Policy-based unit commitment problem: a case in a peaking power generation plant


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Abstract: Unit commitment (UC) along with economic load dispatch (ELD) is an integral optimisation problem in the power generation industry. In this paper, policy-based algorithms are developed to address dispatch problems under different system configurations with the benefit of providing flexibility in addressing several desired policies of decision-makers. A case study is conducted in a diesel-fired, power plant in central Philippines to elucidate the proposed approach. Three policies were created to effectively address the optimisation problem: 1) classic UC model; 2) buying and selling strategy; 3) continuous loading strategy with various issues being considered. Results show that the strategies exhibit a significant decrease in total costs and ease of implementation with respect to the current production schedule of the case firm. Furthermore, the second policy provides the least generated cost which implies that generating firms must consider the option to sell power when market prices reach desired levels.

Keywords: economic load dispatch; ELD; unit commitment; rule-based algorithm; conventional methodology; constrained optimisation; power generation.


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1 Introduction

One of the various ways of generating electricity is through the use of diesel generators. Power generation through diesel generators are usually used as auxiliary supply when the demand for power exceeds the base-load supply. Diesel electric power plants are only used as auxiliary supply units due to the high cost of producing electricity of these plants
because of the diesel fuel (Jell, 2015). Being an auxiliary supply, these power plants need to be reliable to reduce power outage as much as possible. It is ideal for a power grid to be able to maintain a steady supply of electricity. Furthermore, maintaining steady stream of investors from public and private sectors requires power supply to be reliable (Trivedi, 2013). In 2001, state regulations have driven power generation industries from the monopolistic characteristics to competitive wholesale market. This deregulation has been introducing risk and uncertainty to the power sector due to some market and economic conditions (Gurgur and Newes, 2011). Competition is introduced through a spot market entity that acts as a pool-based electricity market (Turingan, 2008).

Following this market competition, power generation firms need to produce electricity at the least possible cost. For this, a century-old economic load dispatch (ELD) becomes highly relevant (Xia and Elaiw, 2010). ELD is characterised by a nonlinear optimisation problem that minimises generation costs subject to meeting different system requirements (Barisal and Prusty, 2015). Due to the broad scope and limits of the ELD problem, there have been a lot of extensions in ELD to effectively address different issues. Some of these issues are minimising total emissions to acceptable limits brought about by state regulations (Mondal et al., 2013; Singh and Kumar, 2015), incorporating renewable energy sources (RES) (Alham et al., in press; Velamuri et al., in press), creating demand response models to balance out demand against supply (O’Connell et al., 2016), and distributed generation which allocates power to those who are far from the power grids (Govardhan and Roy, 2016). The complex behaviour of ELD has challenged many domain scholars in solving the required optimisation problem. Conventional and meta-heuristic approaches were used to address various extensions of the ELD such as MILP model (Wang et al., 2012), differential evolution model (Storn and Prince, 1995) among others. Each of these approaches has its own corresponding strengths and limitations. As of the time being, there is no dominant approach that addresses majority of the ELD problem and its extensions.

Thus, this study attempts to develop an integrated model that highlights unit commitment with ELD problem. This methodology is expected to aid scheduling of generating units and their corresponding production output under a rule-based approach. The proposed method is applied in a diesel-fired, peaking power plant in central Philippines. Having high generation costs, it is ideal for the firm to schedule its generating units optimally. Results were reported in this work. The contribution of this study is the proposed methodology in addressing both unit commitment and ELD problem.

2 Review of related literature

2.1 Basic economic dispatch model

ELD is a significant optimisation problem in the power industry due to the need of generating power at the least possible cost. This has also brought about by the deregulation of the power generation industry that has induced competition among firms (Turingan, 2008). Thus, power generation firms have to find ways to generate power at the least generation cost while meeting system demands and requirements in order to be competitive in the wholesale electricity market (Jadoun et al., 2015). The objective of this optimisation problem is to assign the optimal generation level to different generating
units in a manner that cost is at minimum while satisfying system constraints such as load demand and generators’ limits (Barisal and Prusty, 2015). Barisal and Prusty (2015) described ELD as a high dimensional, non-convex, non-smooth and nonlinear problem that requires a highly efficient optimisation method in order to satisfy all of its requirements. As a consequence, several approaches such as meta-heuristics methods that possess high computing power and efficient computational time have emerged in current literature (Sendaula and Biswas, 1993; Basu, 2014; Subramanian et al., 2015). Due to its importance, it has brought attention to domain researchers and practitioners and has generated a vast literature over a span of century of research. See Wood and Wollenberg (1996) on one of several textbooks available in this field.

