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Consensus-Based Distributed Control for Economic Dispatch Problem with Comprehensive Constraints in a Smart Grid

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FLORIDA STATE UNIVERSITY
COLLEGE OF ENGINEERING

CONSENSUS-BASED DISTRIBUTED CONTROL FOR ECONOMIC DISPATCH
PROBLEM WITH COMPREHENSIVE CONSTRAINTS IN A SMART GRID

By

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ABSTRACT

Over the past few decades, the smart grid technology has been developed rapidly due to its main features of more involvement of customers and abilities to accommodate all renewable energy and distributed storages. More importantly, it offers an improved reliability, power quality and self-healing capability. However, there are many problems and challenges associated the development of smart grid. For example, the economic dispatch problem (EDP) in a smart grid has become more complex and challenging due to special characteristics of smart grid. For example, one of the major characteristics of smart grids is plug-and-play due to its accommodation of distributed energy.

Economic dispatch is the short-term determination of the optimal output of a number of electricity generation facilities, to meet the system load, at the lowest possible cost, subject to transmission line loss and generation constraints. In short, EDP is an optimization problem and its aim is to reduce the total operation cost. Various mathematical and optimization methods have been developed to solve EDP in power systems. Most of the conventional methods collect global information and process commands in a centralized controller.

In a smart grid, it's expensive and unreliable for these conventional centralized methods to achieve a minimum cost when generating a certain amount of power within certain power constraints. There are several reasons why it's not suitable to use centralized methods for EDP in a smart grid. First of all, the centralized controller requires a high level of connectivity to collect all the information among power generators. A failure or error may impair the effectiveness of the centralized controller. Secondly, the topologies of the smart grid and the communication network are likely to be variable in a smart grid. Therefore, a small change in the smart grid may lead to

reconfiguration of the centralized algorithm. Thirdly, the centralized controller is not able to accommodate the plug-and-play characteristic of smart grid.

In this work, we propose a distributed controller based on consensus algorithm to solve the EDP in a smart grid. The consensus algorithm is based on graph theory in the area of communication. Compared with the centralized method, the distributed algorithm features advantages of less information requirement, robustness, and scalability.

In order to present a more practical scenario of EDP, a quadratic cost function and comprehensive constraints are assumed in the problem definition. It's assumed that the valve point effect of the generation unit is negligible. Different from the centralized approach, the proposed algorithm enables each generator to collect the mismatch between power demand and power generations in a distributed manner. The mismatch power is used as a feedback for each generator to adjust its power generation. In order to implement the consensus algorithm, the incremental cost of each generator is selected as the consensus quantity and will converge to a common value eventually.

Simulation results of different case studies are provided to show the effectiveness of the proposed algorithm. Effect of power constraints, communication topology and generator dynamic on the convergence and iteration speed of proposed algorithm is also examined. These case studies are simulated and analyzed in Matlab/Simulink. The convergence speed and total generation cost of proposed algorithm are also compared with the conventional algorithms such as lambda iteration method and particle swarm optimization. The consensus algorithm has a better combined performance of convergence and total generation cost compared to lambda iteration method and particle swarm optimization. In order to validate the consensus algorithm, an *IEEE* 14 bus system

with the proposed algorithm is established in PSCAD/EMTDC and verified by comparing with the analytical results.

CHAPTER ONE

INTRODUCTION

1.1 Background

A smart grid is a modernized electric grid that uses analog or digital information and communication technology to gather and act on information, such as behaviors of suppliers and consumers, in an automated fashion to improve the efficiency, reliability, economics, and sustainability of the production and distribution of electricity [1]. A typical smart grid configuration can be found in Fig. 1.

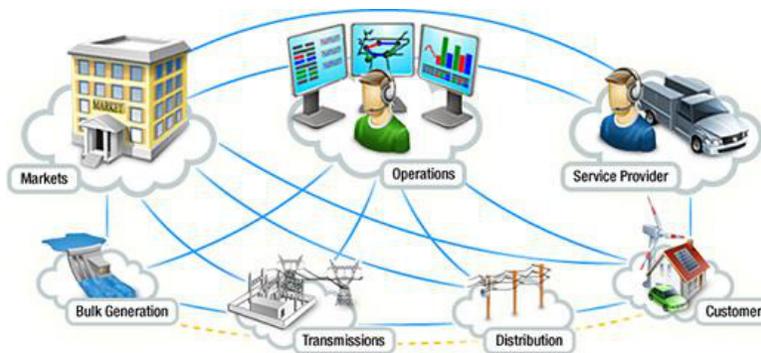


Fig. 1: Smart grid conceptual model.

The smart grid defines several important objects: bulk generation, transmission, distribution, customers, operations, markets and service providers. It shows all communications and power flows connecting each object. Each individual is composed by smart grid elements that are connected to each other through both communications and electric paths.

The bulk generation of the smart grid generates electricity from renewable and non-renewable energy resources in bulk quantities. These resources can also be classified as renewable, variable sources, such as solar and wind energy; renewable, non-variable, such as biomass,

geothermal and pump storage; or non-renewable, non-variable, such as nuclear, coal and gas. Energy storage is also included for later distribution in bulk generation.

Distribution element distributes electricity to and from the customers in the smart grid. The distribution network connects the smart meters and all intelligent field devices, managing and controlling them through a two-way wireless or wireline communications network. It may also connect to energy storage facilities and alternative distributed energy resources at the distribution level.

The customers of the smart grid is where the users of electricity are connected to the electric distribution network through the smart meters. The smart meters control and manage the flow of electricity to and from the customers and provide energy information about energy usage. A customer may also generate, store and manage the use of energy as well as the connection with plug-in vehicles.

The operation of smart grid manages and controls the electricity flow of all other objects in smart grid. It uses a two-way communications network to connect to substations, customer network and other intelligent field devices. It provides monitoring, reporting, controlling and supervision status and important process information and decisions.

The market operates and coordinates all participants in electricity market within the smart grid. It provides the market management, sale, retail and trade of energy services. It also handles energy information operations and information exchange with third-party service providers.

Finally, the service provider of the smart grid handles the third-party operations among the objects. It may also manage other processes for the utilities, such as demand response programs, outage management and field services.

Due to its advantages over conventional power system, smart grid technology has developed and promised around the world for many years. Together with distributed energy and storage technology, smart grid exhibits great benefits such as high reliability, improved power quality, flexibility, and real time operation. Development in power electronics, control algorithms, communication technologies, and information technique have played a critical part in the smart grid technology.

However, increasing use of smart grid will pose many challenges for the future grid. There are a lot of concerns associated with smart grid technology. For example, it becomes expensive and unreliable for a smart grid to solve economic dispatch problem (EDP) if we keep using the conventional method. Fundamentally, EDP is to solve an optimization problem and to reduce the total cost of power generators with certain constraints. It's defined by US Energy Policy Act of 2005 as “the operation of generation facilities to produce energy at the lowest cost to reliably serve consumers, recognizing any operational limits of generation and transmission facilities” [2]. Many conventional methods have been developed to solve the EDP in power system. All the conventional methods require global information via a centralized controller to achieve an optimal power generation and a minimum cost [4]. A simple power system is presented in Fig. 2 to illustrate the idea of EDP.

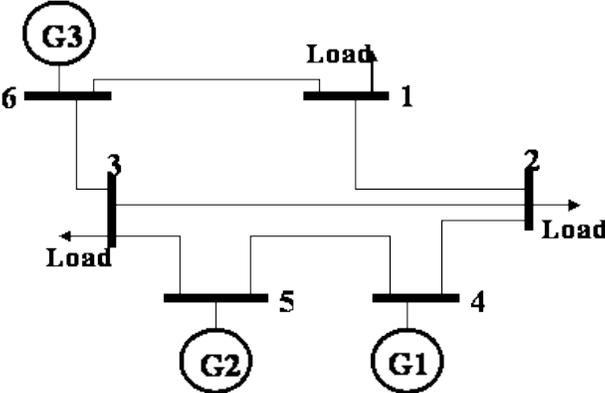


Fig. 2. A simple power system with three units [3].

As shown in Fig. 2, a central controller is required to collect information from all three generation units and distributed loads. After solving the dispatch problem in the controller, the commands of power generation of each unit will be sent out.

However, the centralized algorithm can be impaired due to failures or modeling errors [5]. Moreover, the smart grid topologies and communication network are likely to change. For example, a new generation unit may be added later to Bus 1. The central controller has to collect all information again including the new generation unit and assigns the power output correspondingly. Therefore, a slight change in the smart grid may lead to redesign of the centralized algorithm [6]. Also, collecting global information from each generator may cause extra cost. It can be concluded that the centralized controller is not suitable to solve the EDP in a smart grid.

1.2 Motivation

Economics is one of the most promising characteristics of smart grid technology. With the development of smart grid technology, more and more renewable devices are connected to the smart grid system. For example, solar energy, wind energy, and energy storage are all interfacing with smart grid. Most of them are plug-and-play devices. Therefore, economic dispatch becomes very important for all generation units in smart grid. In order to better solve EDP in a smart grid, a distributed control algorithm is developed in this work. The distributed algorithm enables each generation unit to control its own power output in a distributed manner. Compared with the centralized algorithm, the distributed algorithm features the following advantages. First of all, no centralized controlled or global information is needed by the distributed algorithm. For example, in Fig. 2, no central controller is needed to gather all information from generators and loads. Each generator will have its own generation controller. Moreover, the distributed algorithm is not

affected by the variation of topologies. Therefore, the plug-and-play characteristics of smart grid can be accommodated by the distributed algorithm. The key to the distributed algorithm in the smart grid is for all generated to reach a consensus [7]. There are many variables that can be used as the consensus. For example, in a smart grid, the consensus variables can be voltage, active power, etc. The consensus protocol has been studied widely in a variety of area for many years. It has been applied in system and control areas. It shows great advantages in dealing with EDP in a smart grid. The benefits of consensus algorithm is presented in Chapter 2. In reality, the cost function of a generation unit is non-convex. However, it's approximately represented by a convex equation in most situations. Since the economic dispatch has to meet certain generation and transmission constraints, comprehensive constraints are discussed and implemented in the proposed consensus algorithm.

1.3 Problem Statement

As stated before, it's becoming more and more important for a smart grid to solve EDP in a distributed manner. In this work, a consensus-based distributed controller for EDP in a smart grid is proposed. The distributed algorithm exhibits great advantages than conventional methods. Here are the problem statements of the proposed algorithm.

First of all, a cost function of EDP and generator constraints are defined. A convex cost function is derived based on the non-convex function of power generator. Practically, the generators have to operate within certain operation limits. Meantime, the power balance between generation and demand is also required. For practice, the transmission power loss is also taken into consideration for constraints. Based on graphy theory, the consensus algorithm is developed to solve EDP in the smart grid. A consensus variable in the smart grid is selected as the consensus that will converge to the optimal value for each generator. The communication network can vary for

different smart grids. Therefore, performance of proposed algorithm should be examined in different communication topologies. The dynamics of generators are also examined in this work. In order to validate the effectiveness of the distributed algorithm, it's compared with conventional EDP methods. The transients of the proposed algorithm is also considered by including the dynamics of synchronous machines. The performance is also validated by testing in a practical power system using PSCAD/EMTDC.

CHAPTER TWO

STATE-OF-THE-ART ECONOMIC DISPATCH PROBLEM

2.1 Conventional Methods

The economic dispatch is aiming to supply load at a minimum total cost. The EDP can be summarized as the following equation.

$$\min \left\{ \sum_{k=1}^m C_k(P_k) \right\}$$

where m is the number of generation unit, P_k is the power output of k -th generator, C_k is the generation cost of k -th generator.

There are various numerical and optimization methods developed to solve the EDP in power system. The conventional methods include lambda-iteration method [8], Lagrangian relaxation method [9], gradient projection method [10], and dynamic programming [11].

In [8], the incremental cost of each generator updates itself every iteration in order to meet the power balance. Lambda is the variable introduced in solving constraint optimization problem and called a Lagrange multiplier. Unlike usual iteration methods like gauss seidel and newton-raphson, lambda iteration is different. For example, in gauss seidel method, the next value of the unknown variable can be solved using an equation. However, in lambda iteration, the unknown variable gets its next value based on intuition. It will be projected by interpolating the best possible value when a specified mismatch has been reached.

By using Lagrange multiplier, lambda is equal to the incremental cost of each generator. However, this method requires more computations and takes a longer time to process. And the result may not accurate due to a larger mismatch allowed.

The conventional Lagrangian relaxation method can be applied directly into a non-convex optimization problem by decomposing the non-convex space into a small number of subsets [9]. In this way, the associated EDP is either infeasible or the one solved by the conventional Lagrangian relaxation method. The relaxation is carried out so that the relaxed problem is decomposable to a number of problems corresponding to the periods in the dispatch horizon. These are solved simply by using priority lists. The dual Lagrangian function is optimized using sub-gradient optimization. If an overall solution feasible in all constraints and sufficiently close to a computed best lower bound is discovered during sub-gradient optimization. The cost will be greatly reduced by the decomposed method among all feasible solutions.

A gradient projection method is also presented [10]. The gradient projection is also using incremental cost of generator as the evaluation criterion. The main convergence result is obtained by defining a projected gradient, and proving that the gradient projection method forces the sequence of projected gradients to zero. A consequence of this result is that if the gradient projection method converges to a point of a linearly constrained problem. As an application of EDP, a quadratic programming algorithm that iteratively explore a subspace defined by the active constraints is developed.

Based on the look-ahead technique, EDP finds the number of time intervals to guarantee the solution optimization [11]. An effective technique for finding the optimal solution via the interior point method based linear programming is described. A detailed mathematical derivation of recursive dynamic programming approach for the EDP is presented. It's noted that computation efforts will increase if the optimal look-ahead time interval is not used. Conventional programming based method depends on the size of the discrete capacity used. With a capacity step of one MW, the number of states at each stage is quite large for even a small system.

The methods above are assumed to have a convex cost function. In order to handle a non-convex cost function, many optimization methods are developed, mainly evolutionary programming [12], differential evolution [13], particle swarm optimization [14], genetic algorithm [15], simulated annealing [16], and tabu search [17].

Evolutionary programs with adaptations based on scaled cost, as well as empirical learning rate, have been developed [12]. Evolutionary programming is a stochastic optimization strategy by Lawrence J. Fogel. An initially random population of individuals is created. Mutations are then applied to each individual to create new individuals. Mutations vary in the severity of their effect on the behavior of the individual. The new individuals are then compared in a context to select which should survive to form the new population. In smaller power system, all fast evolutionary programs perform much better than that with Gaussian mutation in terms of convergence rate, solution time, minimum cost, and probability of better solutions. As the size of power system increases, improved fast evolutionary program offers superior performance over other evolutionary programs.

An improved differential evolution method to solve the EDP of generators considering valve-point effects is proposed [13]. Differential evolution is a population-based, stochastic function optimizer using vector differences for perturbing the population. Heuristic crossover technique and gene swap operator are introduced in this approach to improve the convergence characteristic of the differential evolution algorithm. Consequently, it leads to a higher probability of getting the global or near global solution. Like other evolutionary algorithms, the first generation is initialized randomly and further generations evolve through the application of certain evolutionary operator until a stopping criterion is reached. The optimization process is carried with four basic operations: initialization, mutation, crossover and selection.

Particle swarm optimization (PSO), one of the modern heuristic algorithms first introduced by Kennedy and Eberhart, is used to solve EDP in power system [14]. PSO algorithm is motivated by social behavior of organisms such as fish schooling and bird flocking. It provides a population-based search procedure in which individuals called particles change their positions with time. Compared with genetic algorithms, PSO algorithm has been demonstrated to have superior features, including high quality solution, stable converge characteristic, and good computation efficiency.

Genetic algorithm (GA) invented by Holland in the early 1970s is a stochastic global search method that mimics the metaphor of natural biological evolution. It's one of the advanced optimization method to solve the EDP [15]. The main objective of GA method is to find string with a maximum fitness that can be achieved by simply increasing the string bit length.

