THESIS – TI185401

COOPERATIVE GAME THEORY BY CONSIDERING UNCERTAINTY IN ELECTRICITY MASTER PLAN DEVELOPMENT

WIWIT MARTA PANGESTY PUTRI
02411850020003

Supervisor
Dr. Eng. Erwin Widodo, ST., M.Eng.
Prof. Shi-Woei Lin

Department of Industrial and Systems Engineering
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WIWIT MARTA PANGESTY PUTRI
NRP: 02411850020003

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Approved by:
Supervisor:

1. Dr. Eng. Erwin Widodo, ST., M.Eng. ....
   NIP: 197405171999031002
2. Prof. Shi-Woei Lin ....

Head of Industrial and Systems Engineering Department
Faculty of Industrial Technology and Systems Engineering

KEMENTERIAN PENDIDIKAN DAN KEBUDAYAAN
INSTITUT TEKNOLOGI SEPULUH NOPEMBER
FAKULTAS TEKNOLOGI INDUSTRI DAN REKAYASA SISTEM
DEPARTEMEN
TEKNIK SISTEM DAN INDUSTRI

Nurhadi Siswanto, S.T., M.S.I.E., Ph.D
NIP: 197005231996011001

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M10801822

Thesis Advisor:Shi-Woei Lin

碩士學位論文指導教授推薦書

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Department： Department of Industrial Management

Student's Name: Wiwit Marta Pangesty Putri

Thesis title: Cooperative Game Theory by Considering Uncertainty in Electricity Master Plan Development

This is to certify that the thesis submitted by the student named above, has been written under my supervision. I hereby approve this thesis to be applied for examination.

Advisor:Shi-Woei Lin

Co-advisor:

Advisor's Signature: Shi-Woei Lin

Date: 2020 / 06 / 19 (yyyy/mm/dd)

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M10801822
Thesis Advisor:Shi-Woei Lin

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Department:Department of Industrial Management

Student's Name:Wiwit Marta Pangesty Putri

Thesis Title:

Cooperative Game Theory by Considering Uncertainty in Electricity Master Plan Development

This is to certify that the dissertation submitted by the student named above, is qualified and approved by the Examination Committee.

Degree Examination Committee

Members' Signatures: Shi-Woei Lin

Ruey-Huei Yeh

Kung-Jeng Wang

Advisor: Shi-Woei Lin

Program Director's Signature:

Department/Institute Chairman's Signature:

Date: 2020 / 06 / 19 (yyyy/mm/dd)

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AUTHENTICITY STATEMENT SHEET

I, the undersigned below:

Name : Wiwit Marta Pangesty Putri

NRP : 02411850020003

Study program: Master Degree in Industrial and Systems Engineering, ITS

State that thesis with the title

"COOPERATIVE GAME THEORY BY CONSIDERING UNCERTAINTY IN ELECTRICITY MASTER PLAN DEVELOPMENT"

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Wiwit Marta Pangesty Putri

NRP. 02411850020003

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METODE TEORI PERMAINAN KOOPERATIF DENGAN MEMPERTIMBANGKAN KETIDAKPASTIAN PADA PENGEMBANGAN RENCANA INDUK KELISTRIKAN

Nama	: Wiwit Marta Pangesty Putri
NRP	: 02411850020003
Pembimbing	: Dr. Eng. Erwin Widodo, ST., M.Eng. Prof. Shi-Woei Lin

ABSTRAK

Pemodelan ketidakpastian melalui operasi stokastik dalam masalah *economic dispatch* dapat memberikan formulasi yang lebih baik, khususnya pada masalah pengambilan keputusan di dunia nyata. Metode ini juga dapat membantu mengurangi biaya penjadwalan sumber daya jika dibandingkan dengan pendekatan deterministik tradisional. Terlebih, keterlibatan energi terbarukan seperti pembangkit listrik tenaga air, dapat mengurangi biaya lebih jauh. Studi ini mengusulkan pemodelan *economic dispatch* dengan pendekatan stokastik (SED) pada pembangkit listrik tenaga air dan uap untuk mencari biaya distribusi listrik minimum. Model teori permainan kooperatif juga diformulasikan untuk menentukan koalisi yang menghasilkan biaya investasi minimum. Namun, karena masalah optimasi stokastik membutuhkan komputasi yang tinggi, maka model SED dalam penelitian ini didekomposisi menjadi dua tahap berdasarkan *Improved Aggregating-Rule-based Stochastic Optimization* (I-ARSO). Pada tahap pertama, sejumlah N skenario Monte Carlo yang mempertimbangkan permintaan daya dan ketersediaan generator digenerasi, kemudian distribusi daya dioptimalkan menggunakan algoritma hibrid berdasarkan optimasi *particle swarm* dan algoritma *artificial fish swarm*. Pada tahap kedua, setiap skenario yang optimal disimulasikan untuk mengevaluasi biaya operasi yang sesungguhnya. Akhirnya, teori permainan kooperatif akan memilih skenario terbaik untuk semua pemain untuk mendapatkan total biaya minimum. Biaya ini meliputi biaya operasi, biaya tetap, biaya variabel, dan biaya investasi serta alokasi biaya.

Kata kunci: *economic dispatch, improved aggregating-rule-based stochastic optimization* (I-ARSO), teori permainan kooperatif, ketidakpastian

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COOPERATIVE GAME THEORY BY CONSIDERING UNCERTAINTY IN ELECTRICITY MASTER PLAN DEVELOPMENT

Name : Wiwit Marta Pangesty Putri
NRP : 02411850020003
Supervisor : Dr. Eng. Erwin Widodo, ST., M.Eng.
Prof. Shi-Woei Lin

ABSTRACT

Modeling uncertain behavior through stochastic operating strategies in economic dispatch problems may better formulate the nature of real-world decisions and help reduce cost in resource scheduling compared to traditional deterministic approaches. Moreover, the involvement of renewable energy, such as hydro power plant, may further reduce the cost. This study proposes a stochastic economic dispatch (SED) model in thermal and hydro power plants to seek minimum dispatch costs. A cooperative game-theoretic model was also formulated to determine the coalition that will lead to minimum investment cost. In particular, for tackling the issue of high computational requirements when the stochastic optimization problem becomes bigger, SED model in this study was decomposed into two stages based on an improved aggregating-rule-based stochastic optimization (I-ARSO) approach. At the first stage, N Monte Carlo scenarios of power demand and generator availability were generated, and then power dispatch was optimized using the hybrid intelligent algorithm based on particle swarm optimization and artificial fish swarm algorithm. At the second stage, each optimal scenario is simulated to evaluate the corresponding expected operating cost. Finally, cooperative game theory will pick the best arrangement for all players to get the minimum total cost, which includes expected operating cost, fixed cost, variable cost, and investment cost as well as the cost allocation.

Keywords: economic dispatch, improved aggregating-rule-based stochastic optimization (I-ARSO), cooperative game theory, uncertainties

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Praise and gratitude writer prays to the Almighty God for the gracious mercy and tremendous blessing that enables the writer to finish the thesis entitled "Cooperative Game Theory by Considering Uncertainty in Electricity Master Plan Development".

On the process of doing this project, I am fully aware that there are many parties involved in supporting this project to be a success. Therefore, I would like to express special appreciation and gratitude to Prof. Shi-Woei Lin, and Dr. Erwin Widodo, as my supervisors who always give great help, advice, and motivation in finishing this project. I also thank Prof. Kung-Jeng Wang and Prof. Ruey Huei Yeh as my committee members who give advice and suggestion to make the best of this thesis. Additionally, thank you to Dr. Nurhadi Siswanto, as the head of Industrial Engineering Department ITS and Prof. Vincent F. Yu as the head of Industrial Management Department NTUST who give easiness in administration of doing the research.

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The writer also fully aware that this report still lacks in several aspects. Therefore, any critics and suggestion regarding this report is welcomed. Hopefully this final report can give benefit to the readers.

Surabaya, August 2020

Wiwit Marta Pangesty Putri

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CHAPTER 1
INTRODUCTION

This chapter explains about the background containing the problem of research object and brief literature review on the solution methodology, objective, scope and outline of this research.

1.1 Background

Electrical energy becomes the most frequently used form of energy because the distribution is highly efficient and has a reasonable cost (Murty, 2017). Not only it affects individual aspect such as communication, entertainment, home, and food, but it also affects the economic aspects of a country. It aligns with what Tumiran (a member of the National Energy Council) said that electricity is a part of national infrastructure that indeed has a role in developing the economy, especially in creating and developing industry (Sihite, 2017). Therefore, electricity will play an important role as an economic driving force in a country. However, there are several requisites to be an economic driving force through electricity. The power supply must be adequate, reliable, and affordable. The challenge is that today we need to sustain the environment using renewable energy sources instead of the other major non-renewable energy sources (coal, oil, gas, and uranium joined coal). Unfortunately, investment in renewable energy faces far more uncertainty than in the big four because of the availability of renewable power sources (Smardon, 2018). In addition, the load demand is also uncertain. Hence, we must fully utilize available resources. One of the ways is by optimizing the operation cost through appropriate power system scheduling. To be able to distribute the power to the consumer effectively, power plant must decide which power plant, how much power supply, and when the power should be distributed. This problem is known as the economic dispatch (ED) problem.

Indonesia also faces the same problem. It has to utilize the available resources to meet the demand reliably. Furthermore, it begins to consider employing more power plants using renewable energy sources. However, the fact tells that the electricity supply in Indonesia is not adequate to meet the demand. According to Mineral (2017), electricity sales growth in most provinces in Indonesia is not accompanied by additional generator capacity. In Kalimantan, electricity sales grow 10.7% per year (as shown in table 1.1), but the additional generator capacity only grows about 1% per year. The data show that the demands in Indonesia are not satisfied, especially in Kalimantan island with a 9.7% growth gap.

Table 1.1 Kalimantan Electricity Sales Realization (TWh)

Sector	2011	2012	2013	2014	2015	2016
Household	3,481	4,012	4,437	4,958	5,238	5,688
Industry	380	410	431	464	493	531
Business	1,272	1,383	1,488	1,630	1,760	1,907
Social	182	205	237	265	295	316
Government Office Building	180	208	233	257	282	303
Street Lighting	157	161	164	167	166	178
Total	**5,652**	**6,379**	**6,990**	**7,741**	**8,234**	**8,923**

Source: (Kementerian Energi dan Sumber Daya Mineral, 2018)

The electrification ratio is a ratio between residents that have gotten electricity, with those who have not gotten the electricity. Figure 1.1 shows the electrification ratio in Indonesia. The target is 97.1% for year 2018, and per Q3 year 2018 the ratio has reached 98.05%. However, there are still some areas that are still far from year 2019’s target, which is 99%, like in Kalimantan, Sulawesi, Nusa Tenggara, Papua, and Maluku.

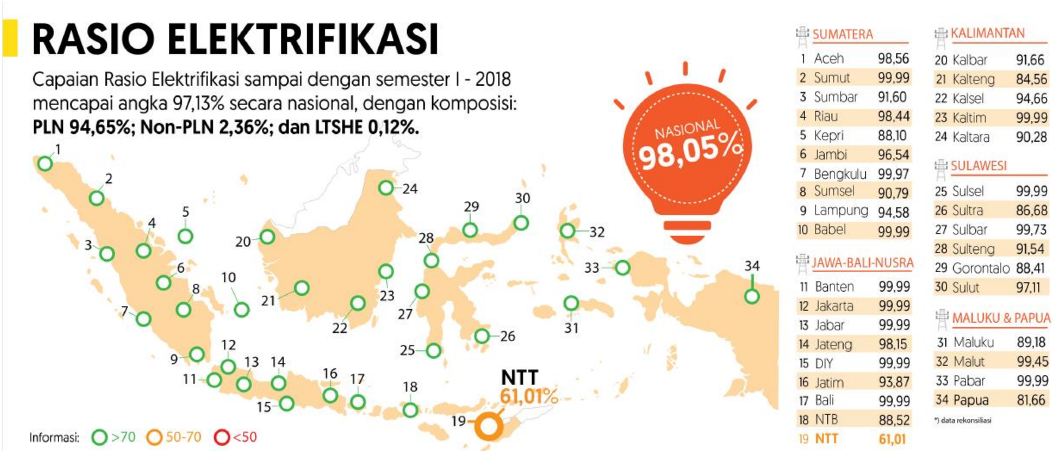

Figure 1.1 Electrification Ratio in Indonesia per 1st semester of 2018

Source: https://www.esdm.go.id

The government has made some programs to overcome the electricity problem, and one of them is the 35.000 MW electricity development program. This program includes generator, transmission network, and substation development. The concern in electricity development is to be able to use renewable energy as the energy source of electricity. It is because according to PwC *et al.* (2018), natural gas reserves will be run out in the next 40 years, assuming that there is no more discovery on the reserves, crude oil in 12-15 years, gas in 30 years, and coal in 60-70 years. Hence the use of natural resources should be utilized optimally to reach the aim. Regarding that matter, Kalimantan master plan is made to increase the capacity of the electricity. There are several choices of energy that PT PLN should consider to satisfy the demand. However, because of the uncertainty of demand and blackout that can happen anytime, PT PLN should choose the appropriate amount of power to be dispatched as well as power plant type and interconnectivity alternatives. This strategy should benefit and accepted by all parties.

Many studies have dealt with ED problem. They focused on developing models to make lower economic dispatch cost under various circumstances like storage and renewable energy and also improving calculation time from the previous research (Du, Grijalva and Harley, 2015; Yildiran and Tacer, 2015; Tang, Member and Jain, 2016; Srikantha and Kundur, 2017; Widodo, 2017; Faria *et al.*, 2018). Several methods have been done to deal with ED problem such as metaheuristic: particle swarm optimization (PSO) (Singh and Kumar, 2015), differential evolution (Biswas *et al.*, 2018), imperialist competitive algorithm (Hazi, Rosmaliati and Misbahuddin, 2014), game theory (Zolezzi and Rudnick, 2002; Du, Grijalva and Harley, 2015), mixed integer linear programming (Fioriti, Giglioli and Poli, 2016), and many more. For ED problem, what's more important is the fast and efficient solution. It means we pursue the most efficient method to obtain proper dispatching methods within a short time. Thus several studies tried to combine different optimization algorithms to form a hybrid intelligent optimization algorithm. This way, it could fully utilize the advantages of various algorithms, and overcome the flaws in a single intelligent optimization algorithm with satisfying results. Sadegheih (2009) and Su *et al.* (2014) found that the hybrid algorithms are superior than the simple ones both in terms of the convergence speed and the accuracy of the optimal solution.

Li et al. (2002) designed widely combined algorithm namely the Artificial Fish Swarm Algorithm (AFSA). This algorithm has shown excellence convergence, but it is not suitable for problem with higher dimensions since it will take long computation time. In this case, PSO solves the problem because it produces higher calculation efficiency and is easier to implement. Even so, it has fewer adjustable parameters and doesn't require the gradient information, thus often resulting in premature solutions that cannot converge to the global optimum (Yuan and Yang, 2019). So, the combination between these two algorithms will complement each other and worth further study.

Today, the problem in ED not only lies in the short calculation time, but also in the uncertainty aspect especially in demand and generator availability uncertainty. Moreover, renewable energy prone to have more variability than fossil fuel. Previously, ED problem was solved by implementing deterministic optimization. This way, we must provide the right amount of reserve margin to cope with load uncertainty. In other word, it ensures limited amount of energy-not-served. However, it must be calibrated with an economical or a probabilistic approach so that it is not producing sub optimal solution with high total cost. To address the problem, stochastic, robust, and interval optimization methodologies have been proposed (Pandzic *et al.*, 2016; Abujarad, Mustafa and Jamian, 2017).

Stochastic optimization (SO) is essential because not only can it estimate the cost more accurately but also enables saving, usually in the range of 0–4% in wide power systems (Niknam, Golestaneh and Malekpour, 2012; Hemmati, Saboori and Saboori, 2016). Moreover, they can reach even 35% in case of the low quality of the forecasts of DO (Quan, Srinivasan and Khosravi, 2016), or 13% for isolated systems with limited storage capacity (Olivares *et al.*, 2015). However, there is tradeoff between solving uncertainty with SO and computation time. To tackle this problem, Fioriti and Poli, (2019a) a two-stage modeling stochastic scenario known as Improved Aggregating-Rule-based Stochastic Optimization (IARSO). It could decompose N scenarios formulation into N deterministic sub problems that led to fewer constraints compared to SO. Thus, resulting in lower computational requirements. So this study propose IARSO combined with the hybrid intelligent algorithm to model stochastic behavior of outage power lines and electrical loads.

We can further decrease the investment cost by implementing collaboration between areas, since they can share information and resources among themselves. By taking advantage of this, it is possible to perform energy management and make decisions based on collaboration (Ni and Ai, 2016). The collaboration allows the agents to utilize transmission lines and resources better (Sore, Rudnick and Zolezzi, 2006), resulting in lower total cost. Cooperation game theory can be utilized to deal such problem and is one of convenient tool to solve cost allocation problems (Zolezzi and Rudnick, 2002). The solution mechanisms behave well in terms of fairness, efficiency, and stability, and qualities required for the correct allocation.