2.2 Extensions of the ELD problem

2.2.1 Economic emission dispatch

Due to the growing concerns of harmful pollutants caused by oxides of carbon, nitrogen and sulphur, which affect all living things and also adds up to the disturbing global warming (Jadoun et al., 2015), power plants around the world are required to produce at an acceptable emission level (Di et al., 2014). Power generation firms have given a large amount of consideration to pollutant emissions since operations would be ceased if they produce pollutants above their allocated limits. In recent years, different methods were proposed to control emissions such as installing emission control equipment in power plants, switching to low sulphur coal, fuel switching, replacing aged fuel burners with newer ones and emission dispatch (Arul et al., 2015). From these methods, emission dispatch is the most preferred approach (Arul et al., 2015) due to its low required capital and ease of implementation (Nwulu and Xia, 2015).

The basic ELD has now been modelled to minimise emissions in addition to minimising total fuel cost while its basic constraints remain the same. Economic emission dispatch (EED) is a multi-objective nonlinear constrained optimisation problem (Di et al., 2014) and both of its objective functions; minimising total generation cost and minimising emission are contradicting due to the fact that they have an inversely proportional relationship (Gopalakrishnan and Krishnan, 2013). The dynamic extension of the EED is also an emerging topic in domain literature, e.g. Jin et al. (2015). Previous studies condensed the problem into a single objective optimisation problem by considering the emission as one of its constraints within a tolerable limit (Granelli et al., 1992) for computational ease but this has a severe trouble in attaining the trade-off relation of cost and emission (El-sobky and Abo-elnaga, 2014). Another approach is by allocating different weights for each objective functions and selecting from a Pareto-optimal set of solutions based on the decision maker’s preference (Arul et al., 2015). On the other hand, Laia et al. (2015) argued that the efficient and simplistic nature of linear models outweigh the complexity of other models in solving EED.

2.2.2 ELD with RES

The growing concern for the environment, depleting fossil fuel sources and increasing greenhouse gases have prompted the power generation industry to look for alternatives that run on renewable sources (Zhou and Botterud, 2014). While RES involve a large
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initial investment that requires expeditious recovery (Plathottam and Salehfar, 2015), this approach leads to sustainability. Nevertheless, its unpredictability nature that depends largely on solar power, wind, hydro power, etc. potentially affects generation schedules. Following this dilemma, most existing power and large energy storage systems are adapting a mix of conventional and renewable sources (Plathottam and Salehfar, 2015). Boqiang and Chuanwen (2009) claimed that among RES available worldwide, wind energy is widely used. Due to the uncertainty behaviour of RES, ELD models have introduced probabilistic variables and constraints (Li et al., 2014).

Modelling RES cost functions are more challenging due the nature of the fuel source of these generating units (Zhou and Botterud, 2014). The probabilistic nature of these generating units also makes the model development even harder that forces the models to impose fuzzy logic in analysing the uncertainty of these generating units (Geetha et al., 2014). However, one emerging approach to address the complexity of this model is through the use of mixed-integer linear programming (MILP) model, e.g. Bakirtzis et al. (2014).

2.2.3 Demand induced dispatch

Generation in conventional power systems run in the ‘load-following’ manner and most of the time gives emphasis on the supply-side of the equation (Zhong et al., 2015). The other side of the equation, the demand side, is assumed constant in the day ahead scheduling processes (Khodaei et al., 2011). However, these models fail to account for capacity shortages during peak hours. To address this issue, former approach lies in building more power plants to satisfy demand during peak hours but would be underutilised during lean hours (Khodaei et al., 2011). Thus, demand induced dispatch became a remarkable approach in addressing this issue. In the demand side, customers are expected to be flexible and reach an understanding with its suppliers by load reduction, load shifting and consumption mode switching (Zhong et al., 2015). To give emphasis to load shifting, Papaioannou et al. (2013) highlighted that load shifting only changes the time of day when the load is switched but the total demand at the end of the day remains the same.

Demand response models address the change in electric usage by end-use customers to their usual consumption rates (Nwulu et al., 2013) which can be either instantaneous or pre-scheduled (Magnago et al., 2015) in response to the volatility of electricity prices, incentives designed to induce lower electricity use at peaking hours, high market prices, and when system reliability becomes an issue (Nwulu et al., 2013). These models are particularly interesting since they consider prices of power at short intervals. These models also have look ahead capabilities in the power generation market that anticipate hourly demand (Tumuluru et al., 2014; Wu et al., 2013). Magnago et al. (2015) highlighted that these models are used by those who distribute or regulate electricity to improve better manageability to system operators, optimising their role in power systems and maximising revenue for the providers. These were classified into two extensive categories: emergency and economic models. Emergency models are allocated when the balance of supply and demand becomes a major concern while economic models are more voluntary to reduce potential demand if compensation is just.
2.2.4 Distributed generation

High costs of transporting fuel and incorporating generating units far from the power grids were one of the problems of large power grids. They were not able to provide reliable and affordable power to those in remote areas far from the power grid. The only solution was to create small scale generating units ‘micro grids’ close to the area. To address this issue, distributed generation or distributed energy is generated and stored by a number of small scale ‘micro grids’, self-contained power plants which are controlled by large power grids but is located near to the load they provide (Ackermann et al., 2001). Micro grids typically operate on RES which means nearly zero emission in the environment but will entail a higher cost than conventional sources (Kayal et al., 2014). They contain a higher risk due to their uncertainties but are now integrating with demand response models to easily curtail power demand (Safdarian et al., 2014). Kayal et al. (2014) argued that distributed generation will have a huge impact on the innovations of power system structures due to its possibilities of providing an eco-friendly, dependable and cost effective electricity to the consumers. Distribution companies are also giving a lot of time on improving the power quality and maximising economic benefit leading to reasonable bill payments.