Simulated annealing algorithm is proposed to solve the optimal dispatch [16]. Simulated annealing is a random search technique for optimization that exploits an analogy between the way in which a metal cools and freezes into a minimum energy crystalline structure and the search for a minimum in a more general system. Numerical studies for a sample test system are presented to demonstrate the performance and applicability of the proposed method.

A multiple tabu search algorithm is presented to solve the dynamic EDP problem [17]. The multiple tabu search algorithm introduces additional mechanism such as initialization, adaptive searches, multiple searches, crossover and restarting process. To show its efficiency, this algorithm is applied to solve constrained EDP of power system with 6 and 15 units. And it's also compared with conventional approaches.

2.2 Decentralized Methods

All the conventional methods require global information via a centralized controller to achieve an optimal power generation and a minimum cost. However, the centralized algorithm may cause a few problems in the smart grid. Firstly, the centralized controller requires a high level of connectivity that may be affected by the failures and modeling errors. Secondly, the topologies of the smart grid and the communication network are likely to be variable. Therefore, a small change in the smart grid may lead to reconfiguration of the centralized algorithm. Thirdly, collecting global information from each generator may cause extra cost. Therefore, it can be concluded that the centralized controller is not suitable to solve the EDP in a smart grid.

In order to solve the EDP in a smart grid, a distributed control algorithm is employed. Compared with the centralized algorithm, the distributed algorithm features advantages of less information requirement, robustness, and scalability. First of all, no centralized controller or global information is needed by the distributed algorithm. Moreover, the distributed algorithm is not affected by the variation of topologies. Therefore, the plug-and-play characteristic of smart grid can be accommodated by the distributed algorithm. The key to the distributed algorithm in the smart grid is for all generators to reach a consensus.

Consensus algorithm has been studied widely for the past two decades. Its applications can be found in the area of system and control [18-19]. The main problem in a consensus algorithm is to reach agreement regarding certain quantity of interest by using local information exchange [19]. The multi-agent system can be categorized as either formation control problems with applications to mobile robots, unmanned air vehicles, autonomous underwater vehicles, satellites, aircraft, spacecraft, and automated highway systems. Lately, consensus algorithm has been utilized in smart grid associated problems [20-21].

For example, a consensus-based algorithm is applied to solve EDP in a smart grid [20]. Effective distributed control algorithms could be embedded in distributed controllers to properly allocate electrical power among connected generators. By selecting the incremental cost of each generator as the consensus variable, the algorithm is able to solve the conventional centralized control problem in a distributed manner. To satisfy the power balance, the mismatch between demand and total generations is fed back to consensus algorithm so that the incremental cost will converge to the optimal point. The communication topology among generators are assumed to be undirected that the information exchange is bidirectional. However, the assumption is not practical since the communication may not be symmetric in real situations [4]. Moreover, the algorithm is not completely distributed since a leader has to be selected to collect all power output from each generator in order to calculate the power mismatch.

Similarly, a decentralized algorithm of self-organizing dynamic agents equipped with consensus protocol is proposed to solve EDP in a smart grid [21]. Modern trends in economic dispatch analysis are oriented towards the deployment of computing architectures that move away from the traditional centralized paradigms to architectures distributed in the field with an increasing pervasion of cooperative smart entities. The solution of the economic dispatch problem is obtained by the agents' network by exchanging and processing local information according to a distributed consensus protocol. Due to this feature, each agent can compute the most important variables characterizing the global power system operation without the need for a centralized center. The effectiveness of proposed algorithm is proved on 118 and 300 *IEEE* test networks. However, these results are obtained by assuming some simplification on the active power loss modeling. And no generator dynamics are considered when evaluating the convergence rate.

A load dispatch model for the system consisting of both thermal generators and wind turbines is developed [25]. The stochastic wind power is included in the model as a constraint. It's shown that under certain conditions, the presented model has a set of closed-form solutions. The availability of closed-form solutions is helpful to gain more fundamental insights, such as the impact of a particular parameter on the optimal solution. Furthermore, the probability distribution and the average of solutions are derived. This is called the wait-and-see approach in the discipline of stochastic programming.

In order to achieve an optimal network operation, it requires a continuous real time monitoring, control and economic dispatch by means of a smart distribution management system [26]. The system counts on high performance algorithms and real time information systems. Three very efficient algorithms are presented, which are: load estimation, ac power flow, and optimal reconfiguration of loss minimization. Furthermore, these algorithms are tested in many real and large scale distribution networks for several utilities.

The prerequisite power generation and load information for decision making is discovered by each distributed generation unit via a multiagent coordination with guaranteed convergence [27]. To avoid a slow convergence speed which potentially increases the generation cost because of the time-varying nature of distributed generation, a heterogeneous wireless network architecture for smart grid is presented. Low cost short range wireless communication devices are used to establish an ad hoc network as a basic information exchange, while auxiliary dual-mode devices with cellular communication capabilities are optionally activated to improve the convergence speed. Two multiagent coordination schemes are proposed for the single-stage and hierarchical operation modes, respectively. The optimal number of activated cellular communication devices is obtained based on the tradeoff between communication and generation cost.

An additional constraint is implemented to ensure the stable islanded operation of a smart grid [28]. A detailed formulation according to the power sharing principle regarding the distributed generation is presented. A test system with 15 units is developed for numerical simulation taking into account the source type and part load performance. The effect of various parameters on the cost is also analyzed.

An intelligent economic operation of smart grid environment facilitating an advanced quantum evolutionary method is presented [29]. Wind generators, PV generation and thermal generators are included in the model. An intelligent quantum inspired evolutionary algorithm is proposed and applied to perform the intelligent economic scheduling operation concerning scheduling and dispatching. The quantum algorithm features intelligent operators such as sophisticated rotation operator, differential operator, etc. The method is tested on a hypothetical power system with 10 units, similar number of hybrid electric vehicles, similar number of solar energy and wind energy.

An approach based on the simultaneous perturbation technique is proposed to deal with the equality and inequality constraints in the economic dispatch problem [30]. The effects of cap-and-trade policies, energy storage, and transmission line flow limits in economic dispatch are discussed. The Lagrangian relaxation includes all the system constraints in the objective function with Lagrange multipliers. In this paper, we have constraints across multiple time periods, such as water resources and ramping constraints. In order to reduce computation time, the inequality constraints are not included in the optimization problem. Instead, we check if the solution satisfies the inequality constraints after converge. If not, then the violated inequality constraints are included into the Lagrangian as binding equality constraints with respective Lagrangian multipliers. Then the optimization continues with the new binding constraints enforced.

2.3 Accuracy of EDP Optimization Methods

There are many criteria to evaluate the performance of EDP optimization methods. For example, the criteria could include the convergence speed, computational complexity, total generation cost, etc. One of the most important criteria is total generation cost because the purpose of optimization is to reduce the cost of the smart grid. There are a lot of work that have been done to evaluate the quality of EDP optimization methods, especially consensus-based methods.

A modified particle swarm optimization algorithm is proposed to improve the performance of particle swarm optimization for economic dispatch problem in power systems [32]. The modified PSO method shows a higher probability of achieving better solutions among the existing methods.

A comparison between lambda iteration method and incremental cost consensus method is carried out [6]. The comparison is based on 6-generator system, 15-generator-system, and 110-generator system, respectively. The solutions of both methods shown that the consensus algorithm has almost the same cost as the lambda iteration method in 6-generator and 15-generator systems. The results of lambda iteration method can be treated as the optimal values that consensus algorithm tries to reach. To be specific, the percentage differences of the corresponding costs is 0.014% and 0.067%, respectively. The two methods have the same generation cost for the 110-generator system when transmission loss is neglected. It means that the difference between them is 0%.

A similar consensus based on auction is proposed to optimize the EDP in the smart grid [5]. In this work, different scenarios of power system are tested to evaluate the quality of proposed auction-based algorithm. The consensus algorithm is compared to most of the centralized algorithms in 10-generator, 15-generator, and 40-generator systems. As compared to the best

optimal results, the percentage differences are 0.022%, 0.094%, and 0.302%, respectively. Although, the consensus algorithm does not have the best optimization results, the difference between the optimal result and the consensus algorithm is negligible. It's noted that most of the centralized algorithms take many trials to obtain the optimal result. However, the consensus algorithm only need 1 single trial. For the heuristic, the results are not deterministic due to special characteristics of heuristic methods. The optimal results vary every trial for heuristic methods. In contrast to the heuristic methods, given the initial parameters, the results of consensus algorithm are always the same for every trial.

It's noted that the percentage difference between consensus algorithm and real optimal result increases as the number of power units in the system increases. The percentage difference between consensus algorithm and real optimal results is summarized in the following table.

TABLE 1
Percentage differences between consensus algorithm and optimal result

No. of Units	Percentage Difference
6	0.014%
10	0.022%
15	0.080%
40	0.302%

It can be seen from Table 1 that percentage differences go up from 0.014% in 6-generator to 0.302% in 40-generator.

Although the differences go up, they are still less than 1% of the optimal solution. It shows that the consensus has a high percentage to achieve the optimal solution of economic dispatch problem.

It's also noted that a more accurate optimal solution may need a bigger iteration steps to achieve the optimal value. The effect of iteration on the performance of EDP algorithms will be analyzed later.

Some might argue that the consensus algorithm may not work because renewable energy is non-dispatched. Renewable energy source is non-dispatchable due to its fluctuating nature, like wind power and solar power. However, with the interaction of energy storage, the renewable energy can be treated as dispatchable sources. Combined with energy storage, the renewable energy can generate relatively constant power. Therefore, the consensus algorithm can be applied to renewable energy system and also smart grids.

CHAPTER THREE

GRAPH THEORY AND CONSENSUS ALGORITHM

3.1 Graph Theory

In this section, basic graph theory is introduced. In mathematics and computer science, graph theory is the study of graphs, which are mathematical structures used to model pairwise relations between objects [31]. An example of graph is shown in Fig. 3.

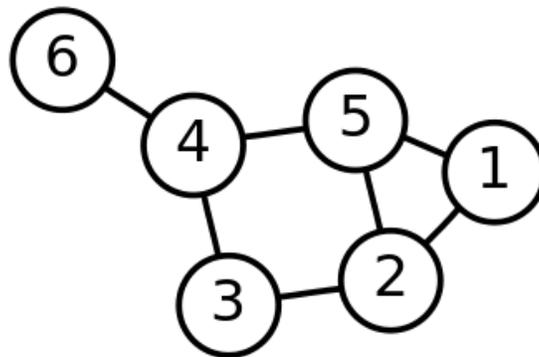


Fig. 3. A drawing of a graph [31].

A graph is composed of nodes and edges. Edges are lines that connect different nodes. A graph may be undirected, meaning that there is no distinction between the two nodes associated with each edge.

Graphs can be used to model many types of relations and processes in physical, biological, social and information systems. Many practical problems can be represented by graphs. In computer science, graphs are used to represent networks of communication, data organization, computational devices, etc.

A graph G is used to model the power system components and the way they exchange information based on communication theory. Let

$$G = (V, E, A) \quad (1)$$

Where V is a set of elements called nodes, E is a set of pairs of distinct nodes called edges, and $A = [a_{ij}] \in R^{n \times n}$ is the adjacency matrix. A directed graph is a graph where the edges have directions associated with them. In a smart grid, nodes represent the buses of the power system, the edges represent the transmission lines between the buses, and the adjacency matrix represent the edge weights. A directed edge from i to j is denoted by a pair $(i, j) \in E$. The pair means that generator j can receive information from generator i . The in-neighbor of the i -th generator is denoted by:

$$N_i^+ = \{j \in V \mid (j, i) \in E\} \quad (2)$$

Likewise, the out-neighbor of the i -th generator is denoted by:

$$N_i^- = \{j \in V \mid (i, j) \in E\} \quad (3)$$

Practically, a generator can receive information from its in-neighbor, and send information to its out-neighbor. The in-degree and out-degree of node i is denoted as:

$$d_i^+ = |N_i^+| \text{ and } d_i^- = |N_i^-| \quad (4)$$

A directed graph is strongly connected if there exists a connection between any pair of two nodes. It's noted that $d_i^- \neq 0$ and $d_i^+ \neq 0$ in a strongly connected graph.

3.2 Consensus Algorithm

Two matrices $P, Q \in R^{n \times n}$ associated with a strongly connected graph $G = (V, E, A)$ are defined as follows:

$$p_{i,j} = \begin{cases} \frac{1}{d_i^+} & j \in N_i^+ \\ 0 & otherwise \end{cases} \quad \forall i, j \in V \quad (5)$$

Likewise,

$$q_{i,j} = \begin{cases} \frac{1}{d_j^-} & j \in N_j^- \\ 0 & \text{otherwise} \end{cases} \quad \forall i, j \in V \quad (6)$$

From the definitions of matrices P and Q , it can be verified that the summation of row elements of P is equal to one, and the summation of column elements of Q is equal to one. It's free to choose the weights of P and Q . And P and Q have to satisfy the following assignments, $p_{i,j} > 0$ if $j \in N_i^+$, $p_{i,j} = 0$ otherwise, $q_{i,j} > 0$ if $i \in N_j^-$, $q_{i,j} = 0$ otherwise. The convergence rate is not affected by the weights.

Considering the following two discrete-time systems:

$$\xi_i(k+1) = \sum_{j \in N_i^+} p_{i,j} \xi_j(k) \quad (7)$$

$$\xi_i'(k+1) = \sum_{j \in N_i^+} q_{i,j} \xi_j'(k) \quad (8)$$

where $\xi_i(k)$ and $\xi_i'(k)$ are state variables associated with node i in graph G at time step k . in a smart grid, the state variable represents a physical quantity such as the output power, incremental cost, power mismatch, etc. Equations (7) and (8) have the same structures but with two different sets of weights. They can be composed in the following format:

$$\xi(k+1) = P\xi(k) \quad (9)$$

$$\xi'(k+1) = Q\xi'(k) \quad (10)$$

where $\xi(k)$ and $\xi'(k)$ are the column stack vectors of $\xi_i(k)$ and $\xi_i'(k)$. In order to investigate the behaviors of (9) and (10), the following theorem is introduced.

Theorem 1[19]: If $A \in \mathbb{R}^{N \times N}$ is a nonnegative and primitive matrix, then

$$\lim_{k \rightarrow \infty} (\rho(A)^{-1} A)^k = \mathbf{x} \mathbf{y}^T > 0 \quad (11)$$

where $A\mathbf{x} = \rho(A)\mathbf{x}$, $\mathbf{y}^T A = \rho(A)\mathbf{y}^T$, $\mathbf{x} > 0$, $\mathbf{y} > 0$, $\mathbf{x}^T \mathbf{y} = 1$, and $\rho(A)$ is the special radius of A .

The symbol “>” means that all the entries in a matrix or vector are larger than zero. Based on the definitions of P and Q , both P and Q are nonnegative and stochastic. Therefore, $\rho(P) = \rho(Q) = 1$. They are derived from a strongly connected graph, and their diagonal elements are positive. Then $P^{N-1} > 0$ and $Q^{N-1} > 0$, i.e., P and Q are primitive. According to theorem 1, we can obtain the following two properties.

$$\lim_{k \rightarrow \infty} P^k = \omega \mathbf{1}^T \quad \text{where } \omega > 0 \quad \text{and} \quad \mathbf{1} \omega^T = 1 \quad (12)$$

$$\lim_{k \rightarrow \infty} Q^k = \mu \mathbf{1}^T \quad \text{where } \mu > 0 \quad \text{and} \quad \mathbf{1}^T \mu = 1 \quad (13)$$

From equations (12) and (13), we can get $\lim_{k \rightarrow \infty} \xi_i(k) = \omega^T \xi(0)$ for equation (7), and $\lim_{k \rightarrow \infty} \xi_i'(k) = \mu_i \sum_{i=1}^N \xi_i'(0)$, where μ_i is the i -th element of μ . In equation (7), all state variables converge to a common value, which depends on the communication topology and initial conditions. Equation (7) represents the consensus algorithm for the first order discrete-time system. While in equation (8), the state variables do not converge to a common value. But the summation of all state variables is constant, i.e., $\sum_{i=1}^N \xi_i'(k) = \sum_{i=1}^N \xi_i'(0), \forall k$.

