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Development of a novel time-of-use tariff algorithm for residential prosumer price-based demand side management

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A B S T R A C T

Through the application of flexible Time-of-Use (ToU) tariffs, demand side management (DSM) can be facilitated in order to alleviate grid congestion problems and potential network reinforcement. In this work, a novel approach to derive ToU tariffs for residential prosumers is described and the potential impact is verified in a pilot network within the distribution grid of Cyprus comprised of three hundred prosumers. This pilot network acts as a test-bed for defining the baseline scenario and subsequently verifying the developed ToU tariffs. The ToU block periods were determined by combining statistical analysis and a hybrid optimization function that utilizes annealing driven pattern search algorithms. The ToU rates were calculated by exploiting an optimization function that maintained a neutral electricity bill in the case where the load profile remained unchanged. The impact of the derived ToU tariffs was first analysed through a sensitivity analysis performed on the seasonal load profiles of the participants. The obtained sensitivity analysis results showed that for the summer and winter season, the maximum Load Factor (LF) was 42.83% and 33.33% respectively and occurred when load was shifted mainly to the off-peak period. Finally, with the ToU tariffs applied to the pilot network of prosumers, the effectiveness and potential response of the prosumers to the imposed tariffs, was verified. The results indicated that the LF was increased while the percentage of total consumption measured during peak hours was reduced by 3.19%, 1.03% and 1.40% for the summer, middle and winter season respectively. This led to the conclusion that the derived ToU tariffs are effective in persuading the prosumers to change their energy behaviour.

1. Introduction

The conventional approach to accommodate the increasing consumption and generation is currently achieved through network reinforcement, which is expensive and time consuming [1]. An alternative and appealing approach to mitigate this effect and at the same time bring benefit to end-customers is to employ demand side management (DSM) aiming to control the demand and allow higher penetration of Renewable Energy Sources (RES) [2–6].

DSM is viewed as an important component of future smart grids and price-based DSM is a very popular smart pricing scheme already applied to a large number of residential consumers in various countries. In particular, price-based DSM schemes provide an alternative to the traditional flat tariffs, offering new schemes such as Critical Peak Pricing (CPP), Real-Time Pricing (RTP) and Time-of-Use (ToU) tariffs [7,8]. Amongst the different price-based schemes, the most common is the ToU tariff. ToU pricing is a tariff structure that typically applies to electricity usage over a period of hours where the price for each period is predetermined and constant. Time is divided into peak, shoulder and off-peak periods which reflect the level of demand on the electricity network. During peak periods electricity prices will be more expensive than at other times. This is absolutely key for the power utilities since it will allow them to decrease demand during typical peak demand times and encourage usage when demand is typically very low. By decreasing peak demand, peak supplied energy can also be lower – and hence, aggregated savings can be passed on to consumers. ToU tariffs are commonly preferred by grid operators because the price

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of energy consumption is fixed for different periods of the day in contrast to other price-based DSM programs, where the price fluctuates following the real-time cost of electricity [7,8]. In addition, consumers and utilities have the advantage of risk-averse attitude to price uncertainties mainly due to fuel price adjustments. A necessary step in the successful and effective implementation of such schemes is the upgrade of appliances with automated smart controllers to defer their operation during high prices [9,10].

Currently, the majority of residential consumers are under a flat tariff scheme. This does not provide consumers with incentives to modify their pattern of consumption in periods when the cost of producing electricity rises [11]. Generally, the variability of the total residential consumption levels depends on the lifestyle, convenience, and preferences of each residential consumer, and it is difficult to significantly change unless appropriate incentives are provided [12]. A flexible energy pricing mechanism is capable of providing economic incentives and generating such a decrease in the variability of consumption levels among hourly segments during the day, which in turn reduces uncertainty of electricity costs [13]. Time-varying prices could offer consumers better economic benefits even if they choose not to change their consumption habits, however, it gives the possibility of additional economic savings by adopting demand flexibility programs that, in the long run, offer additional benefits for load balancing and better grid performance with high penetration of non-dispatchable renewable energy sources [14]. In this way, the design of a suitable system of flexible ToU tariffs can help to operate future distribution and smart grids [15].

The main challenges in the development of ToU tariffs include (i) the quantification of tariff rates (price within each block period) and (ii) the determination of tariff shape (duration of each block period) [1]. Even though the duration of each ToU block period can commonly follow the variation of wholesale prices, it is not feasible to derive the ToU rates only from wholesale prices because network investment and operation costs also need to be included and this information is not always readily available. In this sense, the design of ToU tariffs is different to the existing flat rate tariffs, which are commonly designed by considering all kinds of operation and investment costs. Additionally, since ToU tariffs facilitate DSM, further requirements relevant to the optimization of the electricity provider's objective and constraints, customer response and acceptance and the regulatory restrictions must be considered. As a result, the optimal design of ToU tariffs is a field of growing significance.