2.3 Unit commitment

Raju et al. (2015) described a unit commitment (UC) problem as an elementary level in the scheduling process of power systems. While ELD assumes that all generating units are online, UC determines which units to dispatch, start-up, shut down, ramp-up or ramp-down. UC typically answers the problem “Given that there are a number of subsets of the complete set of N generating units that would satisfy the expected demand, which of these subsets should be used in order to provide the minimum operating cost?” (Wood and Wollenburg, 1996). UC is more applicable for peaking plants since generating units of these plants are not usually online all the time. UC focuses on scheduling generating units to meet the forecasted load demand over a time period under different operational constraints (Coronado et al., 2012). Its prime objective is to reduce total generation cost (Raju et al., 2015). Santillan et al. (2016) were able to show that failure to implement UC model in a peaking power plant increases generation costs at approximately 27%. With the UC problem, ELD becomes a sub problem to be solved. Sendaula and Biswas (1993) developed model that attempt to solve the UC problem and ELD problem simultaneously. UC is deciding out of the current electrical resources to fulfil the load demand and allocate margin of operating reserve over a considerable amount of time (Saravanan et al., 2013). UC problems are usually modelled as MILP problems with some binary variables.

With the deregulation of the power generation industry and the introduction of the power market pool, UC and ELD have been revised to address the growing need for their generation output to be market competitive (Heredia et al., 2010; Laia et al., 2015). These two models have incorporated bilateral contracts in their objective function. This enables production requirements to match customer demands. These models aim to determine prices for each bid (Laia et al., 2015).

UC problems have expanded to the scheduling of not only generating units but also of the maintenance of these units (Subramanian et al., 2015; Rodilla et al., 2014). Furthermore, UC problems have also expanded to include the probability of the
generating units to break down (Tang et al., 2012). These extensions are effective in determining the chance of failure of the generating units and the scheduling of these units. This is useful in both UC and ELD problems since generating units experience wear and tear which entail corresponding costs (Morales-España et al., 2013; Wang and Shahidehpour, 1994; Troy et al., 2012).

2.4 Methodological approaches

Since ELD is characterised by nonlinear, non-convex, non-smooth and multi-variable optimisation problems with extensions which potentially increase their complexity, they require solution methods that are highly efficient with remarkable computing power. For the past couple of decades, there has been a lot of research focusing on different optimisation techniques incorporating multiple constraints. These approaches have been categorised into three main classifications, namely: conventional and soft-computing (meta-heuristics methods) (Xia and Elaiw, 2010).

2.4.1 Conventional/heuristic methods

There are a lot of conventional approaches being used to solve ELD and its extensions such as linear programming (LP), nonlinear programming (NLP), MILP, quadratic programming, Lagrange relaxation (LR), Gauss-Seidel or Newton-Raphson, dynamic programming (DP), gradient search method, fuzzy optimisation (FO) (Wang et al., 2012; Arul et al., 2015; Mishra and Mishra, 2015). These techniques sometimes provide approximations to reduce its complexity and typically are inferior in solution power because some of them usually get stuck at the local optimum solution (Arul et al., 2015). Conventional methods entail the incremental cost curves to be monotonically increasing or piecewise linear (Barisal and Prusty, 2015) and may not be fit to solve nonlinear and discontinuous characteristics (Walters and Sheble, 1993). Wenyuan (1987) developed a successive linear programming to model real-time economic power dispatch with security constraints. Chang et al. (2013) developed an MILP model to answer UC problem with frequency regulating reserve. Wu et al. (2013) also developed an MILP to facilitate day ahead scheduling in power systems which incorporates hourly demand response for uncertainties of RES. Another MILP formulation was modelled by Morales-España et al. (2013) to focus on start-up and shut-down ramping in UC problem.

Advantages of these methods are their ability to compute for the optimal solution, can easily handle large-scale problems and they are computationally fast (Xia and Elaiw, 2010). The downside of conventional methods is that they introduce surplus variables often to force the model to produce a feasible solution (Li, 1987). To cover this problem, Morales-España et al. (2013) developed a model with tighter constraints to reduce the number of variables required. Some of these techniques were reviewed by Morales-España et al. (2013).