3.3 Solution to Economic Dispatch Problem

The communication topology among generators is a strongly connected graph G as described in 3.1. At the beginning, we are not considering power generation constraints.

According to the incremental cost criterion, all generators operate at optimal incremental cost. The incremental cost of i -th generator is derived as:

$$\lambda_i = \frac{dC_i(P_i)}{dP_i} = 2\gamma_i P_i + \beta_i \quad (14)$$

where P_i is the output power of generator i , C_i is the cost of generator i , β_i, γ_i are the cost coefficients of generator i . Therefore, the optimal incremental cost of generators will be:

$$\lambda_i^* = 2\gamma_i P_i^* + \beta_i \quad (15)$$

And the optimal output of generator I can be obtained from equation (15).

$$P_i^* = \frac{\lambda_i^* - \beta_i}{2\gamma_i} \quad (16)$$

Let us denote $\lambda_i(k)$ the estimation of optimal incremental cost of i -th generator, $P_i(k)$ the estimated optimal power output of i -th generator, and $\Delta P_i(k)$ the estimated local power mismatch between power demand and total power generations. And we have the following initializations:

$$\left\{ \begin{array}{l} \lambda_i(0) = \text{any feasible value} \\ P_i(0) = \text{any feasible value} \\ \Delta P_i(0) = \frac{D}{|N_0^-|} - P_i(0) \text{ if } i \in N_0^-, -P_i(0), \text{ otherwise} \end{array} \right. \quad (17)$$

where D is the total power demand, N_0^- is the vertices set that can receive information from vertex 0.

Now we can derive the consensus algorithm:

$$\lambda_i(k+1) = \sum_{j \in N_i^+} p_{i,j} \lambda_j(k) + \varepsilon \Delta P_i(k) \quad (18)$$

$$P_i(k+1) = \lambda_i(k+1) / 2 / \gamma_i - \beta_i / 2 / \gamma_i \quad (19)$$

$$\Delta P_i(k+1) = \sum_{j \in N_i^+} q_{i,j} \Delta P_j(k) - (P_i(k+1) - P_i(k)) \quad (20)$$

where ε is a small positive constant, and k is the time step. $q_{i,j}$ is the element of matrix Q .

The iteration processes stated in equations (18), (19), and (20) only need local information. For example, the iteration of generator i in equation (20) only needs information from its in-neighbor set N_i^+ . Hence, the process is a distributed algorithm.

In order to analyze the properties and convergence of proposed consensus algorithm, equations (18), (19), and (20) are written in the following format:

$$\lambda(k+1) = P\lambda(k) + \varepsilon\Delta P(k) \quad (21)$$

$$P(k+1) = B\lambda(k+1) + \alpha \quad (22)$$

$$\Delta P(k+1) = Q\Delta P(k) - (P(k+1) - P(k)) \quad (23)$$

where \mathbf{P} , $\Delta\mathbf{P}$, α , λ are the column stack vectors of P_i , ΔP_i , $-\beta_i/2/\gamma_i$, λ_i , respectively. And $B = \text{diag}([1/2/\gamma_1, 1/2/\gamma_2, \dots, 1/2/\gamma_N])$.

It can be seen that equation (23) preserves the summation of $P_i + \Delta P_i$. Multiplying equation (23) by $\mathbf{1}^T$, and we can get

$$\mathbf{1}^T \Delta P(k+1) = \mathbf{1}^T Q \Delta P(k) - \mathbf{1}^T (P(k+1) - P(k)) \quad (24)$$

By equation (13), we can have

$$\mathbf{1}^T \Delta P(k+1) + \mathbf{1}^T P(k+1) = \mathbf{1}^T \Delta P(k) + \mathbf{1}^T P(k) \quad (25)$$

Therefore, $\mathbf{1}^T \Delta P(k) + \mathbf{1}^T P(k)$ is a constant for all k . Since $\sum_i P_i(0) + \Delta P_i(0) = D$, $\mathbf{1}^T \Delta P(k)$ will be the actual mismatch between demand and total power generations. It's noticed that this mismatch is collected by a distributed manner instead of a centralized controller. Observed from equation (21), the term $\varepsilon\Delta P(k)$ provides a feedback to the incremental cost so that $\lambda_i(k)$ will converge to the optimal value.

Then we have another theorem stating if constant ε is small enough, then the algorithm is stable. And all variables will converge to the solution to the EDP.

Theorem 2:

for $k \rightarrow \infty, \quad \forall i \in V$

$$\lambda_i(k) \rightarrow \lambda_i^*, P_i(k) \rightarrow P_i^*, \Delta P_i(k) \rightarrow 0 \quad (26)$$

Next, we will prove the theorem 2. Replace \mathbf{P} in equation (23) with λ by using equations (21) and (22), we can get

$$\Delta P(k+1) = (Q - \varepsilon B)\Delta P(k) + B(I - P)\lambda(k) \quad (27)$$

where I is the identity matrix of appropriate dimension.

Combine (21) and (27) together, we can have the following matrix equations:

$$\begin{bmatrix} \lambda(k+1) \\ \Delta P(k+1) \end{bmatrix} = \begin{bmatrix} P & \varepsilon I \\ B(I - P) & Q - \varepsilon B \end{bmatrix} \begin{bmatrix} \lambda(k) \\ \Delta P(k) \end{bmatrix} \quad (28)$$

Let us define

$$M = \begin{bmatrix} P & 0 \\ B(I - P) & Q \end{bmatrix}, \text{ and } \Delta = \begin{bmatrix} 0 & I \\ 0 & -B \end{bmatrix}.$$

The system matrix in equation (28) can be seen as M perturbed by $\varepsilon\Delta$. The eigenvalues of M is the union of the eigenvalues of P and Q . So M has two eigenvalues $\theta_1 = \theta_2 = 1$, and the rest eigenvalues lie in the open unit disk on the complex plane. Denote vectors u_1, u_2 and v_1^T, v_2^T as follows:

$$U = \begin{bmatrix} 0 & I \\ \mu & -\eta\mu \end{bmatrix} \quad (29)$$

where $\eta = \sum_{i=1}^N 1/2/\gamma_i$, and

$$V^T = \begin{bmatrix} 1^T B & 1^T \\ \omega^T & 0^T \end{bmatrix} \quad (30)$$

which are two linearly independent eigenvectors of M . and $V^T U = 1$.

When ε is small the variation of θ_1 and θ_2 perturbed by $\varepsilon\Delta$ can be represented by eigenvalues of $V^T \Delta U$, and

$$V^T U = \begin{bmatrix} 0 & 0 \\ \omega^T \mu & -\eta \omega^T \mu \end{bmatrix} \quad (31)$$

It's found out that θ_1 does not change with ε , and when $\varepsilon > 0$, θ_2 becomes smaller. Since eigenvalues continuously depend on the entries of a matrix, the rest of eigenvalues of $M + \varepsilon A$ continuously depend on ε . Hence, if we choose ε smaller, we can guarantee that the rest eigenvalues will lie in the open unit disk.

As $k \rightarrow \infty$,

$$\begin{bmatrix} \lambda(k) \\ \Delta P(k) \end{bmatrix} \text{converges to } \text{span} \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

That is $\Delta P_i \rightarrow 0$. The demand constraint is satisfied in equation (23). From equation (21), the incremental cost will converge to a common value. Therefore, the incremental cost criterion is satisfied.

3.4 Convergence Study of Consensus Algorithm

Convergence speed is one of the most important factors to evaluate the effectiveness of proposed EDP methods. The convergence performance of traditional methods is discussed in literature [37-42].

A real-parameter quantum evolutionary algorithm from evolutionary algorithm and quantum computing is presented to solve non-linear EDP [37]. Although heuristics which employ history of better solutions obtained in the search process such as genetic algorithm and evolutionary algorithm may have better convergence of solution. However, problems of slow or premature convergence remain. It's proved in [37] that real-parameter quantum evolutionary algorithm has better convergence and quality of solution than other evolutionary algorithms. And it requires a

relatively smaller population size. It's also noted that too small a convergence constant as stated in equation (18) will result in a slow convergence speed.

Moreover, premature convergence of genetic algorithm is accompanied by a very high probability of trap into a local optimization. In order to solve this problem, a bacterial foraging optimization technique is provided to deal with EDP optimization [38]. In the bacterial foraging method, a gradual or sudden changes in the location may occur because of consumption of nutrients or some other influence. This may cause the elimination of a set of bacteria or disperse them to a new environment. Consequently, this will reduce the chances of convergence at local optimal location. It's also mentioned that a small convergence constant may cause slow convergence. While a large one may cause the optimal go past the optimal point without stopping. The convergence characteristics of the bacterial foraging method is evaluated by measuring the fitness function with respect to the number of iterations. It's found out that the bacterial foraging method has a better convergence than other evolutionary algorithms.

Taguchi method that requires less computation is developed to solve the EDP with a non-smooth cost function [39]. The taguchi method is employed that involves the use of orthogonal arrays in estimating the gradient of the cost function. A convergence stopping criterion of 0.01 is proposed to evaluate the convergence of the taguchi method. It means that the improvement of the cost function from one cycle to the next is less than 0.01. Such a choice of the convergence criterion has been shown to be a good choice in this particular method. The taguchi method is six times faster than the fast evolutionary programming and ten times faster than classical evolutionary programming when applied to the economic dispatch problem with 40 generation units. However, one disadvantage of taguchi method is that it is very sensitive to the choice of initial values of parameters.

Due to slow convergence suffered from generic algorithms and evolutionary algorithms, a biogeography-based optimization is presented [40]. Biogeography deals with the geographical distribution of biological species. Mathematical models of biogeography describe how a species arises, migrates from one habitat to another and gets wiped out. It has some common features with other biology-based methods, such as genetic algorithm, particle swarm optimization. Compared to other biology-based methods, it requires fewer computational steps per iteration. Therefore, the biogeography-based optimization will have a faster convergence. Also, the method has a higher probability to reach global optimal in a consistent manner.

A multiobjective evolutionary algorithm for EDP is presented [41]. This approach employs a diversity-preserving mechanism to overcome the premature convergence and search bias problems. A hierarchical clustering algorithm is also imposed to provide the decision maker with a representative and manageable Pareto-optimal set. Moreover, fuzzy set theory is employed to extract the best compromise nondominated solution. Several optimization runs of the proposed approach have been carried out on a standard test system. The results demonstrate the capabilities of the proposed approach to generate well-distributed Pareto-optimal solutions of the multiobjective economic dispatch problem in a single run.

Evolutionary programs with adaptations based on scaled cost, as well as empirical convergence constant, have been developed and examined on three test cases of a power system [42]. In smaller problems, all fast evolutionary programs perform much better than evolutionary programs with Gaussian mutation in terms of convergence rate, solution time, minimum cost, and probability of attaining better solutions. As the size of the problem increases, as in large-scale modern power systems, improved fast evolutionary programs offer superior performance over all other evolutionary programs with both types of adaptations. Though the solution time of improved fast

evolutionary programs in case of larger systems with more nonlinearities is slightly higher than fast evolutionary programs, it offers a higher convergence rate and better solution quality as compared to fast evolutionary programs.

The effect of consensus-based algorithms on convergence solution of economic dispatch is also examined [43-45].

A novel energy planning approach involving the actual wind energy as well as the energy traded with the main grid is introduced [43]. A sample average approximation approach with convergence guarantee is efficiently utilized to deal with the involved multidimensional integral in the expectation function. With the attractive advantages of being computationally efficient and resilient to communication outages, decentralized scheduling over the Microgrid communications network is developed based on the alternating direction method of multipliers. Some objective values of the iteration can be even smaller than the optimal value due to the constraint violation. However, for the day-ahead energy planning problem, alternating direction method of multipliers outperforms alternative distributed solvers thanks to its fast convergence.

An analysis of the distributed average consensus algorithm in networks with stochastic communication failures is presented [44]. It's shown that the problem can be formulated as a linear system with multiplicative noise. For systems with no additive noise, it is shown that the convergence rate of the consensus algorithm can be characterized by the spectral radius of a Lyapunov-like matrix recursion, and they have developed expressions for the multiplicative decay factor in the asymptotic limits of small failure probability and large networks. For systems with additive noise, it is shown that the steady-state total deviation from average is given by the solution of a Lyapunov-like equation. Using this method, these second order statistics for various network topologies can be computed as a function of link failure probability. These computations indicate

that there is a relationship between the network topology, the algorithm parameter, and the probability of failure that is more complex than intuition suggests.

The selection of sampling rate is very important for the overall system convergence performance in distributed consensus algorithm [45]. A proper sampling rate has to be high enough to satisfy the sampling theorem, yet not so high as to incur unnecessary cost or instability. Simulation results show the convergence performance under different selections of sampling rate and different time constants of dynamics. A mathematical formulation of the system consists of both consensus and dynamics is provided in this work. The same formulation methodology can be applied to a system of a discrete consensus system with second-order, third-order, fifth-order, etc. The relationship between the sampling rate and the convergence performance is analyzed.

Overall, there are several factors that can affect the convergence speed of consensus algorithm. Usually, the convergence can be guaranteed by using the consensus algorithm. However, the optimal solution may not be the ideal solution due to the power constraints such as prohibited operating zones, power limits, etc.

CHAPTER FOUR

DEFINITION OF COST FUNCTION AND CONSTRAINTS

4.1 Cost Function Definition

In this section, the EDP with transmission losses and generator constraints in a smart grid is defined. The objective of EDP is to minimize the total cost of power generation.

A typical cost function curve of a power generator is illustrated in Fig. 4.

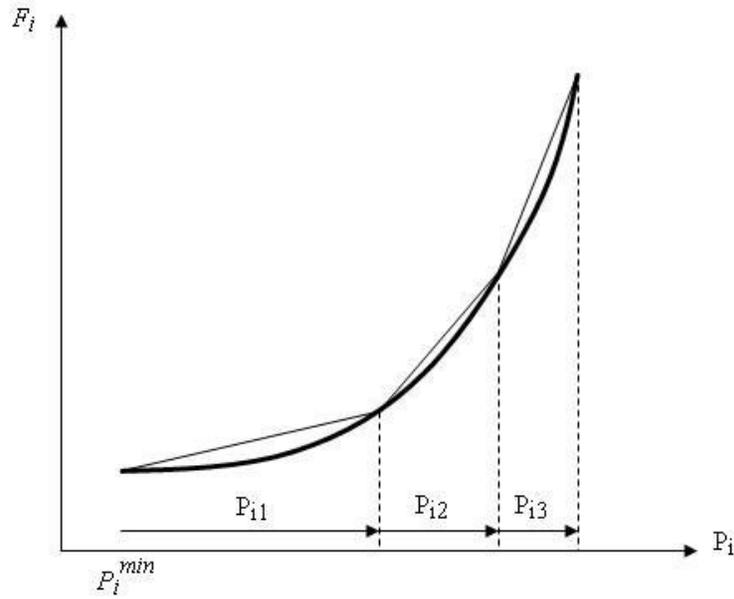


Fig. 4. Cost function curve of a power generator.

A quadratic cost function of i -th generator is given as follows:

$$C_i(P_i) = \gamma_i P_i^2 + \beta_i P_i + \alpha_i \quad (32)$$

Then the total cost of operation for all generators is calculated as:

$$C_t = \sum_{i=1}^m C_i(P_i) = \sum \gamma_i P_i^2 + \beta_i P_i + \alpha_i \quad (33)$$

where m is the number of power generators, P_i is the output power of generator i , $\alpha_i, \beta_i, \gamma_i$ are the cost coefficients of generator i . The purpose of EDP is to minimize C_t .

The total transmission loss is a function of generator power outputs that can be represented using B coefficients [23].

$$P_l = \sum_{i=1}^m \sum_{j=1}^m P_i B_{ij} P_j + \sum_{i=1}^m B_{0i} P_i + B_{00} \quad (34)$$

where B_{ij}, B_{0i}, B_{00} are transmission loss coefficients.

4.2 Constraints Definition

The EDP has to be solved under several generation and transmission constraints. Therefore, the generators have to operate under several constraints. The constraints are categorized into the following groups.