Several studies investigated peak pricing with the consideration of demand uncertainty [16–21], while others extensively investigated peak pricing under supply uncertainty [22–24]. ToU tariffs were firstly introduced during the 80's and were primarily derived based on the experience utilities gained on load consumptions [8]. Recently, new methods and algorithms have been explored in order to determine the ToU structure in both price and duration. More specifically, the peak and valley characterization of the load curve is one of the most important variables to be used as the starting point for a ToU tariff development [9]. Such a simplistic process to develop ToU tariffs based on load time series analysis can be useful only for the deployment of a fundamental two window pattern ToU tariff. This is not the most favourable option since the two-window ToU tariff can easily shift the peak period by a couple of hours after or before the existing peak rather than smoothing the load profile [10].

A more sophisticated approach is to analyze the spectrum of load profiles and extract the peak and valleys of the load curve [25]. Spectrum analysis divides the time series into the superposition of periodic components with different amplitude, phase and frequency [25]. With this approach the load curve can be converted from the time to the frequency domain in the scope of highlighting the effects of all the periodic components contained in the load sequence and allowing the evaluation of the potential effects of a possible ToU tariff on load profiles.

A previous study proposed a mixed-integer program for optimal design of customized ToU tariffs with the most important requirements being the number of rate zones, the start and end times of the ToU zones and the price level of the zones [26]. A specific jump structure to identify the number of rate zones and the duration of each zone was used in order to develop an optimization tool, based on an industry-grade optimization suite (IBM ILOG OPL Studio with the CPLEX solver), which facilitates integration into a data management system allowing to embed the optimized decisions into near-real-time decision-making [26].

Furthermore, in 2007 the Irish Government announced a pilot smart metering program for domestic and small commercial customers. The main scope of this program was to motivate customers to utilize DSM through the development of a ToU tariff. It is worth mentioning that for the participants the electricity during daytime was more expensive compared to the electricity during the night. This in turn, led to lower CO_2 emissions as the base load generators emit fewer pollutant gases. The methodology followed for the development of the ToU tariff comprised of four main principles [27]. Firstly, the new ToU tariff for an average consumer should have cost neutrality. Secondly, all the time blocks should reflect the real cost of electricity and thirdly the tariff structure should be based on the system peak demand. Finally, the ToU tariff should include all the energy costs related with the system operation. The structure of the ToU tariff was based mainly on analysis of existing demand patterns. The analysis showed that the ToU tariff during the winter period was a synthesis of three time blocks with 2 h of peak, shoulder period after and before the peak period and an off peak/night period. In the weekends and in the summer period the ToU structure consisted of only two time blocks, shoulder and off peak/night blocks. Each time block was cost defined using a demand weighted average price. From the calculations made using the demand weighted prices it was demonstrated that the annual cost of electricity for an average customer resulted in higher electricity bill violating the primary set constraint of neutral cost. Therefore, the ToU tariffs were adjusted in order to attain cost neutrality.

Finally, Qiao and Li [28] approached the development of ToU tariffs by applying statistical approaches to the daily load curve. Specifically, the Continuous Load Curve (CLC) was statistically analysed in order to determine the peaks and valleys as well as the duration of each block period. Daily load data over a period of a year were acquired in order to statically derive the CLC which was divided into three segments according to the slope change, which express the peak, valley and flat periods. Subsequently, frequency statistics were applied to determine the frequency of each load point in each load segment in order to calculate the probability index to fit the distribution curve. The probability distribution curve was derived and the time distribution within a confidence interval of a percentile was calculated in order to obtain the peak, valley and flat periods. This approach showed that it can handle the time division better and yield optimal results with respect to the period partition, which is one of the most important specifications for designing ToU tariffs.

Even though ToU tariff schemes offer the advantage of price certainty, the effectiveness of such tariff schemes must be verified prior to implementation because of the eminent high risk of a new peak appearing through load shifts at cheaper price periods, posing negative effects on the optimal operation of system [25–28]. For several years prosumers in Cyprus used to be under feed-in tariff contracts but due to the rapid decrease of the cost of PV systems, the Energy Ministry and the Regulator decided to introduce the new, at the time, net-metering scheme for residential consumers. The net-metering scheme that is currently operational in Cyprus is unique in that prosumers are called upon to cover the system costs for the services that they offer through a yearly capacity payment per kWp installed (3 kWpp for residential consumers). Through a price-based DSM scheme, the local DSO and Regulator aimed to improve the net-metering scheme by creating new energy policies that can benefit both the power utility and prosumers who will inevitably grow in the near future and will become significant contributors to the energy mix.

