been developed which keeps the number of genes and string dimension constant during the searching process for scheduling problems.

Following the canonical GA paradigm, a fixed length binary string has been used. Each gene (a sub-string of
the genotype) contains $T_{\text{miss}}/15$ bits and its decoding (phenotype) is such that a ‘1’ means that the component is on line and ready to start, whilst a ‘0’ means that it has been selected to undergo testing at the corresponding date (multiple of 15 days). Fig. 2 shows the genotype and its decoding (phenotype) for each component, represented by a vector whose elements are the times at which the tests occur.

The presented genotype may be customized to comport different time-steps, however, the computational cost is as well influenced and may, sometimes, be a constraint. In this work, a time-step of 15 days may be adequate to this problem.

3.2. Objective function

The function for evaluating a given genotype (scheduling) is a weighted sum, which considers the reliability of the system along all the mission, computing the impact of outages and total costs related to the proposed maintenance policy.

Eq. (18) presents the integrated impact of a given maintenance policy over the systems reliability:

$$\text{Fun} = T_{\text{miss}}^{-1} \int_0^{T_{\text{miss}}} R_{\text{sis}} \, dt$$

The objective function, then, is a linear combination between Fun (Eq. (18)) and the total costs related to the maintenance policy

$$\text{fit} = W_d \text{Fun} + W_c T_{\text{sis}}^{b-T_{\text{sis}}}$$

(19)

where $W_d$ varies between 0 and 1 and $W_c$ ranges between 0 and $1/(N_{\text{COMP}} \times \text{MAX_INT})$, where $N_{\text{COMP}}$ is the number of components and MAX_INT is the maximum number of maintenance interventions.

The combination is necessary due to the fact that the cost model does not comport itself the influence of component outages among themselves.

4. Results

Aiming to investigate the proposed methodology, as well as to analyze the behavior of the objective function and restriction, $p$, during the GA evolution, the High Pressure Injection System (HPIS) of a typical 4-loop PWR was chosen as object of this study.

This section is subdivided in two parts: initially we give a quick description of the analyzed system, its functionality and operational restrictions and, eventually, the results of the methodology are shown and discussed.

4.1. System description

A typical PWR High Pressure Injection System (HPIS) can be represented by seven main components: three pumps and four valves as shown in Fig. 3. In normal operation its function is to complete the inventory of the primary loop through the reactor coolant system, as well as to guarantee the seal of the pumps of this system. Under accident situations, in which the steam generators are unavailable or there is a rupture in the primary system, the HPIS is used for removing the decay heat. Considering that the reactor in operating with power above 60% and at least two of the three pumps must be available during the mission time, the top event is the unavailability to supply the inventory by both feeders.
4.2. Case study

Here, two possible states for systems’ components are considered: unavailable undergoing maintenance or active (operating or hot-standby). As already mentioned, the Weibull distribution was chosen due to the good representation provided for components under aging effects (increasing failure rate). We have admitted that the outage time for the pumps is 24 h and for the valves, 8 h. Typical values for failure rates, maintenance costs, and repair costs were used according to Harunuzzaman [11].

Four situations considering 360 days missions were investigated. At first several simulations (using different genetic parameters) with \( p = 0 \) and \( W_d \) and \( W_c \) maximum values were done. Such investigation make possible to generate a reference for optimum policies considering 100% probability of perfect maintenance. A typical and representative experiment is shown and analyzed here. Fig. 4 shows the convergence of: (i) the best fitness; (ii) the term related to the unreliability and (iii) the term related to the total costs, in a simulation in which the objective is to minimize the fitness combining both terms.

It is interesting to observe that, in the initial generations, the GA finds configurations that minimize both costs and reliability. After these generations, however, the compromise between the minimization of costs and maximization of reliability is observed. About the 50th generation the unreliability has increased, but on the other hand, the sum of costs related to each component has decreased, resulting in the enhancement of the global fitness. Hence, it is clear that the best scheduling for the system is not necessarily the best for each component individually.

Observe in Table 1 that the GA has proposed schedule that selects aligned components to undergo maintenance at same time, while avoiding this for components in parallel. This fact demonstrates that the GA was able to acquire knowledge, certainly guided by the functional in Eq. (18), which is responsible for reliability maximization.