To the best of the author's knowledge, there is still no paper that considers IARSO combined with the hybrid intelligent algorithm combined with game theory method to seek the lowest investment cost. This finding is the main research gap in this work. By doing this research, a further comprehensive idea in terms of analytical models to elicit some beneficial insights on managing electricity costs is proposed. By performing this research, the impact of applying strategies of electricity master plan under uncertainty in Kalimantan Island can be appropriately examined. Thus, power plant managers might have reliable theoretical as well as practical grips prior to making their managerial decision.

1.2 Research Objectives

This game theory and IARSO combined with the hybrid intelligent algorithm reciprocally induce researchers to contribute their ideas to make economic dispatch performs better and better. The works focused on modeling stochastic behavior to decrease economic dispatch costs considering renewable energy, demand, and generator availability uncertainty. Also, it aims to improve calculation time so that operational decisions can be carried in a fast manner. Lastly, it aims to find the strategy and cost allocation of each player in the electricity master plan, so that the outcome can be accepted by all players in the aforementioned circumstances.

1.3 Scopes and Assumption

Here are the scopes and assumptions of this research:

1. The voltage levels for the power plant is 500 kV.
2. The power source is using river flow as a renewable power source and coal.
3. The object under observation is Kalimantan island.
4. The data used in this research is obtained from PT PLN year 2017 and 2018.
5. The planning horizon is from year 2018 until year 2050.
6. The cost of the transmission of the power source to each plant for the interconnection scenario is the same.
7. The demand in each scenario is generated following a particular distribution from historical data

1.4 Research Outlines

The research outline consists of several chapters that will be explained below.

CHAPTER 1 INTRODUCTION

This chapter explains the background of this research, problem formulation that will be solved, objectives to be achieved, benefits, research scope, and the outline that is used in the research.

CHAPTER 2 LITERATURE REVIEW

This chapter explains the theories and fundamental concepts that will become base to do this research as well as to justify the method used in this research. Theories and the basic concept shown in this chapter are got from books, journal, and the previous research align with the problem. A literature review of several related journals will also be shown in this chapter.

CHAPTER 3 RESEARCH METHODOLOGY

This chapter explains about step by step process to conduct this research presented in the form of a flowchart. A detailed explanation in each step, as well as a mathematical model, will also be shown here.

CHAPTER 4 DATA PROCESSING

This chapter consists of model validation and data processing. Proposed method is validated with the data in journal paper and historical data. Then, the data containing investment cost, operational cost, and fix cost in electricity of Kalimantan Island are collected to generate the value of the payoff matrix. After that, game theory modeling is made. Finally, the best winning power plant coalition is chosen based on the available scenario using cooperative game theory method.

CHAPTER 5 ANALYSIS

This chapter explains about data analysis and interpretation from chapter 4. All of the scenarios generated will be analyzed and interpreted. The best scenario will be recommended for the decision-maker. Comparison of several cost allocation method among players will also be presented.

CHAPTER 6 CONCLUSION AND RECOMMENDATION

This chapter explains the conclusion got from the research that answers the objective of the research. It also contains guidance and reference for the decision-maker of the electricity department in Kalimantan Island. Also, there are suggestions for future research.

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CHAPTER 2
LITERATURE REVIEW

This chapter presents literature review of three prominent aspects of the theses: economic dispatch, game theory, and stochastic modeling. The related research which previously done will also be reviewed in this chapter as the background of the theses.

2.1 Economic Dispatch

Economic Dispatch (ED) is the process of allocating generators to the demand unit such that the constraints are met, and the energy needed is minimized (Farsi *et al.*, 2015). For the interconnected power system, economic dispatch is the process to find total real and reactive power schedules of each interconnected power plant by allocating generators so that the total energy is minimized and the constraints are met. Farsi *et al.* (2015) state that economic dispatch practices can be divided into two stages namely unit commitment and unit dispatch. Unit commitment takes place before real-time operation comes first. It is a process of determining the set of generating units that will be available for dispatch as long as the reactive power vary within certain allowable limits. Unit dispatch occurs in real time. It determines the amount of generation needed from each available generating units.

Beside this main objective of finding the optimum output for each set of available generators, there are other objectives in doing the economic dispatch. It can maximize the total profit by generating the lowest possible total cost and schedule the available generating units output. So it will be able to satisfy uncertain load demand and system constraints while able to minimize operating cost at the same time. This problem is usually solved by deterministic optimization (DO), assuming a perfect forecast of the load and the available renewable production (Fioriti and Poli, 2019b). While in reality, the load demand is uncertain, thus relevant uncertainties are handled by ensuring an adequate amount of generating reserve. However, it can underestimate reliability aspects and produce sub-optimal solutions with high final costs if they are not calibrated with uncertainty. So, stochastic, robust, and interval optimization methodologies have been proposed to cope with uncertainty.

The solution methodologies to ED problem, especially in unit commitment can be broadly grouped into two namely conventional (classical) methods and intelligent methods (Reddy, Reddy and Pradesh, 2013). Each methods has its own advantages and disadvantages. In most cases solved by classical methods, although they are quite flexible and easy to add some constraints, the capability to solve real-world large-scale power system problems are limited. So, they are computationally expensive for solution of a large system. They also have poor convergence and may get stuck at local optimum. While intelligent methods, in most cases, can find the global optimum solution. Moreover, they possess learning ability and fast. However, large dimensionality and the choice of training methodology are some disadvantages of intelligent methods. Table 2.1 below shows the advantages and disadvantages of each methods.

Table 2.1 Advantages and Disadvantages of UC Solution Methods

Author (Year)		**Method**	**Advantage(s)**	**Disadvantage(s)**
Mori and Matsuzaki (2001)	Classical	Priority List	• Good with functional inequality constraints • Good with high constrained problems	• Very slow convergence • Difficult for inequality constraints
Lowery (1966)	Classical	Dynamic Programming	• Converge fast • Handle inequality constraints very well • Flexible formulation	• Convergence characteristics are sensitive to the initial conditions and may even fail to converge due to inappropriate initial conditions • The optimal solution will twnd to float over the limit
Zhuang, Galiana and Member (1988)	Classical	Lagrange Relaxation	• Good for infeasible or divergent starting points • Good for ill conditioned and divergent systems	• Difficulties in obtaining solution of lagrangian programming in large dimension • Difficult in obtaining the convergence of approximating programming cycle
Arthur (1983)	Classical	Branch and Bound	• Efficient, fast and accurate compared to other known linear programming techniques	• Infeasible solution if step size is chosen improperly
Dillon *et al.* (1978)	Classical	Integer and Mixed Integer	• Flexible and accurate modeling capabilities	• Computational complexity • Takes a long time
Zhuang and Galiana (1990)	Intelligent	Simulated Annealing	• Guarantees finding an optimal solution • Easy to code	• Takes a long time to converge • Big T takes a lot of iterations while small T might not adequate before reaching a true optimum
Huang and Huang (1997)	Intelligent	Genetic Algorithms	• Handle the integer or discrete variables • Adaptable to change	• The solution is not guaranteed to be optimum • Deterioration in execution time and the quality of the solution when chromosome length increase
Sisworahardjo and El-Keib (2002)	Intelligent	Ant Colony Optimization	• Inherent parallelism • Rapid discovery of good solution	• Difficult theoretical analysis • Changes in probability distribution per iteration • Uncertain convergence time
Yuan *et al.* (2009)	Intelligent	Particle Swarm Optimization	• High calculation efficiency • Easy to Implement, simple concept	• Has fewer adjustable parameters, thus often resulting in premature solutions that cannot converge to the global optimum

Author (Year)	Method	Advantage(s)	Disadvantage(s)
		• Capable to solve large-scale non convex optimization • Deal with non differentiable and non convex objective functions • Balance in global and local exploration	• Weak local search ability
Li et al. (2002)	Artificial Fish Swarm Algorithm	• Excellence convergence • Good local searching ability	• Not suitable for problems with high dimensions • High time complexity

A research that comes from Singh and Kumar (2015), tried to solve economic dispatch problem to reduce total generation cost and emission minimization using moderate random search PSO. The result shown that MRPSO enhances the ability of particles to explore in the search spaces more effectively and increases their convergence rates.

While Biswas *et al.* (2018) use summation based multi objective differential evolution superiority of feasible solutions (SMODE-SF) and multi objective evolutionary algorithm based on decomposition superiority of feasible solutions (MOEA/D-SF). They consider network security constraints together with constraints on generator capability and prohibited operating zones (POZs). The uncertainty is modeled by utilizing probability of solar power being excess of the scheduled power, and expectation of solar PV power above scheduled power.

For ED problem, what's more important is the fast and efficient solution (Yuan and Yang, 2019). It means we pursue the most efficient method to obtain proper dispatching methods within a short time. Thus several studies tried to combine different optimization algorithms to form a hybrid intelligent optimization algorithm. Lee *et al.* (2008) tried to combine the ant colony algorithm with the genetic algorithm, while Shieh, Kuo and Chiang (2011) tried to combine the Particle Swarm Optimization (PSO) algorithm with the simulated annealing algorithm. This way, it could fully utilize the advantages of various algorithms, and overcome the flaws in a single intelligent optimization algorithm with satisfying results. Sadegheih (2009) and Su *et al.* (2014) found that the hybrid algorithms are superior than the simple ones both in terms of the convergence speed and the accuracy of the optimal solution. Looking at table 2.1, the advantage and disadvantage of PSO and AFSA algorithm seems to complement each other. The combination of those two algorithm should show excellence convergence and higher calculation efficiency with an easy implementation. Therefore, we combined the two algorithms to obtain better results.

2.2 Game Theory

A definition of game theory comes from Leyton-Brown and Shoham (2008), game theory is the study of interaction among independent, self-interested agents. Self-interested agent does not mean that it will always cause harm, but it means that each agent has his own description of which states of the world he likes and the party will make an/some action(s) to make the goal happens. So in game theory method, there are more than one players (decision maker) involved, and each player has its own goal and strategy. The strategy of one player can affect the strategy and decision of another player. According to Osborne (2000), game-theoretic modeling begins with some aspects of interest between the decision makers and then expressed to a model, including the situations that are relevant to the circumstances of the interest.

Du, Grijalva and Harley (2015) had proposed a paper with the title of *Game-Theoretic Formulation of Power Dispatch With Guaranteed Convergence and Prioritized Best Response*. He proposed an ED model as potential games and solved the potential-game formulated ED in a distributed manner by incorporating renewable generators. He used game theory with Cournot dynamics with inertia and spatial adaptive play algorithm to solve the problem. The result shows that computational time decrease. In the same year, Yildiran and Tacer (2015) also solved the economic dispatch problem with game theory approach. It analyzed the economic dispatch of real power generation for the entire system. However, he did not include renewable generators in the system. The result shown that game theory model yield lower cost compared to genetic algorithm and lagrange function. Tang, Member and Jain (2016) have proposed a paper with the title of *Dynamic Economic Dispatch Game: The Value of Storage*. He made a DED model in which each generator has its own electricity storage device. So in this paper, he wanted to see how the agents react to the new business model as the impact of incorporating electricity storage in the market. Srikantha and Kundur (2017) had proposed a paper with the title of *A Game Theoretic Approach to Real-Time Robust Distributed Generation Dispatch*. They aimed to make a distributed dispatch strategy that is highly scalable and robust with strong static and dynamic properties as validated by theoretical and simulation analyses. It is designed to coordinate distributed generators effectively.

Over the years smart grid concept has encouraged researchers to enhance the reliability and reduce the costs of an integrated transmission grid. They study ways of generating power locally in proximity to the customer through combining together loads and distributed generation (DG) in so called microgrids. Thus, there is collaboration between players by sharing information and resources. Pilling, Chang and Luh (2017) study is able to prove that compared to standalone generations, the grids produce lower costs when they collaborate in power exchange regardless of their individual contributions to the power exchange coalition.

Zolezzi and Rudnick (2002) had proposed a paper with the title of *Transmission Cost Allocation by Cooperative Games and Coalition Formation*. They aimed to present a method to allocate charges among users of a transmission system, either in the existing network or expanding one using cooperative game theory and coalitional formation. The result has shown that the presented method allows solving the transmission cost allocation problem and solve the allocation of expansion cost, without any methodological change.

Sore, Rudnick and Zolezzi (2006) had proposed a paper with the title of *Definition of an Efficient Transmission System Using Cooperative Games Theory*. They aimed to find a transmission trunk system (TTS) making use of the cooperative games theory characteristics that allow finding a minimum network that satisfies the system demand at the lowest possible cost. The methodology used is using cooperative game theory. The results succeed in distributing the cost to the agent and government. Another literature on game theory method to solve economic dispatch problem is also presented in table 2.2 below.

Table 2.2 Previous study on game theory method

No	Title	Method	Research Aim	Result	Drawback
1	Hong and Kim (2016)	Game theory based approach	Maximum utilization of resources to minimize the transmission cost	Efficiently utilize the surplus power	No proper pricing medium is adapted to calculate the cost
2	Ni and Ai (2016)	Coalition game theory using Shapley value	Optimal cost including all expenditures	Expenditure reduction up to 34.7%	No proper pricing policy of the micro grids
3	Pilling, Chang and Luh (2017)	Cooperative game theory using Shapley value	Minimize daily generation cost	Reduction in generation up to 202,397 MWh at a cost of $3,977,685 during summer and 159,755MWh at a cost of $2,918,003 during winter	Increase in complexity

4	Karavas, Arvanitis and Papadakis (2017)	Game theory using Nash equilibrium	Meeting load demand with power scarcity	7% higher efficiency and 1.62% reduction in annual cost	Overlooked the system complexity

2.3 Stochastic Modeling

Initially, deterministic optimization is able to solve economic dispatch problem. By implementing deterministic optimization, the problem formulation only need low computational need and low amount of variables. However, we must provide the right amount of reserve margin to cope with load uncertainty. In other word, it ensures limited amount of energy-not-served. However, it must be calibrated with an economical or a probabilistic approach so that it is not producing sub optimal solution with high total cost. To address the problem, stochastic, robust, and interval optimization methodologies have been proposed (Pandzic *et al.*, 2016; Abujarad, Mustafa and Jamian, 2017).

Stochastic processes are collections of random variables defined on the same probability space. The random variables are not usually independent, but some dependency relationships can typically be expressed using conditional expectation or probability (Lanchier, 1998). It models a random phenomenon that evolves over time. A mathematical expression is used to model the relationship between the fixed past and the random future. It means that measurement of the random future depends on random past.

In practice, especially in power system, stochastic variants of grid operations models are not due to their computational difficulty (Papavasiliou and Oren, 2013). It is mainly because of the number of samples required to achieve high-quality, robust solutions (Safta *et al.*, 2017). Despite all the hard work, stochastic optimization (SO) seems able to find the cheapest solutions (Abujarad, Mustafa and Jamian, 2017), because it can capture uncertainties more accurately. For example, through forecast based on the probability density function (PDF) of the forecasting errors. Several studies have utilized stochastic concept to solve economic dispatch problem.

Shaabani, Reza and Kouhanjani (2017) propose a time-varying acceleration particle swarm optimization (TVAC-PSO) combined with Monte Carlo simulations to solve multi-objective optimization of economic emission dispatch. In this study, the uncertain behavior is defined as expected value from Monte Carlo simulation. Once the power and heat values and their associated variance and probability density function (PDF) are obtained. This value will become the input to the next step. The result shows that TVAC-PSO method has good convergence properties and the convergence speed and the simulation time of this method is appropriate.

Solving the same problem, Pourghasem *et al.* (2019) proposed stochastic model along with capacity outage probability table (COPT), exchange market algorithm (EMA) and the weighted sum method. Stochastic problem is addressed through implementation of scenario generation and scenario reduction approaches. First, forecast errors of load demand and wind power are taken as random variables with specific probability density functions (PDF). Afterwards, roulette wheel mechanism is used to generate scenarios. Then, simultaneous backward method is used as scenario reduction technique. This method can produce greater achievements for longer dispatching horizons.

Another research conducted by Fioriti, Giglioli and Poli (2016) had proven that Monte Carlo simulations and mixed integer programming can address short-term operation of a hybrid mini grid problem under load and renewable production uncertainty. By using this approach, the daily fuel cost of the stochastic formulation is 1.4% lower than for the deterministic optimization.

From these previous studies, computation time, uncertainty as well as renewable energy aspect become important in recent years. There is tradeoff between solving uncertainty with stochastic optimization and computation time. It is because a sharp increase in computational time (more than 100 times with respect to the robust approach) was observed in stochastic optimization (Morales-España, Lorca and de Weerdt, 2018). Meanwhile, the dispatch problem must be done quickly, so that the generator will be able to generate the power reliably. Fioriti and Poli (2019) found that Improved Aggregating-Rule-based Stochastic Optimization (IARSO) is at least 34 times faster and 0.1–2.6% cheaper than SO. Hence, IARSO combined with the hybrid intelligent algorithm (PSO and AFSA) is proposed to cope with both uncertainty and computation time.