Power balance

First of all, in order to meet the power demand, the power generations have to be equal to the power demand plus the power transmission loss. The power loss is calculated using equation (34).

$$\sum_{i=1}^m P_i = P_d + P_l \quad (35)$$

where P_d, P_l are power demand and power loss, respectively.

Ramp rate limit

The constraints of ramp rate limits for generation changes are given. When generation increases,

$$P_i - P_i^0 \leq UR_i \quad (36)$$

and when generation decreases,

$$P_i - P_i^0 \geq DR_i \quad (37)$$

where P_i, P_i^0 are the current and previous output power, respectively. UR_i and DR_i are the up ramp and down ramp limits of i -th generator. In discrete-time simulation systems, the UR_i can be defined as the increase limit between two time steps. Similarly, DR_i can be defined as the decrease limit between two time steps.

Generation limit

Each generator has to satisfy its own generation limits. When selecting a power generator, there are inherent limits on the active and reactive power which can be delivered.

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad (38)$$

where P_i^{\min}, P_i^{\max} are the minimum and maximum output of i -th generator, respectively. This property can be illustrated in the following figure.

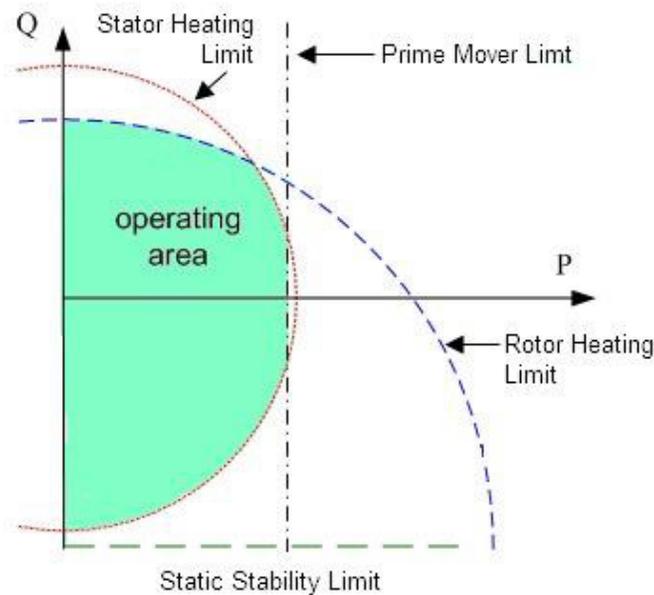


Fig. 5. A typical generator operation area.

Prohibited operation zone

A typical thermal unit with many valve points can generate prohibited operation zones. In practice, a generator has to avoid operating in those prohibited zones. The expression of the operation zones can be found as follows:

$$P_i^{\min} \leq P_i \leq P_{i,1}^l$$

$$P_{i,j-1}^u \leq P_i \leq P_{i,j}^l$$

$$P_{i,n}^u \leq P_i \leq P_i^{\max}, j = 2, 3, \dots, n \quad (39)$$

where n is the number of prohibited zones of generation i .

It's shown in Fig. 6 that the input-output performance curve for a typical thermal unit with many valve points. These valve points generate many prohibited zones.

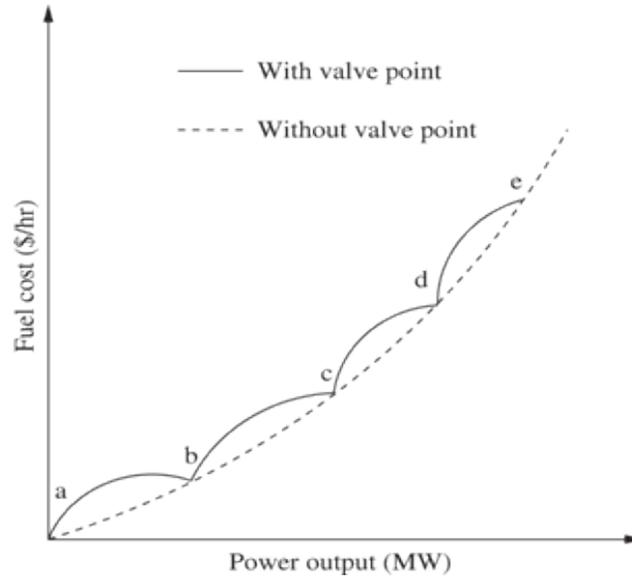


Fig. 6. Input-output curve of a thermal generator with valve points.

For example, there are five valve points in Fig. 6. They are two different curves when there are several valve points for a generation unit.

Line flow constraint

The transmission line power flow should remain less than the maximum capacity that a line carries.

$$|P_{Line,k}| \leq P_{Line,k}^{\max} \quad (40)$$

where $P_{Line,k}$ is the power flow of line k , $P_{Line,k}^{\max}$ is the maximum capacity of line k .

There are some other constraints that are not considered in this work. For example, the constraint of energy storage capacity is not taken into account. Also, the security of the power system is not considered in our model. However, they are not the main constraints of our proposed model.

4.3 Nonlinearity of EDP Optimization

The EDP optimization can be summarized as the solution to the quadratic cost function stated in equation (32). However, this equation is a simplified version of the practical cost function of the generation units. The real-world cost function of generation units with valve point loading is given in (41) [33].

$$C_i(P_i) = \gamma_i P_i^2 + \beta_i P_i + \alpha_i + |e_i \times \sin(f_i \times (P_i^{\min} - P_i))| \quad (41)$$

where P_i is the output power of generator i , α_i , β_i , γ_i are the cost coefficients of generator i , e_i and f_i are introduced to model the valve point loading. The generation cost of generator with valve point is illustrated in Fig. 6.

Large steam turbine generators will have a number of steam admission valves that are opened in sequence to obtain ever-increasing output of the unit. As the unit loading increases, the input to the unit increases and the incremental heat rate decreases between the opening points for any two valves [34]. However, when a valve is first opened, the throttling losses increases rapidly and the incremental heat rate rises suddenly. This is the valve point that leads to a non-smooth, non-convex characteristic.

If the cost function is approximately represented by a quadratic function as in (32), the problem can be solved by using piecewise linear programming method, quadratic programming method [35], [36]. However, none of these methods may be able to find the global optimal solution and most of them get stuck at a local optimum. Practically, the input-output characteristic of modern generation units are highly non-linear in nature due to valve point, ramp rate limits, and prohibited operation zones.

In order to simplify the optimization process, a linear programming approach using piecewise linear cost curves can be applied to solve economic dispatch. The process of linear programming method can be demonstrated in the following figures. The original cost curve is plotted in Fig. 4, which is a nonlinear curve.

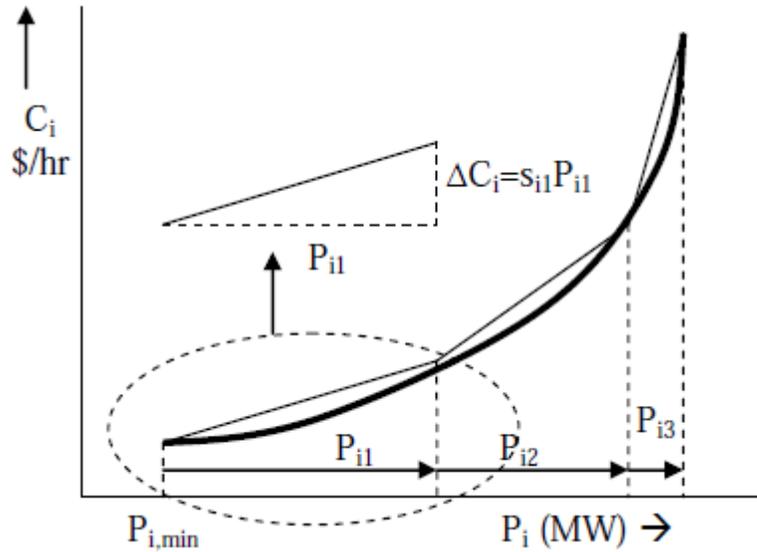


Fig. 7. Piecewise linear cost curve of generation unit.

As shown in Fig. 7, the nonlinear curve of generation units is divided into a series of straight-line segments. P_{i1} , P_{i2} and P_{i3} are power increments, respectively. The slopes of each one of the

line segments are denoted by s_{i1} , s_{i2} , and s_{i3} . Then the increment in cost function to each corresponding line segment is given by

$$\Delta C_i = s_{ik} P_{ik}$$

Therefore, the cost function can be approximated using the line segments, and that approximation can be improved to any desired level by increasing the number of line segments used.

However, the quadratic cost function is still a nonlinear problem because of the equality and inequality constraints. The equality constraint is represented by the power balance equation as shown in (35). The inequality constraints are represented by generation limit, ramp rate limit, prohibited operation zone, and transmission line limit.

Without these constraints, the quadratic cost function can be treated as a linear program if using the linear programming method.

CHAPTER FIVE

ANALYTICAL RESULTS

5.1 System Description

In this section, analytical studies are carried out to evaluate the performance of the proposed consensus-based distributed algorithm. A smart grid system of five generators is developed using Matlab/Simulink in discrete time step.

The simulation models can be divided into three main layers: power layer, communication layer, and control layer. The system of five generators are modeled in the power layer. The simplified synchronous generator in Matlab is used to model the generator dynamic in this layer. Communication network is built up in the communication layer. Communication delay is also considered in this layer. Each generator is connected to other generators by power transmission lines and communication signals. The five-unit smart grid system is shown in Fig. 8.

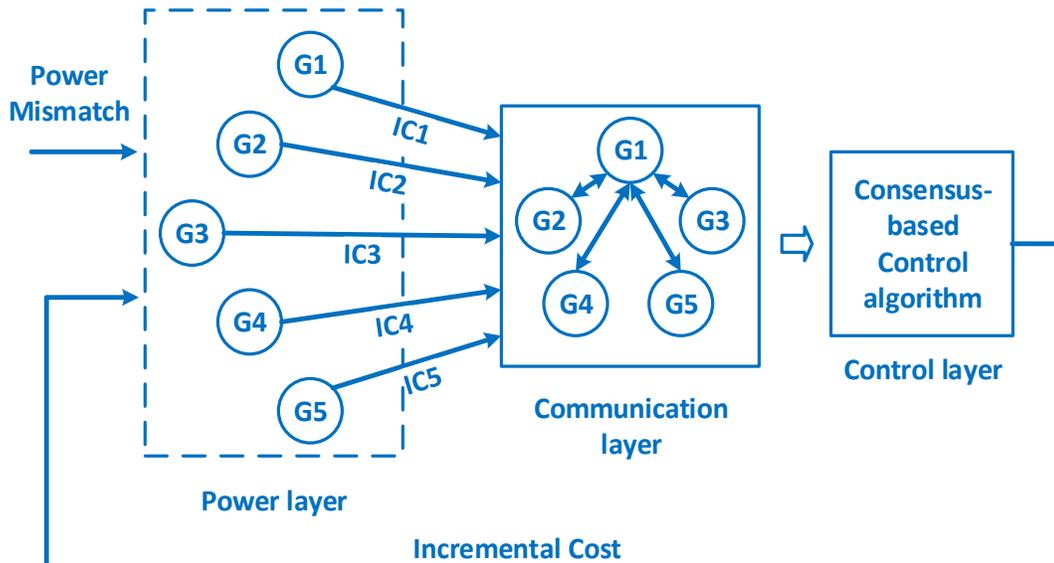


Fig. 8. Five generators smart grid simulation model.

The communication topology for this diagram is shown in Fig. 9.

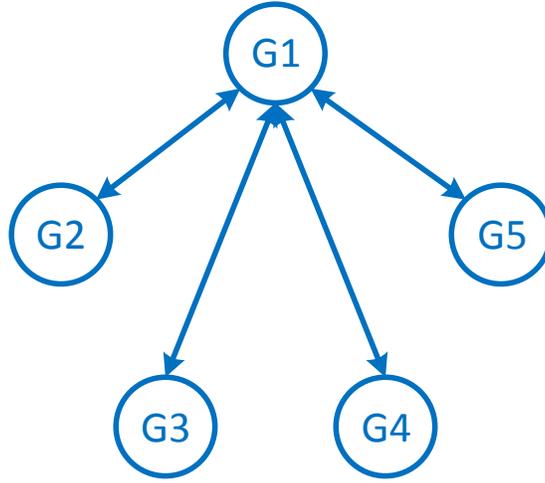


Fig. 9. Communication topology of five generators: star topology.

It's using star topology in Fig. 9. There are bidirectional communications between G1 and the rest four generators. According to equations (5) and (6), matrices P and Q can be derived as:

$$P = \begin{bmatrix} 1/5 & 1/5 & 1/5 & 1/5 & 1/5 \\ 1/2 & 1/2 & 0 & 0 & 0 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 1/2 & 0 & 0 & 1/2 & 0 \\ 1/2 & 0 & 0 & 0 & 1/2 \end{bmatrix}$$

$$Q = \begin{bmatrix} 1/5 & 1/2 & 1/2 & 1/2 & 1/2 \\ 1/5 & 1/2 & 0 & 0 & 0 \\ 1/5 & 0 & 1/2 & 0 & 0 \\ 1/5 & 0 & 0 & 1/2 & 0 \\ 1/5 & 0 & 0 & 0 & 1/2 \end{bmatrix}$$

It's apparent that summation of row elements of P and column elements of Q is equal to one, respectively. The parameters of five generators are shown in Table 2. And constraints are also

listed in Table 3. The load demand for this model is 850 MW. Different case studies are carried out in this work. Their performance are shown in the next section.

TABLE 2
Parameters of the five generators

<i>Gen.</i>	P_i^{min}	P_i^{max}	α_i	β_i	γ_i
1	50	200	561	7.92	0.00156
2	200	500	310	7.85	0.00194
3	50	200	78	7.97	0.00482
4	50	300	561	7.92	0.00156
5	50	200	78	7.97	0.00482

TABLE 3
Constraints of generators

<i>Gen.</i>	<i>UR</i>	<i>DR</i>	<i>Prohibited zones</i>
1	100	120	[90 110]
2	100	120	[350 380]
3	100	120	[90 110]
4	100	120	[90 110]
5	100	120	[90 110]

In Table 2, power limits and cost coefficients of all generators are presented. In Table 3, up rate limit, down rate limit, and prohibited zones of all generators are presented.

5.2 Case Studies

Case Study 1: Without Generator Constraints

In this case study, no generator constraints or transmission line loss is considered. The convergence rate ε is equal to 0.0005. As discussed before, a small convergence rate will guarantee the stability of the simulation. The simulation is carried out at a discrete time step of 0.0001s. The

generator power output, incremental cost of all generators, total power generation, power mismatch, and total generation cost are plotted in the following figures.

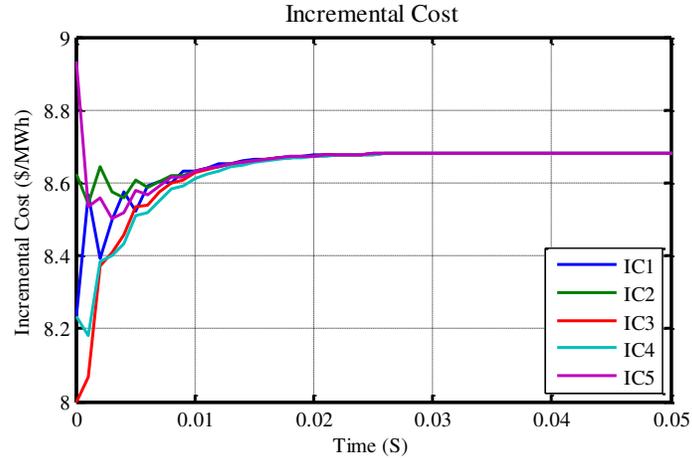


Fig. 10. Case study 1 incremental cost of five generators.

