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**Simulation and Comparison of Pricing Strategies for
Electricity Markets**

Submitted by: Goh Yu Xuan

Matriculation Number: U1422094A

Supervisor: A/P Hu Guo Qiang

School of Electrical & Electronic Engineering

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Abstract

In this paper, I compare the traditional fixed pricing strategy with dynamic pricing strategy, which arose from the introduction of Smart Grids. This involves the simulation of the different pricing models under the strategies - for fixed pricing strategy: Flat-rate pricing model; for dynamic pricing strategy: Time-of-use pricing model and real-time pricing model.

A power system, which consists of several power consumers and a power provider is considered. Each consumer has an electricity consumption controller (ECC) unit in their smart meter. This allows a two-way communication between consumers and the provider through the transmission of data stored in the smart meter. By referencing the existing algorithms from previous studies, coupled with using particle swarm optimization (PSO) to produce optimal decision variables, thus allowing instantaneous matching of supply and demand of electricity, I simulate the optimal consumption levels for each consumer.

The simulation results are then obtained and the effectiveness of each pricing strategy is observed and compared. Simulation results confirm that Real-Time pricing is the most optimal pricing model among the three as it generates a price based on the consumption level in real time. This allows consumers to adapt by changing their consumption as price changes, thus improving the utility of electricity. This reduces costs for the producers, and at the same time increases the welfare of the consumers, thus maximizing the aggregate welfare of all stakeholders.

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Chapter 1 Introduction

1.1 Background

The demand for electricity has surged over the past 20 years, and from 2016 to 2060, the demand for electricity will have doubled [1]. The growing demand of electricity consumption can mainly be attributed by the world population growth and rising standards of living. The United Nations predicts the world population growth to rise from the current 7.3 billion to 9.2 billion in 2040 [2]. Rapidly developing countries such as China and India consume over 70% of the increased demand to fuel their ever-growing economies. This trend is expected to increase even further, with China already overtaken US as the prevailing largest energy consumer. Coupled with the rising standards of living and urbanization of those in the developing countries, the demand for electricity will not diminish.

Steam turbine generators produces more than half of the world's electricity today [3]. The burning of fossil fuels to produce electricity is a non-renewable approach. With the increasing concerns over climate change, there is more emphasis placed on renewable supply. However, besides being costly, it is also difficult to maintain a consistent supply of renewable energy since natural sources such as the sun and wind are required to generate electricity. Thus, energy providers have to take into account such limitations to ensure the profitability of the production and the ability to meet the ever-rising demands of electricity consumption.

High fluctuations in electricity during peak and non-peak periods also pose a problem to power companies as additional infrastructures are required to meet the electricity demand. These infrastructures will also be underutilized during non-peak period. Over the past few decades, many types of pricing strategies were introduced to the electricity markets. These pricing plans have two roles; to maximize the welfare of consumers through affordable pricing of electricity while spreading the peak demand of electricity to lower costs. The averaging out of demand across different periods aids suppliers in producing adequate supply of electricity without the need for more infrastructures [4].

1.2 Fixed Pricing and Dynamic Pricing Strategies

Improvements in technology has led to the introduction of Smart grid. Smart grid is the next generation power grid which uses modern technology to its advantage to achieve power control and management. It uses two-way communication technologies and control systems that allows information to be disseminated and collected by the operators and consumers almost instantaneously [5]. With the aid of these smart meters and sensors, power companies can lower the electricity price on non-peak periods so as to provide incentives for consumers to consume more electricity, thus achieving a more average electricity demand curve. Consumers can also receive real-time information on electricity prices and divert their demand to non-peak periods easily.

Traditionally, fixed pricing is used by producers to charge electricity prices, which uses a flat-rate pricing model. It is a pricing strategy where the price of electricity consumption is equal for all periods of time [6]. The rise of smart grid paves the way to the birth of dynamic pricing strategies which uses pricing models such as real-time and time-of-use pricing models. Dynamic pricing is where the price of electricity consumption changes over different periods based on the demand response [7]. This allows the electricity provider to influence the electricity consumption of users by charging higher rates during peak period to shift the electricity demand to non-peak periods so as to balance the load demand curve. Since electricity is vital in today's world, the need for more efficient way of pricing electricity is crucial to ensure our modern way of life is not restricted by shortages in energy.

1.3 Research Objective

The aim of this paper is to simulate and compare fixed and dynamic pricing strategies. In this paper, we focus on simulating different types of pricing algorithms to compare their advantages and disadvantages to ascertain which pricing strategy is the most efficient in maximizing the welfare of all stakeholders in the electricity market. This paper is summarized below:

- Flat-rate, real-time, and time-of use pricing algorithms are obtained and decision variables are optimized with particle swarm optimization (PSO). Simulations are ran to produce results on the utility of the users and the costs to the provider.
- Simulation results are obtained to compare the advantages and disadvantages of each pricing strategy.
- The desired strategy is determined and conclusions are made.

This paper is organized as follows. Chapter 2 offers the literature review of the papers that I have researched on. Chapter 3 describes the theories, formulae and methods that I used for each individual pricing strategy. Chapter 4 provides the results of the simulations and the analysis on the effectiveness of the strategy, in particular the welfare and consumption amount of power consumers and the price and capacity of electricity providers. This includes tables of data obtained and graphs from the simulations. The conclusion is drawn in Chapter 5.

Chapter 2 Literature Review

In this section, previous studies on electricity pricing algorithms will be reviewed. The literature review will be divided into two parts, namely (a) the formulation and theories of fixed and real-time pricing algorithms; and (b) the optimization of the algorithms with particle swarm optimization (PSO). This section will end with a reiteration of the aims behind this research.

In past research, studies investigated the properties and assumptions made to formulate the electricity pricing algorithms [8], [9]. The studies proposed algorithms that allow the maximization of the utility of the consumers and at the same time minimizes the total cost for the producer. Based on the algorithm, consumers change their consumption by reacting to the price changes, and in the same way, providers charge prices by reacting to the consumption levels.

Another study proposes using particle swarm optimization (PSO) to produce optimal decision variables, thereby allowing real time matching of supply and demand of electricity [10]. This optimizes the matching of price to the consumption level at real-time, maximizing the utility of electricity.

So far, little research is done on using PSO algorithm on a centralized distribution network. To widen the scope of the previous studies, I will assess the different pricing algorithms and optimize the decision variables with PSO. Next, I will simulate these algorithms to compare their advantages and disadvantages. Finally, the desired pricing strategy will be determined.