The Improved ARSO (I-ARSO) approach is based on a novel cost-based aggregating rule (Fioriti and Poli, 2019b). It is a novel approach based on standard ARSO methodology because of a cost-based rule for the aggregator in the second stage shown in figure 2.2 below. Monte Carlo simulation generates a given number of scenarios of load and renewable production profiles. Then deterministic optimization is conducted to get the optimal dispatching that minimizes the operating costs in each scenario independently. The result will then be simulated to evaluate the corresponding expected operating costs. Finally, the final dispatching is selected according to the cost-based aggregator.

In the initialization stage, the proposed operating strategy begins by forecasting the load and the available renewable production. The PDF of forecasting error is used to draw N scenarios, consisting of a possible power profile of the load and the available renewable production.

In the first stage, for every scenario generated in the initialization phase, the optimal deterministic scheduling of the system will be calculated by a standard deterministic optimization technique and solved by solver such as in (Fioriti, Giglioli and Poli, 2016), (Schulze and McKinnon, 2016) and (Pandzic *et al.*, 2016). The objective function is to minimize overall electricity costs.

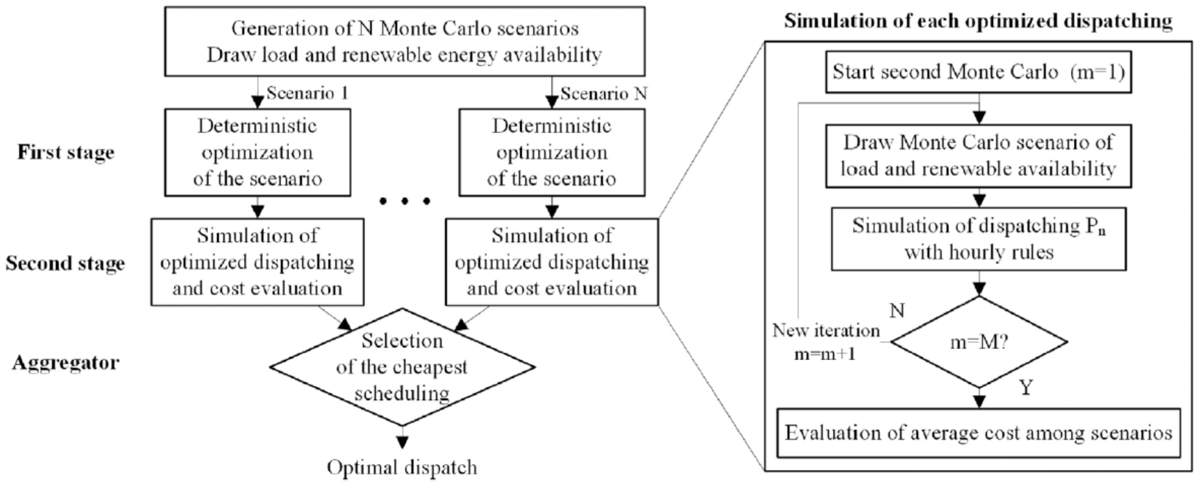


Figure 2.1 Improved Aggregating-Rule-based Optimization

In the second stage, since the results in the first stage only relevant to the corresponding scenario, they do not represent the uncertainty. In this case, the result will be in the expected operating cost (EOC) of the whole stochastic process. Therefore, in M different Monte Carlo scenarios (having occurrence probability πm) will be generated to simulate real-time operations. Finally, the final dispatching with the lowest EOC is selected according to cost-based aggregator.

2.4 Related Research

To find out the latest research developments, reviews of previous researches were conducted to determine the position and differences of current research. The research on the ED topic with various methods and similar methods used in various problems are compared and analyzed. There are plenty of research papers discussing about solving economic dispatch problem. The summary of related researches are shown in table 2.3 and 2.4 below.

Table 2.3 List of Reviewed Papers

No	Author	Year	Title	Method	Research Aim	Result	Drawback
1	Zolezzi, Juan M.; Rudnick, Hugh	2002	Transmission Cost Allocation by Cooperative Games and Coalition Formation	Cooperative games and coalition formation	To present a method to allocate charges among users of a transmission system, either in existing network or expanding one	The presented a method allows solving the transmission cost allocation problem and solve the allocation of expansion cost, without any methodological change	Handling of dimension of the game, which grows with ratio 2^N, with N being the number of agents.
2	Sore, Francko; Rudnick, Hugh; Zolezzi, Juan	2006	Definition of an Efficient Transmission System Using Cooperative Games Theory	Cooperative game theory	To finds a TTS making use of the cooperative games theory characteristics that allow finding a minimum network that satisfies the system demand at the lowest possible cost.	The modeling of the regulated and private games allows covering 100% of the cost of the respective resulting TTS lines, because the calculation of the Shapley value allows distributing the costs associated to the large coalition	Adding revenue, investment and operational cost to the model
3	Du, Liang & Santiago Grijalva	2015	Game-Theoretic Formulation of Power Dispatch With Guaranteed Convergence and Prioritized Best Response	Game theory, cournot dynamics with inertia and spatial adaptive play algorithm	Model the ED as potential games and solve the potential-game formulated ED in a distributed manner	Present potential-game formulation of the constrained ED problem by incorporating renewable generators	Does not consider cost and profit functions of renewable resources
4	Yildiran, Nezihe & Emin Tacer	2015	Game Theory Approach to Solve Economic Dispatch Problem	Game theory	Analyze the economic dispatch of real power generation for the entire system	Present game theory model to yield lower cost compared to Genetic Algorithm and Lagrange function	Does not consider transmission loss & renewable energy

No	Author	Year	Title	Method	Research Aim	Result	Drawback
5	Singh, Nagendra; Kumar, Yogendra	2015	Multiobjective Economic Load Dispatch Problem Solved by New PSO	Moderate random search PSO	Solve the economic load dispatch problem to reduce the total generation cost of the thermal power plant and deals with environmental emission minimization	MRPSO enhances the ability of particles to explore in the search spaces more effectively and increases their convergence rates.	Does not consider generation, and distribution cost and profit functions
6	Fioriti, Davide; Romano Giglioli; Davide Poli	2016	Short-term Operation of a Hybrid Minigrid under Load and Renewable Production Uncertainty	Monte Carlo simulations and mixed integer programming	Minimizes the sum of fuel costs, load curtailment, and maintenance cost	A proper unit commitment and dispatching method improves the quality of supply while reducing the costs.	Does not accommodate long term simulations, the computation time is long.
7	Tang, Wenyuan	2016	Dynamic Economic Dispatch Game: The Value of Storage	Game theory	Make a DED model in which each generator has its own electricity storage device	Present simplified model DED model incorporatig the value of storage	Extend to a larger class of scenarios, and generalize the results to the stochastic setting.
8	Srikantha, Pirathayini	2017	A Game Theoretic Approach to Real-Time Robust Distributed Generation Dispatch	Game theory	Make a distributed dispatch strategy that is highly scalable and robust with strong static and dynamic properties as validated by theoretical and simulation analyses	Present generation dispatch strategy that can effectively coordinate a large number of distributed generators	Inherent generation variability of DGs.
9	Melati, Alfiyyah Azzah	2017	*Analisa Strategi* Economic Dispatch *dengan Pendekatan* Game Theory *pada Sistem Kelistrikan* Jawa Bali 500kV	Game theory	Minimizing cost of electricity by considering the interest of gas generator and coal generator	Win win solution between coal generator and gas generator has been reached with top-pull strategy for coal generator and take or pay strategy for gas generator	Does not consider transmission losses

No	Author	Year	Title	Method	Research Aim	Result	Drawback
10	Shaabani, Yousef ali et al.	2017	Stochastic multi-objective optimization of combined heat and power economic emission dispatch	Time-varying acceleration particle swarm optimization (TVAC-PSO) combined with monte carlo simulations	Solving economic dispatch and emission reduction problems simultaneously and stochastically	TVAC-PSO method has good convergence properties and the convergence speed and the simulation time of this method is appropriate	• The uncertain bahavior is defined as expected value from Monte Carlo simulation • Optimization based on reliability has not been done
11	Safta, Cosmin	2017	Efficient Uncertainty Quantification in Stochastic Economic Dispatch	PolynomialChaos Expansions (PCEs) approachwith a novel renewable power scenario generation technique based on Karhunen-Lo`eve expansions (KLEs).	Minimize the expected total production and loss-of-load costs	• These representations enable efficient and accurate propagation of uncertainties in model parameters, using sparse quadrature methods. • Reduction in computational cost • Dramatically reduce the computational difficulty of stochastic grid operations problems	Faces the curse-of dimensionality challenge, as the number of samples required by the PCE method exhibits a near exponential dependence on the number of stochastic dimensions.
12	Biswas, Partha P. et al.	2018	Stochastic multi-objective dynamic dispatch of renewable and CHP-based islanded microgrids	Stochastic model along with capacity outage probability table (COPT), exchange market algorithm (EMA) and the weighted sum method	Minimization of both generation cost and emission	• It calculates the expected energy not supplied • By including emission and EENS in economic dispatch problem, greater achievements can be reached for longer dispatching horizons	The approach has not consider robust and opportunity functions and also renewable energy sources and energy storage systems
13	Xiang, Mengyuan et al.	2018	Computing non-stationary (s, S) policies using mixed integer linear programming	MINLP model and a binary search approach	Introduce two new heuristics to compute near-optimal (s , S) policy parameters	Optimality gaps of these models are less than 0.3% of the optimal policy cost and computational times are reasonable	

No	Author	Year	Title	Method	Research Aim	Result	Drawback
14	Fioriti, Davide; Davide Poli	2019	A novel stochastic method to dispatch micro grids using Monte Carlo scenarios	Improved Aggregating-Rule-based Stochastic Optimization (IARSO)	Minimize the operating costs related to fuel, maintenance, load curtailment, and the equivalent cost of discharging the battery more than the preset final value	• Interesting savings in operational costs, up to 5%, • Sharply reduces the computational requirements, even more than 5–100 times with respect to traditional stochastic approaches • The solutions with I-ARSO turned out to be more resilient than the standard SO, both in terms of computational requirements and optimality of the solution	None declared
15	Pourghasem, Pouya et al.	2019	Multiobjective economic-environmental power dispatch with stochastic wind-solar-small hydro power	Summation based multiobjective differential evolution superiority of feasible solutions (SMODE-SF) and multiobjective evolutionary algorithm based on decomposition superiority of feasible solutions (MOEA/D-SF)	Determine output of each generating unit so that fuel cost and amount of emission are minimized while the electrical demand is provided by more reliable units and operational constraints are met	Considers network security constraints together with constraints on generator capability and prohibited operating zones (POZs)	Making stochastic behavior become deterministic because it uses expected value

Table 2.4 Research Position

No	Author	Title	Year	Journal Name	Method	Economic dispatch			Uncertainty	Renewable Energy
						Generation	Transmission	Distribution		

No	Author	Title	Year	Journal Name	Method	Economic dispatch			Uncertainty	Renewable Energy
						Generation	Transmission	Distribution		
1	Zolezzi, Juan M.; Rudnick, Hugh	Transmission Cost Allocation by Cooperative Games and Coalition Formation	2002	IEEE Transactions on Power System	Cooperative games and coalition formation		v			
2	Sore, Franko; Rudnick, Hugh; Zolezzi, Juan	Definition of an Efficient Transmission System Using Cooperative Games Theory	2006	IEEE Transactions on Power System	Cooperative game theory		v			
3	Du, Liang & Santiago Grijalva	Game-Theoretic Formulation of Power Dispatch With Guaranteed Convergence and Prioritized Best Response	2015	IEEE Transactions on Sustainable Energy	Game theory, Cournot dynamics with inertia and spatial adaptive play algorithm	v		v		v
4	Yildiran, Nezihe & Emin Tacer	Game Theory Approach to Solve Economic Dispatch Problem	2015	International Journal of Trade, Economics, and Finance	Game theory		v	v		v
5	Singh, Nagendra; Kumar, Yogendra	Multiobjective Economic Load Dispatch Problem Solved by New PSO	2015	Advances in Electrical Engineering	Moderate random search PSO		v	v		v
6	Fioriti, Davide; Romano Giglioli; Davide Poli	Short-term Operation of a Hybrid Minigrid under Load and Renewable	2016	IEEE 2016 Global Humanitarian Technology Conference	Monte Carlo simulations and mixed integer programming	v			v	v

No	Author	Title	Year	Journal Name	Method	Economic dispatch			Uncertainty	Renewable Energy
						Generation	Transmission	Distribution		
		Production Uncertainty								
7	Tang, Wenyuan	Dynamic Economic Dispatch Game: The Value of Storage	2016	IEEE Transactions on Smart Grid	Game theory	v		v		
8	Srikantha, Pirathayini	A Game Theoretic Approach to Real-Time Robust Distributed Generation Dispatch	2017	IEEE Transactions on Industrial Informatics	Game theory	v	v	v		
9	Davidov, Sreten & Milo's Panto's	Stochastic Assessment of Investment Efficiency in A Power System	2017	Energy	Simulation & cost benefit analysis	v	v		v	
10	Zou, Dexuan	A new global particle swarm optimization for the economic emission dispatch with or without transmission losses	2017	Energy Conversion and Management	Global particle swarm optimization		v	v	v	
11	Shaabani, Yousef ali et al.	Stochastic multi-objective optimization of combined heat and power economic emission dispatch	2017	Energy	Time-varying acceleration particle swarm optimization (TVAC-PSO) combined with monte carlo simulations	v			v	

No	Author	Title	Year	Journal Name	Method	Economic dispatch			Uncertainty	Renewable Energy
						Generation	Transmission	Distribution		
12	Safta, Cosmin	Efficient Uncertainty Quantification in Stochastic Economic Dispatch	2017	IEEE Transaction on Power Systems	Improved Aggregating-Rule-based Stochastic Optimization (IARSO)	v			v	v
13	Biswas, Partha P. et al.	Stochastic multi-objective dynamic dispatch of renewable and CHP-based islanded microgrids	2018	Electric Power Systems Research	MINLP model and a binary search approach	v			v	v
14	Fioriti, Davide; Davide Poli	A novel stochastic method to dispatch micro grids using Monte Carlo scenarios	2019	Electric Power Systems Research	Stochastic model along with capacity outage probability table (COPT), exchange market algorithm (EMA) and the weighted sum method	v			v	v
15	Pourghasem, Pouya et al.	Multiobjective economic-environmental power dispatch with stochastic wind-solar-small hydro power	2019		Summation based multiobjective differential evolution superiority of feasible solutions (SMODE-SF) and multiobjective evolutionary algorithm based on decomposition superiority of feasible solutions (MOEA/D-SF)	v	v		v	v
16	This research				IARSO combined with the hybrid intelligent algorithm (PSO and AFSA) and game	v	v		v	v

No	Author	Title	Year	Journal Name	Method	Economic dispatch			Uncertainty	Renewable Energy
						Generation	Transmission	Distribution		
					theory					

Based on the literature review, game theory mostly applied when handling multi-player economic dispatch problem. Moreover, year published of most of the papers applying game theory as a solution technique indicates that game theory is one of the recent issues on multi-player economic dispatch problem. Most of the papers are concerned about electricity cost minimization. While cost minimization considering renewable energy, uncertainty and investment decision making still lack paper which concerned about especially for hydro power plant. Based on the review on these two perspectives: modeling stochastic behavior of power system using IARSO combined with the hybrid intelligent algorithm (PSO and AFSA) to solve ED problem and utilizing game theory to seek lowest investment cost is keen to state that proposed idea in this work is original and beneficial.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter mainly contains three aspects, which are the research flowchart, materials and methodology to be used in this research and finally model development as well as the steps taken to solve research problem.

3.1 Research Flowchart

In this chapter, the steps taken in conducting study are explained. Figure 3.1 below shows the flowchart of the research.