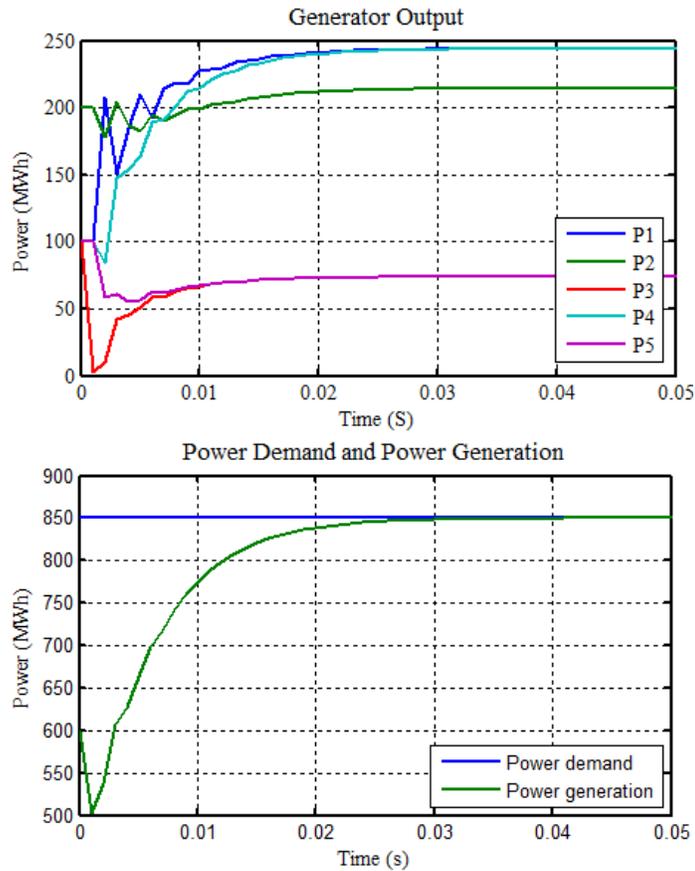


Fig. 11. Case study 1 power generation and power demand.

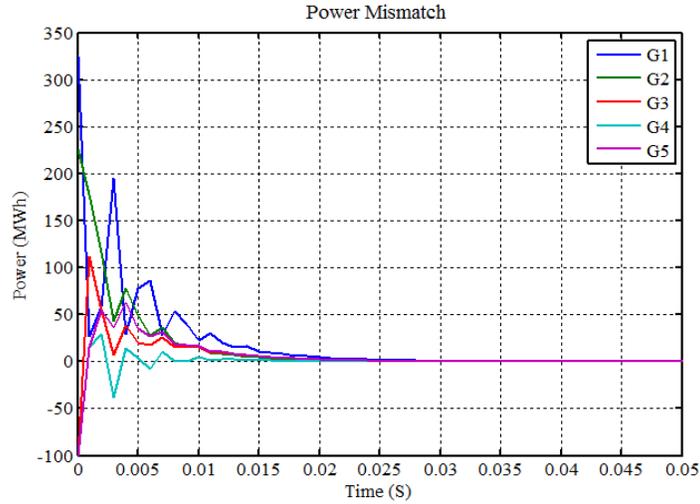


Fig. 12. Case study 1 power mismatch of all generators.

Figure 10 shows that incremental cost of five generators all converge to the optimal value, i.e., $\lambda^* = 8.682\$/MWh$. The corresponding power output of generators are: 243.9MW, 214.4MW, 73.86MW, 243.9MW, and 73.86MW. The comparison between power demand and total power generation is given in Fig. 11. It can be seen that the optimal power generation is achieved at 0.04s. The local power mismatch of each generator will converge to zero as shown in Fig. 12.

Case Study 2: With Generator Constraints

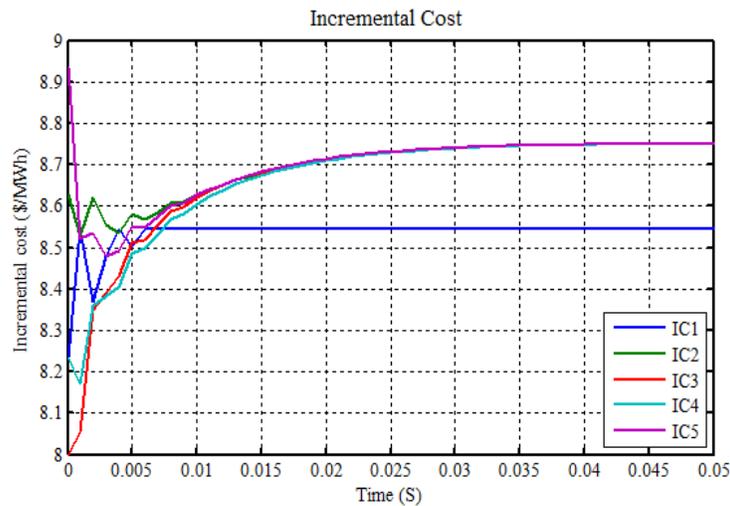


Fig. 13. Case study 2 incremental cost of five generators.

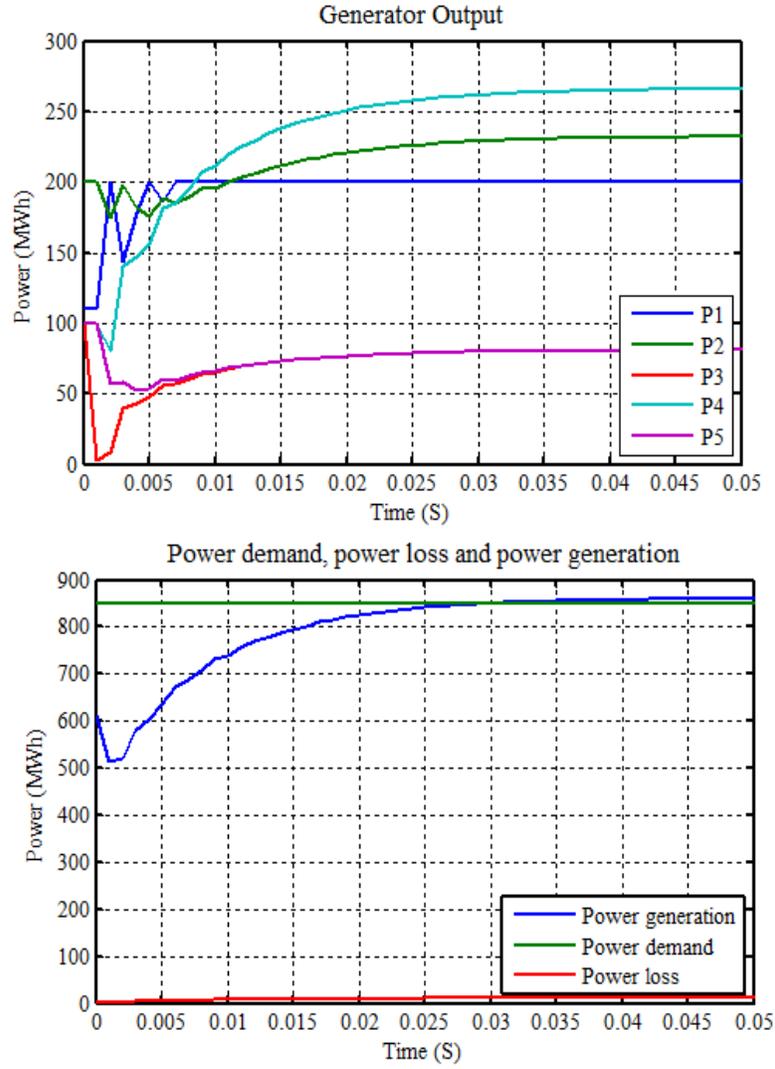


Fig. 14. Case study 2 power generation, power loss and power demand.

In order to calculate the transmission power loss, the transmission power loss coefficients are given in the following.

$$B_{ij} = 1.0e - 5 * \begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & -1 & -0.6 \\ -0.5 & -0.6 & -1 & 12.9 & -0.2 \\ -0.2 & -0.1 & -0.6 & -0.2 & 15 \end{bmatrix},$$

$$B_{oi} = 1.0e - 2 * [-0.3908; -0.1297; 0.7047; 0.2161; -0.6635], \quad B_{oo} = 0.056.$$

In this case study, the generator's constraints and transmission line loss are considered for a more practical situation. For example, the generator should satisfy its operation constraints including operation limits, UR/DR rates, and prohibited zones. The incremental costs and power generations are presented in Fig. 13 and Fig. 14, respectively.

It can be seen that generator 1 reaches its limit at 0.008 sec. and its incremental cost settles at $\lambda_1 = 8.545$ \$/MWh. However, in order to satisfy power balance, the other four generators have to generate more power. And the corresponding incremental cost will increase as indicated by Fig. 13. The new optimal incremental cost for the four generators λ^* is equal to 8.752 \$/MWh. The optimal power output are: 200MW, 232.5MW, 81.12MW, 266.3MW, and 81.12MW. The power generation and power loss are 861.04MW and 11.04MW, respectively.

Case Study 3: With a Different Communication Topology

In this study, a different communication topology is presented in order to test the capability of the proposed algorithm. Different from Fig. 9, a new topology is provided in Fig. 15.

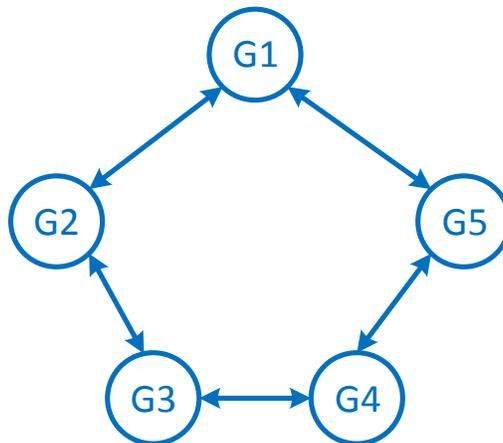


Fig. 15. Communication topology of five generators: loop connection.

Similarly, the corresponding matrices P and Q are derived as follows.

$$P = \begin{bmatrix} 1/3 & 1/3 & 0 & 0 & 1/3 \\ 1/3 & 1/3 & 1/3 & 0 & 0 \\ 0 & 1/3 & 1/3 & 1/3 & 0 \\ 0 & 0 & 1/3 & 1/3 & 1/3 \\ 1/3 & 0 & 0 & 1/3 & 1/3 \end{bmatrix}$$

$$Q = \begin{bmatrix} 1/3 & 1/3 & 0 & 0 & 1/3 \\ 1/3 & 1/3 & 1/3 & 0 & 0 \\ 0 & 1/3 & 1/3 & 1/3 & 0 \\ 0 & 0 & 1/3 & 1/3 & 1/3 \\ 1/3 & 0 & 0 & 1/3 & 1/3 \end{bmatrix}$$

The incremental costs are plotted in Fig. 16.

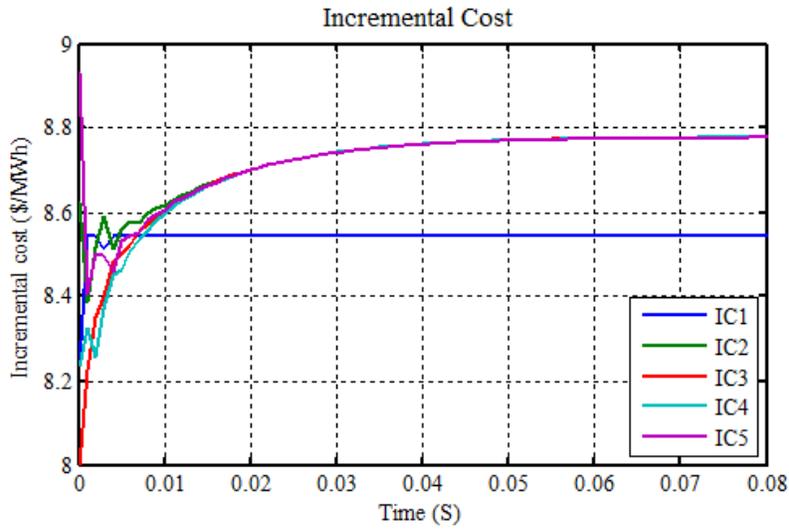


Fig. 16. Case study 3 incremental cost of five generators.

It's observed that this topology has a slightly higher incremental cost than topology in case study 1. The optimal incremental cost for the four generators is 8.779 \$/MWh. The power output of generators are also shown in Fig. 17.

Comparing with case study 2, it takes slightly more time for the generators in case study 3 to reach the optimal generations. It's also requiring more generations from the generators. The power output of five generators are: 200MW, 239.2MW, 83.86MW, 274.8MW, and 83.81MW. The corresponding power generation and power loss are: 881.67MW and 31.67MW, respectively.

It can be concluded that different topologies can have different effects on the consensus algorithm.

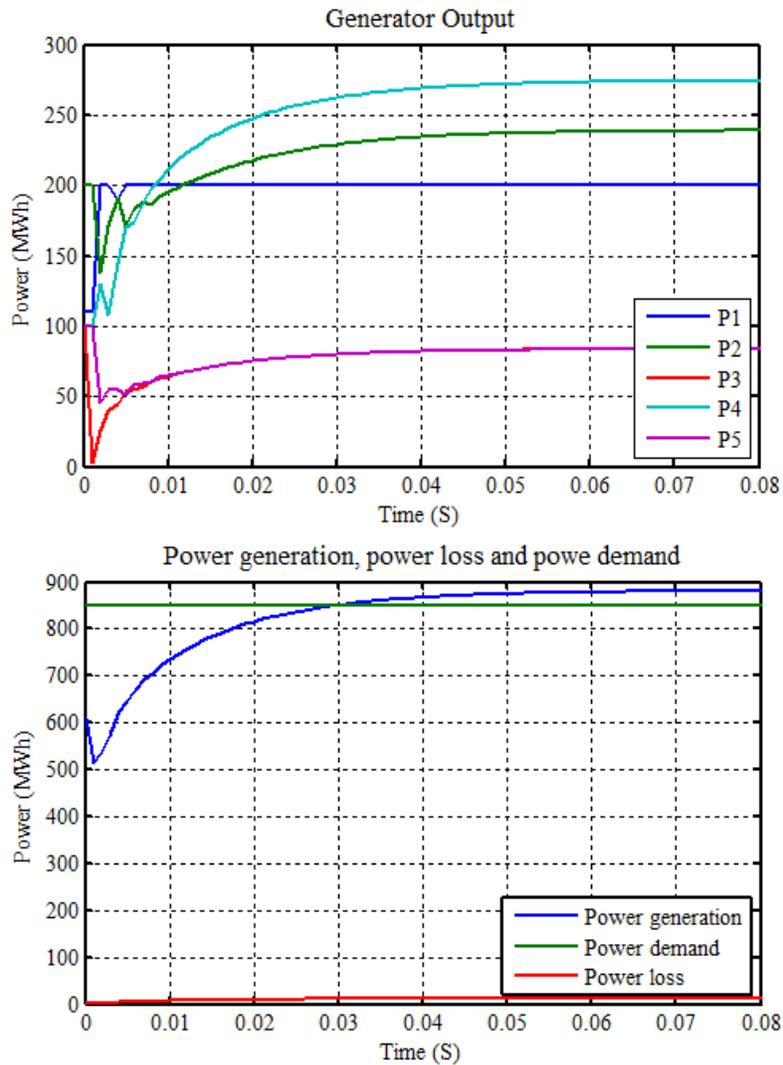


Fig. 17. Case study 3 power generation, power loss and power demand.