Chapter 3 Theories and Methods

3.1 Definitions of the pricing strategies

The 3 different types of pricing strategies that I will be assessing are Flat-rate pricing and Time-of-use pricing, and real-time pricing.

Flat Rate pricing refers to the price charged for consumption that is equal for all periods of time. It is one of the earliest approach to be used. [11]

Time-of-use pricing refers to the price of electricity consumption to be charged based on broad blocks of hours and will not be updated as often as real-time pricing. [12]

Real-Time pricing refers to the price of electricity consumption that changes quickly for different periods of time during the same day based on the communications between users and the provider. This allows consumers to decide the amount of electricity to use for each period. [13]

3.2 System Model

For the simulations, assuming a power system involving a single electricity provider, a number of consumers and a power regulatory authority. The proposed period of time of the consumers is broken up into T time slots, where $T \triangleq |T|$, and T is the set of all time slots. This is based on the nature of the consumers and their electricity demand trends. Examples includes peak time slots, block time slots, off-peak time slots and normal load time slots. Let \mathbb{N} represent the set of all consumers, where $N \triangleq |\mathbb{N}|$. For each consumer $n \in N$, let x_n^t represent the amount of electricity consumed by user n in time slot t while satisfying $m_n^t \leq x_n^t \leq M_n^t$, where m_n^t and M_n^t represents the minimum and the maximum electricity consumption of consumer n respectively. The inclusion of minimum and maximum consumption levels represents the assumption that each consumer will at least consume some electricity while at the same time there is a maximum amount of consumption that can be achieved in time slot t . The generation capacity in individual time slot

$t \in T$ is represented by E_t , which may change at different periods. The power regulatory authority is set up to ensure the electricity provider fulfils the minimum capacity, E_t^{\min} needed to account for the minimum electricity consumption of all consumers for each time slot.

$$E_t^{\min} \triangleq \sum_{n \in N} m_n^t, \forall t \in T \quad (1)$$

Let E_t^{\max} be the maximum generation capacity in each time slot $t \in T$.

3.2.1 Consumer's Preference & Utility Function

Every single consumer in the system is an individual entity that behaves separately. Each consumer's energy demand differs based on various conditions such as electricity price elasticity and the time period. The difference in response to electricity price can be modelled based on the utility function concept from microeconomics. [14] The different choices made by the consumers on their utility functions can model their behavior. [15] The utility functions of the corresponding consumers can be represented by $U(x, w)$, where x is the electricity consumption level of the consumer. w is a parameter that represents the consumers' valuation of electricity and it differs among consumers. The utility functions serves as the satisfaction levels of the consumers based on their electricity consumption. The following assumptions are made for the utility functions' properties.

- 1) Property *I*: Utility functions are non-decreasing. This suggests that marginal benefit is always positive and can be represented as:

$$\frac{\partial U(x, w)}{\partial x} \geq 0. \quad (2)$$

- 2) Property *II*: The marginal benefit of consumers is a non-increasing function. Mathematically, this is define by:

$$\frac{\partial^2 U(x, w)}{\partial^2 x} \leq 0. \quad (3)$$

Specifically, the utility functions are concave. Although the class of utility functions that satisfy (2) and (3) is very big, it is convenient to have a linear marginal benefit. [15] [16]

- 3) Property *III* : When consumption level x is fixed, $U(x, w)$ increases as w increases, which can be considered as:

$$\frac{\partial U(x, w)}{\partial w} > 0. \quad (4)$$

- 4) Property *IV* : For zero consumption level, the utility function can be expressed as:

$$U(0, w) = 0, \quad \forall w > 0. \quad (5)$$

As electricity price increases, consumers are assumed to prioritize only on the important tasks to reduce consumption. This suggests the total electricity consumption models a decreasing marginal benefit and an increasing and concave utility function. It is also assumed that a greater w signifies a greater utility value. Since utility functions represents the level of satisfaction among consumers, consuming zero electricity should result in a zero utility value. Past reports indicate that specific utility functions models correctly the behavior of electricity consumers.[16] For this system, a quadratic utility function corresponding to linearly decreasing marginal benefit will be used [17]:

$$U(x, w) = \begin{cases} wx - \frac{\alpha}{2} x^2 & \text{if } 0 \leq x \leq \frac{w}{\alpha}, \\ \frac{w^2}{2\alpha} & \text{if } x > \frac{w}{\alpha}, \end{cases} \quad (6)$$

where α is a known fixed parameter. Figure 1 illustrates a few cases of utility functions from this model. The point where the utility function gets saturated and remains stagnant corresponds to the maximum electricity requirement of the consumer.

