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Game-Theory based dynamic pricing strategies for demand side management in smart grids

Dipti Srinivasan [a,*], Sanjana Rajgarhia [a], Bharat Menon Radhakrishnan [a], Anurag Sharma [a], H.P. Khincha [b]

[a] Department of Electrical and Computer Engineering, National University of Singapore 4, Engineering Drive 3, 117583, Singapore
[b] Department of Electrical Engineering, Indian Institute of Science, C V Raman Ave, Bengaluru, Karnataka, 560012, India

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ABSTRACT

With the increasing demand for electricity and the advent of smart grids, developed countries are establishing demand side management (DSM) techniques to influence consumption patterns. The use of dynamic pricing strategies has emerged as a powerful DSM tool to optimize the energy consumption pattern of consumers and simultaneously improve the overall efficacy of the energy market. The main objective of the dynamic pricing strategy is to encourage consumers to participate in peak load reduction and obtain respective incentives in return. In this work, a game theory based dynamic pricing strategy is evaluated for Singapore electricity market, with focus on the residential and commercial sector. The proposed pricing model is tested with five load and price datasets to spread across all possible scenarios including weekdays, weekends, public holidays and the highest/lowest demand in the year. Three pricing strategies are evaluated and compared, namely, the half-hourly Real-Time Pricing (RTP), Time-of-Use (TOU) Pricing and Day-Night (DN) Pricing. The results demonstrate that RTP maximizes peak load reduction for the residential sector and commercial sector by 10% and 5%, respectively. Moreover, the profits are increased by 15.5% and 18.7%, respectively, while total load reduction is minimized to ensure a realistic scenario.

1. Introduction

Electricity has grown to become an essential part of human life. A reliable and seamless supply is required to facilitate economic and industrial growth as well as to improve quality of life. Global electricity demand has been increasing exponentially and is expected to double in value between 2002 and 2030 [1]. Electricity is a non-storable commodity; its wholesale price varies across time periods depending on demands [2]. In most cases however, the consumer is charged a fixed price and the price fluctuations are borne by the utility company. Since consumers are unaffected by wholesale price changes, their demand shows drastic fluctuations with low valleys at night and high peaks during the day. These fluctuations decrease supply reliability, system efficiency and reduce profits for utility companies. Moreover, many countries have also chosen to restructure their power industry and introduce deregulation in their electricity markets. Hence, companies need to establish Demand-Side Management (DSM) strategies to influence user consumption patterns and thereby achieve peak-load reduction. The increasing penetration of renewables and market deregulation has further bolstered the need for operational flexibility in the grid and resulted in development of efficient DSM techniques [3–6]. It is noted that the availability of renewable generation will impact the dynamic pricing strategy and thus, the DSM techniques based on its intermittency and cheaper generation cost.

Demand response techniques can control and modify user consumption patterns through incentive based dynamic pricing techniques. Demand response algorithms have been widely adopted in the literature as they result in significant electricity bill savings and avoid undesirable peaks in the daily load demand, thereby improving the efficiency of the system [7–14]. Today, several developed countries such as USA, Canada and many parts of Europe have successfully developed and implemented dynamic pricing strategies to perform DSM. A 2010 survey conducted by the Federal Energy Regulatory Commission of USA shows that demand response methods could lead to a 7.6% decrease in peak load

* Corresponding author.
E-mail addresses: elesd@nus.edu.sg (D. Srinivasan), anurag@u.nus.edu (A. Sharma).

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demand and among various time based pricing techniques, TOU pricing is proved to be the most effective [15]. Project Intekellion conducted by the German Government shows that time-variable tariffs for households bring about a 6% energy saving [16].

The electricity demand in Singapore is growing at an annual rate of 5% approximately; 16% of the consumption comes from the residential sector, 38% from the commercial and 46% from industrial sector [17]. Currently, 75% of its market is liberalized and moving towards complete liberalization soon. The residential sector is still considered non-contestable and has a flat pricing of 256.5SGD/MWh throughout the year [18]. The peak period typically occurs at mid-day especially during the afternoons (can be explained by the tropical climate) and non-peak period is seen especially at late night when the consumption is at its lowest. With the increasing standards of living, and the global city status that Singapore now enjoys, it is essential that electricity supply is continuous and seamless. A dynamic pricing strategy is necessary to manage electricity demand and supply patterns as it will help meet user demands, boost profits for generation companies and ensure a reliable supply of electricity at all times of the day.

Dynamic pricing includes techniques such as Real-Time Pricing (RTP), Time-Of-Use pricing (TOU) and Critical-Peak Pricing (CPP). RTP refers to a strategy where prices change for every period of the day: utility companies forecast prices on a day-ahead or hour-ahead basis. TOU pricing divides the day into intervals and charges fixed rates within each interval. These pricing strategies have been studied using different approaches, and tested on academic and practical systems across the world. Yang, Tang and Nehorai proposed an interesting game-theoretic approach for implementing TOU pricing in Ref. [19]. The study uses a multi-stage approach and backward induction to develop a strategy that maximizes profits for both consumers as well as the utility company. In Ref. [20], a RTP based demand response algorithm is proposed to determine the optimal power consumption pattern and pricing, and maximizing the comfort level of the consumers. An equal-incremental cost rule is proposed as a rational solution to determine the electricity pricing in Ref. [21]. It is noted that incremental cost rule refers to a pricing rule which determines the profit maximization based on the incremental cost of power required to satisfy any variation in load demand. The effectiveness of the method was tested with two types of simulated power markets. The price elasticity of the customers was not taken into consideration. A theoretical framework for RTP based on the switched Markov chain model has been developed in Ref. [22]. However most of the above mentioned algorithms and models have been tested using numerical simulations and have not been evaluated using real and practical data sets.

Game Theory has been proven to be an essential tool in capturing the complex and strategic interactions among market participants and for strategic analysis of situations involving multiple independent players. In the previous studies, game theory has been applied to various problems pertaining to electricity markets and demand side management [23,24]. In this work, the main aim is to demonstrate the ability of the proposed game theory based dynamic pricing strategy [19], to implement demand side management, using the real and practical data sets of Singapore. The problem has been formulated based on the modified pricing model to accommodate the Singapore load and market scenario. Moreover, extensive case studies are implemented to evaluate dynamic pricing strategies for Singapore using half-hourly Real-Time Pricing (RTP), Time-of-Use (TOU) Pricing and Day-Night (DN) pricing for residential, commercial and industrial sector (with special focus on the residential and commercial sector). The pricing strategies are tested on practical load and price datasets from Singapore, and all possible scenarios have been considered to accurately measure the robustness of the proposed model. The use of practical data sets of Singapore is essential in the case studies to make the test scenarios more realistic. The results as demonstrated in the 5 case studies for 5 different load and price data sets, including weekdays, weekends, public holidays and the highest/lowest demand in the year, validate the use of proposed dynamic price strategy to encourage the residential and commercial consumers in Singapore to opt for demand side management. It is noted that the data for load demand and market price are taken from Energy Market Company (EMC) of Singapore [18], while the price elasticity of demand (PED) in Singapore is hypothesized from the USA data based on Ameren Illinois studies [19,25–27]. The rest of the paper is organized as follows: Section 2 introduces the proposed pricing model, Section 3 discusses the data collected and methodologies used, Sections 4–6 discuss the results obtained for the residential sector, commercial and industrial sectors respectively and the paper is concluded in Section 7.

2. The proposed pricing model

In this work, a game-theoretic based pricing model is developed to achieve an efficient demand response technique. A multi-stage game approach is adopted to maximize benefits for both consumers and utility companies. The electricity demand, consumption patterns, and Price Elasticity Demand (PED) are observed to vary drastically for different sectors i.e. residential, commercial and industrial sector. Hence, a single-sector approach has been adopted in this work, where-in the sectors are optimized individually to ensure that different strategies could be chosen for different sectors. The pricing model developed in this work defines RTP pricing as well as block pricing.

The utility company aims at maximizing profits while simultaneously adhering to industry regulations and customers' demands. On the contrary, the customers aim at minimizing electricity bills and expect a reliable, uninterrupted power supply. The end result is expected to be a matrix p consisting of electricity sales prices for different sectors over N time intervals. These prices result in reduction of peak load leading to a flattened load curve l.