In this work, the methodology followed to derive the ToU tariffs is presented in the scope of incentivizing residential prosumers, to adapt their consumption and reduce electricity costs through DSM. The ToU tariffs were determined based on both statistical analysis and optimization algorithms applied to the residential prosumer profiles. These price-based DSM schemes will have a significant impact both on the demand and on the grid as prosumers will benefit from a lower electricity bill and at the same time peak demands are mitigated, since the ToU tariffs aim to motivate prosumers to shift loads from peak to valley low-price periods. The effects of the developed ToU tariffs were first analysed through the results obtained from a sensitivity analysis performed to emulate the potential response of three hundred prosumers, present within the pilot network, who have been offered the ToU tariffs. The emulated results were subsequently verified through the load demand data acquired from the pilot network developed in Cyprus for this purpose, which acts as a test-bed for the assessment of the implemented ToU tariffs. The comparability of the ToU and non-ToU (i.e. flat tariffs) samples is ensured by taking into account only data from the same season (summer period 2015 – prosumers were charged with flat tariffs and summer period 2016 – prosumers were charged with ToU tariffs). In this way the impact of smart metering implementation on consumer billing options, consumption sensitivities, consumer energy-related behaviours and cost-benefit implications for network owners and operators (financial impact) can be observed on a real world platform.

The rest of the paper is structured as follows: Section 2 covers the approach followed for the development of the ToU block periods and their respective rates as well as the methodology used for investigating the potential impact of the developed tariffs through a sensitivity analysis. Additionally, the methodology for estimating the peak kWh reductions due to various ToU price ratios is also presented in this section. The results of this analysis and the outcome of applying the developed tariffs on a real pilot network are presented in Section 3. Important concluding remarks appear in Section 4 of the paper.

2. Methodology

The methodology followed for establishing the ToU tariffs (block periods and the corresponding rates) is presented in this section. The developed ToU tariffs aim to enable a price-based DSM scheme that can reduce the system cost and improve system efficiency. For this purpose, energy consumption and production profiles of three hundred consumers-producers (prosumers) all around Cyprus were examined. Data collection is essential in order to appropriately design a ToU tariff scheme that is capable of providing incentives to participating prosumers and as a result improving the system efficiency. The flowchart in Fig. 1 depicts the methodology followed for developing and benchmarking ToU tariffs.

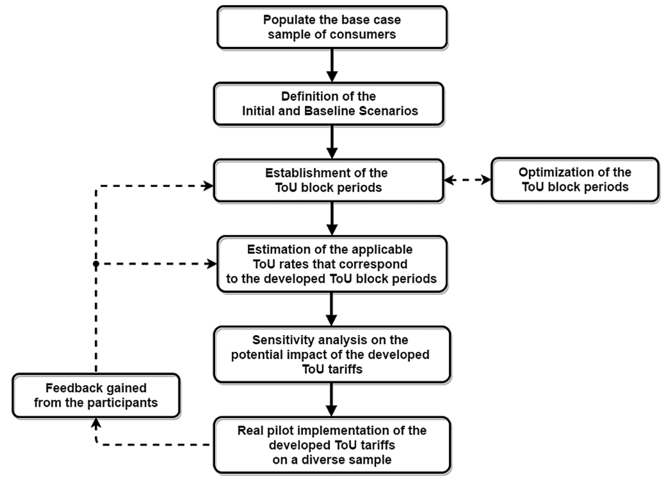

Fig. 1. Flowchart of the methodology followed for benchmarking the developed ToU tariffs.

2.1. Populate the base case sample of consumers

In support of this work, three hundred prosumers in Cyprus have been selected, in order to collect consumption and production datasets from a real-pilot network that emulates a representative sample of the Cypriot residential prosumers connected to the grid with a flat tariff scheme. All participating prosumers were geographically spread throughout Cyprus, in order to cover different socio-geographical situations, with 2/3 of prosumers residing in urban areas and 1/3 in rural areas. All participants completed a questionnaire regarding their energy patterns and all the energy-intensive appliances as well as the flexible (deferrable) loads located at their premises. Smart meters (SMs) were installed to acquire consumption and production profile datasets for each prosumer. The analysis of usage patterns of each prosumer is crucial for understanding the variations in peak usage profiles and deciding a DSM policy that will be acceptable and beneficial [29]. The smart meters operate as communication systems transmitting 30 min average consumption data to a central database platform. This provided the opportunity to the prosumers and the utility to monitor their energy consumption for at least one year prior to the implementation period commenced when the ToU tariffs were applied.