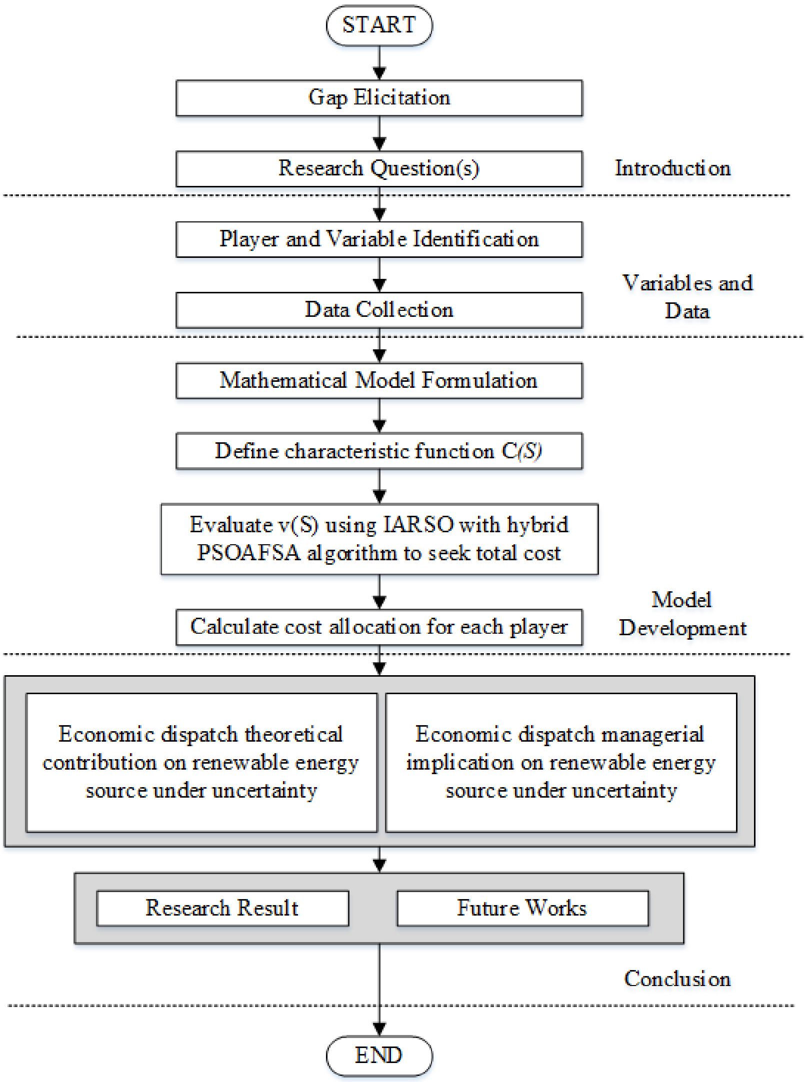


Figure 3.1 Research Flowchart

The study starts with introduction phase. It consists of gap elicitation and building research question. In this phase, the gap is elicited based on the up-to-date studies in economic dispatch under uncertainty and the author's research series about economic dispatch in Kalimantan electricity master plan. In addition, economic dispatch drawbacks also become one of consideration in finding the research gap. Several literature reviews are conducted to search the best method in solving stochastic economic dispatch problem. After that, research question is generated based on the existing condition of the object and the research gap.

The second phase is variables and data identification. This phase identifies the variables, players involved in the study. It also presents the source of data used in the study. Moreover, it presents the scenarios considered in the study. The next phase is model development. This phase presents the mathematical model formulation to solve ED problem and characteristic cost function as the utility for cooperative game theory. Then, I-ARSO approach to model stochastic behavior along with the hybrid intelligent algorithm based on particle swarm optimization and artificial fish swarm algorithm to optimize power dispatch is presented.

The final phase is drawing a conclusion to answers to the research objective. The conclusion is also got from the analysis result of the research. It results in economic dispatch theoretical contribution and managerial implication on renewable energy sources under uncertainty. Moreover, suggestions about the development of future research are given.

3.2 Variables and Data

In this stage, the player and variable is defined. The object under discussion is Kalimantan electricity master plan. It is divided into three areas, namely “Khatulistiwa” system in West Kalimantan (Area-1), “Barito” system in South - Middle Kalimantan (Area-2), and “Mahakam” system in East - North Kalimantan (Area-3) as the electricity system in Kalimantan Island. The players in the game are groups of power plants in area 1, 2, and 3 or the coalition among the players. The coalition consists of S_{12}, S_{23}, and S_{123}. A total of 27 generators in area 1 and 2, and 22 generators in area 3 are modeled in this study. The detailed information can be seen in table 3.1. The list of power plant as well as the variables used in this study are got from *Rencana Usaha Penyediaan Tenaga Listrik (RUPTL) Tahun 2018-2027 PT PLN* (Persero), Interim Report of Kalimantan Electricity Master Plan Development and primary data from the company.

Kalimantan electricity master plan has two system alternatives, namely regional balance and interconnectivity system.

1. Regional Balance System
   Regional balance system is a situation where the electricity needs of a region are met by generators in its own region and do not depend much on the power transfer across region through interconnection transmission lines. With this principle, the need for interconnection transmission between regions will be minimal.
2. Interconnectivity System
   Interconnection system is an electric power system that consists of several generators and several substations (GI) interconnected each other through a transmission line. This system is able to supply the load in its connected area. For example, interconnection of Area 1 and 2 means Area 1 (Khatulistiwa) and Area 2 (Barito) support each other to meet the demand (power will be transferred if needed), while Area 3 (Mahakam) supplies its own region.

Based on the previous research and company's consideration, there are several scenarios that will be considered in this study shown in table 3.1 below.

Table 3.1 Lists of Scenarios

Scenario	**Plant Types**	**System**	**#HPP**		**#TPP**		
			A2	**A3**	**A1**	**A2**	**A3**
1	HPP	Regional balance	1	2	27	26	19
2	TPP	Regional balance	0	0	27	27	22
3	TPP & HPP	Regional balance	0	2	27	27	19
4	HPP& TPP	Regional balance	1	0	27	26	22
5	HPP& TPP	Interconnectivity 1-2	1	2	27	26	19
6	TPP	Interconnectivity 1-2	0	0	27	27	22
7	HPP& TPP	Interconnectivity 2-3	1	2	27	26	19
8	TPP	Interconnectivity 2-3	0	0	27	27	22
9	HPP& TPP	Interconnectivity 1-2-3	1	2	27	26	19
10	TPP	Interconnectivity 1-2-3	0	0	27	27	22

3.3 Model Development

In this stage, we calculate the total demand needed in Kalimantan electricity master plan and generator data as the input to calculate operational cost. In addition, the total investment cost, fix cost and variable cost are also calculated. In order to calculate the operational cost, IARSO with hybrid PSOAFSA algorithm will be utilized. Sub-section 3.3.1 below shows the objective function of the operational cost.

3.3.1 Mathematical Model Formulation

In this phase, the mathematical model of the system is built. The model consists of the objective function, constraint, and cost formulation shown below.

Variables:

$F_{jt}(P_{jt})$ = the cost function of the jth generating unit per hour t (Rp)

P_{jt} = the real output of the jth generating units per hour t (MW)

PD_t = total system demand every hour (MW)

PL_t = total losses that occur in the system (MW)

Parameters:

a_j, b_j, c_j = the cost coefficients of the jth generating unit

N_g = the total number of generators in the power system.

T = the total number of time steps in the power system.

B_{ij} = the jth element of the loss coefficient square matrix

B_{i0} = the ith element of the loss coefficient vector

B_{00} = the loss coefficient constant.

P_j^{min} = minimum power capacity of generator j (MW)

P_j^{max} = maximum power capacity of generator j (MW).

Objective function:

$$F_{cost} = MIN \sum_{t=1}^{T} \sum_{j=1}^{Ng} F_{jt}(P_{jt}) \quad (3.1)$$

Where $F_{jt}(P_{jt})$ is modeled as:

$$F_{jt}(P_{jt}) = a_j P_{jt}^2 + b_j P_{jt} + c_j \quad (3.2)$$

s.t.

$$\sum_{t=1}^{T}\sum_{j=1}^{Ng} P_{jt} = \sum_{t=1}^{T}(PD_t + PL_t) \tag{3.3}$$

$$PL_t = \sum_{j=1}^{N}\sum_{i=1}^{N} P_{jt}B_{ij}P_{it} + \sum_{i=1}^{N} B_{i0}P_{it} + B_{00} \tag{3.4}$$

$$P_j^{min} \leq P_j \leq P_j^{max} \tag{3.5}$$

The objective function is to minimize the generation cost especially the operational cost that is related to fuel consumption in an hourly basis (24 hour). Equation 3.2 elaborate how the cost function is obtained. It is got from the multiplication of cost coefficient of each generating unit with the power to be dispatched. Constraint 3.3 ensures that the demand in each hour is satisfied regardless of the transmission loss occurred. Constraint 3.4 calculates the amount of transmission loss in every hour. While constraint 3.5 contains the generator limit, which is the minimum and maximum amount the generator is allowed to operate.

3.3.2 Defining Characteristic Cost Function

Characteristic function tells how much collective payoff a set of players pay by forming a coalition. Here, the characteristic cost function is defined as:

C(S) = EPC cost + development cost + fix cost + variable cost (3.6)

where EPC cost consists of transmission line cost, installation, coal and ash handling system, switchyard, turbine, FGD, stack and steam generator cost. While development cost consists of land acquisition, site preparation, and consulting service cost. Fix cost consists of employee’s wage, property tax and assurance. Finally, variable cost consists of operational and supply cost.

3.3.3 Utilizing IARSO with Hybrid Intelligent Algorithms (PSO and AFSA)

Here are several core components of IARSO with hybrid intelligent algorithm and (PSO AFSA).

1. The Hybrid Intelligent Algorithm (PSO and AFSA)

According to (Yuan and Yang, 2019), suppose that in a D-dimensional objective search space, there is community made up by N particles, where the i^{th} particle is represented as a D- dimensional vector: $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, i=1, 2, …, N. The “flying” velocity of the ith particle is also a D-dimensional vector, written as: $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$, i=1, 2, …, N. The optimal position found by the ith particle so far is called the individual extremum, written as: $P_{best} = (p_{i1}, p_{i2}, \ldots, p_{iD})$, i=1, 2, …, N. The optimal position found by the entire particle swarm so far is called the global extremum, written as: $G_{best} = (p_{g1}, p_{g2}, \ldots, p_{gD})$.

When these two optimal values are found, the particles will update their velocity and position according to Equations 3.7 and 3.8 below:

$$v_{id} = w * v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 \left(p_{gd} - x_{id}\right) \tag{3.7}$$

$$x_{id} = x_{id} + v_{id} \tag{3.8}$$

where c_1 and c_2 are learning factors, also called the acceleration constants, and r_1 and r_2 are uniform random numbers in the range of [0, 1]. Let i = 1, 2, …, D, and v_{id} be the velocity of the particle

After the above transformation, the position of the particle is updated according to AF_{follow} or AF_{swarm}. The velocity and position after transformation are shown in Equations 3.9 and 3.10 below:

$$v_{id} = w * v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 \left(p_{gd} - x_{id}\right) \tag{3.9}$$

$$x_{id} = \alpha x_{id} + \beta (AF_{follow} \ or \ AF_{swarm}) \tag{3.10}$$

where α and β are the position transformation weights ($\alpha + \beta = 1$). The weights here are mainly to avoid reaching premature solutions or local optimal solutions of the particle swarm. The value of a is an increasing function to the changing weight. The pseudocode and detailed steps of this algorithm is shown in table 3.2 below.

2. Monte Carlo

Monte Carlo simulation is a technique used to understand the impact of risk and uncertainty in financial, project management, cost, and other forecasting models (Shaabani, Seifi and Kouhanjani, 2017). Whenever a forecasting model is made, the best thing we can do is estimate the expected value based on historical data. Moreover, there will always be some inherent uncertainty and risk because it’s an estimate of an unknown value. When there is already a range of values as a result, how likely the resulting outcomes will be accurately estimated.

In a Monte Carlo simulation, a random value is generated based on the range of estimates. The result of the model is recorded, and the process is repeated hundreds or thousands of times randomly. The result is random based on random input. These results are used to describe the likelihood or probability of the model.

3. IARSO

IARSO methodologies decompose the SO problem into N deterministic sub problems. This methodology consists of two stages. The first stage is optimizing each sub problem and using an aggregating rule to select the optimal scheduling of resources among the previous solutions. While the second stage evaluates the EOCs over the whole stochastic process.

In the novel Improved Aggregating-Rule-based Stochastic Optimization (IARSO), standard DO technique calculates the optimal deterministic scheduling of the system for every load and RES scenario drawn in the initialization phase. However, because a great number of generators must be scheduled on an hourly basis, metaheuristic algorithm will be applied so that the calculation time will be faster. Hybrid Intelligent Algorithms (PSO and AFSA) will be used as the method to solve the economic dispatch problem since it will lead to excellent stability, better convergence, and quick calculation time (Yuan and Yang, 2019). Figure 3.2 below shows the proposed method.

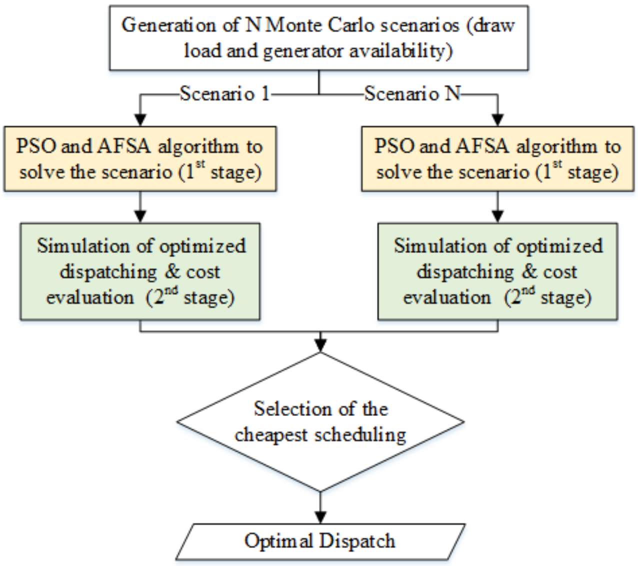


Figure 3.2 IARSO combined with Hybrid Intelligent Algorithms (PSO & AFSA)

In the initialization stage, the proposed operating strategy begins by forecasting the load and the available renewable production in hourly basis. The procedure of demand scenario generations begins with a distribution fitting. Distribution fitting is a process to define a distribution type of data. Minitab 19.1.1 (64-bit) is used to obtain these parameters. The PDF of forecasting error is used to draw N scenarios, consisting of a possible power profile of the load and generator availability. For the generator availability generation, the availabilities are determined from available historical data on the outages in a power network. A uniformly distributed random number is defined in s-th scenario, which holds a value between a = 0 and b = 1, as shown in equation 3.11 below:

$$RU_s = U(b, a) \tag{3.11}$$

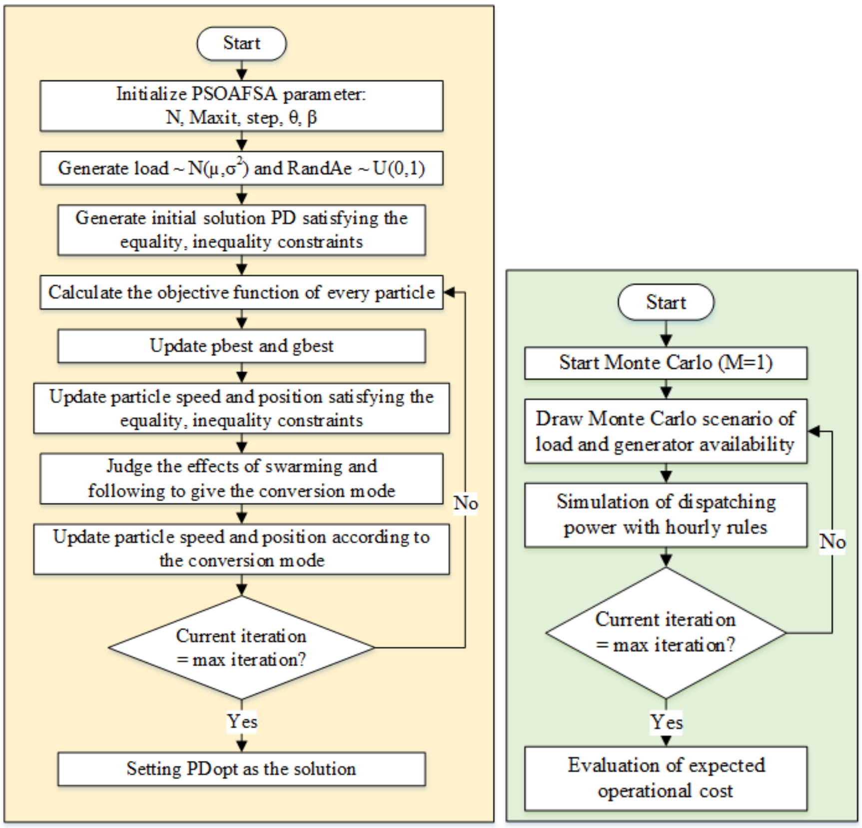
Equation 3.12 define the status of the generator. It is set to 1 (in service) when the random value is less than the e-th element's availability Ae; otherwise, is set to 0 (outage). While equation 3.13 shows the availability calculation.

$$Generator\ status \begin{cases} 1\ (in\ service), & RU_s \leq A_e \\ 0 (outage), & RU_s > A_e \end{cases} \tag{3.12}$$

$$A_e = \frac{m_e}{m_e + r_e} \tag{3.13}$$

where the A_e represents e-th element's availability, m_e represents e-th element mean time to failure and r_e represents e-th element mean time to repair.

In the first stage, the optimal scheduling of the system will be calculated by the hybrid intelligent algorithm (PSO and AFSA) as shown in figure 3.3(a). It applies to every scenario generated in the initialization phase. The objective function is to minimize overall operational costs related to fuel as shown in sub-chapter 3.3.1.