2.1. Variable and function definitions

2.1.1. Time period (N)

The day is divided into N time intervals to reflect different values for each variable. The subscript k corresponds to a particular period in the day and can take values from 1 to N.

2.1.2. Electricity cost (c_k), price (p_k) and price elasticity of demand (e_k)

The *marginal cost of electricity* "c_k" sis the cost paid by the electricity company and varies depending on the time of day, electricity market and demand.

The *unit sales price of electricity* "p_k" corresponds to the price the utility company will charge its customers and varies depending on the time of the day. This price is fixed by the electricity company and is obtained as a result of the mathematical simulations in this model.

The *fixed price* "n_k" can be interpreted as the price the consumers are currently being charged for the electricity supplied and varies according to the country/sector in picture. Both c_k and n_k are considered as input data for the pricing model developed.

The *short-run price elasticity of demand (PED)* "e_k" is used to represent responsiveness or sensitivity of the quantity demanded to the price change. It essentially provides the percentage change in quantity demanded for every 1% change in price. It helps to understand the consumption patterns and estimate the change in customers' responses with change in price. It depends on the country/sector being considered and is also considered as input data for the model. These values are obtained for N time periods or for fixed blocks in the day. It is important to consider short-run values while performing price calculations because the immediate consumption response must be estimated. Using longer-run values would give incorrect results because they refer to customers' responses to seasonal average prices. The values for this function will always be negative and less than 1 as the quantity consumed is always inversely proportionate to the price.

Mathematically, the coefficient of the PED '*e*' can be represented by (1) below.

$$e = \frac{dQ}{dP} \tag{1}$$

2.1.3. Electricity demand (d_k) and generation (g_k)

The *user demand* "d_k" under fixed price, refers to the quantity of electricity that is currently being consumed by the customers. These values vary depending on the time of the day, electricity market and demand, and hence must to be considered as input data.

The *electricity generation capacity* "g_k" refers to quantity of electricity that is produced by the company. Since electricity is a commodity that cannot be stored and must always be readily available to the customers, in real life scenarios, g_k can be said to be the same as d_k.

The *user load response to dynamic prices* "l_k" is calculated through the model and is used in the optimization process.

2.2. Evaluation indices

The *user satisfaction function* "s_k" is used to define the user's satisfaction in mathematical terms. It is essentially the difference between the nominal user demand d_k and the user load in response to the dynamic price l_k. The different possible outcomes for the satisfaction function are summarized in Table 1. The satisfaction function s_k includes a variable weight MU_S as seen in Eq. (2) and since it's used on a comparative basis, units are not important.

$$s_k = MU_S * d_k \beta_k \left[\left(\frac{l_k}{d_k} \right)^{\alpha_k} - 1 \right] \tag{2}$$

where

$$\alpha_k = \frac{1}{e_k} + 1 (always < 1) \tag{3}$$

$$\beta_k = -\frac{n_k}{\alpha_k} \tag{4}$$

It is noted that satisfaction is defined in terms of e_k and n_k i.e. price elasticity of demand (PED) and current price (fixed) the consumers are charged, along with nominal user demand (d_k) and new load demand (l_k) under the influence of the proposed dynamic pricing strategy.

The *load fluctuation function* "$f(l)$" defines the difference between the periodic user load response l_k and the day's average l_{avg}. It displays a cost that is borne by the electricity company and should ideally be as low as possible so as to allow the company to have a predictable demand pattern that they can always satisfy. It is used on a comparison basis and can be calculated using Eq. (5) below. It also includes a variable weight MU_F.

$$f(l) = MU_F * \sum_{k=1}^{N} (l_k - l_{avg})^2 \tag{5}$$

where

$$l_{avg} = \frac{1}{N} \sum_{k=1}^{N} l_k \tag{6}$$

It is noted that MU_F and MU_S refer to the weight that is associated with the load fluctuation and user satisfaction function. As mentioned in the manuscript, these weights are not fixed and are varied depending on the sector chosen i.e. residential, commercial or industrial area, and their respective set of elasticity values. The main use of these weights is to increase the flexibility of the proposed dynamic pricing model to increase the importance given to different parties i.e. utility or the consumer.

Profits for the utility company are calculated and included in their respective utility function. They include the absolute profits as well as change with respect to that of flat pricing. They can be represented by (7) and (8) below.

$$Profits = \sum_{k=1}^{N} p_k l_k - \sum_{k=1}^{N} c_k l_k \tag{7}$$

$$Change\ in\ Profits = \frac{profits_{dynamic} - profits_{flat}}{profits_{flat}} \times 100 \tag{8}$$

where, $profits_{dynamic}$ is the profits achieved using the dynamic pricing strategy and $profits_{flat}$ refers to the profits achieved due to a flat pricing scheme.

Total load reduction measures the effect of dynamic pricing on total consumption and must be minimized. Similarly, *peak load reduction* measures the effectiveness of peak clipping and hence must be maximized. The total load and peak load reduction are calculated according to Eqs. (9) and (10).

$$total\ load\ reduction = \frac{l_{total} - d_{total}}{d_{total}} \times 100 \tag{9}$$

$$peak\ load\ reduction = \frac{l_{peak} - d_{peak}}{d_{peak}} \times 100 \tag{10}$$

where, the terms l_{total}, d_{total}, l_{peak}, and d_{peak} are defined in Table 2.

Table 1
Summary of satisfaction function.

s_k value	Mathematical condition	User status
Positive	$l_k < d_k$	The user consumes less than it would have under nominal conditions, hence is unsatisfied.
Negative	$l_k > d_k$	The user consumes more than it would have under nominal conditions and is hence satisfied.
Zero	$l_k = d_k$	The user consumes as much as it would have under nominal conditions and is hence neutral.

2.3. Utility functions and game theoretic approach

In this section, the utility functions considering the perspective of both the utility as well as the consumer is defined.

2.3.1. Utility function 1 (U_1 for the company)

The utility company wishes to maximize the profit, minimize the deviation of load (hence the negative sign) as well as fulfill its obligation to serve the public and satisfy the electricity users. Therefore the utility function of the company is its profit minus the satisfaction cost of the users, i.e.

$$U_1 = \sum_{k=1}^{N} p_k l_k - \sum_{k=1}^{N} c_k l_k - \sum_{k=1}^{N} s_k - f(l) \tag{11}$$

2.3.2. Utility function 2 (U_2 for the consumer)

The consumers on the other hand are interested in maximizing their satisfaction (negative sign before s_k can be explained based on Table 1 i.e. negative s_k means greater satisfaction) while simultaneously minimizing their costs. Their utility function is the negative of the company's cost function, and is denoted as U_2 as represented below.

$$U_2 = -\sum_{k=1}^{N} p_k l_k - \sum_{k=1}^{N} s_k \tag{12}$$

The goal is to maximize the utility function U_1 and U_2 under certain constraints. The optimization problem is formulated as

$$(p^*, l^*) = \mathrm{arg}max\ U_1 \tag{13}$$

$$l^* = \mathrm{arg}max\ U_2 \tag{14}$$

$$\begin{aligned}&\text{Subject to,}\ \ l_{k,min} \le l_k \le l_{k,max},\ k = 1, 2, \ldots, N\\ &c_k \le p_k,\ k = 1, 2, \ldots, N\end{aligned} \tag{15}$$

2.3.3. Game theory approach

The proposed game model adopts a multi-stage approach. The utility company acts as the first mover by setting the price and the consumer responds to it accordingly. The user response is considered as a function p.

The proposed pricing strategy P is explained using Eqs. (16) and (17). The pricing model identifies the optimal price $p^* \varepsilon$ P, and optimal load response $l^* \varepsilon\ \mathscr{L}$ in order to obtain a Nash equilibrium (p^*, l^*)ε P x $\mathscr{L}$, between the user and the utility company.

$$\forall\ p\ \varepsilon\ \mathrm{P},\ p \ne p^*\ \ :\ \ u1(p^*, l) \ge u1(p, l^*) \tag{16}$$

$$\forall\ l\ \varepsilon\ \mathscr{L},\ l \ne l^*\ \ :\ \ u2(p, l^*) \ge u2(p^*, l) \tag{17}$$

Next, the principle of backward induction is implemented in this model to optimize the problem, and hence U_2 is first maximized with respect to $\{l_k\}_{k=1}^N$ to identify the optimal load as $l_k^* = \left(\frac{p_k}{n}\right)^{\varepsilon^k} d_k$. The calculated optimal load is then plugged back into U_1 which is subsequently maximized w.r.t $\{p_k\}_{k=1}^N$ to obtain optimal dynamic prices.