2.4.2 Soft computing and meta-heuristics

There are several meta-heuristic approaches to ELD namely differential evolution (DE), particle swarm optimisation (PSO), harmony search (HS), genetic algorithm (GA), simulated annealing (SA), evolutionary programming (EP), artificial immune system (AIS) (Storn and Price, 1995; Jadoun et al., 2015; Arul et al., 2015; Mishra and Mishra,
Dubey et al. (2014) conducted a review on bio-inspired optimisation techniques for the ELD problem. These methods however suffer from long computational time, difficult to handle complex constraints, being trapped into local optima due to premature convergence, loss of diversity and performance in optimisation process and slow convergence to achieving the optimal solution which is not fit to be used in real time operation.


The techniques mentioned can reveal local optima but cannot generate an optimal solution (Afzalan and Joorabian, 2013). The complexity in developing these soft-computing models and its high computational complexity does not justify its efficiency in solving. New optimisation techniques with slight modifications of current meta-heuristic methods are being used to generate global or near global optimal solutions and the advantages of these algorithms is that they have less or no limitations on the shape of cost functions and constraints (Barisal and Prusty, 2015). These techniques were created to address different drawbacks of each method in order to generate a more global optimal solution. However, they are rather delicate to several parameters tuning (Barisal and Prusty, 2015).

3 Background on basic power generation optimisation models

The following discussions were lifted from the work of Wood and Wollenberg (1996).

3.1 Basic economic dispatch model

3.1.1 Objective function

Given that there is N number of generating units with cost rate \( F_i \) (in Php/MW) and output of \( P_i \) (in MW), the cost of generation for unit \( i \) is a cost function of \( F_i \) in terms of \( P_i \), i.e. \( F_i(P_i) \). The objective is to minimise the total generation cost. Hence, the objective function can be written as

\[
\min \sum_{i=1}^{N} F_i(P_i)
\]  

The cost rate \( F_i(P_i) \) is a polynomial function with an arbitrary degree depending on the formulation the problem. The cost rate is taken from the gross input and net output curve of the generating unit. The input is defined as the total expense of the unit; fuel consumption and usually includes, labour cost, etc. The output of the unit is the total power generated by the unit in terms of MW. \( F_i(P_i) \) is a polynomial

\[
F_i(P_i) = a_i P_i^2 + b_i P_i + c_i
\]

where \( a_i, b_i \) and \( c_i \) are constants of the cost function generated through curve fitting techniques.
3.1.2 Constraints

The constraints of a basic ELD normally consist only of the energy balance and the generator limits.

1. The energy balance in terms of the total generation is equal to the sum of the total system demand \( (P_D) \) and the system loss \( (P_L) \)

   \[
   P_D + P_L = \sum_{i=1}^{N} P_i
   \]  

   (3)

2. The generator limit constraint is defined as the limitation of the generating unit. It is expressed as:

   \[
   P_{\text{min},i} \leq P_i \leq P_{\text{max},i}
   \]

   (4)

   where \( P_{\text{min},i} \) is the minimum load the generating unit can operate efficiently and \( P_{\text{max},i} \) is the maximum load the generating unit can handle.

3.2 Unit commitment model

3.2.1 Objective function

Since unit commitment is usually a sub problem of ELD and is simultaneously solved, it has the same objective function which is to minimise total generation cost but now includes start up and shut down costs since it assumes the generators are offline while ELD considers all generators online. Unit commitment also considers the ramp rates of the generating units. Unit commitment is also a stochastic problem since it considers the needed demand for time interval \( t \) for the entire set \( T \).

The optimisation problem now minimises the cost of generating including the start-up and shut down cost of generating units at a given interval. The objective function is now modelled as

\[
\min \sum_{t=1}^{T} \sum_{i=1}^{N} \left[ F_i \left( P_i^t \right) + \text{Startup or shutdown cost of } i \text{ at interval } t \right] U_i^t
\]

(5)

where \( P_i^t \) is the load required of generating unit \( i \) at interval \( t \), and \( U_i^t \) is the commitment state of generating unit \( i \) at interval \( t \). \( U_i^t \) is a binary variable where 1 for online state and 0 for offline state for a generator \( i \) at an interval \( t \).

3.2.2 Constraints

UC has roughly the same constraints as ELD but with a few case-specific additions.

3.2.3 Ramp rate limits

Ramp rates are taken into account in unit commitment since generating units have different rates as to how fast it could change its load. The ramp-up and ramp down limits are represented as follows

\[
P_{i,t}^{t-1} - P_{i,t} \leq DR_{i,t}, \text{ if power generation decreases}
\]

(6)
\[ P_{i,t} - P_{i,t-1} \leq UR_i \quad \text{if power generation increases} \quad (7) \]

where \( P_{i,t} \) is previous hour power generation of the \( i^{th} \) unit. UR, and DR, are the upper and down ramp rate limits of the \( i^{th} \) unit, respectively.

Upper ramp rate is the rate of increase in the load of the generating unit. Down ramp rate is the rate of decrease of the load of the generating unit.