Effective and targeted training is of paramount importance in an attempt to maximize the benefits from the application of DSM [30]. Hence, all the participants were educated and informed by trained staff in order to effectively utilize the ToU tariffs based on their needs and habits.

Apart from the prosumers the pilot network includes seventeen weather stations over the geographical spread of the island, urban and rural areas along with mountainous, inner-country and seaside locations. The aim is to collect real consumption, generation and meteorological data to enable the improvement of different policies (net metering, self-consumption, etc.) through the verification and optimization of models developed towards smart grid networks.

2.2. Initial and baseline scenario

Peak demand management does not necessarily decrease the total energy consumption, but could be expected to reduce the need for investments in networks for meeting peak demands. Hence, the developed ToU tariffs applied in the residential sector should be able, if adopted by consumers, to reduce the peak demands of the total aggregate (residential, commercial, industrial and public lighting) consumption. Collecting consumption data is a vital aspect of developing ToU tariffs that can achieve the desired peak demand reduction. The progress of collecting consumption datasets began in 2015 and that year will be referred to as the reference year. The annual total aggregated consumption of Cyprus for the reference year was provided by the Transmission System Operator (TSO) of Cyprus. This represents the initial scenario and any DSM schemes affecting the total aggregate consumption will be reflected on the electricity power network. Furthermore, for the reference year, annual consumption datasets were collected from the installed smart meters in order to validate that the developed ToU tariffs can benefit the power utility. This is considered as the baseline scenario and will be compared to the initial scenario to ensure that the average consumption of the selected sample is representative of the total aggregate consumption. Also, the baseline scenario can be a good anchoring point for future evaluations and can be used to determine the critical success factors for benchmarking. The seasonal comparisons between the normalized initial and baseline scenario are illustrated in Fig. 2.

The comparison between the two scenarios shows a strong correlation equal to 96.7%, 97.8% and 96.1% for the summer, middle and winter season respectively. The correlation coefficients signified that the prosumers' consumption profiles (baseline scenario) show similar behaviour with the total aggregate consumption (initial scenario). Therefore, the prosumers' profiles used for deriving the ToU tariffs can be considered as representative of the total aggregate consumption profile and any improvement made, due to the application of ToU tariffs, will positively affect the power utility.

To summarize, the following definitions will be used throughout the rest of the paper:

- Reference year: Is the year 2015, where the participants were under the flat tariff, had no knowledge of ToU tariffs and their energy behaviour was monitored.
- Implementation year: Is the year 2016, where participants were under the developed ToU tariffs.
- Initial Scenario: Seasonal total aggregate consumption profile for the whole of Cyprus for the reference year.
- Baseline Scenario: Seasonal consumption profile of the participants for the reference year as recorded through the SMs.

2.3. Establishment of the ToU block periods

The first step in the development of the ToU block periods was to identify the seasonal electricity demand by utilizing the participants' load profiles that were recorded during the reference year. The annual load profile was categorized into three seasons (winter, middle and summer) and the process of finding the inflection points (i.e. the points on a curve at which the curve changes from being concave downward to convex upward, or vice versa) was then applied to the load duration curve (LDC) of each seasonal residential load profile. Fig. 3 demonstrates the LDC of the collected data for the winter season of the reference year which was further used to characterize the overall response and behaviour of the LDC.

The inflection points indicate points on a curve at which the sign of the curvature changes, therefore indicating a behavioural change in load consumption in this case. Four clear inflection points are observed in Fig. 3, demonstrating that during the winter season the load profile can be divided into five load segments (split by the vertical lines: the peak, shoulder and valley block periods). For each segment (derived from the inflection points) the value of the