In order to find a user's optimal demand response to the price set by the utility company, we consider the electricity prices of different time periods $\{p_k\}_{k=1}^N$ as given, and take the first and second order derivatives of U_2 with respect to $\{l_k\}_{k=1}^N$,

Table 2
Definition of load functions.

Terms	Definition
l_{total}	It refers to the total load demand by the users in response to the proposed dynamic pricing strategy
d_{total}	It refers to the total nominal load demand by the users
l_{peak}	It refers to the peak load demand by the users in response to the proposed dynamic pricing strategy
d_{lpeak}	It refers to the peak nominal load demand by the users

$$\frac{\partial U_2}{\partial l_k} = -p_k - \alpha_k \beta_k \left(\frac{l_k}{d_k}\right)^{\alpha_k - 1} \tag{18}$$

$$\text{Setting(17)equal to zero,}\quad l_k^* = \left(-\frac{p_k}{\alpha_k \beta_k}\right)^{\frac{1}{\alpha_k - 1}} d_k \tag{19}$$

The second-order derivative of U_2 is

$$\frac{\partial^2 U_2}{\partial l_k \partial l_i} = \begin{cases} -\alpha_k \beta_k (\alpha_k - 1)\dfrac{l_k^{\alpha_k - 2}}{d_k^{\alpha_k - 1}} & when\ k = i \\ 0 & when\ k \ne i \end{cases} \tag{20}$$

Since $\alpha_k < 1$ and $\alpha_k \beta_k < 0$, the diagonal elements of the Hessian matrix are all negative, and the off-diagonal elements are all zero. The Hessian matrix is negative definite, meaning that $\{l_k^*\}_{k=1}^N$ is the optimal user load given price p. Let

$$\in_k = \frac{1}{\alpha_k - 1} < 0,\ k = 1, 2, \ldots, N \tag{21}$$

$$\text{and}\ n_k = \alpha_k \beta_k > 0,\ k\ = 1, 2, \ldots, N \tag{22}$$

We can rewrite (19) as

$$l_k^* = \left(\frac{p_k}{n_k}\right)^{\in_k} d_k,\ k = 1, 2, \ldots, N \tag{23}$$

Optimal pricing based on l_k^*

Substituting (23) into the utility function U_1 we determine its value only in terms of p (earlier involved both p and l)

$$U_1(p) = \sum_{k=1}^{N} \left\{ p_k\ l_k^*(p_k\ ) - c_k\ l_k^*(p_k\ ) - s_k \left[l_k^*(p_k\ ), d_k \right] \right\} - f\left[l^*(p)\right] \tag{24}$$

The constraints on user loads can be rewritten as,

$$p_k = \left(\frac{l_k}{d_k}\right)^{\frac{1}{\in_k}} n_k \tag{25}$$

Since, (25) is a decreasing function of l_k, the constraints on pricing can be written as

$$p_{k,min} < p_k < p_{k,max} \tag{26}$$

where, $p_{k,min} = \max\left\{ c_k,\ (l_{k,max}/d_k)^{\frac{1}{\in_k}} \right\}$ and $p_{k,max} = \left\{ (l_{k,min}/d_k)^{\frac{1}{\in_k}} n_k \right\}$. The optimization of U_1 with respect to prices $\boldsymbol{p}$

now becomes

$$\max_{p.} U1\,(p_k) \tag{27}$$

$$p_{min} < p_k < p_{max} \tag{28}$$

$$A^*p = 0 \tag{29}$$

It is noted that the objective function for this problem is presented in Eq. (27) and solved as a single-objective optimization problem, subject to constraints in (28) and (29).

The following conditions must be taken into consideration while developing upper bound p_{max} and lower bound p_{min}.

1) The actual load demanded by the user l_k cannot exceed the minimum value between the maximum generation capacity and maximum user load.
2) The user load should also always be less than the generation capacity of the total system ($l_k < g_k$).
3) User demand must always be met ($g_k = d_k$).
4) The company should limit the sale price to ensure a minimum load $l_{k,\,min}$ (The corresponding price can be calculated as$n_k * \frac{l_{k,\,min}}{d_k}{}^{1}/_{\varepsilon_k}$).
5) The sale price must always be greater than or equal to cost price$c_k \le p_k$.

The final lower and upper bound functions p_{min} and p_{max} are presented in Eqs. (30) and (31) respectively. The formulated bound function are capable of accounting for anomalies as well.

$$\boldsymbol{p_{min}} = max\left\{ c_{k,}\ n_k * \frac{l_{k,\,max}}{d_k}{}^{1}/_{\varepsilon_k} \right\} \tag{30}$$

$$\mathbf{p_{max}} = \max\left\{ \mathrm{p_{min}}\ \mathrm{n_k} * \frac{\mathrm{l_{k,\,min}}}{\mathrm{d_k}}{}^{1}/_{\varepsilon_k} \right\} \tag{31}$$

The maximum and minimum loads are sector-specific percentages which indicate the load boundaries. *A* refers to an NxN constraint matrix used to limit prices within defined blocks. It consists of values in the range [−1, 0, 1], and varies based on the pricing strategy and sector. It is noted that more details about the fosrmulation of the optimization function and modelling of the solution can be found in Ref. [19].

3. Data and methodology used

The proposed model is implemented to evaluate dynamic pricing strategies for Singapore, focusing particularly on the residential sector. However, a brief study is conducted for the commercial and industrial sectors as well, and the results are limited due to insufficient information on consumption trends. A day is divided into N = 48 periods and consumption data c_k and d_k are obtained from the Energy Market Company (EMC) of Singapore [25]. The fixed price $n = 256.5$ SGD/MWh.

The following assumptions have been made:

1) The total load data d_k for Singapore can be divided into three sectors namely residential (16%), commercial (38%) and industrial (46%).
2) All consumers implement the same utility function.
3) The maximum and minimum load ratios percentages are assumed to be 90 & 125 for residential, and 75 & 120 for commercial respectively.

The values for PED (ε_k) have been adopted from the following datasets:

3.1. Residential sector

1) Weekday values for summer 2010 data for 10,000 households are used from Ref. [26] and weekend values from summer 2008 data for 3000 households are used from Ref. [27]. These values were used by Navigant Consulting Research for Ameren Illinois' Power Smart Pricing Program (USA).
2) These values are hypothesized for weekdays, Saturdays and Sundays/Public Holidays to represent Singapore data.

Commercial and Industrial Sector

1) Weekday values for 2010 summer USA data based on Ameren Illinois studies over 4 years for 11,000 customers are taken from Ref. [19].

Table 3
Description of scenarios.

Scenario	Date	Description
1	25/9/13	Average Weekday
2	24/7/13	Highest Electricity Demand for 2013
3	14/9/13	Average Saturday
4	15/9/13	Average Sunday
5	01/2/14	Public Holiday (Lowest Demand- Chinese New Year Period)

Table 4
Block definitions for TOU and DN pricing – residential sector.

Block	Timings
TOU pricing	
Off-Peak	12 a.m.–7 a.m.
Semi-Peak	7 a.m. – 9am, 6 p.m.–12 a.m.
Peak	9 a.m. – 6pm
DN pricing	
Day	6 a.m.–10 p.m.
Night	10 p.m.–6 a.m.