### 3.2.4 Spinning reserve constraints

This constraint defines how much spinning reserve a plant must have available.

Spinning reserve is defined as the load that can be dispatched immediately. It can be dispatched immediately since the spinning reserve is the excess capacity of a generating unit that has not yet been dispatched.

This constraint is defined as:

\[ r_i \leq (P_{\max,i} - P_i) \quad (8) \]

\[ SP = \sum_{i=1}^{N} r_i \quad (9) \]

where \( r_i \) is the available spinning reserve for generating unit \( i \) and SP is the total spinning reserve the plant needs to have available.

### 4 Case study

#### 4.1 Background of the case

East Asia Utilities Corporation (EAUC) is the subject of the case. The company was established on May 28, 1998. It is a peaking-diesel fired power plant located in Barangay Ibo, MEPZ, Mactan Cebu and a subsidiary of the Aboitiz Power. It has a nameplate capacity of 50 MW and with a dependable net capacity of 43 MW. It supplies 22 MW to MEPZ and 5 MW to Balamban Energy Zone (BEZ). The rest of the generated power will be sold to Wholesale Electricity Spot Market (WESM). At the moment, it has 47 regular employees and also has contractual and sub-contractual employees.

The company currently has four diesel fired engines type 16V 52/55 A diesel engine, manufactured by MAN B&W 1983 in Augsburg, Germany. Each engines contains a nameplate rating of 12,824 KW/unit and speed of 450 rpm, a mean effective pressure of 18.3 BAR, a mean piston speed of 8.25 m/s and firing pressure of 130 BAR. It is installed with a turbocharger by MAN B&W; type NA 57 that has a mode of supercharging that is constant pressure.

Due to the different managerial decisions being made by EAUC, different policies are drafter to address different concerns independently. The first policy created was the classic UC which strategically provides different loading to each generator in order to achieve minimal cost. The policy is essential to effectively determine which units to run. The second policy focused on selling electricity to WESM. If demand is lesser than the plant capacity and prices are within profitable range, EAUC considered selling electricity in order to maximise profit. The third policy is the continuity loading strategy considered
giving priority to the units that have already been committed. However, if WESM prices are lower than production costs, purchasing power will be given priority rather than online units to continue to satisfy objective function.

4.2 Current production cost

The firm’s one week of production scheduling was taken for brevity in simulation and comparison. The month of September was chosen since this month expresses a normal power market behaviour. The first week of the month was chosen since this week also greatly expresses the normal behaviour of the power market in terms of price and demand.

For proper comparison, the cost of fuel in their actual production schedule was calculated. The company has set a value of Php 3,733.90 per megawatts (MW) to get the fuel cost. However this is through assuming that the cost function is a straight-line function. This method does not properly reflect the costs of the generators since the true cost functions per generator are not linear.

Fuel cost curves of the generating units were generated by plotting the fuel consumption per generating unit in one hour to certain loading (MW) intervals, from the minimum to the maximum. The relationship of the price (Php) of fuel per litre (L) and the volume of fuel per hour (L/h) is retrieved through a quadratic curve.

For DG1, the quadratic curve is

Figure 1 Fuel cost rate of DG1

![Figure 1](image1)

Figure 1 generates a regression equation in the form \( F_1(P_1) = -6.8264P_1^2 + 2,995P_1 + 3,925.4 \) with coefficient of determination \((R^2)\) of 0.99424.

For DG2, the quadratic curve is

Figure 2 Fuel cost rate of DG2

![Figure 2](image2)
Figure 2 generates a regression equation in the form $F_2(P_2) = -82.1P_2^2 + 3,868.9P_2 + 2,458.6$ with $R^2 = 0.99647$.

For DG3, the quadratic curve is

\[
F_3(P_3) = -82.1P_3^2 + 3,868.9P_3 + 2,458.6
\]

with $R^2 = 0.99898$.

For DG4, the quadratic curve is

\[
F_4(P_4) = -28.13P_4^2 + 3,207.9P_4 + 3,591.7
\]

with $R^2 = 0.99709$.

Using the cost functions above, actual loading per interval is plugged in into the equation to get the exact actual fuel cost per interval. The cost is shown in the succeeding sections.

4.3 Policy 1 – adoption of classic unit commitment

Prior to developing and applying other different policies which are discussed in the next sub-sections, the classic UC model is adapted in order to obtain the optimal solution. UC model focuses on minimising total generation cost while meeting system requirements. The results of this adoption are used in comparing the results of other succeeding policies. The objective function of the model is derived from (5) which is the most basic and widely used function. Start-up and shutdown costs are neglected since it is insignificant.

\[
\min \sum_{t=1}^{T} \sum_{i=1}^{N} \left[ F_i \left( P_i^t \right) \right] U_i^t + WP^i(B)(U_i^t)
\]  

(10)

where

$WP^i$ WESM price for the interval.
Table 1

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Policy-based unit commitment problem