Case Study 4: With Generator Dynamics

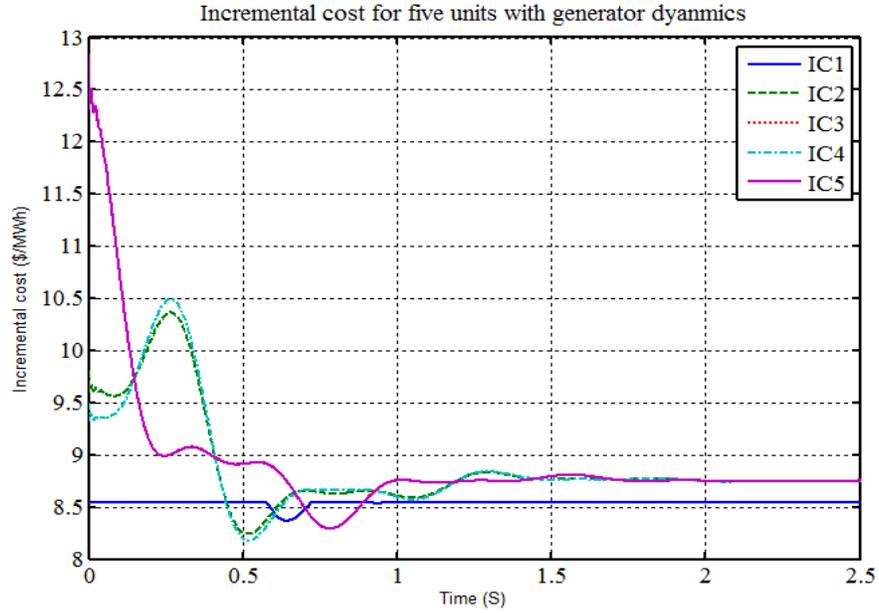


Fig. 18. Case study 4 incremental cost for five generators.

In this case study, the dynamics of generators are taken into consideration. The characteristics of generators are modeled using the simplified synchronous generator from Matlab/Simulink. The simulation results are shown in the Fig. 18, Fig. 19 and Fig. 20.

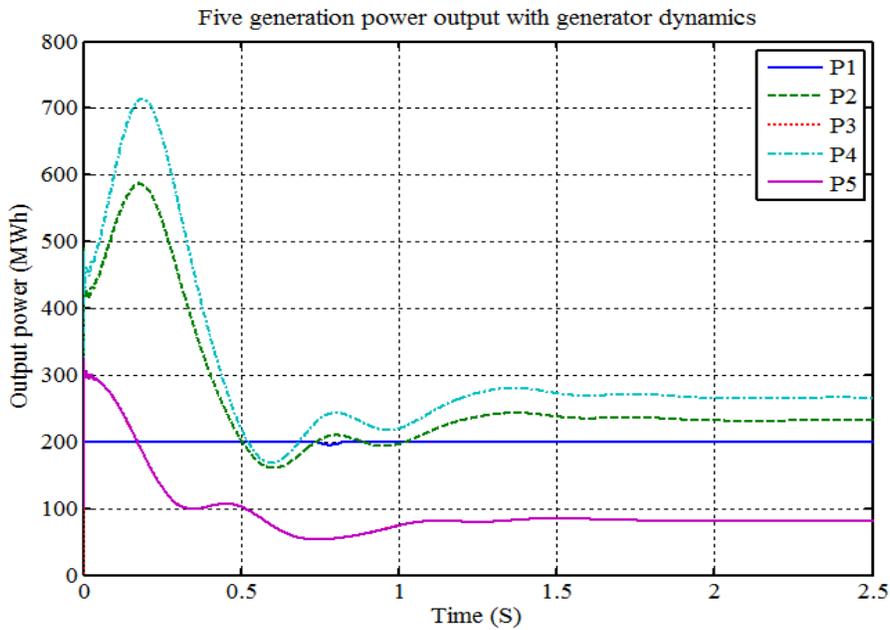


Fig. 19. Case study 4 generator output.

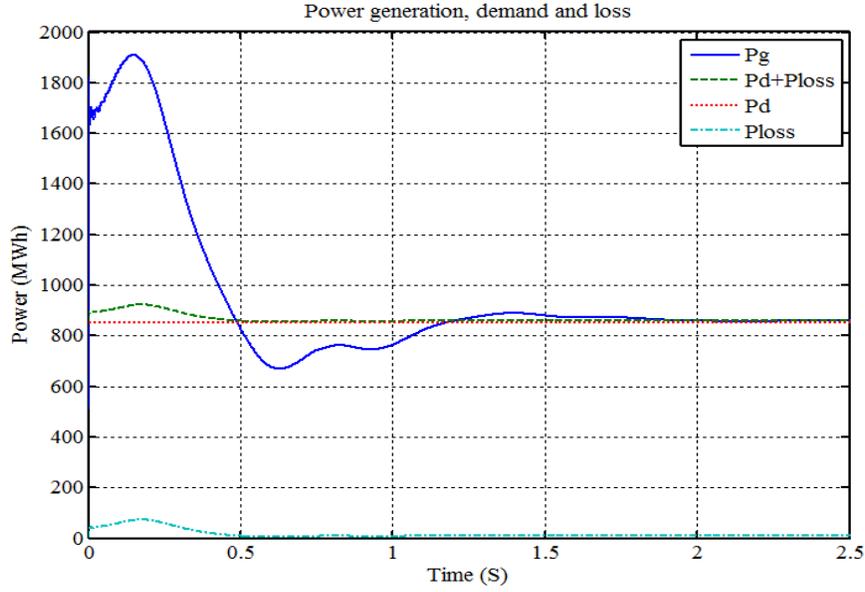


Fig. 20. Case study 4 power generation, power loss and power demand.

It's noticed that it's taking a longer time for generators to reach consensus due to the inertia of the generator. After about 2s, the generation reach the same consensus as that in case study 2. And there is a large transient in power generations. The optimal incremental cost of all generators is 8.752 \$/MWh. And the corresponding power generations are: 200MW, 232.5MW, 81.12MW, 266.3MW, and 81.12MW, respectively. Likewise, the similar dynamics are exhibited in the power generations. The generator power output are presented in Fig. 19. And the power balance is validated in Fig. 20. The power generation and power loss are: 881.67MW and 31.67MW, respectively.

Case Study 5: With Different Convergence Constants

It's noticed that different convergence constant ε has different effect on convergence speed of consensus algorithm. And it's been discussed that a relatively larger convergence constant causes a better convergence solution. However, a very large convergence constant will cause the

optimization to be unstable. Three different convergence constants are presented and compared with $\varepsilon = 5e-4$.

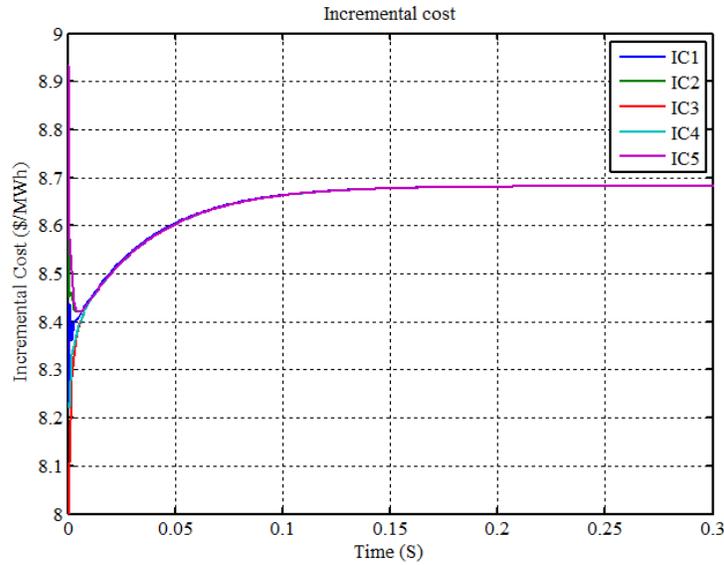


Fig. 21. Case study 5 incremental cost of five generators with $\varepsilon = 1e-4$.

Fig. shows the incremental cost of five generators with $\varepsilon = 1e-4$. It's shown that with a smaller convergence constant, the consensus algorithm can still obtain the optimal solution. However, it takes more than 0.2s to achieve the optimal point.

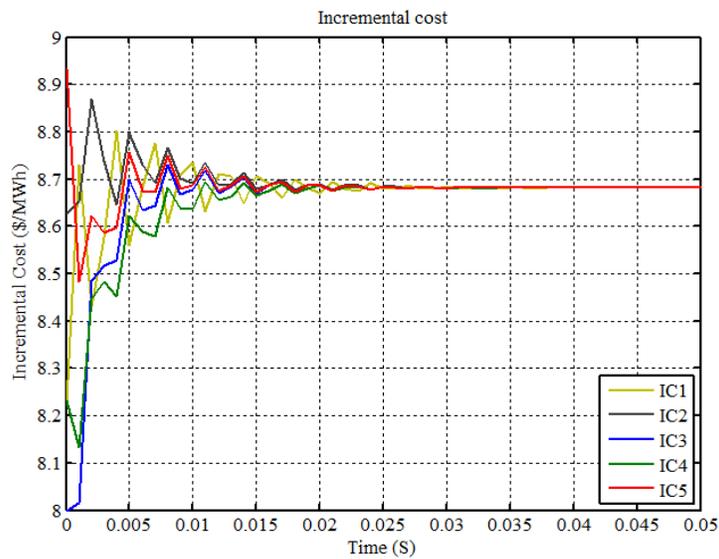


Fig. 22. Case study 5 incremental cost of five generators with $\varepsilon = 10e-4$.

When the convergence constant is increased to $10e-4$, it takes less time for the generator to achieve the consensus point. However, the oscillation of incremental cost becomes larger as the constant goes up.

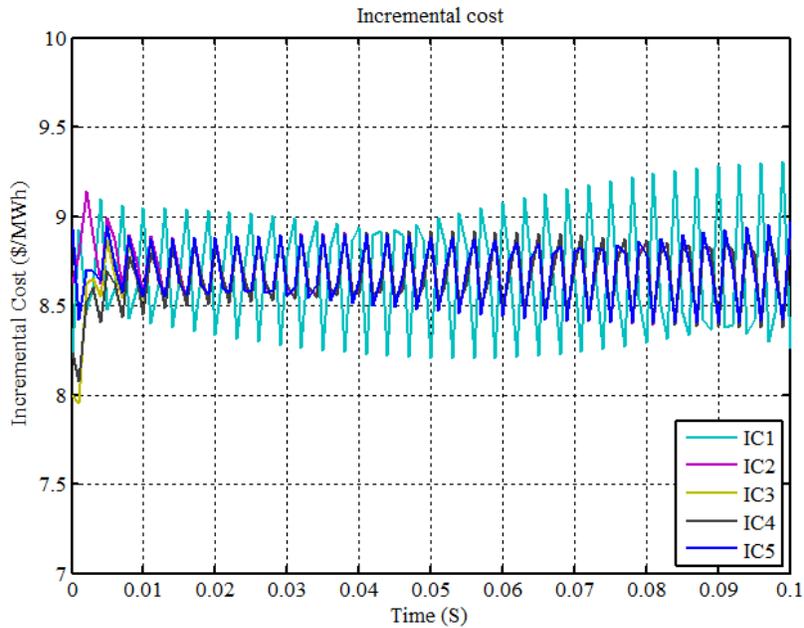


Fig. 23. Case study 5 incremental cost of five generators with $\varepsilon = 16e-4$.

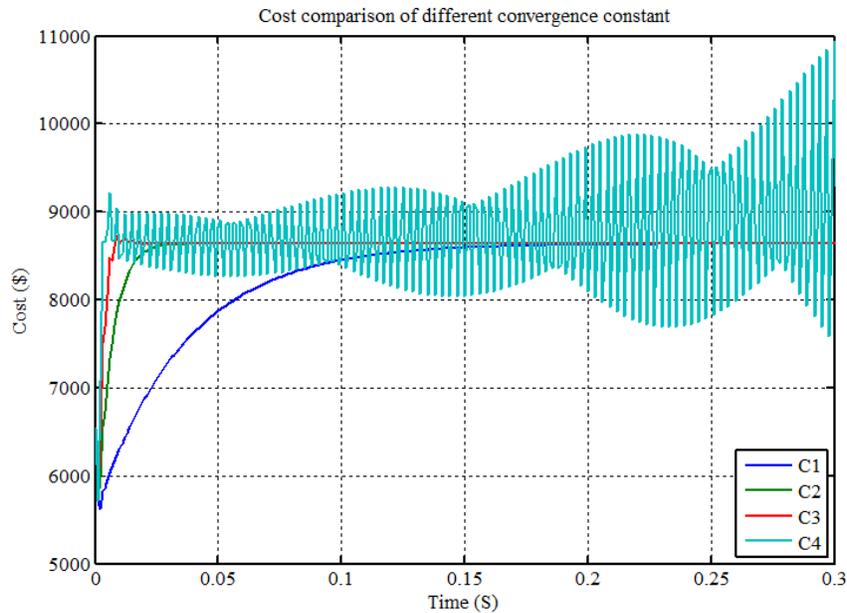


Fig. 24. Case study 5 cost comparison of four different convergence constants.

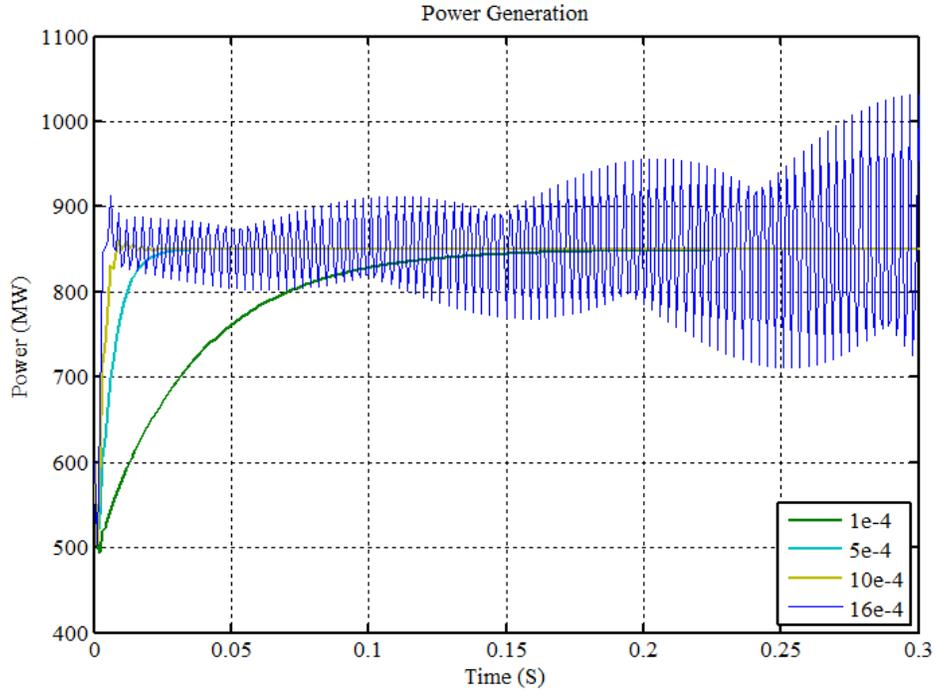


Fig. 25. Case study 5 power comparison of four different convergence constants.

When convergence constant ε increases to $16e-4s$, the oscillation becomes larger and larger that the incremental cost goes unstable.

By comparing the generation costs and total power generations under four different convergence constants, it can be concluded that a larger convergence constant will lead to a faster convergence. However, a larger convergence constant will increase the oscillation. And it may cause the system to be unstable.

5.3 Comparison with Conventional Methods

In this section, the performance of proposed consensus algorithm is compared with conventional EDP solutions. Lambda iteration and particle swarm optimization (PSO) are chosen as examples to compare with consensus-based distributed algorithm.

First of all, these two methods are described in the following.