(a) (b)

Figure 3.3 IARSO (a) first stage (b) second stage

For every scenario generated in the initialization phase, the solution process of the power system dispatching problem is mainly to randomly generate a swarm of intelligent particles based on the constraints, and evaluate the problem based on cost function described in sub-chapter 3.3.1. And then update the values of the intelligent particles by the Particle Swarm Optimization-Artificial Fish Swarm Algorithm. The algorithm process for the integrated weighted dispatching optimization model, as shown in equation 3.10. Below is the steps for the algorithm:

Step 1: Initialize a swarm of intelligent particles (with a size of n particles), including their initial position and initial speed (interval position corresponding to the constraints).

Step 2: Check if all constraints are met; if yes, proceed to the next step; if balance constraint is violated, re-allocate demand excess or surplus to randomly selected generator as long as the boundary constraint is met.

Step 3: Evaluate the fitness value of each particle by using the value of the objective function, as shown in equation 3.1.

Step 4: For each particle, compare its fitness value with its best position pbest. If its fitness value is better, then use it to replace pbest.

Step 5: For each particle, compare its fitness value with its best position gbest. If its fitness value is better, then use it to replace gbest.

Step 6: Update the particle speed and the position (in accordance with the strategy in Equation 3.7 and 3.8).

Step 7: The individuals would update themselves by swarming and following behavior, or generate a new intelligent particle swarm.

Step 8: Evaluate all individuals. If an individual is better than the Bulletin Board, then use this individual to replace the Bulletin Board.

Step 9: Check whether the terminal conditions of the algorithm are met (If met, then end the algorithm; if not, go back to Step 3).

a. Second stage

In the second stage, since the technical-economical results are only relevant to the corresponding load and generator availability scenario, they do not represent the total power cost (TC) of the whole stochastic process. Therefore, a Sample Average Approximation (SAA) method (Kim and Ryu, 2011) has been introduced in equation 3.14 to evaluate TC_n that are expected in the real-time system operation when generating resources are scheduled according to the *n*-th dispatching strategy issued by the first stage (n =1 …N). This method allows evaluating the EOCs over the whole stochastic process, as required by the aggregator as shown in figure 3.3(b). For each scheduling configuration, the procedure simulates the real-time operation of the power system in *M* different

Monte Carlo scenarios (having occurrence probability *πm*) that model the possible deviations of load and transmission loss with respect to their forecasted power profiles. During each simulation, the real-time rules adjust the scheduled dispatching to balance the load with the current power production; operating costs *Ceq*,*m*, which account for fuel consumption (*CF*,*n*,*m*) and curtailment (*CC*,*n*,*m*), as detailed in equation 3.15, are calculated and recorded. The costs are calculated and recorded.

$$\forall\, n\ EOC_n = \sum_{m=1}^{M} \pi_m C_{eq,n,m} = \frac{1}{M}\sum_{m=1}^{M} C_{eq,m} \tag{3.14}$$

$$\forall\, n,m\ C_{eq,n,m} = CF_{n,m} + CC_{n,m} \tag{3.15}$$

Finally, the aggregator selects as final dispatching PD_t the scheduling $PD_{\hat{\imath},t}$ optimized in the first stage that has the lowest expected cost $EOC_{\hat{\imath}}$, as shown in equation 3.16 below. The pseudocode and detailed steps of this monte carlo generation is shown in table 3.3 below

$$PD_t = \left\{ PD_{\hat{\imath},t} \middle| \hat{\imath} = argmin_{i=1..N}\{EOC\} \right\} \tag{3.16}$$

Table 3.2 Pseudocode of the Proposed Hybrid PSOAFSA

Input: dgen (contains PDmin, PDmax, a, b, c, AeData, CC),
  dpar (contain μ, σ^2), N, maxit, Rep, Rep2, teta, beta, step
Output: G_{best}, $F(G_{best})$, computation_time
for q = 1 to Rep
  Generate $load_q \sim N(\mu, \sigma^2)$
  Generate RandAe ~ U(0,1)
  if RandAe <= AeData
    Ae = 1
  else
    Ae = 0
  end
  for i = 1 to N
    PD_i ← initialize the position of the ith particle
    Compute objective value $F(PD_i)$
    $P_{best}i = PD_i$
    if $F(P_{best}i) < F(G_{best})$
      $G_{best} = P_{best}i$
    end
    v_i = initialize the velocity of the ith particle
  end
  for t = 1 to maxiter
    $PD_c = \sum_{j \in N} PD_j / N$

Compute objective value $F(PD_c)$
for i = 1 to N
$v_i \leftarrow$ update the velocity of the ith particle
$PD_i(t) = PD_i(t-1) + v_i$
Compute objective value $F(PD_i)$
if $F(G_{best}) < F(PD_i)$
$PD_{ifollow}(t) = PD_i(t) + \frac{G_{best} - \mathrm{PDi(t)}}{\|G_{best} - \mathrm{PDi(t)}\|} . step . rand()$
else
$PD_{ifollow}(t) = PD_i(t)$
end
Compute objective value $F(PD_{ifollow})$
if $F(PD_c) < F(PD_i)$
$PD_{iswarm}(t) = PD_i(t) + \frac{\mathrm{PDc} - \mathrm{PDi(t)}}{\|\mathrm{PDc} - \mathrm{PDi(t)}\|} . step . rand()$
else
$PD_{iswarm}(t) = PD_i(t)$
end
Compute objective value $F(PD_{iswarm})$
$PDAF_i = \alpha PD_i(t-1) + \beta(PD_{ifollow}$ or $PD_{iswarm})$
Compute objective value $F(PDAF_i(t))$
if $F(PDAF_i) < F(P_{best}i)$
$PD_i = PDAF_i$
else
$PD_i = PD_i$
end
end
Compute objective value $F(PD_i)$
if $F(PD_i) < F(P_{best}i)$
$P_{best}i = PD_i$
if $F(P_{best}i) < F(G_{best})$
$G_{best} = P_{best}i$
end
end
end
end

Table 3.3 Pseudocode of the second stage

Input: dgen (contains PDmin, PDmax, a, b, c, AeData, CC),
dpar (contain μ, σ^2), G_{best}, Rep2, teta, beta, step
Output: PDopt, TCmin, computation_time
for k = 1 to Rep2
Generate $load_q \sim N(\mu, \sigma^2)$
Generate RandAe ~ U(0,1)
if RandAe <= AeData
Ae = 1
else

```
        Ae = 0
    end
    Compute objective value F(G_best) and curtailment cost
end
```

$EOC_q = \sum_{q=1}^{Rep} \pi_q F\left(PD_q\right) + CC * PC_q$

$PD_{opt} = \left\{PD_q | \hat{q} = argmin_{q=1..Rep}\{EOC\}\right\}$

TC_{min} = min(EOQ)

3.3.4 Cost Allocation

After the total cost has been calculated, the players need to know how much benefits and cost they should pay in the coalition. Cooperation game theory is one of convenient tool to solve cost allocation problems (Zolezzi and Rudnick, 2002). The solution mechanisms behave well in terms of fairness, efficiency, and stability, and qualities required for the correct allocation. Thus, it is expected to improve system efficiency. For the player to join the coalition, not only the system cost should be lower but also each member of the coalition. Therefore, cost allocation mechanisms is needed to allocate the cost to each player fairly. Hence, the players are convinced to join the coalition and none of the agents has the incentive to leave the coalition or group in a different manner, as no alternative coalition may improve the allocation. The following are several cost allocation methods based on cooperative game theory.

1. Cooperative Game Theory

Coalitional game is a model which contains interaction of decision maker and focus on the actions and behavior of the groups of player, rather than acting individually. The outcomes consist of a partition of the sets of player into groups and the actions taken. A right coalition should have satisfied numbers of fairness criteria, or we refer that as coalition properties. In this section, some of the most common coalition properties are described.

Let *S* is a subset of participants of a grand coalition *N* all participants. It is assumed that all players have the same opportunity to join or form a coalition. The cost of the coalition as *C(S)* is generated when coalition *S* operates. It is obtained from the characteristic cost function. The first common property in the cost allocation mechanism is *efficient.* Cost allocation is said to be *efficient* if the following constraints hold:

$$\sum_{j=N} y_j = C(N) \qquad (3.17)$$

where *yj* is the cost allocated to each player *j* in *N*. Equation 3.17 states that the total cost of grand coalition *N*, *C(N),* is split among the players j according to the value of *y*.

The second property is *individual rational* property. This happen if no player in the coalition spends more than its stand-alone cost *c{j}*, which is the cost before coalition is formed. The *individual rational* property can be express as equation 3.18 below.

$$y_j \leq c\{j\}, \;\; \forall j \in N \qquad (3.18)$$

The cost allocation, y, is called the *core* of the game if it satisfies equation 3.17 and 3.19 below.

$$\sum_{j=S} y_j \leq C(S), S \subset N \qquad (3.19)$$

Equation 3.19 ensure the stability of alliance. It means no partition that no of the sets of player would get better pay-off than acting individually. To measure how far the cost allocation is from the core we can use excess, *e(S, y),* expressed in equation 3.20 below. Excess tells the difference between the cost of the coalition and the total cost allocated to player *j*.

$$e(S, y) = C(S) - \sum_{j=S} y_j \qquad (3.20)$$

If there is at least one excess is negative, the coalition is not in the core. The next property is *monotone*. The game is said to be monotone if there is no cost decrease when a new player is included in the game, as expressed in equation 3.21 below.

$$C(S) \leq C(T), S \subset T \subset N \qquad (3.21)$$

It can also mean that the coalition cost will increase if there is additional player in the game.

The last property is *proper.* Proper property implies that the more player involved in the coalition, the more profitable (or at least not unprofitable) we will get. It can be expressed mathematically in equation 3.22 below.

$$C(S) + C(T) \geq C(S \cup T), S \cap T = \emptyset \qquad (3.22)$$

2. Shapley Value

Shapley Value is frequently used methods in cooperative game. This method allocates cost to each player *j* based on its average marginal cost of the participants based on the assumption that the grand coalition is formed by entering the participants into this coalition one at a time. The cost assigned to *j* can be calculated as shown in equation 3.23 below.

$$y_j = \sum_{S \subseteq N: j \in S} \frac{(|S|-1)!(|N|-|S|)!}{|N|} [C(S) - C(S - \{j\})] \tag{3.23}$$

N denotes the number of players in the coalition. $(S) - C(S - \{j\})$ implies the marginal cost of player *j* concerning coalition $S - \{j\}$. The Shapley value satisfies four axioms or properties, which are *efficient, symmetry, dummy property,* and *additivity.* However, this method does not guarantee the stability in the coalition.

3. Egalitarian Allocation Method

The egalitarian method is the simplest one (Tijs and Driessen, 1986). It allocates the cost, y, among each player *j* equally as shown in equation 3.24 below. This egalitarian method is efficient, monotonic in the aggregate, but it fails to take strategic aspects into consideration: the allocation is not usually individually rational. This method is only feasible if all players are a part of the grand coalition, and the allocated cost is lower than the stand-alone cost.

$$y_j = \frac{1}{n} C(N) \tag{3.24}$$

4. Proportional Repartition of Total Gains

Moriarity (1976) invented the proportional repartition. This approach shares the cost among players based on the proportion of its stand-alone cost with respect to the total cost of the grand coalition as shown in equation 3.25 below.

$$y_j = \frac{c_j}{\sum_{j \in N} c_j} C(N) \tag{3.25}$$

5. Volume-based Allocation

Volume-based allocation allocates the cost among players based on its shipped volume or demand, D_j. It is expected that the player with higher demand will expend more charge in the coalition as shown in equation 3.26 below.

$$y_j = \frac{D_j}{\sum_{j \in N} D_j} C(N) \qquad (3.26)$$

6. Equal Profit Method

Frisk *et al.* (2010) believe that there is drawback from the previous mechanisms. That is the acceptance of the cost allocation among players. The reason is because it is hard to prove that all players have similar gains from the coalition. Thus, it would be beneficial if we can minimize the difference in pairwise relative savings. That is the goal of this mechanism as shown in equation 3.27 and 3.28 below. Of course, this mechanism will have to meet efficient and individual rational property.

$$Z = min\, f' \qquad (3.27)$$

$$f' \geq \frac{y_i}{c_{\{j\}}} - \frac{y_j}{c_{\{j\}}},\ \forall i, j \in N, i \neq j \qquad (3.28)$$

7. Proportional Charge Method

The concept of PCM is adapted from proportional repartition method by Moriarity (1976). It allocates the cost among players based on its marginal cost with respect to the grand coalition as shown in equation 3.29 below.

$$y_j = \frac{m_j}{\sum_{j \in N} m_j} C(N) \qquad (3.29)$$

CHAPTER 4
DATA PROCESSING

This chapter shows the data collection and data processing of area 3 especially year 2027 in electricity master plan development as an example on how to calculate the result. The complete result will be shown in chapter 5.

4.1 Data Collection and Processing

This sub-chapter consists of the data that is needed in the analysis. The data is got from governmental documents like Rencana Usaha Penyediaan Tenaga Listrik (RUPTL) PT PLN and Interim Report of Kalimantan Electricity Master Plan Development as well as primary data from the company.

In this case study, the planning horizon is 32 years beginning in year 2018-2050. It is divided into two phase: preconstruction phase (year 2018-2020) and construction phase (year 2021-2050). The base year is year 2018.

1. Inflation

Inflation used in this final project is using Indonesia's inflation. Inflation data is obtained from consumer price index. Inflation calculation is using formula in equation 4.1 below.

$$Inflation = \frac{CPI_n - CPI_{n-1}}{CPI_{n-1}} x100\% \quad (4.1)$$

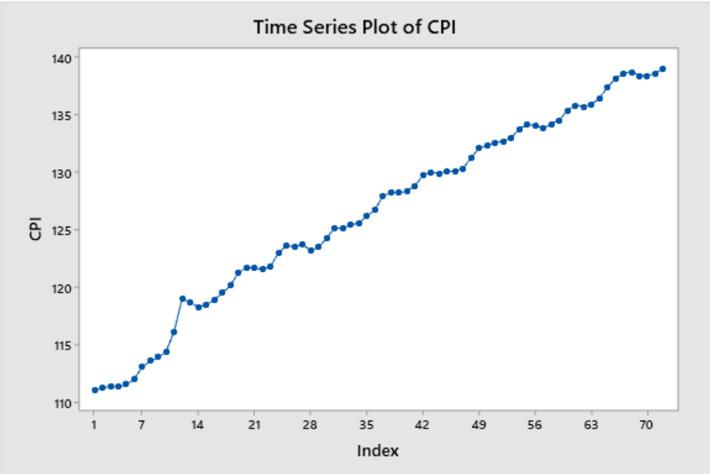


Figure 4.1 CPI Plot of Year 2014-2019

Plotted CPI data is represented in figure 4.1 above. As we can see in the figure, the pattern is showing certain trend with slight seasonal pattern. Thus, double exponential smoothing method will be used to forecast the data. Then, Minitab 19 software forecast the CPI data to calculate the inflation rate. Table 4.1 below shows the result of inflation rate from year 2018 until 2050. Later, this data will be used to predict investment, fix, and variable costs in the future year.

Table 4.1 Inflation Rate of Year 2018-2050

Year	Inflation	Year	Inflation	Year	Inflation	Year	Inflation	Year	Inflation
2018	3.09%	2025	2.66%	2032	2.24%	2039	1.94%	2046	1.71%
2019	2.69%	2026	2.59%	2033	2.19%	2040	1.90%	2047	1.68%
2020	3.13%	2027	2.53%	2034	2.15%	2041	1.87%	2048	1.65%
2021	2.98%	2028	2.46%	2035	2.10%	2042	1.83%	2049	1.62%
2022	2.89%	2029	2.40%	2036	2.06%	2043	1.80%	2050	1.60%
2023	2.81%	2030	2.35%	2037	2.02%	2044	1.77%		
2024	2.73%	2031	2.29%	2038	1.98%	2045	1.74%		

2. Exchange Rate

This study will use the exchange rate from USD to IDR. Exchange rate data is got from Bank Indonesia’s transaction from January 2013 until April 2020. Then we forecast the monthly exchange rate data using double exponential smoothing for year 2021-2050. Table 4.2 below shows the forecasting result.

Table 4.2 Exchange Rate of Year 2018-2050

Year	Exchange Rate	Year	Exchange Rate	Year	Exchange Rate	Year	Exchange Rate
2018	Rp 14,237	2027	Rp 16,479	2035	Rp 19,393	2043	Rp 22,307
2019	Rp 14,148	2028	Rp 16,843	2036	Rp 19,757	2044	Rp 22,671
2020	Rp 13,925	2029	Rp 17,207	2037	Rp 20,121	2045	Rp 23,035
2021	Rp 14,293	2030	Rp 17,571	2038	Rp 20,485	2046	Rp 23,399
2022	Rp 14,657	2031	Rp 17,936	2039	Rp 20,850	2047	Rp 23,764
2023	Rp 15,022	2032	Rp 18,300	2040	Rp 21,214	2048	Rp 24,128
2024	Rp 15,386	2033	Rp 18,664	2041	Rp 21,578	2049	Rp 24,492
2025	Rp 15,750	2034	Rp 19,028	2042	Rp 21,942	2050	Rp 24,856
2026	Rp 16,114						

3. Transmission and Distribution Loss

Table 4.3 below shows the percentage of transmission and distribution loss during operation from year 2016-2050.