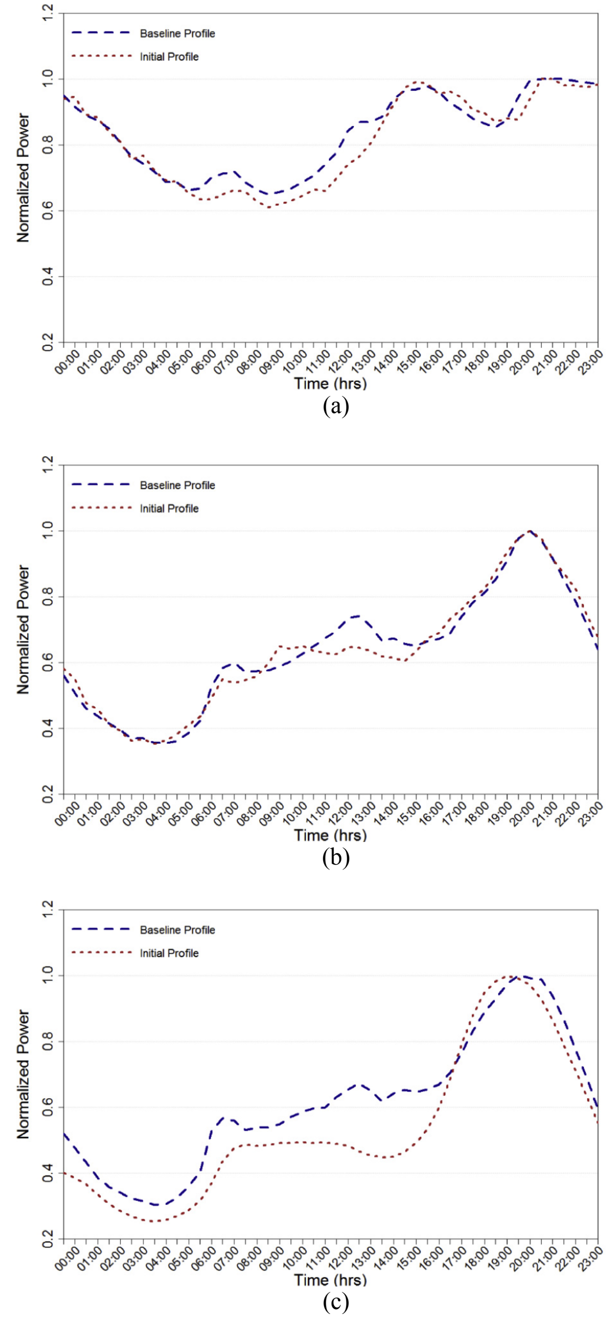

Fig. 2. Comparison between the normalized initial and the baseline scenario for: (a) summer, (b) middle and (c) winter season.

cumulative frequency of the hourly load was extracted as an hourly load frequency histogram with boundary values representing the ToU block periods.

The above statistical analysis is capable of deriving the ToU block periods based on the analysis of the maximum and minimum consumption load segments and identification of the duration of the block periods from the constructed hourly load frequency histogram of each segment. The deviation between the evaluated ToU block periods and the seasonal residential prosumer load profile, was assessed by utilizing the mean absolute percentage error (MAPE) and root mean square error (RMSE) metrics, which resulted in an annual average MAPE and RMSE of 8.65% and 19.95%, respectively. The errors are quite high hinting that the derived ToU

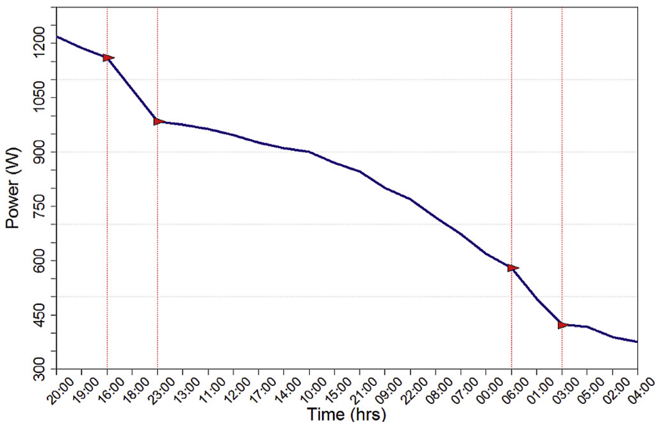

Fig. 3. Load Duration Curve (LDC) of the annual typical residential power demand for the winter season of the reference year.

block periods are insufficient to accurately describe the energy behaviour of the investigated sample.

2.4. Optimization of the ToU block periods

In order to optimize the statistically derived ToU block periods, the blocks obtained by utilizing the seasonal LDC were used as the initial conditions of an optimization algorithm. The objective function of the optimization algorithm aims to minimize the RMSE between the power demand of the derived block periods and the selected load profile, which is given as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(P_{ToUbk} - P_k)^2} \quad (1)$$

where, P_{ToUbk} is the power demand of the derived block period, P_k is the load profile and n is the total sampling interval. Based on this equation, P_{ToUbk} is the variable to be optimized and changes according to the desired levels. In particular, the first iteration of the optimization procedure uses the output ToU block period (P_{ToUbk}) of the statistical model as the initial condition. Then, a hybrid function to calculate the optimized ToU block periods was developed. The hybrid function is an optimization function that combines Simulated Annealing (SA) [31] and Pattern Search (PS) [32] algorithms to improve the value of the RMSE.