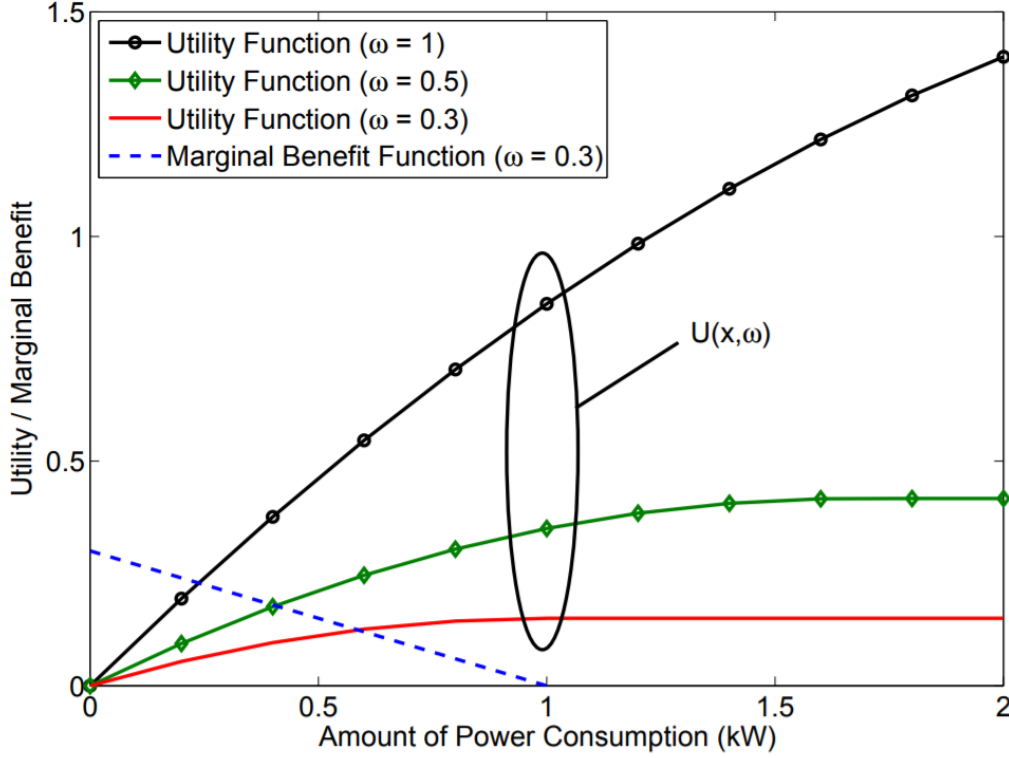


Figure 1: Utility functions for electricity consumers where $\alpha = 0.3$. [9]

Let p be the amount of dollars charged to consume x amount of electricity. Hence consumers have to pay the cost of px dollars for consuming electricity. The welfare function of each consumer is shown as follows:

$$W(x, w) = U(x, w) - px, \quad (7)$$

where $W(x, w)$ is the consumer's welfare function. Each consumer will change its consumption level based on the variation of price incurred to maximize its welfare. This is done by equating the derivative of (7) to zero, resulting in the marginal benefit to be the same as the price at optimal consumption level. Figure 2 shows the consumer's consumption response to 2 different types of prices.

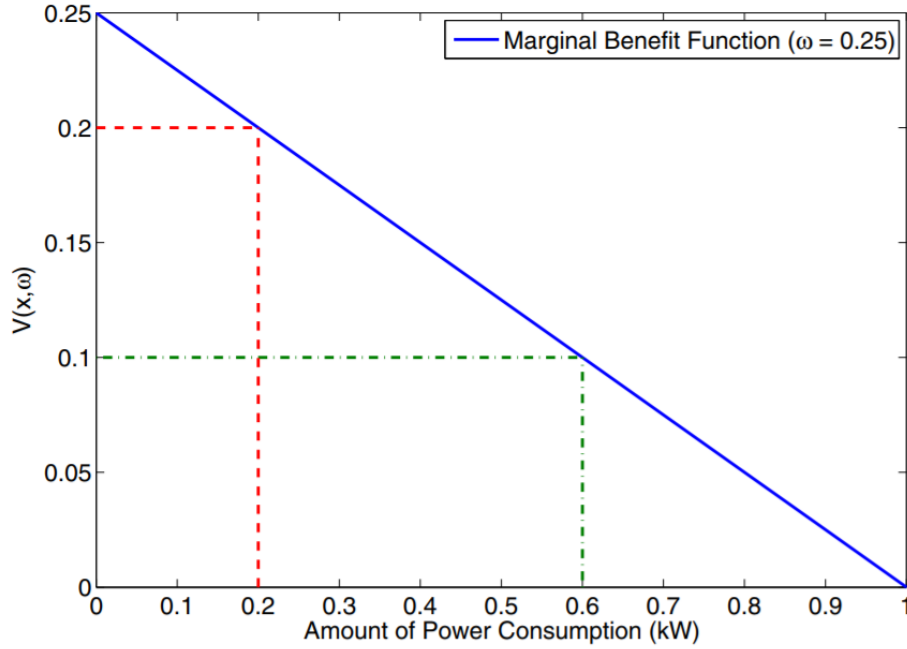


Figure 2: Electricity consumption response on 2 different prices where $P1 = \$0.20$, $P2 = \$0.10$ and $\alpha = 0.25$. [8]

3.2.2 Electricity Cost Model

For each time slot t , the electricity provider incurs the cost of producing E_t units of electricity which follows the cost function $C_t(E_t)$. The subsequent assumptions are made:

Assumption I : The cost function increases relatively with the total electricity capacity.

Assumption II : The cost function is strictly convex.

Assumption III : There exists a differentiable, convex, non-decreasing function $p_t(q)$ over $q \geq 0$ for each $t \in T$, with $p_t(0) \geq 0$ and $p_t(q) \rightarrow \infty$ as $q \rightarrow \infty$, such that for $q \geq 0$

$$C_t(q) = \int_0^q p_t(z) dz. \quad (8)$$

Quadratic functions are a good example that fulfils all the above assumptions and thus will be considered. [18]

$$C_t(E_t) = a_t E_t^2 + b_t E_t + c_t, \quad (9)$$

where $a_t > 0$, $b_t \geq 0$ and $c_t \geq 0$ are fixed parameters.

3.3 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) algorithm is a populace based optimizing approach first introduced by Kennedy and Eberhart in 1995.[19, 20] This method mimics the movement and social behavior of groups of animals in search of a common goal. Each animal in the group represents a particle in the search space, which is decided by the dimension space that is specified to achieve the objective. PSO algorithm first initializes each particle with random velocity and position in the search space. Every particle will communicate with one another to exchange information on their local best position so as to finally obtain the global best position among all the particles and ensures that they converge to the goal.

The procedure of executing the PSO algorithm is as follows:

- 1) Initialize each particle with random velocities and positions in the d dimension.
- 2) Assess each particle's suitable optimization fitness function f_{id}^t in d variables.
- 3) Compare the assessment of each particles with their particle's $pbest$ (local best position).
Replace the $pbest$ value with the current value only if the current value is more optimal.
Update the new $pbest$ location with the current location in the dimensional space.

$$f_{i,best}^t = f_i^t, p_i^t = x_i^t \quad \text{if } f_i^t \leq f_{i,best}^t \quad (10)$$

- 4) Compare the fitness assessment to the population's assessment. Replace the $gbest$ (global best position) value with the current value only if the current value is more optimal. Update the new $gbest$ location with the current location in the dimensional space.

$$f_{g,best}^t = f_i^t, p_g^t = x_i^t \quad \text{if } f_i^t \leq f_{g,best}^t \quad (11)$$

- 5) Update the particles' positions and velocities.

$$v_{id}^{t+1} = wv_{id}^t + c_1r_1(p_{id}^t - x_{id}^t) + c_2r_2(p_{gd}^t - x_{id}^t) \quad (12)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^t \quad (13)$$

- 6) Return to step 2) until the maximum iterations has reached.[19]