Table 4.3 Transmission and Distribution Loss Percentage

No	Province	2016	2017	2020	2025	2030	2035	2040	2045	2050
1	West Kalimantan	14.8	13.5	12.6	11.3	10.6	10.3	10.2	10.2	10.2
2	Middle Kalimantan	10.9	10.8	10.7	10.6	10.5	10.4	10.3	10.2	10.2
3	South Kalimantan	12.4	12.3	12.1	11.9	11.6	11.4	11.2	11.1	10.9
4	East Kalimantan	8.1	8.2	8.3	8.4	8.3	8.2	8.2	8.2	8.2
5	North Kalimantan	7.3	7.4	7.3	7.2	7.1	7.0	6.9	6.8	6.8

4. Demand Data

Demand data are generated based on sub-chapter 3.3.3. Based on distribution fitting done in minitab 19, the best distribution to represent the demand is normal distribution with p-value > 0.05. The table 4.4 below shows the mean and standard deviation of demand data on area 3 year 2027.

Table 4.4 Demand Data Year 2027

Hour	Mean	Std	Hour	Mean	Std	Hour	Mean	Std
1	631.02	2,756.37	9	703.24	1,398.88	17	727.92	732.93
2	602.84	2,310.62	10	718.51	1,920.24	18	736.84	419.01
3	584.30	2,790.79	11	731.98	2,356.17	19	795.85	43.11
4	573.42	3,547.73	12	724.60	1,492.73	20	804.42	6.00
5	585.77	2,648.83	13	691.61	702.99	21	782.52	54.27
6	646.08	2,025.58	14	743.36	2,511.72	22	743.56	119.63
7	630.63	684.76	15	741.90	1,614.02	23	693.02	273.29
8	645.60	788.01	16	729.89	1,278.14	24	653.10	219.36

5. Generator Data

Table 4.5 below shows generator data of area 3 electricity year 2027 in regional balance scenario using both thermal and hydro power plant. Pdmin and Pdmax represents power minimum and maximum that a generator will produce. While a, b, c are cost coefficients of generating unit and Ae is the availability of each generator.

Table 4.5 Generator Data Area 3 Year 2027

	G1	G2	G3	G4	G5	G6
Pdmin	69	69	69	69	69	69
Pdmax	100	100	100	100	100	100
a	2.33E-03	2.33E-03	2.33E-03	2.33E-03	2.33E-03	2.33E-03
b	375,274	375,274	375,274	375,274	375,274	375,274
c	3,500,531	3,500,531	3,500,531	3,500,531	3,500,531	3,500,531
Ae	0.97	0.97	0.98	0.99	0.99	0.99

	G7	G8	G9	G10	G11
Pdmin	69	69	69	69	37.95
Pdmax	100	100	100	100	55
a	2.33E-03	2.33E-03	2.33E-03	2.33E-03	0.00E+00
b	375,274	375,274	375,274	375,274	5,265
c	3,500,531	3,500,531	3,500,531	3,500,531	1,277,203
Ae	0.99	0.99	0.97	0.99	0.99

These generator and demand data become input for running the hybrid PSOAFSA algorithm to obtain optimum dispatch for each hour so that the expected operation cost will be minimum. Table 4.6 below shows the result of power dispatch for each generator and each hour in area 3 year 2027. Gi represents the i-th generator available to fulfill the demand in the area. From this power dispatch, we got Rp 7,778,379,258 as the EOC generated within a day. This value will be multiplied by 30 days and 12 months to obtain EOC in a year. So the operational cost in year 2027 is Rp 2,800,216,533,134. This procedure is applied from year 2018-2050 for all areas and all scenarios.

Table 4.6 Load Dispatch for Year 2027 (Cont.)

2027	Area 3										
Hour	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11
1	69.0	83.4	69.0	69.0	100.0	69.0	95.5	100.0	100.0	89.8	55.0
2	76.5	69.0	69.3	84.4	69.0	0.0	69.0	69.0	69.0	100.0	40.6
3	74.8	69.7	100.0	81.6	69.0	71.0	100.0	69.0	69.0	70.0	38.0
4	100.0	100.0	69.0	69.0	81.8	100.0	100.0	69.0	100.0	100.0	38.0
5	69.0	71.8	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	55.0
6	74.1	75.6	69.0	69.0	69.0	89.5	69.0	69.0	71.1	82.0	51.5
7	69.0	100.0	81.1	69.0	69.0	76.1	71.2	69.0	100.0	100.0	38.0
8	69.0	0.0	100.0	69.0	100.0	69.0	69.0	95.2	69.0	69.0	38.0
9	76.9	73.8	82.0	69.0	87.1	69.0	100.0	69.0	69.0	82.9	47.3
10	69.0	76.0	69.0	69.0	72.4	69.0	73.0	69.0	69.0	79.0	48.5
11	98.1	99.9	84.8	0.0	69.0	69.0	69.0	100.0	69.0	69.3	49.0
12	69.0	75.0	69.0	83.2	69.0	100.0	94.4	69.0	0.0	98.2	55.0
13	84.3	69.0	0.0	100.0	100.0	91.1	69.0	69.0	69.0	69.0	45.2
14	76.5	100.0	69.0	69.0	69.4	100.0	69.0	76.4	69.0	100.0	55.0
15	69.0	71.3	78.9	69.0	79.3	69.0	69.0	83.3	69.0	69.0	55.0
16	69.0	69.0	69.0	100.0	69.0	76.0	100.0	69.0	100.0	75.8	55.0
17	69.0	69.0	69.0	100.0	69.0	86.4	69.0	69.0	69.0	69.0	55.0
18	75.0	73.1	69.0	69.0	98.4	77.3	69.0	100.0	69.0	69.0	48.0
19	69.0	69.0	69.0	69.0	100.0	100.0	88.6	69.0	99.8	69.0	43.4
20	98.0	100.0	69.0	69.0	76.0	69.0	100.0	69.0	69.0	100.0	52.8
21	69.0	100.0	100.0	100.0	69.0	69.0	69.0	69.0	74.4	69.0	55.0
22	69.0	69.0	69.0	84.5	86.5	69.0	79.7	94.5	100.0	71.6	55.0
23	100.0	70.2	72.6	85.0	69.0	100.0	69.0	95.9	69.0	69.9	38.0
24	0.0	69.0	74.0	69.0	88.7	94.2	100.0	100.0	69.0	73.0	38.0

Table A.2 in the appendix shows the result of power dispatch for each generator and each hour year 2018. If blackout happens, the PD value will be 0.

4.2 Cost Summary

Beside the calculation above, there are several costs that compose total investment cost including engineering procurement construction (EPC) cost, fix cost, and variable cost. These funding needs is based on historical data from PT PLN which is adjusted by inflation rate. Table 4.7 below shows the investment, variable and fix cost for area 3 year 2027 RB scenario. While table 4.8 shows the cost summary. This procedure is applied from year 2018-2050 for all areas. Thus we can get the total PV during the time horizon. It is also applied to all scenarios

Table 4.7 Investment, Fix and Variable Cost

Investment Cost (IDR)			
EPC Cost	**1,935,970,794,934**	**Development Cost**	**95,436,674,138**
Steam Generator	-	Land Acquisition	48,408,775,760
Stack	-	Site Preparation	26,592,318,877
FGD	-	Consulting Service	20,435,579,501
Turbine	560,286,733,670	**Other Cost**	**573,308,527,398**
Switchyard	28,720,758,649	Price Escalation	368,822,569,463
Coal, Ash handling system	721,816,662,702	Contingency	116,957,306,188
EPC Installation	625,146,639,912	Administration Cost	25,251,607,791
Materials for 500 kV T/L	-	Tax and Duties	62,277,043,957
Variable Cost (IDR)		Fix Cost (IDR)	
Total Variable Cost	**2,800,228,929,755**	**Total Fix Cost**	**21,851,223,934**
Operational Cost	2,800,216,533,134	Management Wage	728,395,471
Supply Cost	12,396,621	Staff Wage	4,621,207,604
		Property Taxes	16,501,620,859

Table 4.8 Cost Summary

EPC Cost	1,935,970,794,934
Development Cost	95,436,674,138
Other Cost	573,308,527,398
Total Fix Cost	21,851,223,934
Total Variable Cost	2,800,228,929,755
Total	5,426,796,150,159
PV	1,956,957,095,279

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CHAPTER 5
RESULT AND DISCUSSION

The proposed hybrid PSOAFSA algorithm is implemented in Matlab R2019b and run on a computer with an Intel® Core™ i5-8500 CPU at 3.00 GHz and 24 GB of RAM under Windows 10 Professional. In order to see its performance, the proposed algorithm is tested on 3 benchmark instances, which are adapted from ED instances without valve-point effects provided by Zou *et al.* (2017). Afterward, the proposed algorithm is applied to solve the actual problem.

5.1 Parameter Setting for Hybrid Intelligent Algorithms (PSO and AFSA)

Parameter setting plays big role in determining the solution quality. So, this sub-chapter is conducted to find the best parameter combination for proposed algorithm. There are five parameters tested in this study. The following parameter values are considered in the parameter setting.

θ : 0.4, 0.6, 0.8, 1, 1.5
Step : 0.5, 1, 1.5, 2
β : 0.2, 0.4, 0.6, 0.7, 0.8
N : 100, 500, 1000, 2000
Iter : 50, 300, 500, 1000, 5000

The parameter combination is chosen based on design of experiment using 2k factorial design result. In order to do that, initial experiment using one-factor-at-time (OFAT) analysis is done to determine the low and high value of the parameter. The experiment is done by changing one value of the parameter at one time. The value of each experiment is got from the average of five-time execution. A six-unit generator instances are selected from Zou *et al.* (2017) benchmark instances for the analysis. The overall result of OFAT experiments can be seen in Appendix 1. Table 5.1 shows the two selected low and high value from OFAT result.

Table 5.1 Parameter Values for 2k Factorial Design

Parameter	**Low**	**High**

Parameter	Low	High
θ	0.4	0.6
Step	0.5	1
β	0.7	0.8
N	1000	2000
Iter	500	5000

Proceeding the result in the 2k factorial design, 32 parameter combination need to be evaluated. Considering objective function and computation time, the result shows that parameter setting with θ = 0.6, step=1, β = 0.7, N = 1000, Iter = 500 seems to give the best solution. Thus, this parameter will be used to solve the benchmark instances and the real problem.

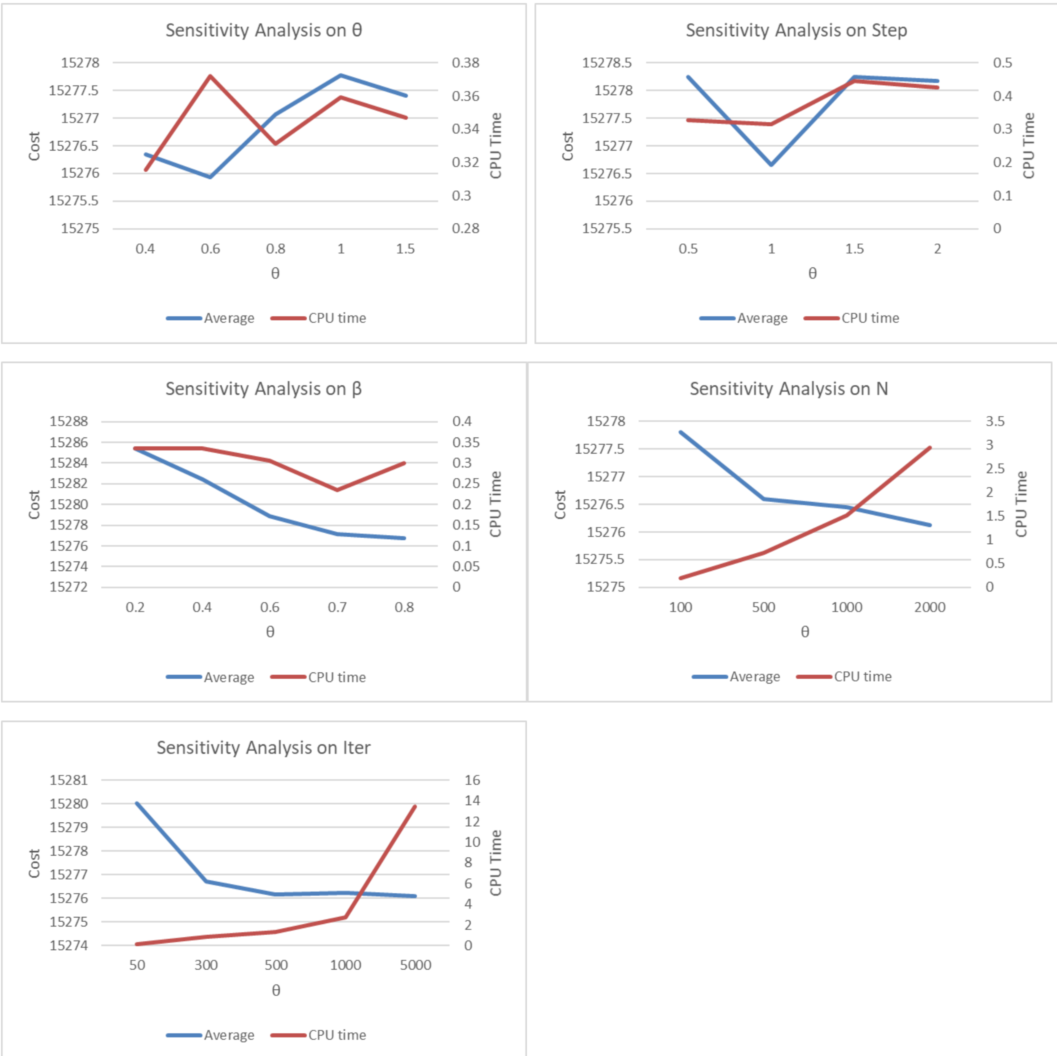

Figure 5.1 Sensitivity Analysis of Parameter

The result from OFAT experiment will then be used for sensitivity analysis. Figure 5.1 above shows sensitivity analysis result. From this figure, we can see how the effect of each parameter on the solution obtained from the proposed algorithm, specifically on the objective function and computational time is.

Generally, when parameter θ decrease the solution quality will improve. The best solution is obtained when θ value is 0.6. But, it is not the case for computation time because there seem to be no correlation between them.

Meanwhile, parameter *Step* seems to have no correlation to the objective function. The best value is obtained when step is 1. Other than that, the solution quality deteriorates. Nonetheless, as the step decrease the computation time will also decrease.

Parameter β appears to have a similar effect on both performance indicators. When the step increase, the computational time tends to be slower and the objective function decreases. However, the computation time increases after it reaches 0.7.

Parameter *N* and *Iter* seem to give opposite effect on objective function and computation time. As number of N becomes higher, the objective function becomes smaller. This could happen because there are a lot more area to be searched by initial particle, so the chance to have a solution near the global optimal solution is higher. However, the computation time will increase. Although utilizing high number of N will improve solution quality, it takes more time to compute the algorithm. So, we must pay attention to the trade-off between the solution quality and computation efficiency. Meanwhile, as iter increases, the solution quality will also increase but the computation time will decrease. From the figure we notice that on iter 500 and above, the solution quality seems to be stagnant. It means that there is only a little difference in solution quality improvement. Hence we can utilize iter 500 as the parameter as it will give better solution quality with minimum amount of computation time.

Since the stochastic approaches under test rely on input scenarios, so the number of scenarios do have important part in bringing the result into convergence. Thus, beside the parameters for optimization, there are two other parameters tested in this study related to the stochastic process. N and M is the number of scenarios of the 1st and 2nd stages of I-ARSO. The following parameter values are considered in the parameter setting.

N : 10, 30, 50, 100, 250, 500

M : 50, 500, 1000

This parameter setting along with the chosen PSOAFSA parameters in the previous step is applied to the case study. Specifically, in area 3 year 2029, composed by a 11 thermal power plants and 3 hydro power plants. Table 5.2 and 5.3 below shows the generator and demand data used for parameter setting.