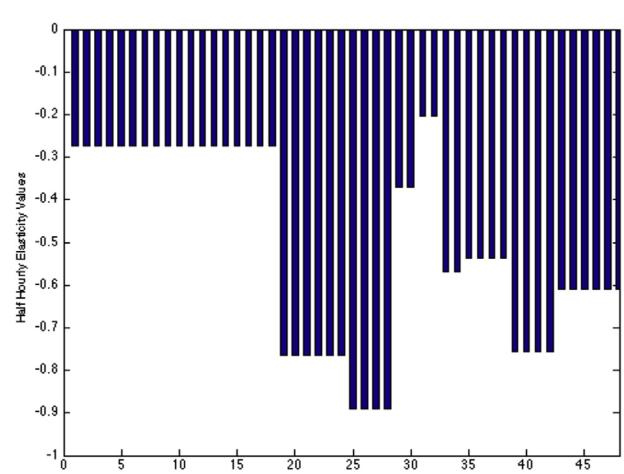

Fig. 1. Half-Hourly PED Values for Weekdays from USA residential data.

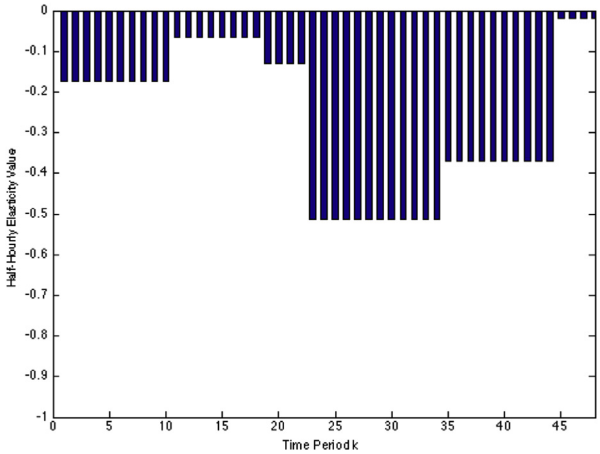

Fig. 2. Half-Hourly PED Values for Weekends from USA residential data.

2) The values from the above dataset are modified to represent Singapore data consumption on weekdays.

The proposed model is tested on five wide-spread scenarios that provide unique trends in consumption data as shown in Table 3.

Three pricing strategies have been implemented and evaluated viz. Half-Hourly RTP Pricing, TOU Block Pricing and Day-Night Pricing. The best combination of MU_S and MU_F values has been chosen based on maximum peak-load reduction and minimum total-load reduction. The optimization for this problem is performed using the KNITRO MATLAB software as it is considered to be very reliable and provides stable and accurate results. The interior or direct optimization algorithm is used, as it is known to price the best results especially in the cases where the Hessian and Lagrangian are not considered.

4. Results and discussions – the residential sector

The proposed pricing model is initially implemented and evaluated for the residential sector. The strategy-wise time-block definitions for the residential sector are presented in Table 4. For TOU pricing, the peak period is identified to be during the day while the off-peak period is mostly observed either during late night or early morning. The results are discussed using both the PED data of USA and the hypothesized data for Singapore.

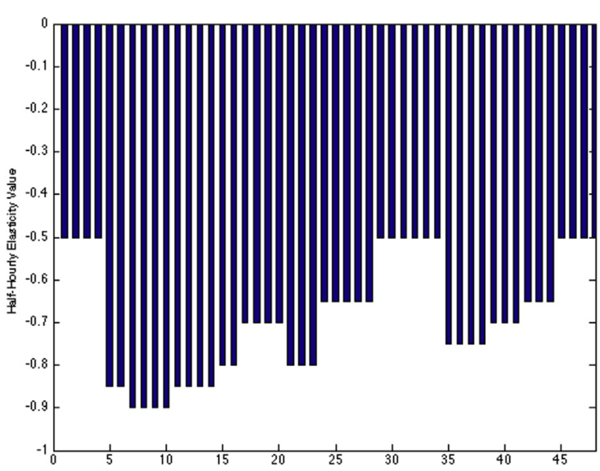

Fig. 3. Half-Hourly hypothesized PED values for weekdays.

4.1. Using USA PED data

PED datasets from Navigant Consulting Research for both weekday and weekend are presented in Fig. 1 and Fig. 2 respectively.

4.1.1. Weekdays

Results with $MU_F = 2$ and $MU_S = 1$ provide the highest peak load reduction and highest profits for all three cases, however they also cause a very high total load reduction. This is reflected in the satisfaction function with a very high positive value (of the order 106), thereby indicating that consumer demands are not met. It is evident that these values are not applicable for Singapore load data. Using $MU_F = 3$ and $MU_S = 1.5$, a very high peak load reduction is achieved, however the 7% decrease in total load consumption for RTP pricing appears unrealistic as reflected in high positive values for the satisfaction function. The combination $MU_F = 4$, $MU_S = 2$ is chosen as the best combination that maximizes peak and minimize total load reduction. RTP pricing appears to be the most suitable strategy as it provides a maximum peak load reduction of 7%, earns maximum profits and achieves minimum fluctuation. Although this dataset provides results for scenario 1, it is unable to model scenario 2 as block constraints (A matrix) could not be met. For example, the PED value is as low as −0.274 during the night and goes up to a value of −0.891 during the day, especially in the afternoon.

4.1.2. Weekends and holidays

The PED from USA data need to be adapted for Singapore weekend data. Values during the day are high, implying a very elastic condition whereas those during the night are extremely low implying an almost inelastic situation. The following impacts are seen on the results. Numerous simulations are completed in order to find a suitable combination of values for MU_F and MU_S.

$MU_F = 4$ and $MU_S = 2$ (as used in the case for weekdays) leads to erroneous results such as massive load reduction with no peak-trimming. The load curve after dynamic pricing follows the exact trend as that before the change but scaled down drastically.

4.2. Using hypothesized PED data

Due to a large difference in the consumption patterns in USA and Singapore data, the PEDs for USA can not be applied on Singapore data. The elasticity values have therefore been hypothesized to represent the current trend for Singapore's residential electricity consumption using the actual load data. Two datasets have been developed to reflect trends for weekdays and weekends, including public holidays as illustrated in Figs. 3 and 4.

4.2.1. Weekdays

The hypothesized half-hourly PED values for average weekdays in Singapore are presented in Fig. 3. The lowest PED is seen at the peak afternoon time between 2 and 5 p.m. (k = 29–34) and during the night due to the expected use air-conditioner. The highest elasticity is observed late in the night and early in the morning. MU_F and MU_S values are chosen based on simulations conducted on data for any particular day and the results are presented. $MU_F = 2$ and $MU_S = 1$ gives the highest peak load change of an average of −9.67% across all different pricing strategies while an average total load reduction of −1.67%. The profits are seen to be the highest as compared to any other combination of values as well. $MU_F = 3$ and $MU_S = 1.5$ lead to a very minimal peak load change with an average of −1.67% and a very high change in total load consumption with an average of 7%. Profits are lower than in the case of $MU_F = 2$ and $MU_S = 1$ since the satisfaction function is highly negative

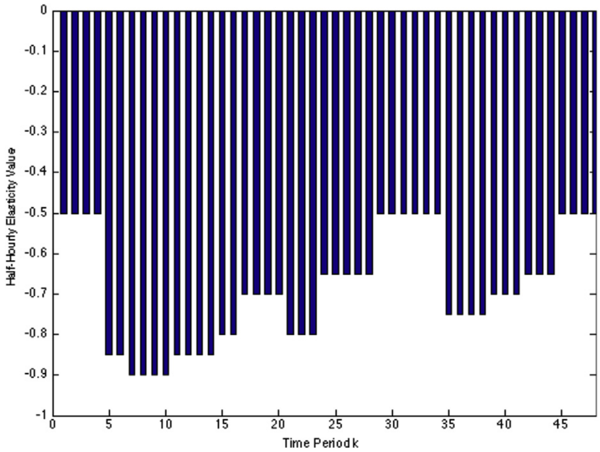

Fig. 4. Half-Hourly hypothesized PED values for weekends.

(approximately 10^6). This indicates that customers consume more electricity than they would without dynamic pricing, which is a highly unlikely scenario.

$MU_F = 4$ and $MU_S = 2$ leads in 0% peak load change and very high increase in total load consumption with an average of 8.67%. Satisfaction is higher in value than in the previous case that pushes profits down even further. Hence, the final values chosen are $MU_F = 2$ and $MU_S = 1$.