Next two scenarios are intended to investigate the situations in which only one term of the objective function (or cost or reliability) is considered. Fig. 5 shows the behavior of the total fitness and the part related to the cost in a simulation with \( W_c = 0 \).

Note that even when the cost factor weight is zero, the GA finds, during the initial 30 generations, policies, which, by coincidence, also minimize the cost. This fact indicates that some regions in the search space, mainly where candidates that are not too specialized neither in cost nor in reliability features, the search takes a coincident preferable direction. However, when the search process reach regions in which the cost and unreliability minimization are conflicting tasks, more expensive and reliable schedules are proposed.

This situation is ratified in the other scenario in which the reliability term is put away (\( W_d = 0 \)). See Fig. 6.

In this cost (only) based optimization, in order to reduce the costs reaching the half of the value obtained by simulations based in cost and reliability (\( W_d \neq 0 \) and \( W_c \neq 0 \)), it is necessary to reach very low levels of reliability. In the last experiments, for hundreds of generations, the GA could not find schedules which improve the fitness as a whole. When it did that, the reliability levels were intolerable.

![Fig. 4. GA convergence](image1)

![Fig. 5. Fitness and cost term evolution during the GA generations.](image2)

Table 1

<table>
<thead>
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<th>Best scheduling for the first scenario</th>
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<tr>
<td>1st stop</td>
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<tr>
<td>----------</td>
</tr>
<tr>
<td>Pump 1</td>
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<tr>
<td>Pump 2</td>
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<td>Pump 3</td>
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<td>Valve 1</td>
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<tr>
<td>Valve 2</td>
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<tr>
<td>Valve 3</td>
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<td>Valve 4</td>
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</table>

Fig. 4. GA convergence (i) the best fitness; (ii) the term related to the unreliability and (iii) the term related to the total costs (Eq. (18)).
Table 2 presents one of maintenance schedules obtained in the last case study ($W_d=0$). Note that the number of maintenance interventions is reduced and no alignment among the components is observed. The schedule shown in Table 2, which was considered very good in terms of cost, is therefore, an absurd proposal (namely, almost all components of the system undergoing maintenance at same time) while observed by the reliability point of view.

At last, the same case study considering the weighted fitness (Fig. 4) will be repeated, however, using $p=0.05$ (5% of the maintenance interventions are not effective). Fig. 7 shows obtained results. It can be observed that the systems’ unreliability increases significantly when compared to the scenario in which the probability of imperfect maintenance was not considered. In Table 3, it can be observed that the GA proposes policies with low maintenance interventions frequency, due to the penalization imposed by the probability of inefficient maintenance. The extreme limit is the case in which no maintenance policy is able to produce benefits to the system. By computational simulations it could be verified that $p=20\%$ for valves and 25% for pumps has lead to such situation. In other words, no policy was able to satisfy Eq. (9).

5. Conclusions

Analyzing the obtained results, it is clear that considering both cost and unreliability weighted must contemplate the minimization of the unreliability functional. By applying the proposed cost-reliability model, it is possible to find preventive maintenance policies which provide a high level of reliability with low costs (Fig. 4). If the main goal is to privilege reliability (for example in safety systems) the obtained costs may be not so low (Fig. 5). Results shown in Fig. 6 and Table 2 outline that the cost is only a measurement of the financial importance of the repair or maintenance and should not be applied as the unique objective if reliability is required.

A continuation of this work intends to investigate more realistic situations, where the costs contemplate other kinds of impacts obtained by more elaborated models. Another interesting possibility, is the investigation of a multi-objective genetic algorithm (MOGA) in the search for non-dominated solutions, avoiding the necessity of combining multiple criteria into an unique objective function. Busacca et al. [4] has shown the use of MOGAs in safety systems. In the same direction, the present approach will have its standard GA replaced by a MOGA.

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<th>Table 2</th>
<th>Best based scheduling with $W_d=0$</th>
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<td>Pump 1</td>
<td>180</td>
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<td>Pump 2</td>
<td>195</td>
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<td>Pump 3</td>
<td>195</td>
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<td>195</td>
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