Table 5.2 Generator Data of Area 3 Year 2029

Pi	Type	P min	P max	ai	bi	ci
1	HPP	0	55	0	375,275.56	1,408,288.15
2	HPP	0	360	0	388,911.68	18,445,744.07
3	HPP	0	900	0	425,209.29	21,208,097.64
4	TPP	288	600	-7.454E-07	456,671.74	6,285,060.82
5	TPP	126	300	2.5796E-05	473,265.47	6,524,324.51
6	TPP	126	300	2.5796E-05	490,462.16	6,783,460.05
7	TPP	126	300	-5.049E-05	499,293.46	7,529,112.32
8	TPP	126	300	-7.315E-05	508,283.75	7,840,405.13
9	TPP	126	300	-5.033E-06	517,435.89	7,218,824.71
10	TPP	126	300	2.5796E-05	526,752.83	8,238,715.97
11	TPP	126	300	-5.033E-06	536,237.56	8,271,486.63

Table 5.3 Demand Data of Area 3 Year 2029

Hour	Mean	Std	Hour	Mean	Std	Hour	Mean	Std
1	2,296.82	191.10	9	2,559.69	136.14	17	2,649.53	98.54
2	2,194.24	174.96	10	2,615.29	159.50	18	2,682.00	74.51
3	2,126.79	192.29	11	2,664.30	176.68	19	2,896.78	23.90
4	2,087.17	216.80	12	2,637.45	140.63	20	2,927.98	8.92
5	2,132.14	187.33	13	2,517.36	96.51	21	2,848.25	26.81
6	2,351.63	163.82	14	2,705.72	182.42	22	2,706.47	39.81
7	2,295.39	95.25	15	2,700.41	146.23	23	2,522.50	60.17
8	2,349.91	102.18	16	2,656.70	130.13	24	2,377.20	53.91

Table 5.4 below shows the result and standard deviation of proposed algorithm for each N and M setting. While figure 5.2 below displays the % Standard Deviation & EOC of Each Combinations for N and M parameter setting

Table 5.4 EOC and Computation Time of Each Parameter Setting Combination

Combination	N	M	EOC (IDR in million)	CompTime	Std EOC	%std EOC
1	10	50	34,184.63	235.8	511.4	1.50%
2		500	33,981.00	229.1	332.2	0.98%
3		1000	34,120.30	230.3	316.4	0.93%
4	30	50	33,592.27	684.0	484.7	1.44%
5		500	33,896.67	688.7	392.1	1.16%
6		1000	33,758.01	690.7	388.4	1.15%
7	50	50	33,987.77	1,152.3	398.7	1.17%
8		500	33,468.53	1,126.9	416.0	1.24%
9		1000	33,805.60	1,171.2	393.3	1.16%
10	100	50	33,681.18	2,265.8	371.6	1.10%
11		500	33,621.32	2,277.8	413.0	1.23%
12		1000	33,743.47	2,336.2	418.3	1.24%
13	250	50	33,513.46	5,466.3	410.9	1.23%
14		500	33,472.92	5,475.6	395.8	1.18%
15		1000	33,493.36	5,829.8	387.5	1.16%
16	500	50	33,636.42	11,058.3	397.4	1.18%
17		500	33,617.84	10,971.1	428.0	1.27%
18		1000	33,611.49	11,022.5	402.9	1.20%

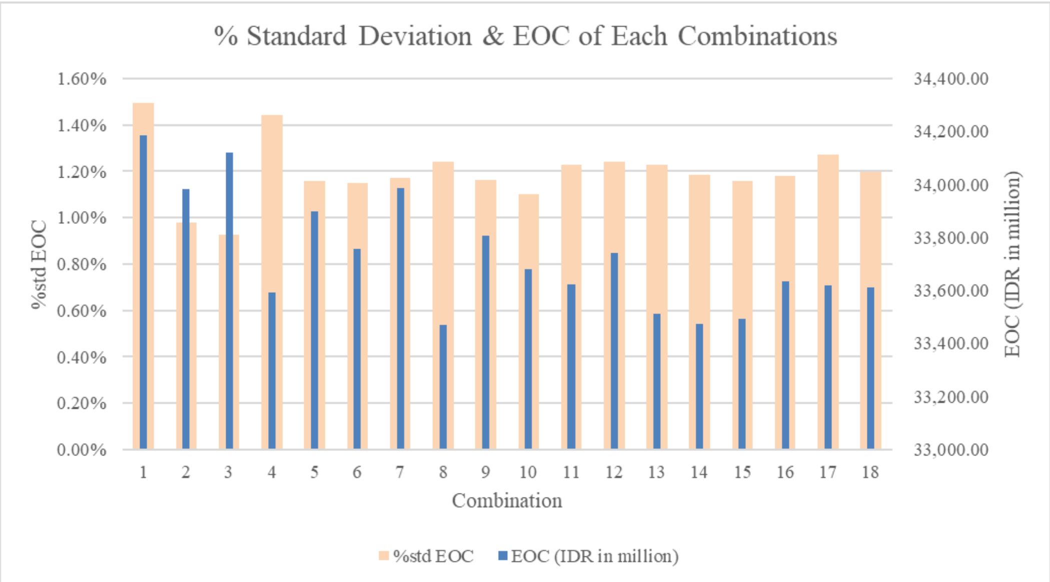

Figure 5.2 %Standard Deviation & EOC of Each Combinations

The performance in figure 5.2 shows that generally as the number of N increase, the cheaper EOC will be. This is because increasing N enables better sampling of uncertainties since more load and generator availability will be covered. Moreover, it also makes the procedure to generate more dispatching scenarios in the second stage. Thus, leading to achieve cheaper solutions. While for M, standard deviation reduces as it increases. The computation time standard deviation in I-ARSO is very low (below 2% for each N). It means that the solutions are achieved almost in the same amount of time. From here we also can see the method robustness. Considering objective function and computation time, the result shows that parameter setting with N = 50 and M=500 seems to be a good compromise as it gives the cheapest EOC with acceptable computation time.

5.2 Algorithm Testing on Benchmark Instance

To evaluate the performance of the proposed PSOAFSA algorithm, the algorithm is tested on 3 benchmark instances of economic dispatch problem. The units are ranging from 2 to 6. Table 5.5 below describes the details for each instance.

Table 5.5 ED Benchmark Instances Data

	2 unit case		**3 unit case**			
Pmin	20.00	20.00	150.00	100.00	50.00	
Pmax	200.00	200.00	600.00	400.00	200.00	
a	0.01	0.02	0.001562	0.001940	0.004820	
b	5.00	4.00	7.92	7.85	7.97	
c	400.00	600.00	561.00	310.00	78.00	
Demand (MW)	**250**		**850**			
			6 unit case			
Pmin	100.00	50.00	80.00	50.00	50.00	50.00
Pmax	500.00	200.00	300.00	150.00	200.00	120.00
a	0.007	0.01	0.009	0.009	0.008	0.0075
b	7.00	10.00	8.50	11.00	10.50	12.00
c	240.00	200.00	220.00	200.00	220.00	190.00
Demand (MW)			**1263**			

Notation *Pmin* and *Pmax* denotes the minimum and maximum power capacity of generator to be dispatched. While notation *a*, *b*, and *c* indicates the fuel cost coefficient of each generator.

This study presents IARSO combined with game theory concepts in solving the ED & investment decision problems, which consider cooperative strategy enabling the use of same transmission facilities as the backbone. Thus, resource sharing between players is enabled. To address the ED problem, an IARSO with hybrid PSO AFSA algorithm is developed. Hence, in non-cooperative strategy, the algorithm is tested on these benchmark instances to assess its performance. In cooperative strategy, the allied generators are influenced by transmission structure and will be calculated accordingly.

These ED benchmark instances were provided by Zou *et al.* (2017). The ED solution consists of power generated in each hour which met the constraint. The results from the benchmark testing are being compared to the results of related researches (Zou *et al.*, 2017). Zou *et al.* (2017) developed an improved differential evolution algorithm to solve ED problem. The proposed algorithm is also compared with memory based differential evolution (MBDE), self-adapting control parameters (SADE), modified differential evolution (MDE), particle swarm optimization (PSO), and artificial fish swarm algorithm (AFSA). Table 5.7 shows the comparison of the computational result between the proposed hybrid PSOAFSA and the previous researches, based on the average run.

Based on the table 5.6, it can be seen that the proposed algorithm manages to find the optimal solution for the 3 instances benchmark. The algorithm performance can be seen through cost standard deviation and computational time. Overall, the proposed algorithm has nearly zero standard deviation to the previous research. This means the optimality gap is nearly zero. Moreover, the computational time of the proposed algorithm has outperformed the previous method. In conclusion, the proposed algorithm is relatively good to solve the aforementioned problem. It is also compared to individual PSO and AFSA algorithm. The result shows that overall, hybrid method performs better in computation time compared to the two algorithm. Thus, the proposed hybrid PSO AFSA can be applied to solve the real problem of the study.

Table 5.6 Comparison of Zou's Benchmark Instances

Problems	Algorithms	Beta	Inersia	N	Gmax	CPU Time	Costmin	Costmax	Costmean	Coststd
2-unit case	MBDE				300	0.574	2515	2515	2515	0
(PD 250 MW)	SADE				300	0.507	2515	2515	2515	0
	MDE				300	0.58	2515	2515	2515	0
	IDE				300	0.551	2515	2515	2515	0
	PSO		1	**200**	**300**	**0.124**	**2,515**	**2,515.0**	**2,515.0**	**0**
	AFSA			200	400	1.133	2,515	2,515.2	2,515.0	0.062145547
	PSOAFSA	0.7	0.6	**100**	**150**	**0.415**	**2,515**	**2,515.0**	**2,515.0**	**0**
3-unit case	MBDE				**300**	**0.557**	**8194.36**	**8194.36**	**8194.36**	4.34E-12
(PD 850 MW)	SADE				300	0.577	8194.36	8194.36	8194.36	3.70E-12
	MDE				300	0.746	8194.36	8194.36	8194.36	3.41E-12
	IDE				300	0.632	8194.36	8194.36	8194.36	**3.56E-12**
	PSO		0.6	300	700	0.735	8194.36	8194.86	8194.38	9.43E-02
	AFSA			200	400	1.521	8194.36	8194.80	8194.50	1.39E-01
	PSOAFSA	0.7	0.6	**100**	**500**	**0.506**	**8194.36**	**8194.36**	**8194.36**	**3.70E-12**
6-unit case	MBDE				600	1.264	15275.93	15275.93	15275.93	6.62E-12
(PD 1263 MW)	SADE				600	**1.254**	15275.93	15275.93	15275.93	5.51E-09
	MDE				600	1.761	15275.93	15275.93	15275.93	6.16E-12
	IDE				**600**	1.290	**15275.93**	**15275.93**	**15275.93**	**5.71E-12**
	PSO		0.5	1000	3000	0.983	15275.93	15279.00	15277.01	1.03E+00
	AFSA			500	800	7.562	15275.93	15278.00	15277.53	5.78E-01
	PSOAFSA	0.7	0.6	**100**	**600**	**0.610**	**15275.93**	**15275.93**	**15275.93**	**5.55E-12**

5.3 Algorithm Testing on Area 3 (Mahakam System)

The algorithm testing in the case study aims to investigate the benefits of SO strategies, where significant uncertainties affect forecasting procedures of both the load and the generator availability. The proposed algorithm along with deterministic optimization, PSO and AFSA algorithm are tested on in area 3 year 2029 with the generator data detail is depicted in table 5.2 and deterministic demand data is using the mean in table 5.3. The deterministic optimization is calculated using Lingo 11 software with global solver method, while the algorithms are calculated using Matlab R2019b and run on a computer with an Intel® Core™ i5-8500 CPU at 3.00 GHz and 24 GB of RAM under Windows 10 Professional. Table 5.7 below shows the comparison between the three approaches.

Table 5.7 Comparison Between Algorithms

	N	**Max Iter**	**Catlculation Time**	**TC (in million)**	**TC Saving (in million)**	**% Saving /Day**
Data				Rp 31,954.25		
DO		37914	2	Rp 31,905.05	Rp 49.20	0.15%
PSOED	1000	500	150.32	Rp 31,870.25	Rp 84.00	0.26%
AFSAED	1000	500	29.26	Rp 31,562.58	Rp 391.67	1.23%
PSOAFSAED	1000	500	23.76	Rp 31,353.00	Rp 601.25	1.88%

The result shows that the proposed algorithm generally performs better both in the objective function and the computation time. It enables to save up to 1.88% cost per day compared to deterministic optimization which amount to 601.25 million rupiahs. It is also cheaper than the other two algorithms. The computational time is also shorter than the other two algorithms which is 6.5 times shorter compared to PSO and 1.26 times shorter compared to AFSA. Thus this algorithm will be used to calculate the load dispatch in the real case.

5.4 Cooperation Evaluation

A comparative study between non-cooperation and cooperation scenario is carried on to evaluate the performance of the cooperation strategy in the electricity master plan development. In non-cooperation (RB) scenario, each area will fulfill its demand by using its own resources. Therefore, we will find the solution by determining the load dispatch of each generator in area 1, 2, and 3 independently. Whereas in a cooperation (IC) scenario, the load and resources available in each area are combined. Cooperation scenario allows one area to fulfill the demand in another area as long as they are in the same coalition. For example, in scenario IC 12 year 2025, area 1 has 10 TPP generators and 431.8 MW demand, while area 2 has 11 TPP generators and 1,081.1 MW demand. Thus, in IC scenario, the problem consists of 21 generators and 1,512.9 MW demand.

By using the parameters in sub section 5.2.1, we compute the result for cooperation (IC) and non-cooperation (RB) scenario from year 2018 until year 2050. There are 10 scenarios in the case study. Table 5.8 below shows the operational and total investment costs comparison result between scenarios. The initial cost using the company’s formula is also compared.

Table 5.7 Cost Comparison Between Scenarios

Plant Types	Scenario	Operational Cost (in million)	
TPP	Initial	**Rp**	**308,679,373.25**
	Area 1	Rp	72,387,878.08
	Area 2	Rp	117,029,349.02
	Area 3	Rp	119,262,146.15
	RB	**Rp**	**289,928,310.08**
TPP	Area 1	Rp	69,394,010.20
TPP & HPP	Area 2	Rp	114,637,715.20
TPP & HPP	Area 3	Rp	105,896,584.68
	RB	**Rp**	**291,701,016.28**
TPP	Area 1	Rp	69,394,010.20
TPP	Area 2	Rp	115,222,785.13
TPP	Area 3	Rp	107,084,220.95
TPP	RB	**Rp**	**288,766,710.47**

Plant Types	Scenario	Operational Cost (in million)	
TPP TPP & HPP	Area 1	Rp	69,394,010.20
	Area 2	Rp	113,476,115.59
	Area 3	Rp	105,896,584.68
	RB	**Rp**	**289,581,714.65**
	Area 1	Rp	69,394,010.20
TPP	Area 2	Rp	113,103,483.50
TPP & HPP TPP	Area 3	Rp	107,084,220.95
	IC12	**Rp**	**286,876,733.35**
TPP & HPP	Area 12	Rp	180,980,148.68
	Area 3	Rp	105,896,584.68
	IC12	**Rp**	**288,236,983.92**
TPP	Area 12	Rp	181,152,762.97
	Area 3	Rp	107,084,220.95
	IC23	**Rp**	**288,511,128.60**
TPP & HPP	Area 1	Rp	69,394,010.20
	Area 23	Rp	219,117,118.39
	IC23	**Rp**	**290,538,555.79**
TPP	Area 1	Rp	69,394,010.20
	Area 23	Rp	221,144,545.59
TPP & HPP	IC123	**Rp**	**286,680,755.38**
TPP	IC123	**Rp**	**288,446,776.84**

From table 5.8 above, it can be seen that the cooperation scenario spends a lower total cost than the non-cooperation scenario. This condition might be happened due to inefficiency of resource usage and the absence of backbone support. As we know, in a regional balance system, area 1, 2, and 3 act independently, which means that if there is blackout or demand insufficiency in certain area the other area cannot support the lacking area with its power generation. This will lead to higher penalty cost from the unsatisfied demand as well as higher overall operational cost

The results imply that the cooperation scenario dominates the non-cooperation scenario one. About 7.13% of the total cost can be reduced by implementing the cooperation strategy for TPP and HPP scenario and about 6.55% of the total cost can be reduced by implementing the strategy for TPP scenario. This results are able to save IDR 21,998,617.88 million and IDR 20,232,596.42 consecutively compared to company's calculation

Moreover, we can see that involvement of renewable energy which is hydro power plant is indeed beneficial in the long run. It is proven by the involvement of is hydro power plant in the scenarios always outperform the thermal power plant only scenarios by an average of 0.6%. These findings can be elaborated by the reduction in power generation during the operation as well as percentage of unsatisfied demand. It means that cooperation strategy helps to better utilize the capacity of the resources during power distribution process.

5.5 Cost Allocation

After the total cooperation cost is obtained, the next question is how to allocate the cost to each player fairly, so that the players are convinced to join the coalition and none of the agents has the incentive to leave the coalition or group in a different manner, as no alternative coalition may improve the allocation. From the previous section, cooperation scenario indeed is more beneficial than non-cooperation scenario as it results in lower total cost. Then, the company will be interested on how much the cost saving will be obtained if they play cooperation scenario. Therefore, cost allocation mechanism, and estimation of the cost saving generated in collaboration need to be presented before companies decide to ally with each other.

In order to allocate the post-cooperation cost for each company as fair as possible, we adopt several cost allocation mechanism based on cooperative game theory method. There are seven methods considered in the analysis, such as the core, egalitarian allocation (EA), equal profit method (EPM), proportional charge method (PCM), proportional repartition method (PRM), Shapley value, and volume-based allocation (VBA), as explained in sub chapter 3.3.4. Through the analysis, we try to find the most stable and fairest cost allocation among all method used so that the players will not move to another coalition or act independently. The result of the cost allocation analysis and the estimation of cost saving for each company are presented in table 5.9 and table 5.10.