Figs. 5–7 show the obtained results for the pricing and load curves for RTP, TOU and DN pricing respectively with $MU_F = 2$ and $MU_S = 1$ applied to Scenario 1. All three load curves show peak trimming and valley filling indicating that the pricing strategies have the desired impact on consumer consumption. The pricing trends appear to be correct as they show higher prices for the peak periods of the day (afternoons) making these PED values appear more suitable for Singapore data. Block Pricing results show a sharp drop at k = 14 in the load curve that is caused by the change in the block period and the sudden increase in the price. This is a sharp theoretical drop although in real-life this might not be the case. RTP pricing achieves the least load fluctuation of the order 10^4 as compared to other strategies where fluctuations are of the order 10^5.It is observed from Figs. 5 and 6 that the maximum peak load reduction is 10%. TOU Pricing ensures no change in total load consumed and hence has the lowest (ideal) satisfaction function value indicating that customers are the most satisfied. Other strategies show minimal total load changes. RTP pricing shows the maximum profits because it has the lowest combination of satisfaction and fluctuation.

Thus, RTP Pricing is found to be most suitable for Singapore's data as it maximizes peak load reduction, profits and satisfaction, and minimizes total load reduction and fluctuation. It is observed that the hypothesized elasticity values fit the Singapore data well. There is an average peak load reduction of 9.67% and a slight decrease in average overall consumption at 1.67%.

4.2.2. Weekdays and holidays

The chosen values are similar to those for weekdays except for a few minor changes. Saturday in general is considered slightly less elastic as more people are expected to be at home and using maximum electricity. Thus especially during the day, the values are slightly lower than that on a weekday. Figs. 8–10 show the obtained results for the pricing and load curves for RTP, TOU and DN pricing respectively with $MU_F = 2$ and $MU_S = 1$ applied to Scenario 3.

The results are observed to have similar characteristics to those presented for weekdays. Successful peak trimming, valley filling and correct pricing trends are achieved. A sharp drop in block pricing (k = 4) is observed as seen in Figs. 9 and 10. The lowest fluctuation, highest profits and maximum peak load reduction are observed for RTP Pricing whereas the lowest peak load reduction is for DN Pricing and lowest total load reduction is for TOU Pricing respectively. The total load reduction is higher than in the case of weekdays at an average of 3.33% across all sectors. This is reflected with generally higher satisfaction function values. Hence, perhaps the PED values hypothesized for this scenario are not as accurate as those presented for weekdays. Once again RTP Pricing is observed to be most suitable. Hypothesized PED values appear to fit Singapore data (average peak load reduction of 9% and average total load change of −3.337%). These results are good, but not as good as those during weekdays indicating that the values can be improved. Table 5 and Table 6 list out the various model parameters for Scenario 1(Weekday) and Scenario 3 (Weekend).

5. Results/discussions – commercial sector

This section presents and discusses the results obtained using dynamic pricing strategies for the commercial sector using PED values. The values for the weekdays are taken from the USA data that is based on Ameren Illinois data for four years and 11,000

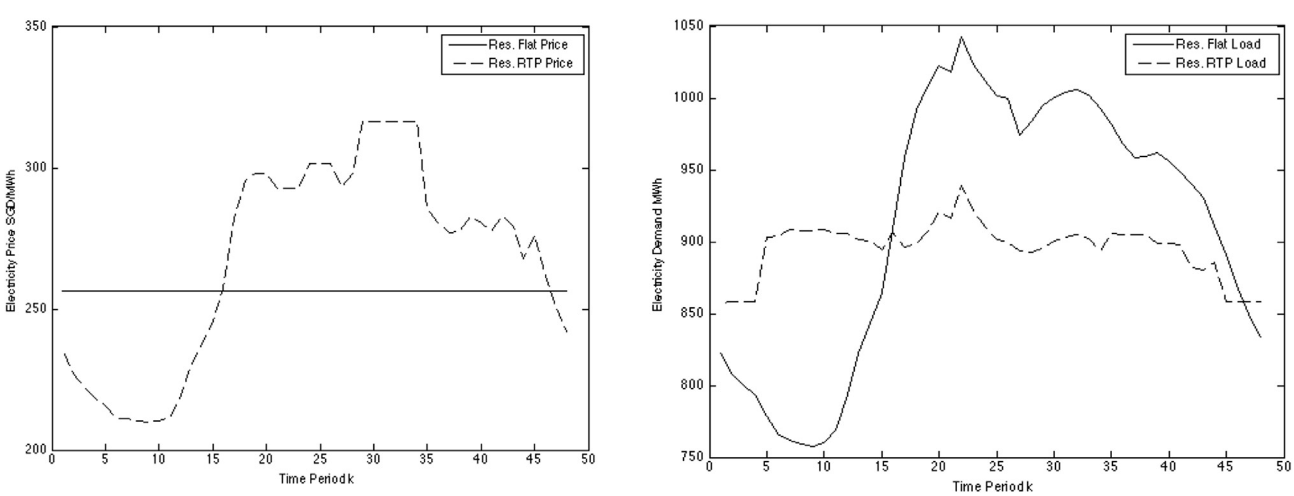

Fig. 5. Pricing (left) and load (right) results for RTP pricing – Scenario 1 Residential sector.

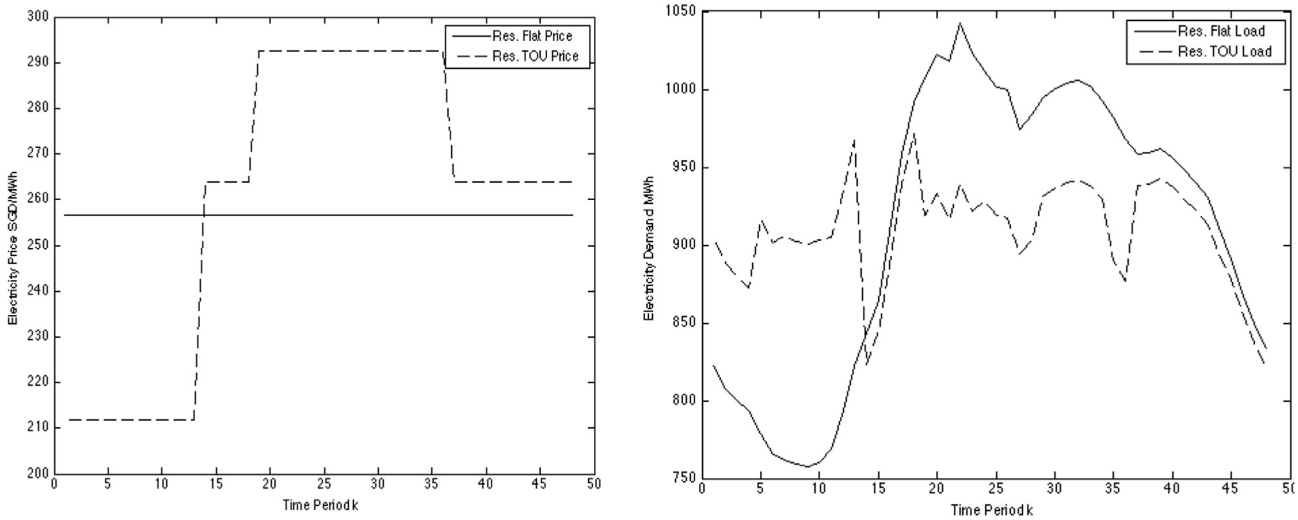

Fig. 6. Pricing (left) and load (right) results for TOU pricing – Scenario 1 Residential sector.