Results of 24-hour interval of Policy 1
Alongside with this objective function is the energy balance constraint which is the equality of the total generation and the sum of the total system demand and internal consumption. The computation of this constraint is taken from (3) which is now,

$$D_1 + (0.0339)(U_1 + U_2 + U_3 + U_4)^2 + (0.6229)(U_1 + U_2 + U_3 + U_4) = P_1U_1 + P_1U_2 + P_1U_3 + P_1U_4 + P_2U_5$$

This policy shows the most basic optimisation process in power generation. It is considered to be optimal solution however it does not have other constraints that limit the feasible area. Results are shown in Table 1. As basis for comparison, actual production costs are obtained using (5). It is evident that the difference of the results of this policy from the actual production costs proves that this strategy produces lesser generation costs. Due to its high computing power in locating the global-optimal solution, the model successfully identifies which generators to dispatch at any given interval which the firm does not effectively consider. This issue shows the inefficiency of not using optimisation techniques in generating power generation schedule. Despite its capabilities, it has limited scope in terms of policies it can handle.

4.4 **Policy 2 – buying and selling strategy by a rule-based algorithm**

This policy is brought about by the capability of the firm to participate in the power trading market. The algorithm assists the firm in its strategy in deciding how much to produce and dispatch to meet contracted demand while maximising sales to the wholesale market. The algorithm decides as when to produce given the firm’s conditions when to sell. The algorithm serves as a unit commitment model that addresses the intentions of the firm to be able to sell power at an optimal level. The operations of the algorithm require obtaining solutions of ELD. The algorithm is shown in Figure 5.

The steps of the algorithm are as follows:

**Step 1** The algorithm determines the demand required of the firm from contracted customers.

**Step 2** The available capacity is taken; this is by subtracting the plant capacity with the demand required. The available capacity is then the amount of power that the firm can sell to the power market.

**Step 3** The algorithm first determines if the market price is viable for it to participate in the selling of power. The algorithm decides if the market price is greater than Php 1,000.00 compared to the firm’s set price. If it is greater, the algorithm opts to sell. If not, the algorithm opts to buy or produce only.

**Step 4a** If the algorithm opts to sell, it initiates an optimisation problem, ELD, with a new variable. This variable is the sell variable, which determines how much should be sold. This variable is seen as a negative number in the objective function, as the revenues lessen the costs.

**Step 4b** If the algorithm opts to buy, then it initiates an optimisation problem, ELD, with just a normal model with an option to buy. There is no sell variable included here, only a buy variable.

**Step 5** The algorithm reverts back to the beginning for a new interval.
The buy only model includes in the objective function the buy variable. This optimisation model is the same as the classic ELD. It also has the same constraints and parameters. The sell model has an addition of a sell variable in the objective function and added constraints to address different requirements for selling. The objective function is,

\[
\sum_{i=1}^{N} F_i^t (P_i^t)(U_i^t) + WP^t (B^t)(U_{ih}^t) - WP^t (S^t)(U_{ik}^t)
\]  \hspace{1cm} (12)

The parameter $WP^t$ is the current market price for power at time interval $t$. The new variable introduced is $S^t$. It is the amount of power that the firm should sell at time interval $t$. This is expressed as a negative value since it is selling and reduces costs. There is an added constraint for the limits of the sell function. This constraint ensures that the model does not sell everything to the market. This also ensures that the contracted demands from its bilateral customers are satisfied first before selling to the market.

\[
0 \leq S^t \leq 43 - D^t
\]  \hspace{1cm} (13)
The demand $D_t$ is the demand of its bilateral customers for time interval $t$. This limits the sell variable to only sell the excess power after addressing the contract.

The power balance constraint has been modified to address the additional production schedule brought about by the option to sell.

$$D_t^i + S_t^i + P_L^i = \sum_{t=1}^{N_{tt}} F_t^i (P_t^i) (U_t^i) + B^i (U_B^i)$$  \hspace{1cm} (13)

The constraint shows on the left side the total required power output of the firm. On the right, the amount each generator should produce and how much to buy to ensure it meets output requirements.

The whole optimisation model now is,

$$\min \sum_{t=1}^{T} \sum_{i=1}^{N} \left[ F_t (P_t^i) \right] U_t^i + WP^i (B) (U_B) - WP^i (S) (U_S)$$  \hspace{1cm} (14)

Subject to

$$6 \leq P_i \leq 11.1 \hspace{1cm} (15)$$
$$6 \leq P_2 \leq 11 \hspace{1cm} (16)$$
$$6 \leq P_3 \leq 11.5 \hspace{1cm} (17)$$
$$6 \leq P_4 \leq 11.1 \hspace{1cm} (18)$$
$$0 \leq B \leq 43 \hspace{1cm} (19)$$
$$0 \leq S \leq 43 - D \hspace{1cm} (20)$$
$$U_1, U_2, U_3, U_4, U_B, U_S = 1, 0 \hspace{1cm} (21)$$

$$D + S + \left( -0.0339 (U_1 + U_2 + U_3 + U_4) \right)^2 + 0.6229 (U_1 + U_2 + U_3 + U_4) \hspace{1cm} (22)$$

$$= P_1 (U_1) + P_2 (U_2) + P_3 (U_3) + P_4 (U_4) + B (U_B)$$

The model shows a lesser cost compared to the actual production. Also this model through the introduction of a selling option has produced negative costs at given intervals due to the high prices of the market. Also the model has identified properly when to produce and when to buy. Unlike the current production system that fails to properly consider how much to procure or produce and when to procure and produce, the model easily addresses that problem mathematically. This model gives a mathematical justification as to decision-making on production.