-
- 1: Initialization
 - 2: For each $t \in \text{MaxIterations}$
 - 3: Obtain the individual particle's position and velocity
 - 4: Compare and replace the local best position only if it is more optimal than the current value.
 - 5: Next, compare and replace the global best position only if it is more optimal than the current value.
 - 6: Update the particles' positions and velocities.
 - 7: End
-

where x_{id}^t , v_{id}^t , p_{id}^t , p_{gd}^t is the position, velocity, local best position, global best position of particle i at iteration t in dimension d . r_1 and r_2 are random numbers. c_1 and c_2 are the weighting factors that pulls each particle towards the $pbest$ and $gbest$ locations. Small values in c_1 and c_2 causes the particles to move further from the target region.[19, 20] Desired choices of inertia weight w is important as it will strike a balance between the local and global exploration and exploitation.[19]

Primarily, the inertia weight is set as:

$$w^{t+1} = w_{\max} - \left(\frac{w_{\max} - w_{\min}}{t_{\max}} \right) t, \quad (14)$$

where w_{\max} and w_{\min} are the maximum and minimum inertia weight, and t_{\max} is the maximum number of iterations. There is a maximum velocity that the particles can travel. The greater the maximum velocity that the particles can achieved, the more freedom in movement they have to find the global best position.

3.4 Pricing Strategy Development

Here I will derived the formulas for the communications between the consumers and the electricity provider for different pricing strategies as an optimization problem by implementing PSO. From a social equity perspective, it is preferable to maximize the usage of electricity produced within the electricity provider's capacity to achieve the minimum cost incurred and the maximum sum of welfare functions for all consumers. But, each consumer will only consider to maximize his or her own welfare function in (7). The optimal consumption levels of each individual consumer may not

be socially optimal for the price given by the electricity provider. In order to solve this, the objective function uses the sum of all welfare functions subtracting the electricity cost needed to produce electricity while the total consumption levels are subjected to the limited available generation capacity. Using a centralized distribution where complete information is provided on all the consumers' needs, an adequate electricity consumption schedule can solve the following problem:

$$\begin{aligned} & \underset{\substack{x_n \in X_n, n \in N \\ E_t^{\min} \leq E_t \leq E_t^{\max}}}{\text{maximize}} \sum_{t \in T} \sum_{n \in N} W(x_n^t, w_n^t) - C_t(E_t) \\ & \text{subject to} \quad \sum_{n \in N} x_n^t \leq E_t, \quad \forall t \in T, \end{aligned} \quad (15)$$

where $W(x_n^t, w_n^t)$ is the welfare function in (7), $C_t(E_t)$ is the electricity cost function in (9), x_n^t is the consumption level and w_n^t is the w parameter of consumer n in time slot t .

This is a concave maximization problem and can be solved by using convex programming methods. In this paper, the PSO method will be used to solve (15) in a central manner.

3.4.1 Flat-rate Pricing Algorithm

Consider the flat-rate pricing algorithm. In line 1, the consumption levels of each consumer is initialized and the information is made available to the electricity provider. Lines 2 & 3 refers to the iteration of each individual consumer n and each time slot t till every consumer and time slot is fulfilled. Finally Lines 4 to 8 describes the implementation of PSO algorithm to achieve the optimum values of decision variables of capacity levels E_t and thereby the consumption level x_n^t , where the values are solved at each step. The value of price p_t is fixed throughout the whole period.

Flat-rate Pricing Algorithm

- 1: Initialization
- 2: For each $n \in N$
- 3: For each $t \in T$
- 4: Call PSO algorithm to do the following:
- 5: Find and update the optimal utility value $U(x, w)$ by solving (6)

- 6: Find and update the optimal welfare value $W(x, w)$ by solving (7)
 - 7: Find and update the optimal electricity cost value $C_t(E_t)$ by solving (9)
 - 8: Find and update the total consumption value $\sum_{n \in N} x_n^t$ by solving (15)
 - 9: End
-

3.4.2 Time-of-use Pricing Algorithm

Consider the time-of-use pricing algorithm. In line 1, the consumption levels of each consumer is initialized and the information is made available to the electricity provider. Lines 2 & 3 refers to the iteration of each individual consumer n and each time slot t till every consumer and time slot is fulfilled. Finally Lines 4 to 8 describes the implementation of PSO algorithm to achieve the optimum values of decision variables of capacity levels E_t and thereby the consumption level x_n^t , where the values are solved at each step. The value of price p_t is set at 3 different values to represent the 3 different periods of the day, namely morning, afternoon and night.

Time-of-use Pricing Algorithm

- 1: Initialization
 - 2: For each $n \in N$
 - 3: For each $t \in T$
 - 4: Call PSO algorithm to do the following:
 - 5: Find and update the optimal utility value $U(x, w)$ by solving (6)
 - 6: Find and update the optimal welfare value $W(x, w)$ by solving (7)
 - 7: Find and update the optimal electricity cost value $C_t(E_t)$ by solving (9)
 - 8: Find and update the total consumption value $\sum_{n \in N} x_n^t$ by solving (15)
 - 9: End
-

3.4.3 Real-time Pricing Algorithm

Consider the real-time pricing algorithm. In line 1, the consumption levels of each consumer is initialized and the information is made available to the electricity provider. Lines 2 & 3 refers to the iteration of each individual consumer n and each time slot t till every consumer and time slot is fulfilled. Finally Lines 4 to 8 describes the implementation of PSO algorithm to achieve the

optimum values of decision variables of price p_t , capacity levels E_t and thereby the consumption level x_n^t , where the values are solved at each step.

Real-time Pricing Algorithm

- 1: Initialization
 - 2: For each $n \in N$
 - 3: For each $t \in T$
 - 4: Call PSO algorithm to do the following:
 - 5: Find and update the optimal utility value $U(x, w)$ by solving (6)
 - 6: Find and update the optimal welfare value $W(x, w)$ by solving (7)
 - 7: Find and update the optimal electricity cost value $C_t(E_t)$ by solving (9)
 - 8: Find and update the total consumption value $\sum_{n \in N} x_n^t$ by solving (15)
 - 9: End
-

Chapter 4 Results and Discussions

For this section, I will present the simulation results and evaluate the performance of the proposed pricing strategies. For the system, it is assumed to have $N = 10$ consumers and $T = 24$ time slots that depicts the 24 hours in a day. It is also assumed that the electricity provider's minimum generating capacity is able to fulfill the minimum electricity consumption of all consumers, while at the same time the maximum generating capacity is the same as the maximum total electricity consumption. The w parameter in the utility and welfare functions is randomly chosen for each consumer between the range from $[1, 4]$. At the same time the α parameter in the utility function is set at 0.1 and the parameters of the electricity cost function in (9) are selected to be $a_t = 0.01$, $b_t = 0$ and $c_t = 0$.