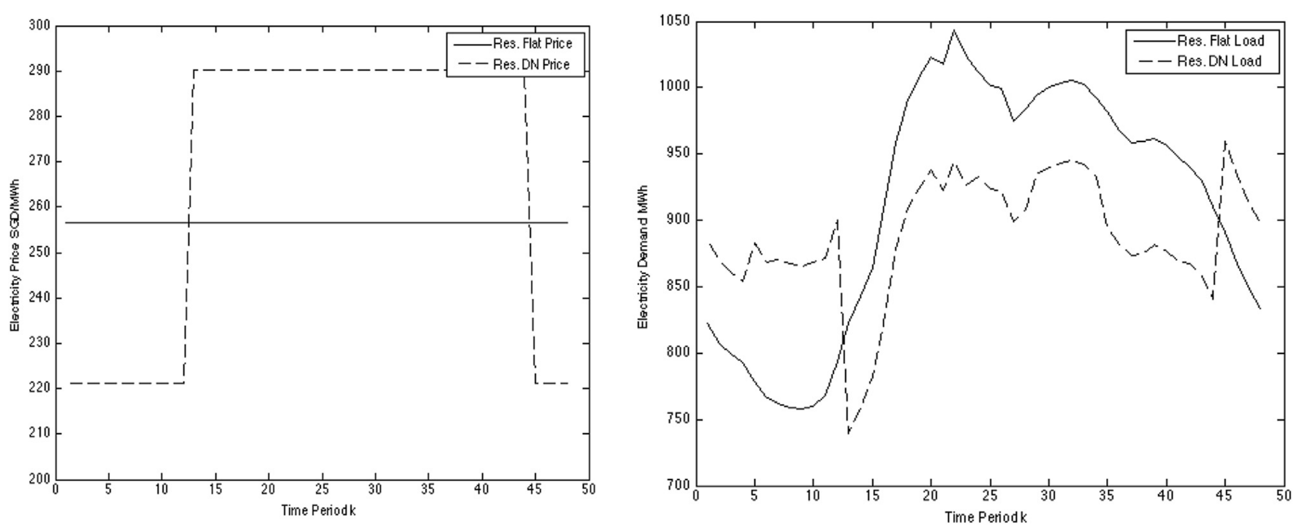

Fig. 7. Pricing (left) and load (right) results for DN pricing for –Scenario 1 Residential sector.

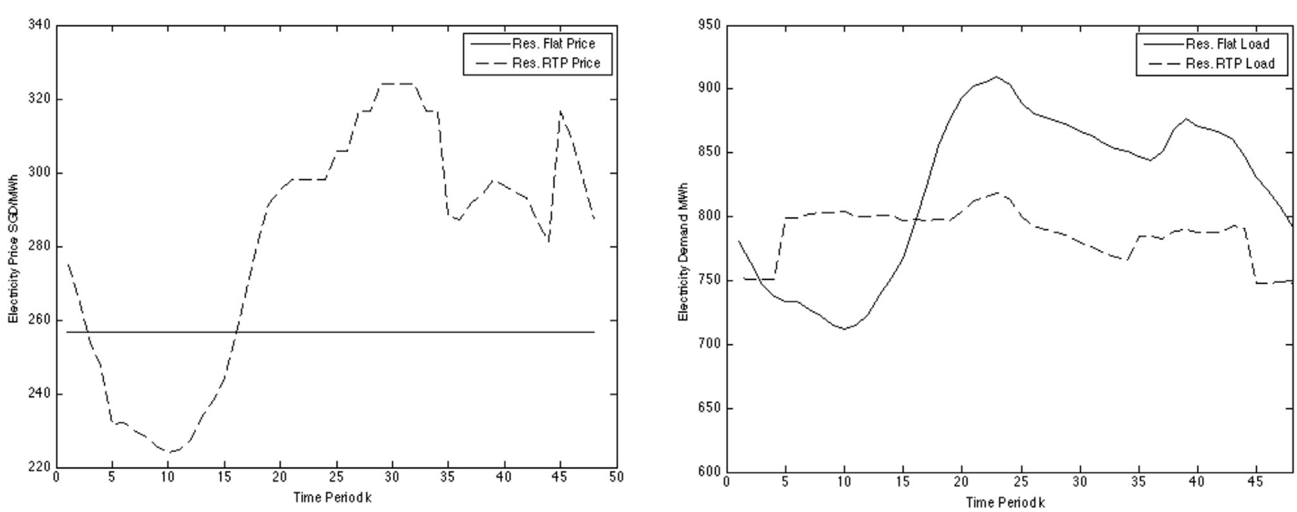

Fig. 8. Pricing (left) and load (right) results for RTP pricing – Scenario 3 Residential sector.

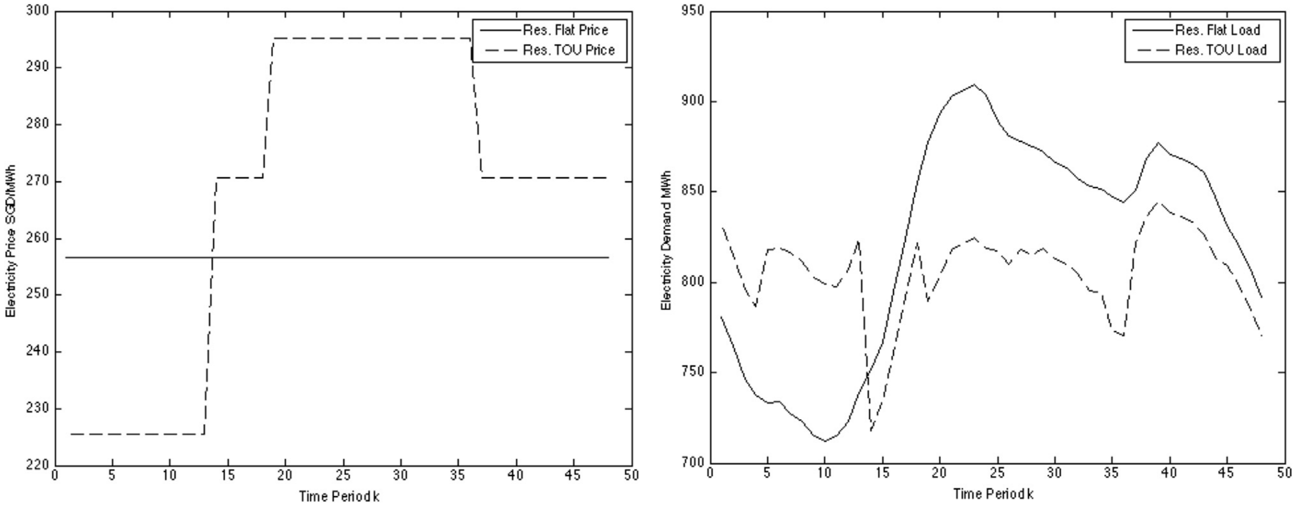

Fig. 9. Pricing (left) and load (right) results for TOU pricing – Scenario 3 Residential sector.

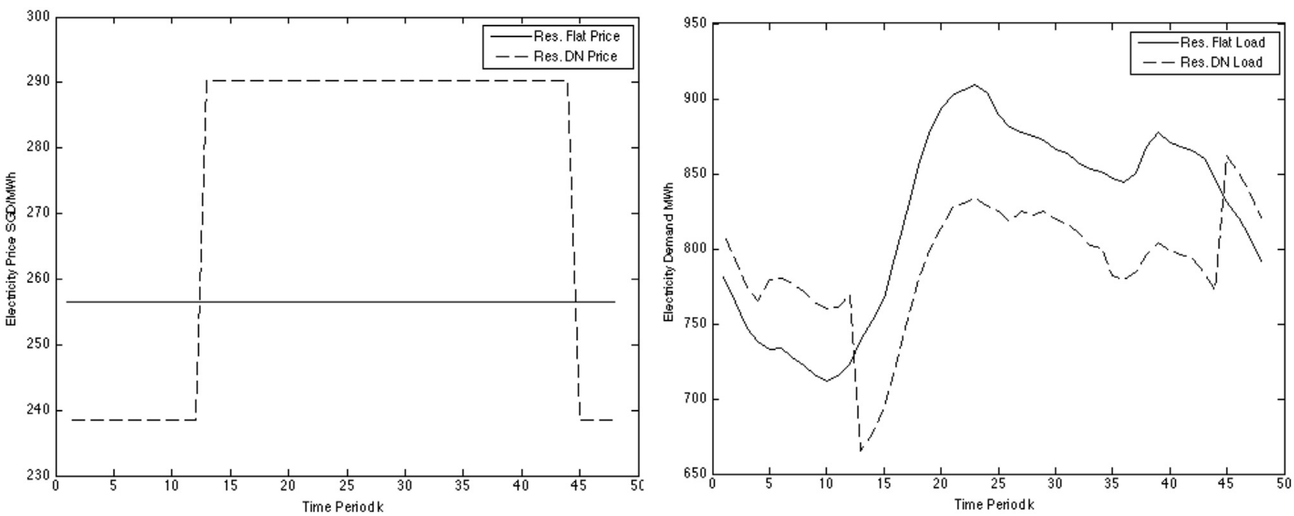

Fig. 10. Pricing (left) and load (right) results for DN pricing for – Scenario 3 Residential sector.