Table 5.8 Cost Allocation for Area 1, 2, and 3

Cost Allocation Mechanism	**Cost (IDR in million)**			**C(N)**
	Area 1	**Area 2**	**Area 3**	
Pre-collaboration	69,394,010	114,637,715	105,896,585	289,928,310
Core	69,394,010	111,390,200	105,896,600	286,680,810
Shapley Value	68,357,991	112,645,001	105,677,763	286,680,755
Egalitarian Allocation	95,560,252	95,560,252	95,560,252	286,680,755
Proportional Repartition	68,616,712	113,353,631	104,710,412	286,680,755
Volume-based Allocation	59,195,519	121,963,180	105,522,056	286,680,755
Equal Profit Method	68,243,330	112,736,800	105,700,600	286,680,755
Proportional Charge Method	68,163,420	111,878,391	106,638,944	286,680,755

Table 5.9 Cost and Saving Ratio of Area 1, 2, and 3

Cost Allocation Mechanism	**Area 1**		**Area 2**		**Area 3**	
	Cost Ratio	**Saving Ratio**	**Cost Ratio**	**Saving Ratio**	**Cost Ratio**	**Saving Ratio**
Pre-collaboration	100.0%	0.0%	100.0%	0.0%	100.0%	0.0%
Core	100.0%	0.0%	97.2%	2.8%	100.0%	0.0%
Shapley Value	98.5%	1.5%	98.3%	1.7%	99.8%	0.2%
Egalitarian Allocation	137.7%	0.0%	83.4%	16.6%	90.2%	9.8%
Proportional Repartition	98.9%	1.1%	98.9%	1.1%	98.9%	1.1%
Volume-based Allocation	85.3%	14.7%	106.4%	0.0%	99.6%	0.4%
Equal Profit Method	98.3%	1.7%	98.3%	1.7%	99.8%	0.2%
Proportional Charge Method	98.2%	1.8%	97.6%	2.4%	100.7%	0.0%

Table 5.10 shows that the cost allocation mechanisms result is varied. Every mechanism has its own allocation. However, not all allocation satisfied the individual rational property of the coalition, in which the allocated cost is not higher than the stand-alone cost, such as in EA, PCM, and VBA. Thus, these three allocation do not seem applicable.

In EA, the cost is allocated equally to each company. This method is simple and easy to explain to all companies involved. However, there are some drawbacks in this method. First, it does not take into account each company stand-alone cost. Moreover, it also does not include the added value of each player (marginal benefit). Hence, one can be benefited more than the other. In this case, player 2 and 3 are more profitable by 54.3% and 47.5% compared to area 1. Moreover, area 1 has to pay 37.7% more than it pays in the stand alone cost. For sure, this allocation in not irrational and unstable. The PCM method also does not seem to be applicable because the cost in area 3 is slightly higher than its stand alone cost.

The VBA divides the cost based on the company's distributed power dispatch. The company with higher demand will be allocated more cost than the one with lower demand. Table 5.11 below shows the percentage of demand satisfied for each area per day. The weakness of this allocation mechanism is, in a bigger allocation, it can lead companies to pay more than its stand alone cost. It also does not consider the number of generator in each area. So, the investment cost is not taken into account. For example, in this case area 1, 2, and 3 has 27, 27 and 22 generators respectively. Because area 2 has lower investment cost and higher capacity, area 2 has to fulfill the demand 2 times higher than area 1 (some of allocated demand in area 1 is transferred to area 2). However, the cost is allocated to area 2 more than the other area because it only cares about the volume. In consequence, resulting the cost in area 2 is slightly higher than its stand alone cost.

Table 5.10 Percentage of Satisfied Demand Per Day

Area	1	2	3
Demand (mw)	59,027.7	121,617.5	105,222.9

% Demand	21%	43%	37%

The cost allocation based on the core, only gives benefit to area 2. It can be seen as an unfair allocation because only area 2 manages to save the expense.

Among the cost allocation mechanisms, the EPM, PRM, and Shapley value generate more stable allocation. These methods consider saving, stand-alone cost and the marginal cost of each company. The most evenly allocated costs is provided by the PRM. The PRM allocates the cost based on the proportion of the stand-alone cost concerning the grand coalition cost, while the EPM allocates the cost by minimizing the difference of savings generated by the company. Through EPM, it ensures that all company involved will get a similar savings ratio to produce a fair collaboration. Meanwhile, Shapley value allocates the cost by considering the marginal cost of each player. The cost saving between these methods are in the range of 0.2% - 2.5%.

Every cost allocation mechanism has its own advantages and disadvantages. Therefore, the selected mechanism would be different for various cases. It is also stated by Dai and Chen (2012) that there is no universally accepted fairness criteria exist for the cost or profit allocation in a cooperation problem. However, it is very common to use Shapley value as the mechanism to allocate the cost in economic dispatch problem. So, table 5.9 and 5.10 are presented to give options and better overview to allocate the cost for each player. Moreover, the result clearly shows that cooperation strategy especially using renewable energy is indeed beneficial.

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CHAPTER 6
CONCLUSION AND RECOMMENDATION

This chapter consists of conclusion and the recommendation of the research. The conclusion contains the insight of the reseach. It also can be used as a guide and reference to the decision maker, while the recommendations is for the betterment of future research.

6.1 Conclusion

Developing economic dispatch model that is able to accommodate demand uncertainty and generator availability in a quick way has inspired this study in the first place. Moreover, this study also formulates a cooperative game-theoretic model to determine the coalition that will lead to minimum investment cost as well as how to allocate the costs into the players. According to such concern, the result of this study concludes that:

1. Improved aggregating-rule-based stochastic optimization (I-ARSO) approach is used to solve stochastic economic dispatch (SED) problem. This approach will use hybrid intelligent algorithm (particle swarm optimization and artificial fish swarm algorithm) to solve optimization problem for N Monte Carlo scenarios of power demand and unavailability in the first stage. In the second stage, each optimal scenario is simulated to evaluate the corresponding expected operating cost. Finally, cooperative game theory will pick the best arrangement for all players to get the minimum total cost. The proposed method is able to save IDR 21,998,617.88 million or about 7.13% compared to company’s calculation.
2. From available scenario, cooperation scenario (interconnectivity) is proven to outperform the non-cooperation scenario and combination between thermal and hydro power plant scenario is also proven to outperform the thermal power plant scenario. Hence, cooperation scenario (interconnectivity) between area 1, 2, and 3 using combination of thermal and hydro power plant is the best option

to choose. The company will need to invest IDR 286,680,755.38 million for year 2018-2050.

3. For better perspective on the cooperation in the involved players, comparison of several cost allocation mechanism is done. It turns out that EPM, PRM, and Shapley value generate more stable allocation. Through the cost allocation analysis, it can be seen that cooperation strategy can reduce the total cost of entire system as well as the expenses for each area.

6.2 Recommendation for Future Research

This study only evaluates the utility from cost occurred. Future research might evaluate the utility from different perspective such as profit. Furthermore, environmental aspect can also be considered since it becomes concerning aspect nowadays. Beside using two stage approach to deal with stochastic behavior, future research might try to incorporate probability in the mathematical model and make a joint probability for the independent sources of uncertainty (in this case load and generator availability). Finally, because this research only model about aleatory uncertainty, taking consideration on epistemic uncertainty in the stochastic model can also enhance the contribution in this field.

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APPENDIX

Table A.1 Result of One-Factor-at-Time (OFAT) Experiments

Combination	θ	Step	β	N	Iter	#1	#2	#3	#4	#5	Average	Low	High
	0.4	1	0.8	100	50	15277.3	15276.1	15276.1	15276.3	15275.9	15276.34755		
	0.6	1	0.8	100	50	15275.9	15275.9	15275.9	15275.9	15275.9	15275.93539		
a	0.8	1	0.8	100	50	15276.4	15276	15277.7	15276.4	15278.8	15277.06516		
	1	1	0.8	100	50	15277.2	15279.1	15278.8	15276.7	15277.1	15277.77547		
	1.5	1	0.8	100	50	15277.3	15278.7	15277.1	15277.6	15276.3	15277.41204		
	1	0.5	0.8	100	50	15277.9	15282.6	15276.5	15277.5	15276.7	15278.24763		
b	1	1	0.8	100	50	15276.7	15277.2	15276.8	15276	15276.6	15276.65444		
	1	1.5	0.8	100	50	15278.8	15276.2	15277.4	15276.7	15282	15278.24767		
	1	2	0.8	100	50	15278	15277.3	15277.3	15278.1	15280.1	15278.17298		
	1	1	0.2	100	50	15283.3	15288.8	15282.4	15285.1	15287.5	15285.39838		
	1	1	0.4	100	50	15278.2	15294.5	15281.3	15280.6	15277.4	15282.39731		
c	1	1	0.6	100	50	15281.7	15278.7	15278.2	15278.6	15277.3	15278.89693		
	1	1	0.7	100	50	15276.4	15277.3	15277.4	15276.9	15277.6	15277.11496		
	1	1	0.8	100	50	15276.5	15276.2	15277.2	15277.3	15276.6	15276.75409		
	1	1	0.8	100	50	15278.1	15277.5	15279.2	15277.2	15276.9	15277.80004		
d	1	1	0.8	500	50	15276.2	15277	15276.8	15276.5	15276.4	15276.59249		
	1	1	0.8	1000	50	15276.2	15276.2	15276.4	15277.3	15276.1	15276.44741		
	1	1	0.8	2000	50	15276.1	15276.3	15276.2	15276	15276.1	15276.12233		
	1	1	0.8	100	50	15279	15277.8	15278.3	15284.8	15280.2	15280.02917		
	1	1	0.8	100	300	15276.2	15276.5	15277.5	15276.6	15276.8	15276.7179		
e	1	1	0.8	100	500	15276.4	15276.2	15276.2	15276	15276.2	15276.17705		
	1	1	0.8	100	1000	15276.2	15276.2	15276.5	15276.1	15276.2	15276.22338		
	1	1	0.8	100	5000	15276.2	15276	15276.1	15276	15276.2	15276.10256		

Table A.2 Load Dispatch for Year 2018

2018	Area 1							Area 2									
Hour	G1	G2	G3	G4	G5	G6	G7	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
1	69.0	69.0	69.0	0.0	69.0	77.6	83.6	69.0	77.7	90.9	69.0	69.0	69.0	100.0	90.4	69.0	100.0
2	96.3	69.0	100.0	93.3	95.3	69.0	78.5	69.0	0.0	69.0	75.7	100.0	98.7	69.0	77.0	92.4	69.0
3	84.8	100.0	69.2	100.0	69.0	83.8	78.7	97.7	79.8	81.4	100.0	71.8	69.0	69.0	71.4	69.0	69.0
4	69.0	69.0	69.0	70.9	100.0	69.0	69.0	69.0	69.0	69.0	69.0	95.6	80.2	84.8	95.3	69.0	100.0
5	69.0	88.1	69.0	74.2	92.3	100.0	69.0	69.0	70.1	74.0	69.0	69.0	100.0	69.0	69.0	69.0	69.0
6	69.0	69.0	69.0	69.0	99.6	84.2	75.0	69.0	84.6	69.0	81.8	100.0	69.0	69.0	90.3	69.0	100.0
7	81.1	89.7	69.0	81.1	78.3	91.2	69.0	69.0	87.0	100.0	98.1	100.0	100.0	69.0	73.4	100.0	100.0
8	96.1	72.8	69.0	86.3	100.0	69.0	70.9	69.0	100.0	69.0	69.0	85.9	69.0	69.0	90.0	69.0	69.0
9	69.0	86.6	69.0	100.0	100.0	81.9	69.0	69.0	73.1	71.3	71.5	93.4	69.0	100.0	69.0	69.0	69.0
10	73.9	69.0	98.4	69.0	69.0	69.0	89.3	69.0	100.0	69.0	69.0	69.0	69.0	69.0	69.0	94.4	69.0
11	100.0	70.8	100.0	100.0	69.0	100.0	69.0	86.0	69.0	85.0	69.0	69.0	100.0	71.8	69.0	69.0	79.5
12	100.0	69.0	69.0	69.0	69.0	71.3	69.0	100.0	69.0	69.0	69.0	69.0	100.0	70.9	69.0	69.0	88.6
13	69.0	0.0	86.8	81.5	69.0	69.0	69.0	69.0	100.0	93.2	100.0	78.2	69.0	69.0	69.0	69.0	69.0
14	69.0	73.4	92.2	69.0	69.0	69.0	86.8	100.0	90.1	69.0	80.5	69.0	100.0	100.0	92.9	85.8	69.0
15	92.2	69.0	69.0	80.7	82.0	69.0	73.6	69.0	69.0	100.0	96.5	71.0	100.0	95.8	92.6	70.8	78.7
16	91.0	69.0	92.5	75.0	73.2	69.0	69.0	92.1	69.0	80.3	69.0	69.0	69.0	69.0	95.0	69.7	69.0
17	69.0	74.6	69.0	69.0	69.0	80.5	69.5	69.0	76.4	69.0	100.0	69.0	100.0	84.6	69.0	69.0	100.0
18	69.0	69.0	74.8	84.9	72.3	69.0	76.4	69.0	69.0	96.9	97.0	69.0	69.0	69.0	100.0	83.1	80.6
19	0.0	69.0	100.0	69.0	69.0	69.0	100.0	69.0	99.2	72.3	87.4	100.0	69.0	69.0	88.6	83.7	69.0
20	94.6	100.0	69.0	100.0	69.0	89.1	100.0	80.6	69.0	82.3	85.8	69.0	69.0	100.0	69.0	100.0	100.0
21	69.0	100.0	100.0	92.1	100.0	83.4	69.0	95.3	69.0	93.5	98.9	100.0	69.0	100.0	100.0	85.4	69.0
22	74.1	69.0	100.0	69.0	69.0	100.0	100.0	69.0	95.8	69.0	72.3	76.9	100.0	96.2	82.5	88.9	69.0
23	86.5	100.0	69.0	94.4	69.0	80.8	69.0	69.0	100.0	69.0	69.0	69.0	69.1	71.9	80.7	90.1	69.0
24	100.0	73.3	100.0	69.0	83.7	69.0	69.0	100.0	69.0	100.0	78.4	100.0	70.4	78.8	81.2	70.7	69.0

Table A.2 Load Dispatch for Year 2018 (Cont.)

2018	Area 3									
Hour	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
1	85.8	69.0	100.0	69.0	73.2	69.0	74.6	100.0	0.0	100.0
2	79.2	0.0	71.9	71.0	69.0	71.2	69.0	73.9	71.6	100.0
3	85.7	69.0	69.0	79.9	69.0	69.0	100.0	100.0	69.0	100.0
4	76.7	95.1	100.0	69.0	100.0	69.0	69.0	100.0	69.0	100.0
5	77.3	90.4	100.0	79.8	0.0	69.0	83.6	69.0	69.0	100.0
6	95.1	95.9	69.9	69.0	75.9	69.0	69.0	69.0	90.7	69.0
7	69.0	0.0	80.2	100.0	69.0	86.4	71.1	69.0	69.0	84.6
8	100.0	69.0	74.9	72.4	69.0	100.0	80.0	85.0	69.0	69.0
9	100.0	100.0	74.6	84.5	100.0	69.0	75.1	91.9	90.7	100.0
10	69.0	99.9	69.0	83.2	70.8	69.0	100.0	69.0	69.0	100.0
11	81.4	69.6	74.2	69.0	69.0	100.0	69.0	69.0	77.8	100.0
12	69.0	89.7	70.4	69.0	100.0	88.4	73.5	69.0	100.0	69.0
13	69.0	100.0	69.0	100.0	69.0	83.8	73.5	100.0	69.0	87.0
14	70.2	100.0	72.7	85.0	76.4	88.4	100.0	69.0	100.0	69.0
15	100.0	100.0	83.8	100.0	100.0	82.0	98.9	100.0	86.1	69.0
16	69.0	83.4	100.0	69.0	100.0	85.5	69.0	69.0	69.0	71.0
17	94.9	100.0	100.0	69.0	69.0	69.0	100.0	70.7	70.0	79.8
18	100.0	82.9	69.0	69.0	99.5	85.9	83.4	69.0	82.1	86.3
19	70.6	69.0	70.7	69.0	69.0	70.3	100.0	69.0	69.0	88.1
20	78.7	89.8	92.4	69.0	98.3	69.0	70.0	69.0	69.0	69.0
21	100.0	94.5	100.0	78.4	75.1	82.3	90.9	69.0	100.0	69.0
22	69.0	0.0	100.0	100.0	100.0	69.0	69.0	69.0	70.7	77.8
23	76.3	84.5	69.4	69.0	69.0	70.3	100.0	74.8	69.7	72.6
24	69.0	69.0	100.0	95.5	100.0	100.0	69.0	100.0	75.9	96.2