For the PSO algorithm, the values of c_1 and c_2 are set to 2, while r_1 and r_2 ranges between $[0, 1]$. The inertia weight w is set as 1. The population size is fix as 200 while the maximum number of iterations is fix as 300.

4.1 Flat-rate Pricing Algorithm Evaluation

By running the algorithm, simulation results for the total consumption of electricity in a 24 hours period is presented in Figure 3. It shows that the demand for electricity consumption is very volatile which is not ideal for the electricity provider. While Figure 4 shows the best cost value when using the PSO algorithm. In this paper's context, the best cost refers to the optimized total electricity consumption in a 24 hours period and it is shown to converge to a fix value of about 1500kW after running the maximum number of iterations. The price p_t is fixed at \$1.20.

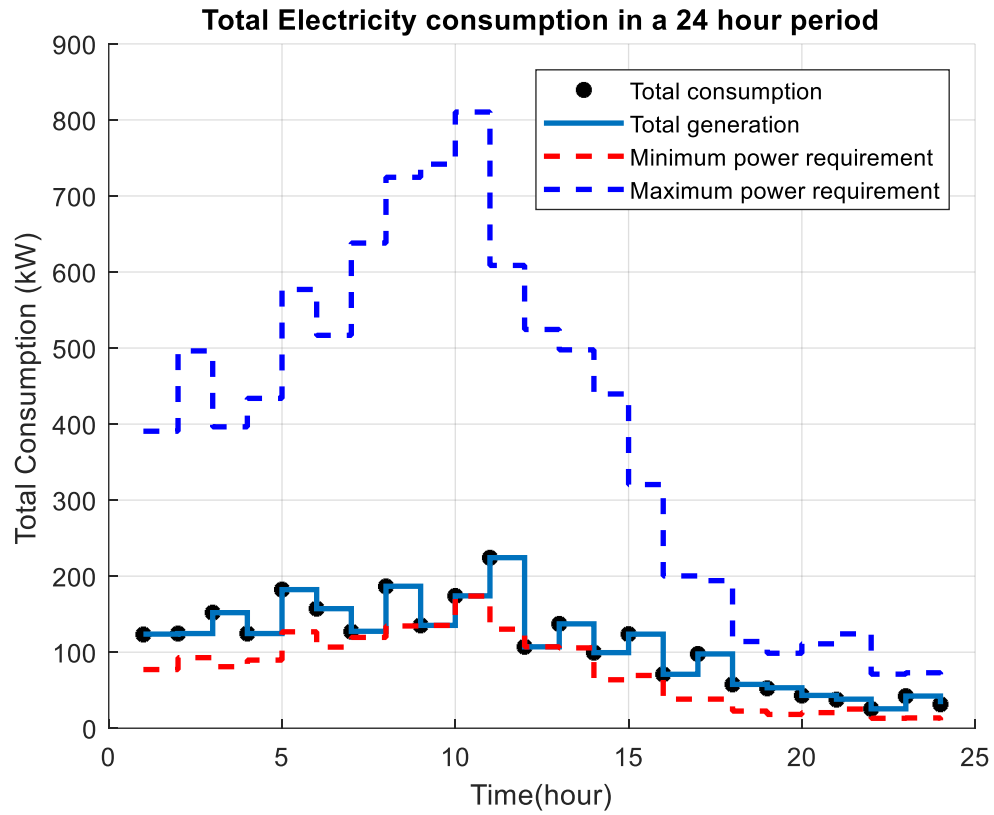


Figure 3: Total Electricity consumption for Flat-rate pricing

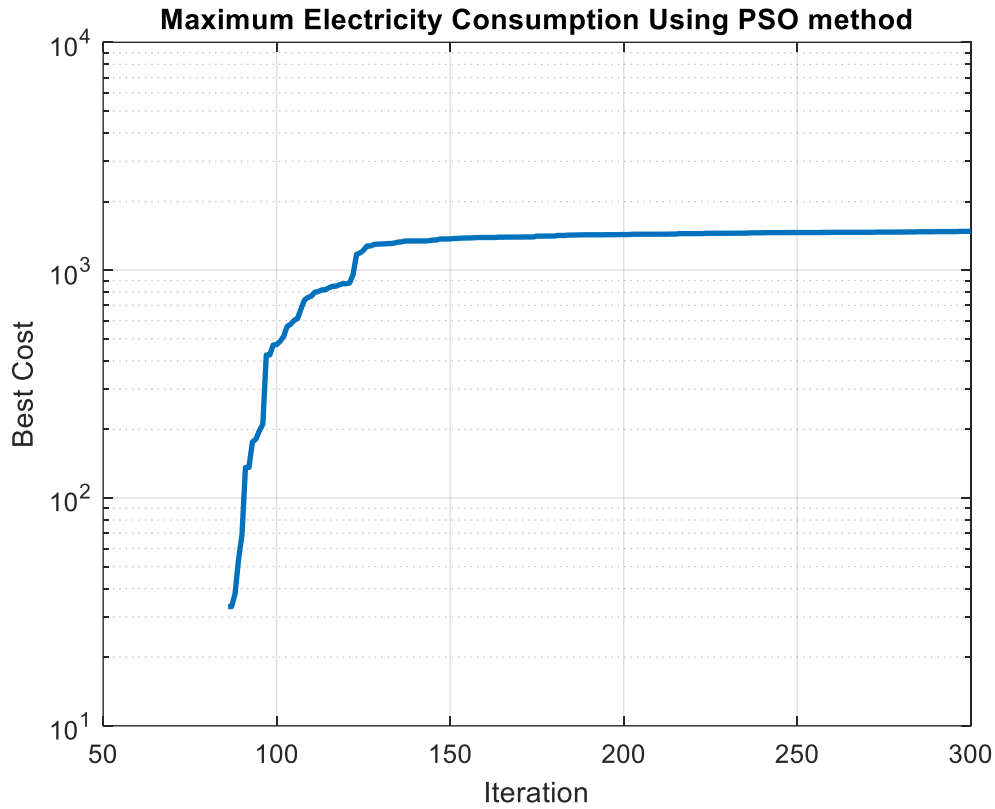


Figure 4: Maximum Electricity consumption for Flat-rate pricing

4.2 Time-of-use Pricing Algorithm Evaluation

Figure 5 and figure 6 shows the respective simulation outcome of the total consumption value and best cost value for the time-of-use pricing. It shows that the demand for electricity consumption is relatively less volatile and only spikes after a price change is announced. While the best cost value converges to about 2500kW. For $1 \leq t \leq 8$, the value of price p_t is set at a value of \$1.00 while for $9 \leq t \leq 16$, the value of price p_t is set at a value of \$1.20 and for $17 \leq t \leq 24$, the value of price p_t is set at a value of \$1.10.