Table 5
Model parameters for scenario 1 - residential sector.

Strategy	MU_F	MU_s	Utility (*10^6 utils)	Profits (M SGD)	Satisfaction (*10^5)	Fluctuation (*10^5)	Total load change	Peak load change
RTP	2	1	5.00	6.88	12.40	6.45	−10%	−10%
TOU	2	1	4.32	6.18	9.82	8.77	−8%	−9%
DN	2	1	4.15	5.56	7.71	6.33	−6%	−9%
RTP	3	1.5	4.17	5.87	1.26	4.40	−7%	−10%
TOU	3	1.5	3.57	4.63	5.95	4.66	−3%	−9%
DN	3	1.5	3.64	4.88	7.11	5.25	−4%	−9%
RTP	4	2	3.90	3.71	−3.87	1.96	3%	−7%
TOU	4	2	3.44	3.44	−4.54	4.51	3%	−4%
DN	4	2	3.28	4.36	3.77	7.09	−1%	−6%

Table 6
Model parameters for scenario 3 – residential sector.

Strategy	Utility(*10^6 *utils*)	Profits (M SGD)	Satisfaction (*10^5)	Fluctuation (*10^4)	Total load change	Peak load change
RTP	4.40	4.94	5.06	3.73	−4%	−10%
TOU	4.27	4.57	2.45	5.87	−2%	−9%
DN	3.81	4.6	6.48	23.1	−4%	−8%

Table 7
Block definitions for TOU and DN pricing – residential sector.

Block	Timings
TOU pricing	
1	10pm – 7am
2	7 a.m. –10 a.m., 8 p.m.–10 p.m.
3	10 a.m.–1 p.m., 5 p.m. – 8pm
4	1 p.m.–5 p.m.
DN pricing	
Day	8 a.m.–8 p.m.
Night	8 p.m.–8 a.m.

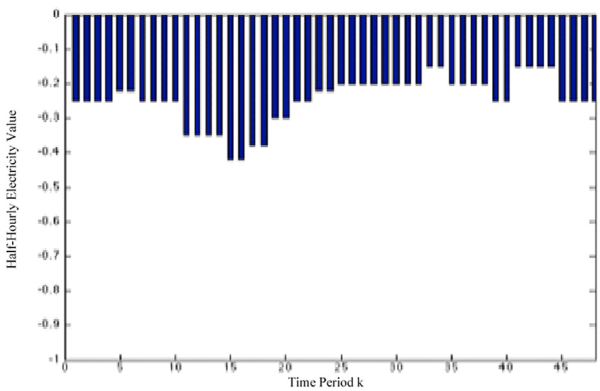

Fig. 11. Half hourly hypothesized PED values for weekdays.

customers [12]. Hypothesized values are obtained by modifying this data in order to reflect peak period during the afternoon. The block definitions for TOU and DN pricing strategies are defined below in Table 7. Since the hypothesized data is obtained by slightly modifying the US PED data, the results are discussed directly for the hypothesized data only. Since we are dealing with the commercial sector, only the weekday scenario is taken into consideration. The half-hourly commercial data for weekdays is shown in Fig. 11. $MU_F = 2$ and $MU_S = 2$ are chosen as they give the best results.

Table 8 and Figs. 12–14 show the results obtained when the developed pricing model is applied to Scenario 1. It is clearly observed that the new PED dataset now fits the Singapore patter and favourable results are obtained with the expected price/load trends. RTP Pricing is indeed the most suitable as it provides the highest peak load reduction and highest increase in profits. Overall, a peak load reduction of 4.44% and an increase in profits of 7% are obtained.

6. Results/discussions – industrial sector

This section presents PED values from USA data for weekdays and attempts to use it to model Singapore's industrial sector. Section 2.1 uses values from 2010 Ameren Illinois data that is presented in Ref. [12] and Section 2.2 uses values from 2005 USA data from Ref. [21]. The PED values could not be hypothesized successfully because there isn't enough information on the trend of consumption patterns in Singapore. There are no results to be presented because neither of the dataset was suitable for Singapore. Figs. 15 and 16 represent the PED datasets used for the industrial sector in USA.

6.1. Using 2010 USA PED data from Ref. [12]

This dataset presents very high PED values indicating a unit elastic situation in most cases. PED values are unexpectedly high for expected peak periods, and minimal variation throughout the day makes it harder to identify distinct peak/non-peak periods. This is a very futuristic scenario where loads can be shifted to any part of the

Table 8
Model parameters for scenario 1 – commercial sector.

Strategy	MU_F	MU_S	Utility(10^6 *utils*)	Profits (MSGD)	Increase in profits (%)	Satisfaction ($*10^5$)	Fluctuation ($*10^6$)	Total load change	Peak load change
RTP	2	2	11.1	12.2	18.7%	4.53	0.63	0.27%	−5.00%
TOU	2	2	9.68	11.1	7.97%	1.02	1.27	0.60%	−5.00%
DN	2	2	8.15	9.69	−5.74%	−4.73	2.02	1.34%	−3.32%

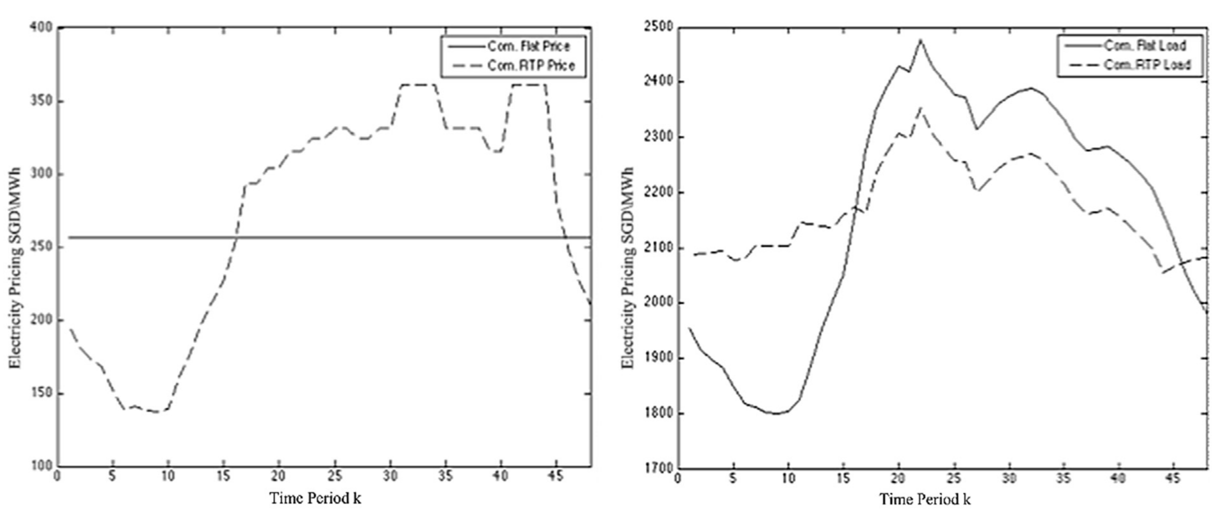

Fig. 12. Pricing (left) and load (right) results for DN pricing for –Scenario 3 Commercial sector.