Lambda iteration method

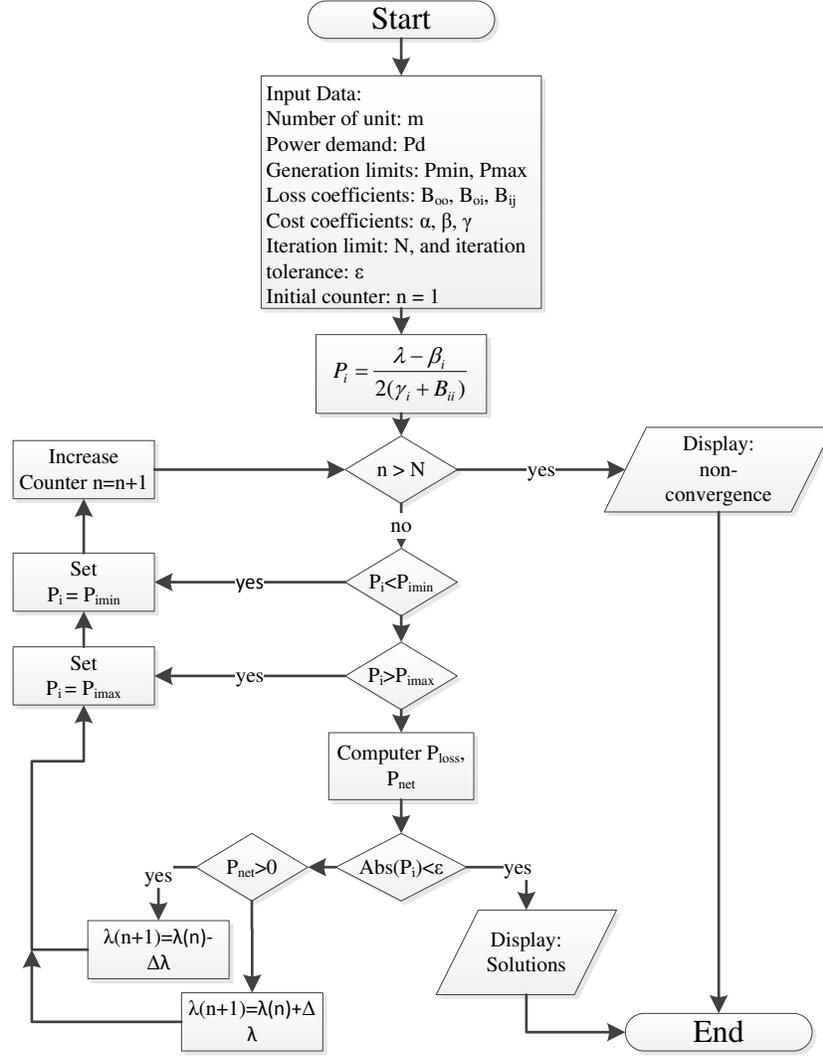


Fig. 26. Flow chart of lambda iteration EDP method.

For the optimal dispatch, the incremental costs of all generators are equal, i. e.:

$$\frac{\partial C_1}{\partial P_1} = \frac{\partial C_2}{\partial P_2} = \dots = \frac{\partial C_m}{\partial P_m} \quad (42)$$

And lambda is equal to:

$$\frac{\partial C_i}{\partial P_i} = \lambda \quad (43)$$

where m is the number of power generators.

The processes of lambda iteration can be summarized as follows [8].

1. Initialization

Input data: number of plants, power demand, generator limits, cost coefficients, iteration number and tolerance.

2. Start counter.

3. Calculate power value for each unit using equation (44).

$$P_i = \frac{\lambda - \beta_i}{2(\gamma_i + B_{ii})} \quad (44)$$

4. Check if iteration limit is exceeded. If yes, display non-convergence and stop. Else, go to step 5.

5. Check if power of generator is less than limit. If yes, set power to lower limit, increase counter and go to step 4. Else, go to step 7.

6. Check if power of generator is more than limit. If yes, set power to upper limit, increase counter and go to step 4. Else, go to step 7.

7. Sum up power for all generators and calculate the power loss using equation (34).

8. Calculate the net power from equation (45).

$$P_{net} = \sum_{i=1}^m P_i - P_D - P_{loss} \quad (45)$$

where P_D , P_{loss} are power demand and power loss, respectively.

9. If absolute value for net power is less than the tolerance value, display calculated power, incremental cost and stop.

10. If net power is greater than zero, reduce the value of the incremental cost, increase counter and go to step 4. Else, increase the value of the incremental cost, increase counter, and go to step 4.

The flow chart of lambda iteration process is shown in Fig. 26.

Particle Swarm Optimization (PSO)

The main procedure of PSO method is shown below.

1. Specify the lower and upper bound generation power of each unit, and calculate F_{max} and F_{min} . Initialize randomly the individuals of the population according to the limit of each unit including individual dimensions, searching points, and velocities. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints. F_{max} and F_{min} are maximum and minimum generation costs among all units in the initial population.
2. For each individual P_g of the population, employ the B coefficients loss formula to calculate the transmission loss P_L .
3. Calculate the evaluation value of each individual P_g in the population using the evaluation function defined by equation (46).

$$f = \frac{1}{F_{cost} + P_{pbc}} \quad (46)$$

where

$$F_{cost} = 1 + abs \frac{(\sum_{i=1}^n F_i(P_i) - F_{min})}{F_{max} - F_{min}}$$

$$P_{pbc} = 1 + (\sum_{i=1}^n P_i - P_D - P_L)$$

4. Compare each individual's evaluation value with its $pbest$. The best evaluation value among the $pbests$ is denoted as $gbest$.
5. Modify the member velocity v of each individual P_{gi} according to (47)

$$v_{id}^{(t+1)} = w \cdot v_i^{(t)} + c_1 \cdot rand() \cdot (pbest_{id} - P_{gid}^{(t)}) + c_2 \cdot rand() \cdot (gbest_d - P_{gid}^{(t)}) \quad (47)$$

$$i = 1, \dots, n. d = 1, \dots, m$$

where n is the population size, m is the number of units, and w value is set in equation (48).

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times iter \quad (48)$$

where $iter_{\max}$ is the maximum number of iterations, and $iter$ is the current number of iterations.

6. If $v_{id}^{(t+1)} > V_d^{\max}$, then $v_{id}^{(t+1)} = V_d^{\max}$. If $v_{id}^{(t+1)} < V_d^{\min}$, then $v_{id}^{(t+1)} = V_d^{\min}$.

7. Modify the member position of individual P_{gi} according to equation (49)

$$Pg_{id}^{(t+1)} = Pg_{id}^{(t)} + v_{id}^{(t+1)} \quad (49)$$

$Pg_{id}^{(t+1)}$ must satisfy the constraints, such as generation limits, ramp rate limits, etc. If $Pg_{id}^{(t+1)}$ violates the constraints, then $Pg_{id}^{(t+1)}$ must be modified toward the near value of the feasible solution.

8. If the evaluation value of each individual is better than the previous $pbest$, the current value is set to be $pbest$. If the best $pbest$ is better than $gbest$, the value is set to be $gbest$.

9. If the number of iterations reaches the maximum, then go to step 10. Otherwise, go to step 2.

10. The individual that generates the latest $gbest$ is the optimal generation power of each nit with the minimum total generation cost.

The scenario in case study 2 is used for comparison. In this case study, the generator's constraints and transmission line loss are considered for a more practical situation. For example, the generator should satisfy its operation constraints including operation limits, UR/DR rates, and prohibited zones.

TABLE 4
Lambda iteration parameters

Name	Value
Iteration limit	2000
Iteration tolerance	0.01

TABLE 5
Particle swarm optimization parameters

Name	Value
Number of population	100
Iteration limit	2000
Number of members in a particle	5
Acceleration constant	2
Max. inertia weight factor	0.9
Min. inertia weight factor	0.4
Initial power generations	[100 200 100 100 100]

Some of the parameters of lambda iteration and PSO methods are presented in the Table 4 and 5. The results of incremental cost and total cost are listed in the following figures. The incremental costs of consensus algorithm and lambda iteration are compared in the figure 27.

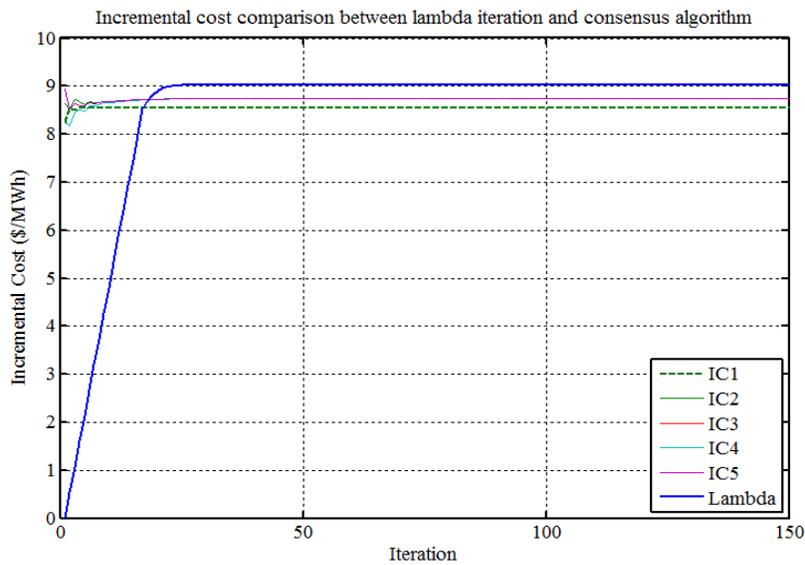


Fig. 27. Incremental cost comparison between lambda iteration and consensus algorithm.

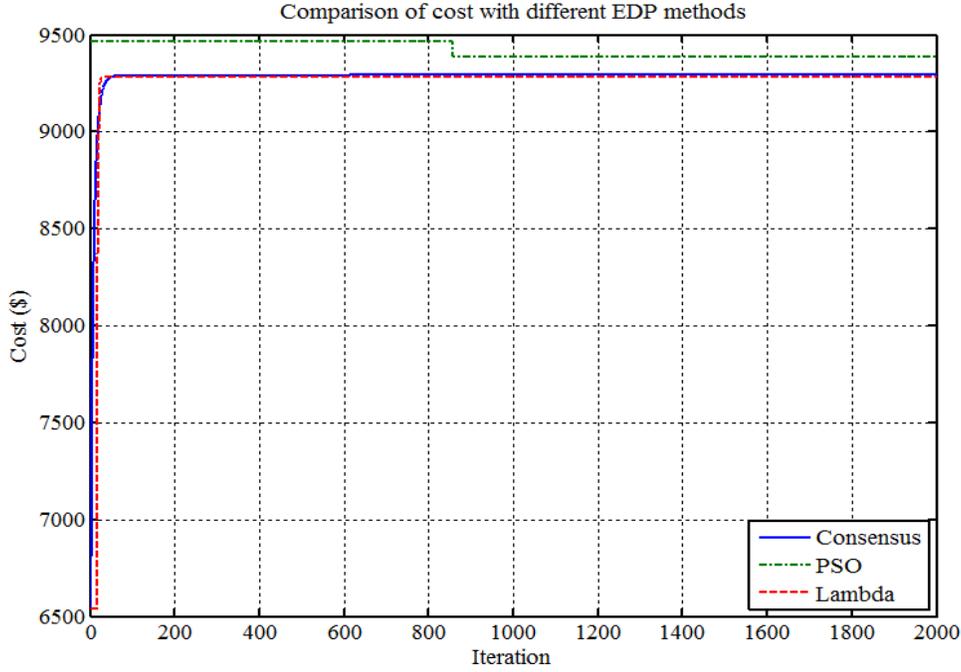


Fig. 28. Total cost between lambda iteration, PSO method and consensus algorithm.

There are several differences between lambda iteration method and consensus algorithm. First of all, there is a system controller that is responsible for all the calculations. Whereas, all the computations are done by individual generator in the consensus algorithm. Secondly, the total power generations and the estimation of lambda are both global information in lambda iteration method. The system controller needs to collect the power generation from each generator, and also send lambda to each generator. However, in consensus algorithm, no global information is needed. To be more specific, both the optimal incremental cost, and power mismatch between demand and generations are estimated by each generator using local information. Thirdly, there is no communication among generators. There are bidirectional communications between the system controller and individual generators. Thus, the communication burden on the system controller will increase. However, in consensus algorithm, the communication is spread among all generators.

Since the incremental cost of first generator is limited at 8.544\$/MWh. The incremental costs of the other four generators are 8.752\$/MWh. While the incremental cost using lambda iteration is 8.978\$/MWh. In terms of iterations, the consensus algorithm requires fewer iterations to reach the optimal point than lambda iteration method.

In terms of total cost, consensus algorithm has similar cost compared to lambda iteration. PSO has the largest total cost among three methods. The costs are listed in the following table.

TABLE 6
Cost comparison of three methods

Method	Cost (\$)
Consensus	9294.5
PSO	9378.1
Lambda	9280.6

It's noticed that PSO method has the largest generation cost among three methods. Lambda iteration method has the smallest generation cost among three methods. The percentage differences of consensus and PSO compared with lambda iteration are: 0.16% and 1.05%, respectively. The consensus has a better convergence solution than PSO method.

And it needs more iterations for PSO to reach optimal point due to its premature convergence. Such a long iteration process may be improved by increasing the population size. However, increasing the population size may greatly increase the computational requirement. Overall, the proposed consensus algorithm has a smaller incremental cost and fewer generation cost than lambda iteration and PSO method.

CHAPTER SIX

SIMULATION TESTS

6.1 PSCAD Simulation Platform

Power Systems Computer Aided Design (PSCAD) is a powerful and flexible graphical user interface to the world-renowned, EMTDC electromagnetic transient simulation engine [24]. PSCAD enables the user to schematically construct a circuit, run a simulation, analyze the results, and manage the data in a completely integrated, graphical environment. PSCAD comes with a library of pre-programmed and tested simulation models, ranging from passive elements and control functions, to more complex systems, such as electric machines, transmission lines and cables. If a required model does not exist, users can construct a module using existing models. The following are some common models found in PSCAD master library:

- Resistors, inductors, capacitors
- Transformers, transmission line, cables.
- Current and voltage sources
- Switches and breakers
- Protection and relays
- Diodes, thyristors, and GTOs
- AC and DC machines, governors, and exciters.
- Meters and measuring functions
- HVDC, SVC, FACTS, Wind source, and turbines.

PSCAD and its simulation engine EMTDC have been developed for about 30 years. And it's one the most powerful tool to simulate and analyze power system.

The applications of PSCAD simulation can be found in power system [46-47], power electronics [50-51], renewable energy [48-49], etc. The main function of PSCAD is simulation of power system in time domain and frequency domain. It also can be used in harmonic research of AC system, analysis of transient torque, the starting of HVDC system and HVDC commutation. For AC/DC system, it can simulate for the electromagnetic transient process of a series or parallel multi-terminal transmission system [52].

6.2 IEEE 14 Bus System

In order to validate the effectiveness of proposed consensus algorithm, a practical power system circuit is constructed in PSCAD. The IEEE 14 bus system is selected as the test circuit to validate the proposed consensus algorithm. The IEEE 14 bus test case represents a portion of the American Electric Power System as of February, 1962. The IEEE 14 bus system has the same generation units as our model. It also has similar generation power capacity as our model. In this model, line constraints are not considered. Transmission line loss is also negligible compared with the power generation. Five power generations are in bus 1, 2, 3, 6, 8. The locations of the five generations can be modified if a different scenario is required. Power load are distributed among different buses. The total power demand of all loads is 850MW. The topology of IEEE 14 bus system is provided in Fig. 29. In order to simplify the simulation, the synchronous compensator is replaced by the power generations. The dynamics of the power generators are not considered in this model. Therefore, the generator is simulated using power generation sources. The reactive power of the IEEE 14 bus system is not analyzed in this model. There are three transformers in this system that are located in bus 4, 6, and 7. The rated apparent power of the system is 100MVA. In practice, all generators all have power generation limits. However, the generation limits are not considered in order to simplify the process of consensus algorithm.

The IEEE 14 bus system is the power layer of the consensus algorithm. There are also communication layer and consensus controller layer. The IEEE 14 bus circuit is modeled in a subsystem. And the communication network is simulated in another subsystem that models the communication among the power generations. The consensus algorithms are implemented in the controller layer that produces the power generation commands. The power generations are connected by both power lines and communication links.