SA is a metaheuristic algorithm that exploits locally optimal solutions. However, unlike a greedy approach, it also explores inferior solutions probabilistically. Such a move helps to avoid getting trapped in the local optimum [33]. This approach can approximately find the optimum solution but it may also miss out and get stuck in local minima. As a result, the developed hybrid function utilizes the PS algorithm as a second optimization procedure. PS is a numerical optimization algorithm for derivative free optimization or non-continuous functions. Hence PS can be used for problems that do not require the gradient of the problem/function. Such optimization solvers belong to the group of direct search methods in which the algorithm searches a set of points around the current point looking for the one which the objective function has a lower value than the value at the current point. More specifically, a pattern is a set of vectors v_i that the PS algorithm uses to determine which points to search at each iteration. Therefore, PS finds a sequence of points, x_0, x_1, x_2, …, that approach an optimal solution. The value of the function at each iteration either decreases or remains the same from each point in the sequence to the next. For the case of using the generating set search (GSS) algorithm with positive basis *2N* pattern, *2N* vectors will be created, where *N* is the number of independent variables for the objective function. For example, if the optimization problem has two independent variables, the pattern will consist of the following four vectors $\{v_i\}$ [32]:

$$\{v_i\} = \{[1 \quad 0],[0 \quad 1],[-1 \quad 0],[0 \quad -1]\} \quad (2)$$

At each step, the algorithm searches a set of points, called a mesh, for a point that improves the objective function. PS forms the mesh by generating a set of vectors $\{d_i\}$ from multiplying each pattern vector v_i by a scalar Δ_m which is the mesh size and in this case is defined as the time difference (1 h). Then the set of vectors $\{d_i\}$ is added to the current point (the initial point or the point which derived the best objective function at the previous step) and the point of this mesh that improves the objective function is selected. If the algorithm successfully obtained a better point, the mesh size Δ_m remains unchanged (multiplying by 1). This is so as to keep an hour difference from the previous point (problem particularities). If the algorithm fails to improve the objective function, the mesh size reduces to half. The optimization procedure stops to operate if one of the following exists: (i) the maximum iterations have been reached, (ii) the objective function cannot be improved furthermore, (iii) the algorithm runs until a time limit has been reached, (iv) the distance between two consecutive iterations and the mesh size is less than a specific tolerance and (v) the number of objective function evaluations performed by the algorithm reaches a maximum value of evaluations.

The combination of the statistical analysis using the LDC on a seasonal basis along with the developed hybrid function for optimizing the derived blocks, yielded a MAPE and RMSE between the evaluated ToU block periods and the seasonal residential consumption that was improved to 2.43% and 7.63%, respectively. The statistically derived and the optimized ToU blocks are depicted in Fig. 4.

The optimization approach clearly demonstrated that the peak consumption period is charged with the higher tariff, while the lowest tariff occurs during the valley period. Once again in this approach another period is clearly identified representing the transitional (shoulder) period from the minima to the maxima and vice-versa. These time periods are important as they can be used by prosumers to cover their needs that can be shifted from the peak periods but cannot wait until the off-peak period (e.g. cooking and devices without smart control). In addition to this, the transitional

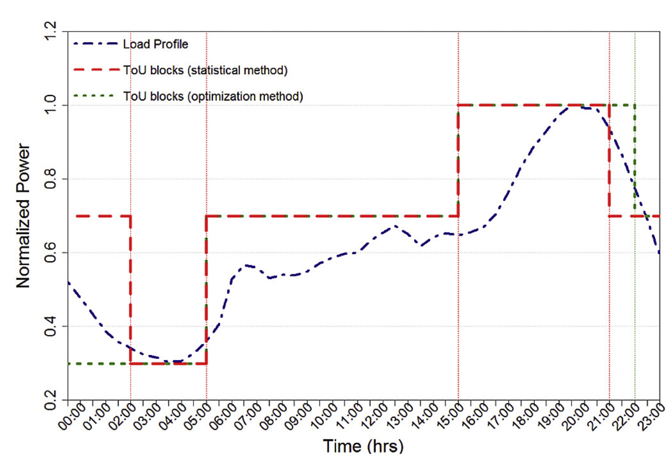

Fig. 4. Seasonal aggregated residential power demand and derived ToU block periods based on the statistical and optimization method.

period smooths the load profile and avoids shifting the peak to other hours of the day [10].