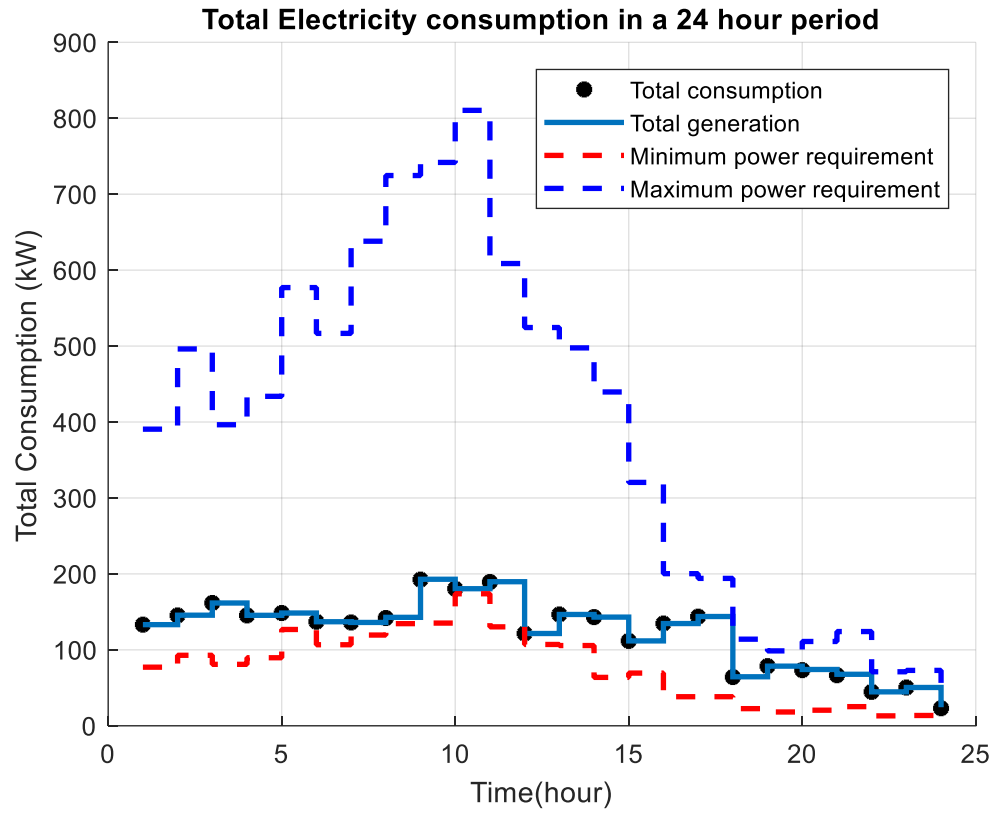


Figure 5: Total Electricity consumption for Time-of-use pricing

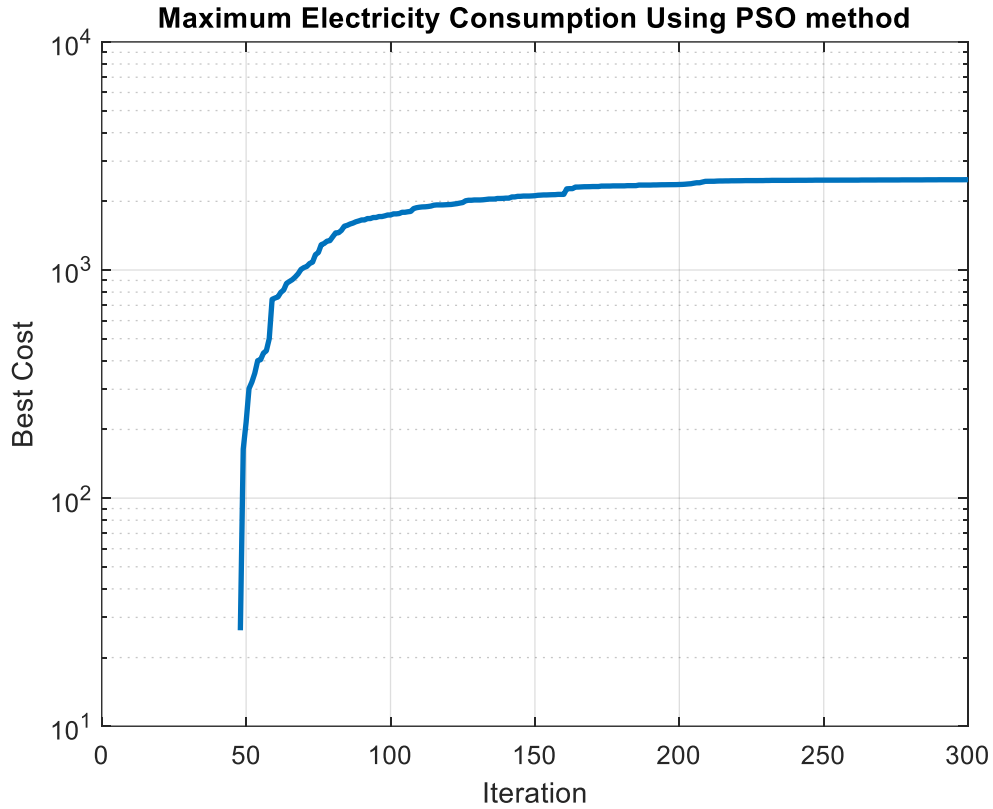


Figure 6: Maximum Electricity consumption for Time-of-use pricing

4.3 Real-time Pricing Algorithm Evaluation

Figure 7 and figure 8 presents the respective simulation outcome of the total consumption value and best cost value for the real-time pricing. It shows that the average electricity consumption in each hour is generally higher and nearer to the maximum capacity. While the best cost value converges to about 3500kW .