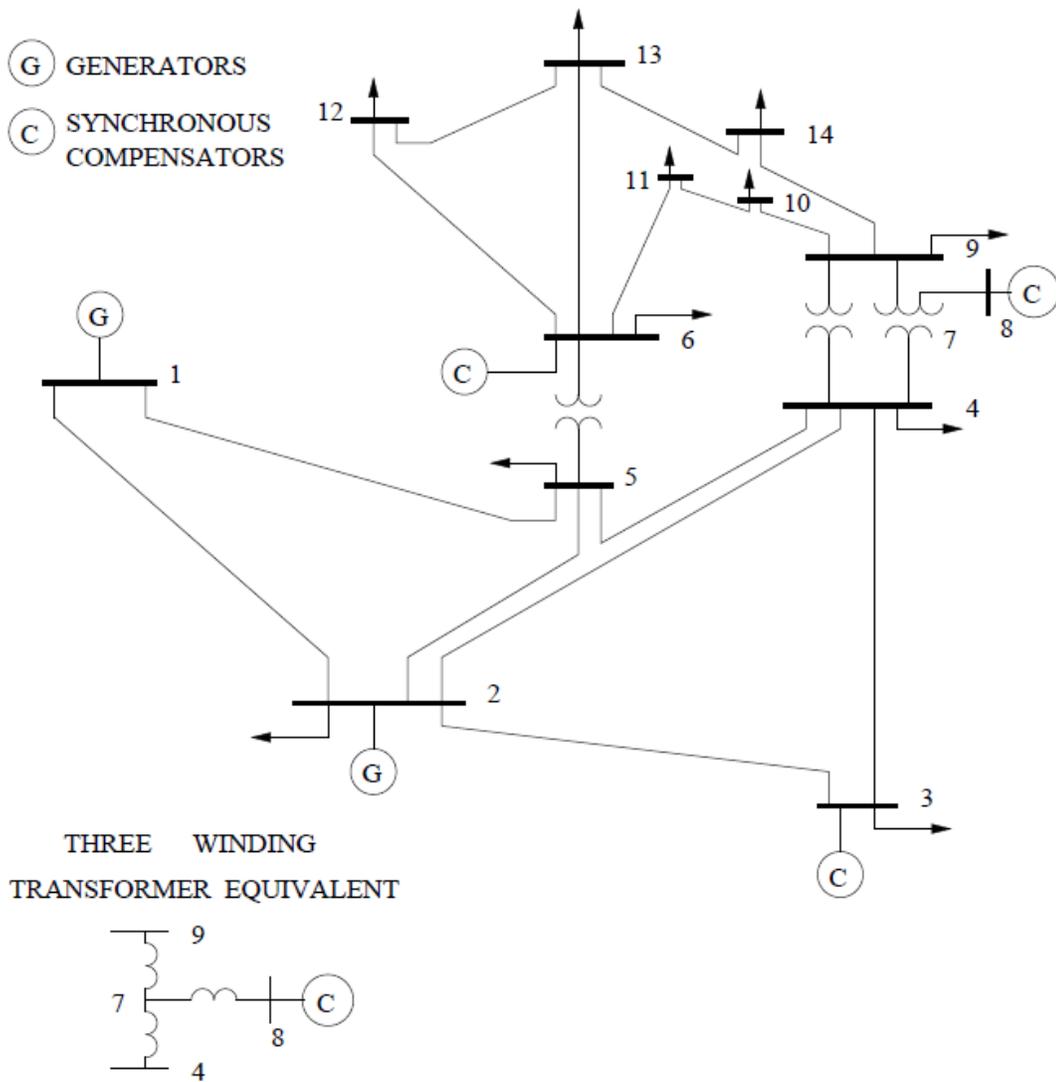


Fig. 29. IEEE 14 bus test system.

The parameters of the IEEE 14 bus system are presented in the following tables. The line data of IEEE 14 bus system is shown in Table 7.

TABLE 7
Line data of IEEE 14 bus system

From Bus	To Bus	Resistance (p.u.)	Reactance (p.u.)	Line charging (p.u.)
1	2	0.01938	0.05917	0.0528
1	5	0.05403	0.22304	0.0492
2	3	0.04699	0.19797	0.0438
2	4	0.05811	0.17632	0.0374
2	5	0.05695	0.17388	0.034
3	4	0.06701	0.17103	0.0346
4	5	0.01335	0.04211	0.0128
4	7	0	0.20912	0
4	9	0	0.55618	0
5	6	0	0.25202	0
6	11	0.09498	0.1989	0
6	12	0.12291	0.25581	0
6	13	0.06615	0.13027	0
7	8	0	0.17615	0
7	9	0	0.1101	0
9	10	0.03181	0.0845	0
9	14	0.12711	0.27038	0
10	11	0.08205	0.19207	0
12	13	0.22092	0.19988	0
13	14	0.17093	0.34802	0

The cost coefficients of five generators and transformer tap setting data are shown as follows.

TABLE 8
Bus data – ieee 14 bus system

<i>Bus number</i>	Magnitude (p.u.)	Phase angle (p.u.)
1	1.06	0
2	1.045	0
3	1.01	0
4	1	0
5	1	0
6	1	0
7	1	0
8	1	0
9	1	0
10	1	0
11	1	0
12	1	0
13	1	0
14	1	0

TABLE 9
Cost coefficients of generators

<i>Gen.</i>	α_i	β_i	γ_i
1	561	7.92	0.00156
2	310	7.85	0.00194
3	78	7.97	0.00482
4	561	7.92	0.00156
5	78	7.97	0.00482

TABLE 10

Transformer tap setting – ieeec 14 bus system

<i>From bus</i>	<i>To bus</i>	<i>Tap setting value (p.u.)</i>
4	7	0.978
4	9	0.969
5	6	0.932

6.3 Simulation Results

Simulation results are shown in this section. For this model, the case study scenario 1 is used in order to evaluate the consensus algorithm. Power generations and incremental cost are presented in the following. Power balance is also validated. The PSCAD simulation results are also compared with the numerical studies in order to validate the effectiveness of the consensus algorithm.

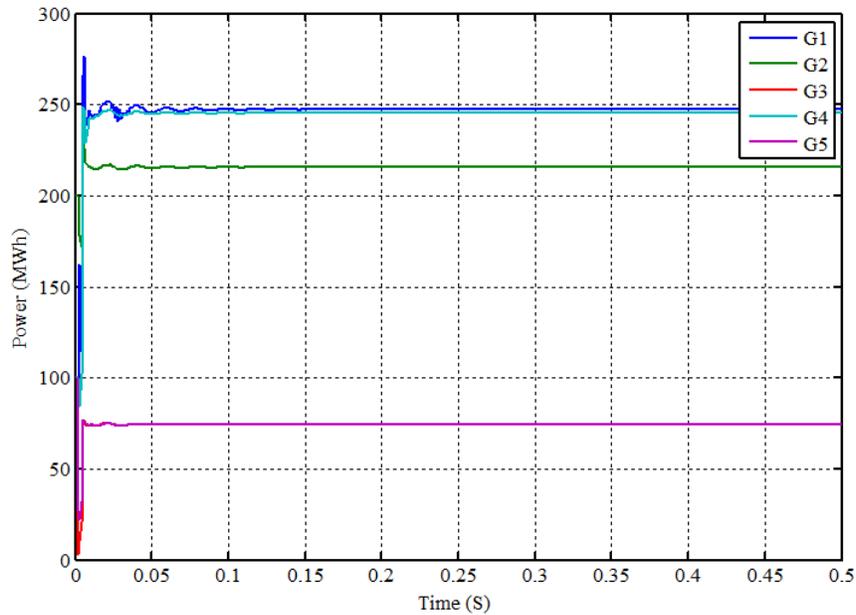


Fig. 30. Power output of five generators.

The corresponding power generations of five generators are: 247.4MW, 215.5MW, 74.3MW, 245.3MW, and 74.3MW, respectively. The total power generation is 856.8MW. It's slightly higher than the power demand due to the small value of transmission loss as shown in the power balance figure.

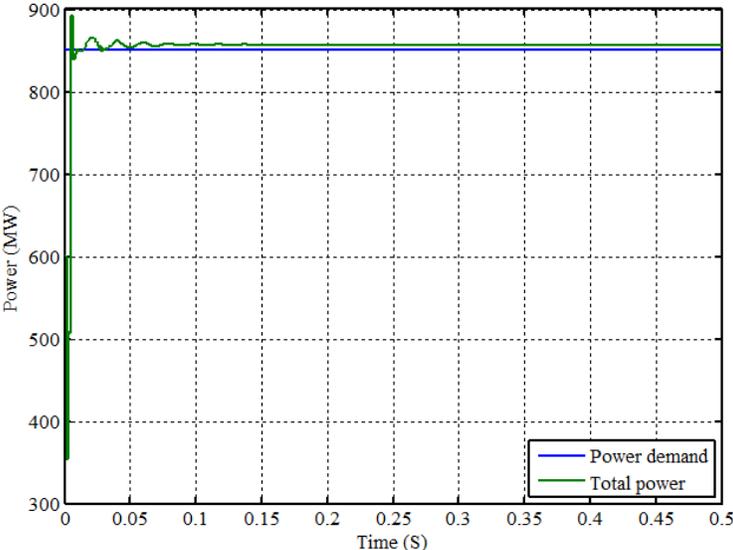


Fig. 31. Power generation and power demand.

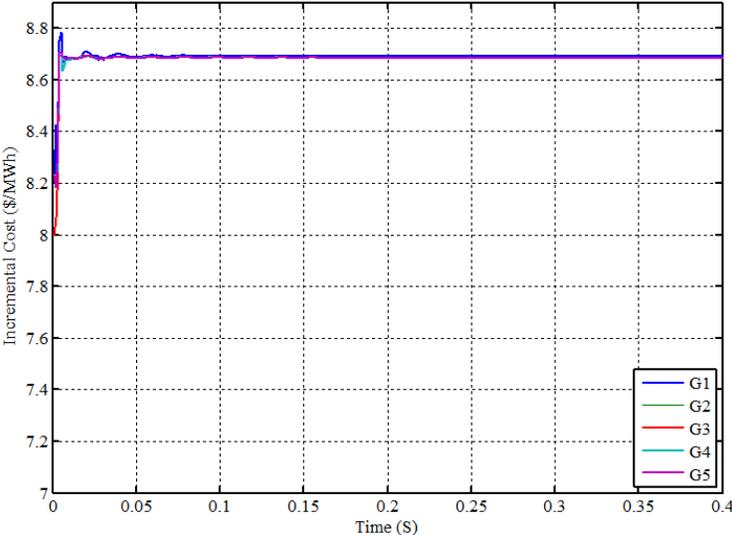


Fig. 32. Incremental cost of five generators.

The power generation of all generators is plotted in Fig. 30. The results are very close to the ones in Matlab simulation. The incremental costs of all generators are: 8.686\$/MWh, 8.682\$/MWh, 8.682\$/MWh, 8.682\$/MWh and 8.682\$/MWh, respectively. The total generation cost is compared with numerical study in the following figure.

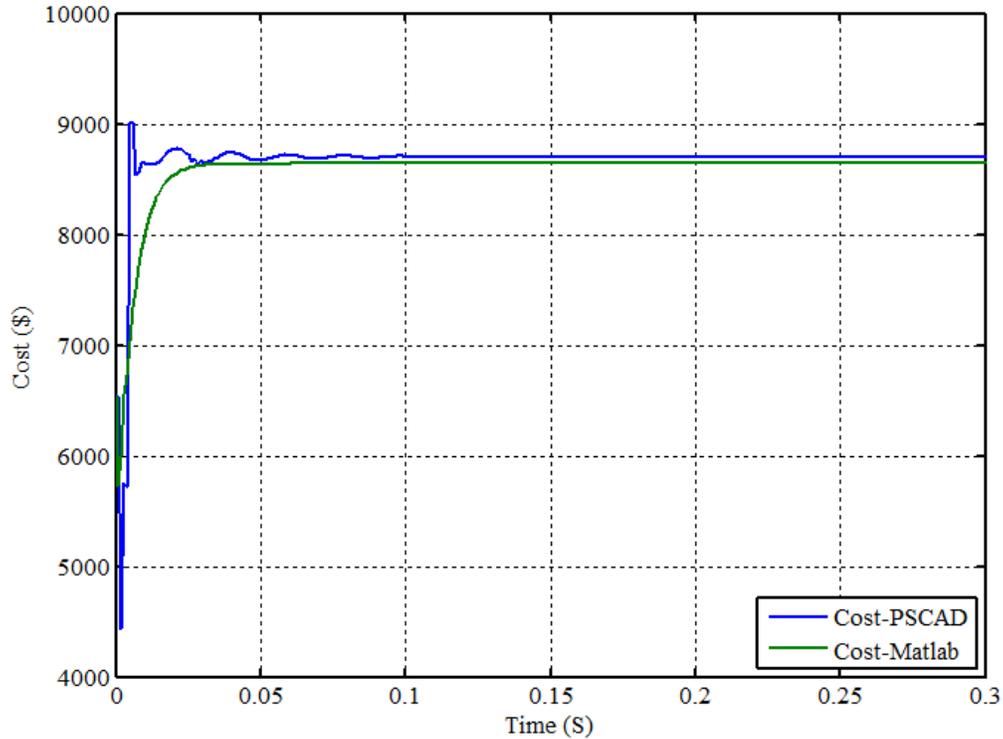


Fig. 33. Total cost of five generators.

It's noted that there is slightly difference between the two generation costs in PSCAD environment and Matlab simulation. To be more specific, the total generation cost are 8700\$ and 8660\$, respectively. Their percentage difference is 0.46%, which is acceptable.

CHAPTER SEVEN

CONCLUSION AND FUTURE WORK

7.1 Conclusion

It's becoming complex and expensive for the centralized controller to solve the economic dispatch problem in smart grids. Therefore, a consensus based distributed algorithm is proposed in this work to solve economic dispatch problem (EDP) in a smart grid. Basic graph theory and consensus algorithm are introduced and their applications are also discussed. The convex cost function with comprehensive constraints is explained in the definition of the EDP. Consensus algorithm is employed among generators to obtain the power mismatch in a distributed manner. Different from conventional centralized algorithm, the locally estimated power mismatch is used to calculate the power generation of each generator. The mismatch power is used as a feedback for each generator to adjust its power generation. Meanwhile, the incremental cost of each generator is selected as the consensus variable. The incremental costs will converge to a common value eventually as required by incremental cost criterion. The effectiveness of the proposed consensus algorithm is evaluated by different case studies. Power constraints, communication topology, and generator dynamic are playing an important role in the performance of the consensus algorithm. Their effects on convergence of proposed algorithm are analyzed. It's observed that different communication topologies have different convergence speeds for consensus algorithm. By comparing with conventional algorithms, such as lambda iteration and particle swarm optimization, it's found that consensus algorithm has a high percentage of achieving the global optimization compared with lambda iteration method. And it also has a smaller generation cost compared to particle swarm optimization. These comparisons are based on numerical models in Matlab/Simulink. The Matlab model contains communication layer, power layer, and distributed

controller layer. Communication network is modeled in the communication layer. The power network which includes power generators is modeled in the power layer. The consensus algorithm is implemented in the distributed controller layer. There are both communication links and power connections between power generators. PSCAD simulation model is also built up to verify the proposed consensus algorithm. The IEEE 14 bus system is used as the model to implement the consensus algorithm. The PSCAD model has the similar results compared to the numerical study. It's concluded that the consensus algorithm works adequately for the economic dispatch problem in smart grid.

7.2 Future Work

The scenario simulated in PSCAD is assumed to be without generator constraints. Transmission line loss is not taken into account in this model. Although the consensus algorithm works successfully without generator constraints or transmission line loss, a more practical situation should be included in future work. Therefore, generator constraints and transmission line loss should be considered in the PSCAD model to observe the effectiveness of the consensus algorithm.

Since the PSCAD model is still a purely simulation model, a real device can be included in the future. For example, the power hardware-in-the-loop (PHIL) can be used to include the hardware and analyze the consensus algorithm. The generator dynamic could be represented by using a synchronous generator. A more complex power system can also be modeled using real time simulation tools.

In terms of convergence, the effect of convergence rate on the performance of proposed consensus algorithm should be examined. For example, the effect of size of power units on the convergence rate of consensus algorithm should be examined. The convergence results should

also be examined whether the results are the global optimization. More communication topologies should be examined to test the effectiveness of consensus algorithm.

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BIOGRAPHICAL SKETCH

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