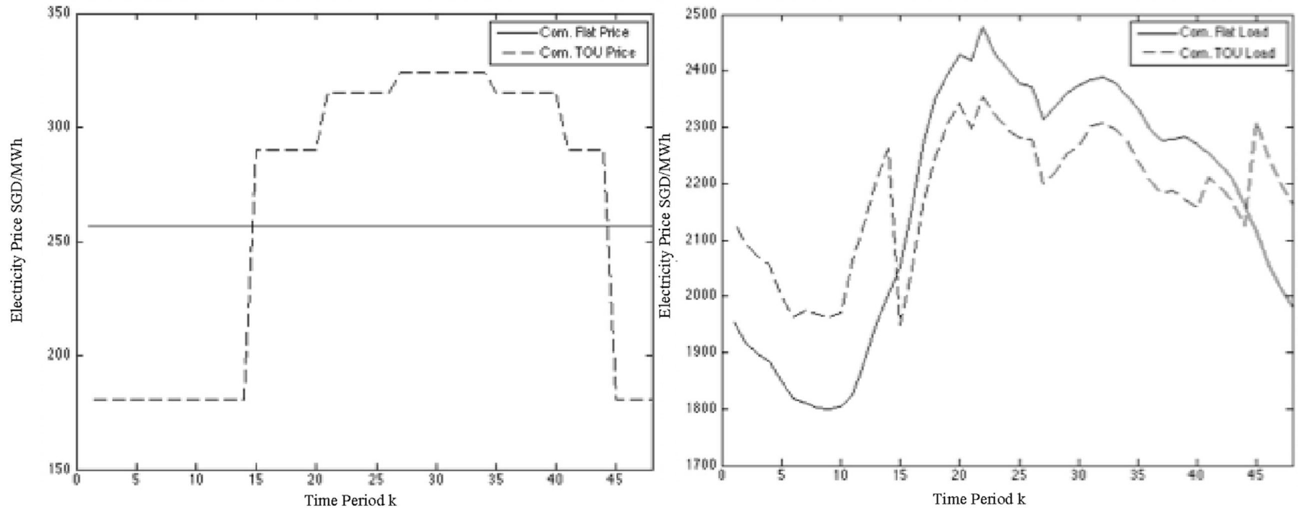

Fig. 13. Pricing (left) and load (right) results for DN pricing for −Scenario 1 Commercial sector.

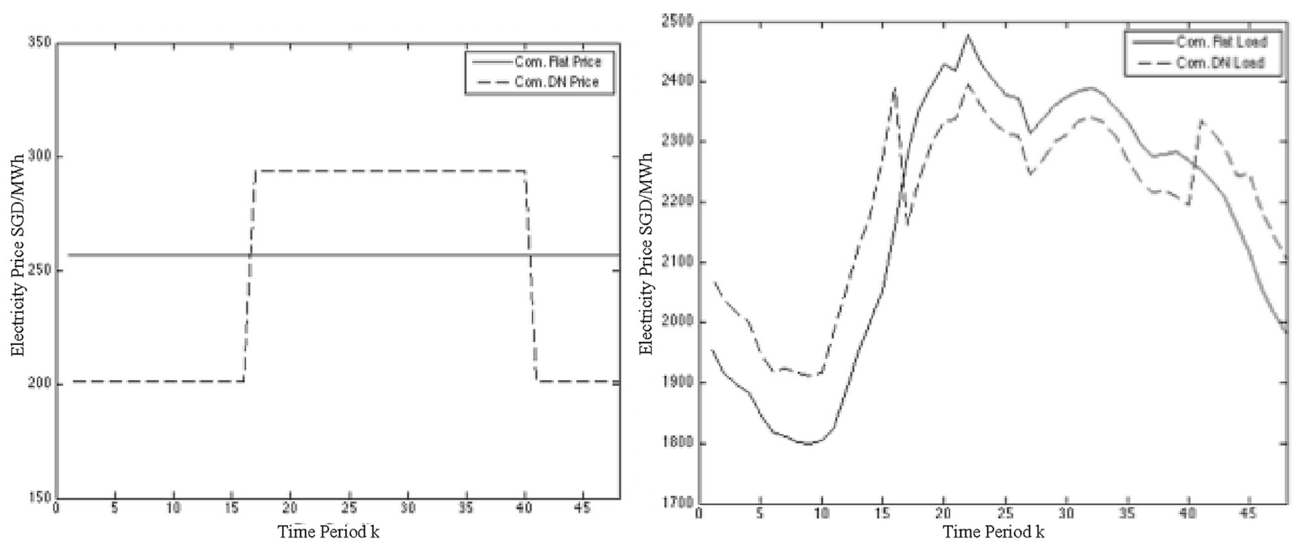

Fig. 14. Pricing (left) and load (right) results for TOU pricing − Scenario 1 Commercial sector.

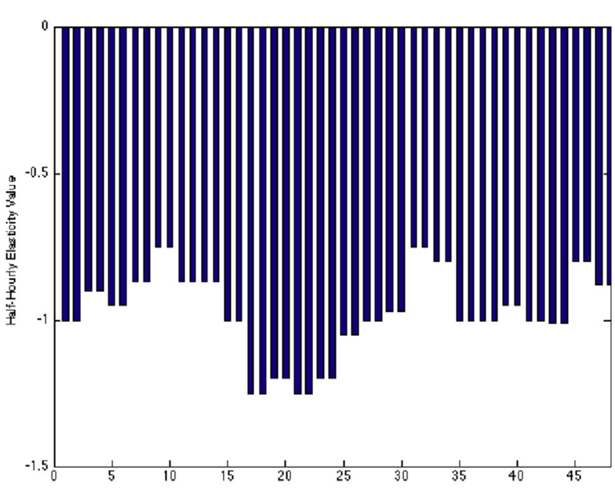

Fig. 15. Half-Hourly hypothesized PED values for weekdays in 2010.

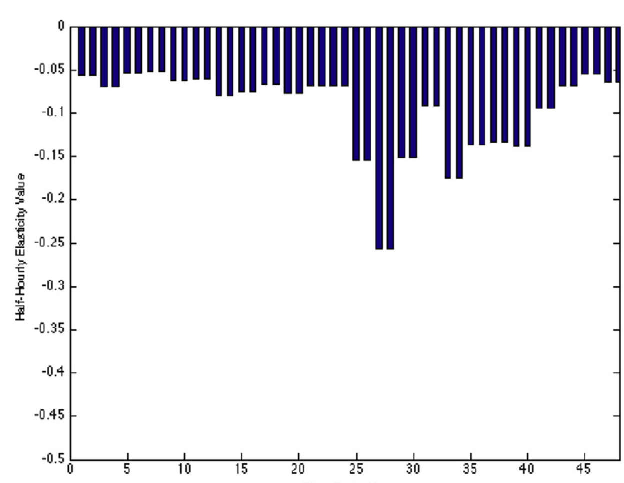

Fig. 16. Half-Hourly hypothesized PED values for weekends in 2010.

day and consumption is almost perfectly elastic. However, considering the current load/price data and the assumption that industrial load is 46% of the total at all times of the day, Singapore's load is not as elastic and cannot be modelled with this dataset.

6.2. Using 2005 USA PED data from Ref. [21]

This dataset presents very low PED values indicating an almost inelastic situation where consumption is not flexible. Since the study was published in 2005, the values can be considered obsolete, as the advent of smart grids has made load shifting far more convenient. Results show unrealistically high prices in the order of ~10^4 with normally used values of MU_F andMU_S. It is also observed that increasing the weights results in negative values for the utility.

7. Conclusion

This work proposes a game-theoretic study of dynamic pricing strategies for the electricity market in Singapore. The pricing models are developed and tested on data obtained from EMC, Singapore. The residential and commercial models are tested extensively to obtain the best pricing strategy. Many load/price datasets from real and practical Singapore consumption data including weekdays, weekends and public holidays are used, and three pricing strategies namely half hourly RTP Pricing, TOU Pricing and DN Pricing are evaluated. Results obtained are very promising: RTP Pricing is identified as the best strategy with a 10% and 5% peak load reduction and a 15.5% and 18.8% increase in profits for the utility company in the residential and commercial sectors respectively. These results indicate that the game-theoretic based dynamic pricing model is indeed a promising strategy for demand side management. With capable and universal energy intelligence systems, this pricing strategy would be very useful for the electricity market.

The model is considerably robust, as it can be used to develop numerous pricing strategies, model multiple sectors, shift focus between the consumer and company's utility by changing the values of MU_F and MU_S) and simultaneously be applied to a wide range of price/load data. The industrial sector is also tested with the model; however, results are limited owing to the insufficient information on Singapore's consumption trends. Future work will include testing on different satisfaction functions, including multiple user types in the case studies, understand the impact of renewable generation sources on DSM considering dynamic pricing technique, and to understand the impact of the dynamic pricing on short-term PEDs for long term. Although the testing and comparison are conducted only using Singapore data, the proposed model can be used to develop pricing strategies for other countries as well.

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