This strategy keeps costs at a lower level due to the introduction of revenue through selling. In this algorithm the selling point is arbitrary. This variability of the selling point is at the discretion of the decision maker. The advantage of this strategy and method is that the decision maker has the flexibility to increase or decrease the price level the firm wants to sell at. The algorithm has the ability to be sensitive to the needs of the decision maker, which is not at the disposal of the classic ELD model.

However due to the arbitrariness of the algorithm, the ability of the decision maker to adjust certain constraints to the algorithm may lead to a local optimal solution. The interference of the decision maker in the rules in the algorithm, forces the model to find a solution that may not be globally optimal compared to the classic ELD problem.
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24-hour interval result of Policy 2

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4.5 Policy 3 – continuous loading strategy by a rule-based algorithm

This strategy was created to eliminate the inconvenience of starting up and shutting down generators. It presents problems to operators having to frequently shut down and start up. The algorithm is shown in Figure 6. The steps of the algorithm are as follows:

Step 1 Determine demand of the given interval.

Step 2 Prioritise units that are online to prevent from starting up and shutting down generators.

Step 3 Assign $U = 1$ for units that are already online for them to be prioritised by the model.

Step 4 Solve ELD in order to identify which generators to dispatch, how much to allocate per generator, and to identify total production cost.

Step 5 The decision maker now identifies whether demand for the next interval exceeds the current capacity of the online generators. If yes, decision maker compares current WESM price against price to produce and decide whether it is more economic to purchase rather than produce. If it is better to produce power, online units are prioritised to cater demand. If it is better to purchase power, online units are de-committed and purchases are made. If no, it is ensured that uncommitted units remain offline.

Figure 6 Continuous loading algorithm

The continuous loading strategy has the objective function similar to that of the classic UC model found in (10). It has the same constraint as that of the classic UC model but with few modifications. Constraint for this strategy is changing over time. For a given interval, if $P_i$ is online it is assigned with a binary variable of $U_i = 1$. From the results provided by the model, it is shown that this strategy has a slight difference to the classic UC model. It shows that the classic UC has the same production cost for day 1 with CL strategy. This also shows that this policy is more optimal than the actual production. However, this policy better incorporates the actual production method of the firm but this policy can better determine the decision whether to continue production or purchase...
instead. Also, this policy produces a lower cost compared to the actual production of the firm due to its efficiency in solving the UC problem. The firm’s criterion for committing units does not necessarily produce the least possible cost. It is brought about by the lack of knowledge in accounting for all of the necessary constraints in the optimisation process.

The advantage of this strategy is that it eliminates the trouble of starting up and shutting down generators. However, the drawback of this strategy is that some of its constraints are dynamic and it is inconvenient to revise the model periodically.

5 Discussion

The studied firm is a peaking power plant which is highly utilised during peak hours. However, it serves several customers during off-peak hours. It contracted part of its generating capacity leaving the excess to be sold in participation of the wholesale market. The firm utilised the priority list method combined with merit order loading to commit and dispatch units. The firm has certain considerations for their operations that do not necessarily lead to an optimum dispatch. The process of operation is arbitrary due to the decision maker’s choice. The decisions made leads to inefficiency. Given certain demands for certain intervals, the firm does not view the optimality of production. It also cannot properly consider or decide when to procure or produce. There are certain instances that the market price is cheaper than the cost to produce and yet the firm opts to produce due to lack of a proper mathematical optimisation.

The study attempts to address the issue of a lack of optimisation in the firm’s production through the use of established mathematical optimisation models, known as the UC and ELD problem. The study introduced a new way to solve the UC problem with the use of a rule-based algorithm in conjunction with an ELD model. The rule-based algorithm is structured to address certain policies the firm would like to implement. The algorithm gives the firm a proper basis now on its decision-making. Several policies have been developed through the rule-based algorithm, which are the buy and sell policy and continuous loading policy. The former aids decision makers when to sell their excess capacity in the power market while the latter aids the firm when to procure energy and how to ensure that they are optimally committing efficient units for long run times. There are significant cost differences that require to pick the units that are cost-efficient. Furthermore, it poses greater consideration when to purchase power when prices are at a low level.