2.5. Estimation of the optimum ToU rates

Besides the identification of the ToU block periods the estimation of the applicable ToU rates for the corresponding periods is essential. The optimized ToU rates were calculated using an optimization algorithm which can derive a constrained minimum of a scalar function of several variables starting from initial conditions and are subject to linear multivariable constraints and bounds. More specifically, the ToU rates were calculated based on the constrained optimization function shown in (3), which finds the minimum off-peak rate ($Rate_{\mathrm{low}}$) while maintaining a constant difference between the peak-shoulder rate and off peak-shoulder rate. This can provide financial incentives to the consumers to consider shifting their consumption from consecutive periods [34]. The constraints depicted in (3.1) and (3.2) were used in order to keep the peak ($Rate_{\mathrm{high}}$) and off-peak rate ($Rate_{\mathrm{low}}$) per kWh higher and lower than the existing flat rate respectively. These relationships are the most important criterion since the peak period should always represent the highest rate whereas the off-peak period the lowest rate and never vice-versa. The development of the ToU rates was also based on the seasonal average prosumers' load profile registered during the reference year, with the constraint of maintaining a neutral electricity bill in the case where the load profile remains unchanged. For this purpose, the existing flat rate, fixed charge and fuel price readjustment were vital in order to calculate the average electricity bill of the prosumers. In addition, a multiplier factor of 0.65 was used as a margin to maintain a balance between the current flat rates and derived ToU rates. These values were included in constraint (3.3) to ensure that the off-peak price per kWh ($Rate_{\mathrm{low}}$) of the ToU rates will never be lower than the electricity production cost. The initial values of the low, medium and high rate were set to 0.1, 0.15 and 0.2 respectively.

Optimization function for the $Rate_{\mathrm{low}}$:

$$\min_{Rate_{low} \in \Re} Rate_{low} = 2 \cdot Rate_{medium} - Rate_{high} \tag{3}$$

Subject to:

$$Rate_{low} < Rate_{flat} \tag{3.1}$$

$$Rate_{high} > Rate_{flat} \tag{3.2}$$

$$Rate_{low} \geq \left(Rate_{flat} - Cost_{fixed} + Cost_{fuel}\right) \cdot 0.65 \tag{3.3}$$

where, $Cost_{\mathrm{fixed}}$ is the fixed cost per kWh and $Cost_{\mathrm{fuel}}$ is the fuel readjustment price per kWh.

2.6. Sensitivity analysis on the potential impact of the developed ToU tariffs

Before applying the derived ToU tariffs on the prosumers comprising the pilot network, their potential impact on the residential load profile was investigated through a sensitivity analysis. The intention was to evaluate the effect of shifting loads due to the application of ToU tariffs. Shifting loads from peak to off-peak and shoulder periods can be considered as a representative reaction that might emerge due to the application of ToU tariffs. More specifically, an optimization function was applied to the participants' average load profile on a seasonal basis in order to maximize the Load Factor (LF) or equally flatten the profile to reduce the variability of the consumption levels. Increasing the LF can be recognized as an outcome of the load shifting technique that could diminish the average unit cost (demand and energy) of the kWh and therefore lead to substantial savings for the power utility and subsequently for the consumers. The LF is defined as the average load divided by the peak load in a specified time period:

$$LF = \frac{Average\ Load}{Maximum\ Load \times Period} \tag{4}$$

This was achieved by exploiting the following optimization function:

$$\max_{x} f(x) = \frac{\sum_{i=1}^{48} x_i}{\max\_x \cdot 48} \tag{5}$$

Subject to:

$$\sum_{i=1}^{48} x_{i,before\ DSM} = \sum_{i=1}^{48} x_{i,after\ DSM} \tag{5.1}$$

$$\max\_x_{before\ DSM} > \max\_x_{after\ DSM} \tag{5.2}$$

where, x is the power at time interval i, $x_{i,before\ DSM}$ and $x_{i,after\ DSM}$ the power before and after applying the DSM technique respectively. The main objective of the optimization function is to maximize the LF of the total residential load profile, at each time interval, by shifting the usage time of a variety of household deferrable appliances by a selected percentage (5–20%).

2.7. Estimation of the peak kWh reduction due to possible various ToU price ratios

In order to estimate the peak kWh reduction due to possible various ToU price ratios, the constant elasticity of substitution (CES) was utilized as an expenditure function. In economic terms, the elasticity of substitution measures the shape of the indifference curves that underlie the consumer's utility function. It is related to the own price and cross price elasticities of demand through the Slutsky equation in microeconomics [35]:

Own price elasticity of demand = compensated own price elasticity of demand + (income elasticity of demand × budget share of commodity in question).