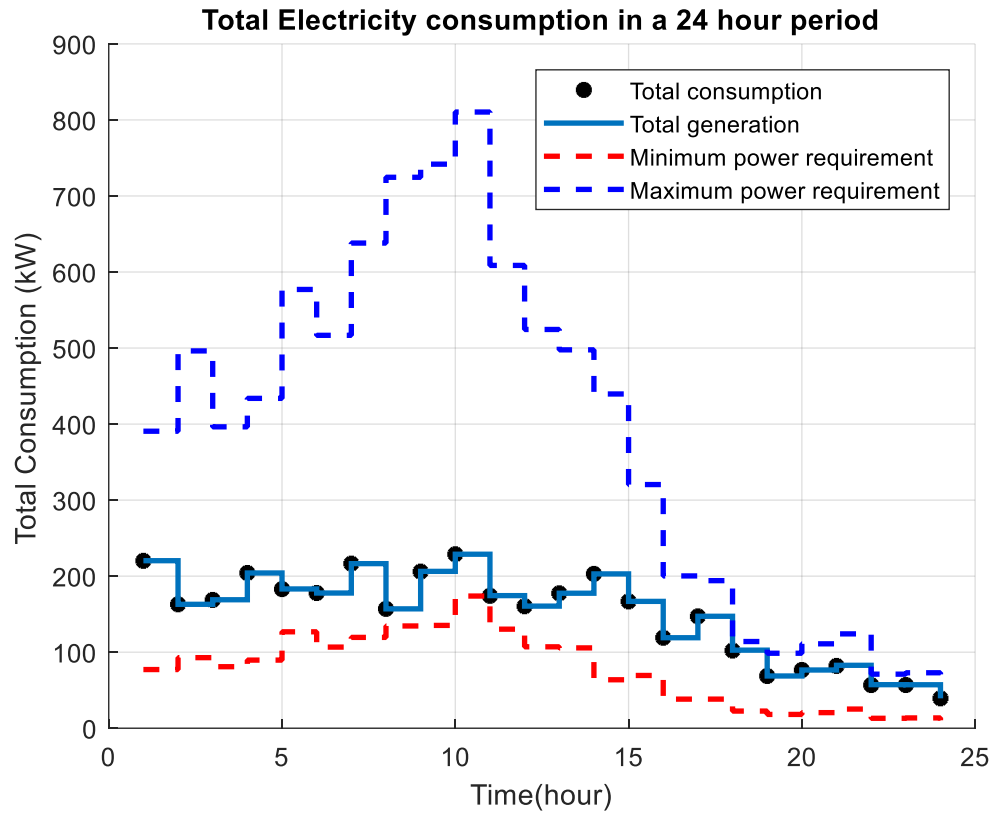


Figure 7: Total Electricity consumption for Real-time pricing

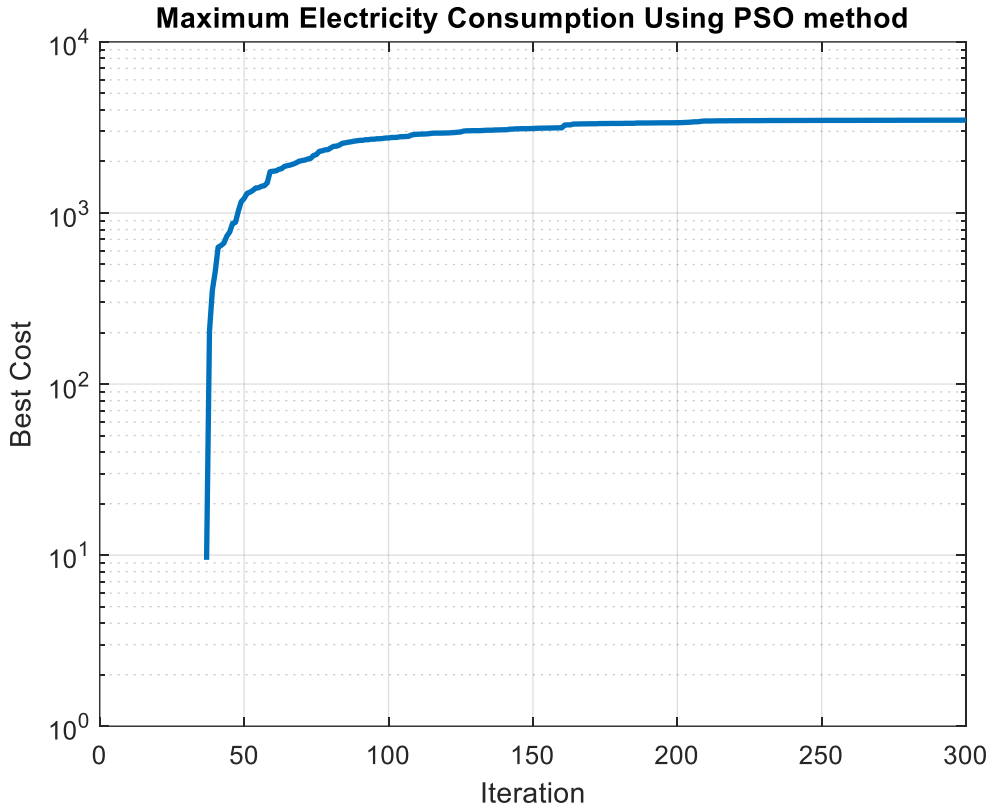


Figure 8: Maximum Electricity consumption for Real-time pricing

Overall when comparing the 3 different pricing strategies, it shows that the real-time pricing actually provides the greatest amount of total electricity consumption while the flat-rate pricing provides the least amount of consumption show in the graphs above. It provides flexibility for the electricity provider to change the price according to the demand shown by the consumers, and hence the consumers stands to benefit from it by being able to consume more electricity. This strategy is the hardest to execute as all the decision variables are constantly changing by the hour, and hence close monitoring is required. Time-of-use pricing provides a certain degree of flexibility as the prices were fixed at 3 different periods as consumers can adjust their demand to a certain extent based on the price differences. However, it is much easier to execute since price rarely changes. Flat-rate pricing provides no degree of flexibility as consumers has only 1 price to depend on and this causes the overall consumption to be the least among the 3 pricing strategies. However it is the easiest to execute as the electricity provider does not need to communicate with the consumers.