Given that the behaviour of the generating units, in terms of productivity, of the firm is the same for any policy the rule-based approach is quite viable for application compared to other approaches. The rule-based algorithm is easy to format according to a policy a decision maker would like to address. The rule-based approach is applicable to any type of generating firm. With few changes to cater to different generating units, the approach can be easily replicated to any firm. To add, the approach is quick and easy to understand and use. This approach is practical for actual operations.

The sensitivity analysis is performed as follows. The algorithm finds points that satisfy the given rules in the algorithm and constraints in the ELD program. Also this policy is able to develop optimal levels even though it considers in selling its excess capacity.
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<th>Total cost</th>
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Table 3: Seven-day policy comparison
Such instances can be seen in the Day 1 interval 22. WESM price is low at Php 2,920.99 that the model prompts to purchase all of the demand instead of producing it. This sees that the purchase is the optimal choice for this situation. For the case of Day 2 interval 14, WESM price is high at Php 4,476.57 but does not satisfy the rules for it to sell power hence it prompts to produce the demand instead of purchasing. For Day 2 interval 11, WESM price is at a high price of Php 7,635.10. This price prompts the algorithm to sell. The algorithm then determines that the firm should produce to satisfy demand and to sell its excess capacity to the wholesale market at a volume determined by the model. The model also gives a prompt to sell of its capacity even without a demand from its contracted customers. Such is the case in Day 6 intervals 14, 15, and 18.

The algorithm is able to adapt to the fluctuating market prices that it is able to give optimal production points that reduces the costs.

The second policy is revised periodically to prevent unnecessary start-up and shut down of generators. However, it still considers purchasing power if the prices are lower than producing power. For example, at Day 3, the model previously committed generator 2 and 3 at the 11th interval. Since the firm follows that if there are generators committed at the previous hour and the cost to purchase power for the next hour is equal or less than 3200 the firm will still continue to commit committed generators. There are also instances where generators are committed at the previous hour but are shut down at the next interval. For example, at Day 3 interval 15, generators 2 and 3 are committed. However, at the 16th interval, WESM price is only Php 2,158.68. So power is purchased as prescribed by the model since its prices are low, rather than remain committed units online.

The decision making whether to commit should rest on the model since it is more accurate and has more reliable results. However, internal decisions are also inevitable but should be minimised as possible if minimising total generation cost is focused on. The rule-based algorithm is generic in nature and easily adapts to the policy determined by the decision maker. It remains true even if it were to be fed different information by applying it in different power generating plants. We focused on different policy separately to effectively address different concerns for each policy and maximise its capabilities. As long as the number of variables and constraints satisfy Lingo’s capabilities, the algorithm can efficiently provide the optimal result.

6 Conclusions and future work

In this paper, a different strategy for power production scheduling is proposed where different issues in generating firms are effectively addressed. The ideal optimal solution is fixed on solving the basic unit commitment problem. Two policies were introduced for the case firm which are the buy and sell strategy and continuous loading strategy. It is shown that the two strategies are considered near-optimal solution since the results are close to the ideal classic unit commitment model.

Case results show that it is beneficial for the firm to use the second policy which is the buying and selling strategy by a rule-based algorithm because it yields with the highest difference from the actual loading schedule among the three policies which means that the firm would be able to save costs using this policy. This shows that if the firm has the chance to sell energy to WESM, it can help in minimising the total production costs. However, considerations such as the internal decision-making
procedures should also be taken into account because these procedures can cause deviation from the results.

For future work, studies might consider different policies to address different issues. Possible policies might be including competitors, load curtailment, running hours, transmission losses, security constraints, and probabilities of failure. The problem is evident that it does not have an optimal strategy and it solely depends on the preferences of the decision-maker. Furthermore there is an option to look for better optimisation programs that can handle more requirements.

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References


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Nomenclature

- $F_i(P_i)$: Cost rate function of generator $i$
- $P_{i}^T$: Load of the generator required at interval $t$
- $a_i, b_i, c_i$: Constants of the cost function $F_i(P_i)$
- $P_d$: Total system demand
- $P_L$: Internal consumption
- $P_{\min,i}$: Minimum capacity of generator $i$
- $P_{\max,i}$: Maximum capacity of generator $i$
- $U_i^t$: Commitment state of generator $i$ at interval $t$
- $P_i^{t-1}$: Previous hour power generation of generator $i$
DR\textsubscript{i}  Down ramp rate of generator i
UR\textsubscript{i}  Upper ramp rate of generator i
R\textsubscript{i}  Available spinning reserve of generator i
SP  Spinning reserve needed to be available
WP\textsuperscript{t}  WESM price at interval t
B\textsuperscript{t}  Purchased power at interval t
U\textsuperscript{t}\textsubscript{B}  Commitment state of purchasing power
S\textsuperscript{t}  Sold power at interval t
U\textsuperscript{t}\textsubscript{S}  Commitment state of sold power
D\textsuperscript{t}  Bilateral contract demand at interval t