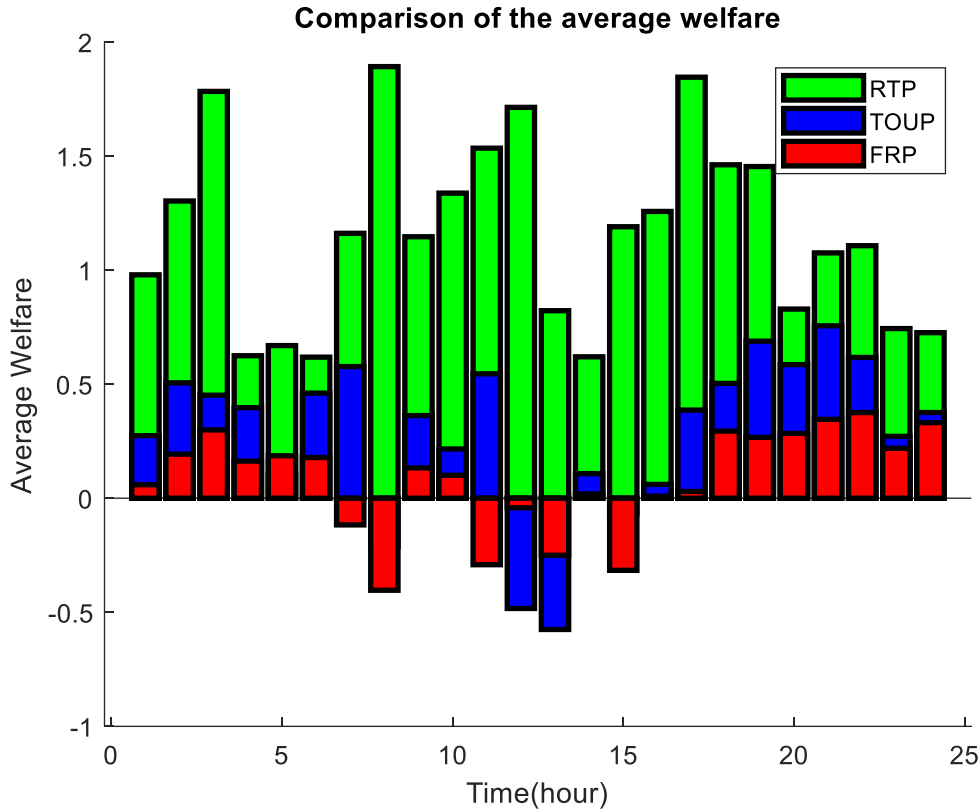


Figure 9: Comparison of the average welfare among the 3 different pricing strategies

As seen in Figure 9 above, real time pricing provides the greatest and positive welfare as consumers are able to consume more electricity. Whereas for flat-rate pricing, the average welfare is the lowest, and sometimes dips to negative values. Hence this is undesirable for the consumers.

4.4 Impacts on the Electricity Market players

In this section, I will be discussing about how the different pricing strategies influence the electricity market players.

The utilities, which are in charge of managing and operating the infrastructures and facilities for the provision of electricity to consumers[21], will stand to benefit more from real-time pricing as the readily changing prices of electricity allows the utilities to prevent the demand from getting too volatile over the time period. This helps to ensure the infrastructures and facilities are well-

equipped to handle the volume of demand throughout the day and reduces the chances of overloading or under usage. This will also help the utilities to save costs which in turn may be passed on to the end consumers by lowering the electricity prices. This is less achievable for the flat-rate pricing since the price is fixed and thus the utilities are unable to carry out the abovementioned preventive measure, while for time-of-use pricing, there will only be a limited effect.

The generation companies who are in charge of producing electricity from power plants or other renewable energy sources plants usually generates electricity in fixed bulk. Due to external factors that affect consumers' preference to consume electricity, there may be excess or shortage of electricity at a specified period of time. Real-time pricing can alleviate this problem by changing the prices of electricity based on the fluctuations of the total consumption rate to ensure they do not exceed the maximum capacity of the power plants. This can also reduce the cost incurred by the generation companies to store excess electricity. Again, flat-rate pricing is unable to do so that while time-of-use pricing has limited effects as consumers will only adjust their consumption to a certain extent.

Since the generation companies are usually located far away from consumers, the grid operators provides the means to connect the generating stations to individual demand centers before distributing electricity to each individual consumer in the area through high voltage transmission lines.[22] As mentioned before, the grid operators have fixed infrastructures and facilities, they will stand to benefit most from real-time pricing as demand will not be volatile. Hence, real-time pricing is more efficient in achieving that when compared to flat-rate pricing and time-of-use pricing.

Lastly, electricity consumers will stand to gain more from real-time pricing as they will be able to consume more electricity when compared to the other two pricing strategies. This is because for time-of-use pricing, electricity providers tend to charge higher rates during peak periods to offset the additional costs incurred, and in the case of flat-rate pricing, the additional premiums will be spread across the whole period, which raises the general price of electricity resulting in the reduction of electricity consumption from consumers who are more price sensitive. As it is assumed that the welfare of consumers increases when more electricity consumption occurs, real-time pricing provides more welfare to consumers.

Chapter 5 Conclusion

This research has attempted to simulate and compare the pricing strategies for electricity markets. I have obtained flat-real, real-time, and time-of-use pricing algorithms and optimized the variables with PSO. Simulations are ran and the results are compared.

From the results generated, it is found out that real-time pricing is the most optimal pricing model as it allows the real-time welfare maximization for the consumers and cost minimization for the electricity provider. These findings supports the past researches which concluded that real-time pricing maximizes the welfare of both consumers and providers.

The assumptions made in formulating the algorithms is a limitation of the research. This has resulted in a simplification of the electricity market compared to the real world.

It is assumed that there is only one energy provider in the system. However, in the real world, there will be more than one energy provider as shown in the recent change in Singapore where it adopted a deregulated electricity market. With competition in the system, this will change the demand and supply in the market, and in turn affect the results. Due to this limitation, it is recommended that further studies can incorporate more energy providers into the system to compare results.

Furthermore, it is also recommended that varying consumer behaviors should also be factored in when considering the most optimal pricing strategy. In the real world, consumers are not only affected by price changes. The psychological needs of consumers when making decisions should also be considered. Moreover, the optimal pricing strategy for a country may not work for another. This is due to different cultural preferences in different countries.

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