In the case of electricity demand, this measures the percentage shift in consumption across time periods (such as peak to off-peak) in response to price changes that alter the price relationship between the two time periods (e.g. changing the price ratio). For example, in the case of a ToU rate, the peak to off-peak elasticity of substitution represents the percentage change in the ratio of peak to off-peak usage that occurs in response to a given change in the ratio of peak to off-peak prices while all other factors are held constant.

The most commonly used [36–39] CES electricity expenditure function is the following:

$$C(P_1, P_2, E) = \left[aP_1^{\rho} + (1-a)P_2^{\rho}\right]^{\frac{1}{\rho}} \cdot F(E) \tag{6}$$

where, P_1 = peak price, P_2 = off-peak price, $F(E)$ = a scalar function of electricity services E (e.g. heating, cooling, lighting etc), the parameter ρ determines the elasticity of substitution and a is a weight.

Using the Shephard's Lemma yields [40], the least-cost peak and off-peak electricity demands are equal to:

$$\partial C/_{\partial P_1} = X_1 = aP_1^{\rho-1}G^{(1/\rho)-1}F(E), \tag{7}$$

$$\partial C/_{\partial P_2} = X_2 = \left(1 - aP_2^{\rho-1}G^{(1/\rho)-1}\right)F(E) \tag{8}$$

where,

$$G = \left[aP_1^{\rho} + (1-a)P_2^{\rho}\right] \tag{9}$$

Although *F(E)* is unobservable, we can use the ToU price ratios and consumption data to estimate the following equation:

$$\ln(X_1/X_2) = \beta_0 + \beta\ln(P_1/P_2) \tag{10}$$

where,

$$\beta_0 = \ln[a(1-a)], \tag{11}$$

$$\beta = \rho - 1 \tag{12}$$

In econometric analysis, the elasticity at a certain range can be estimated from a typical linear regression model using the slope coefficients, the price and quantity estimates. However, in practice it is more convenient to estimate these elasticities by applying a log-linear form, as the elasticities (which will be constant) can be estimated directly from the slope coefficients. Additionally, it is known that:

$$\sigma \equiv \partial\ln(X_1/X_2)/_{\partial\ln(P_1/P_2)} \tag{13}$$

therefore $\sigma = -\beta$

Since $\ln(X_1/X_2)$ varies between participants and seasons, we assume that the intercept β_0 is a linear function that represents the pre-pilot consumption.

For the regression model, we used a modified version of the regression model proposed by C.K. Woo et al. [41]:

$$\ln(X_{1kt}/X_{2kt}) = \gamma + \Theta\ln(Q_{kt}) + \beta\ln(P_{1kt}/P_{2kt}) + \phi_1\ln(H_{kt}) + \phi_2\ln(C_{kt}) + \sum_m \mu_m M_{mt} + \omega_1 W_{dt} + \omega_2 W_{et} + \varepsilon_{kt} \tag{14}$$

The model describes the variation in participant *k*'s peak to off-peak ratio on day *t* where, γ is an intercept, ε_{kt} is a random-error, $\ln(Q_{kt})$ is the pre-pilot consumption and $\ln(P_{1kt}/P_{2kt})$ is the peak to off-peak price ratio whose coefficient is $\beta = -\sigma$.

Additionally, the weather is accounted for by $\ln(H_{kt})$ and $\ln(C_{kt})$ which is the natural logarithm of daily heating and cooling degree hours respectively. Daily heating degree hours (HDH) is the daily sum of max*(20°C − hourly temperature, 0)* for the winter and autumn season, while the daily cooling degree hours (CDH) were estimated by the daily sum of max*(hourly temperature − 20°C, 0)* for the summer and spring season. The ambient temperature datasets were acquired from the installed weather stations. Based on the results of the questionnaire, the primary space-heater of the participants is electric and therefore the variable that distinguishes electric to oil heater owners was not considered.

Furthermore, to capture the effect of each month on the consumption ratio, twelve month-of-the-year binary indicators were used. The variable M_{mt} is equal to unity if day *t* is in month *m* and zero otherwise, where $m = \{1, \ldots, 12\}$ for each month of the year. Similarly, two binary indicators, W_{dt} and W_{et}, were utilized in order to capture the effect of the weekdays and weekends on the consumption ratio.

To estimate the regression coefficients three methods were employed. The first one is the ordinary least squares (OLS), which is one of the most commonly used methods to produce initial results [42,43].

For the second method, the clustered robust standard errors (CRSE) were used for gauging the coefficient estimates' precision and *p-values* [44].

Finally, due to the huge sample size, panel-data analysis was also performed. To implement this a) a fixed-effects and b) a random effects model was employed. CRSE were used for both the aforementioned models.

The hourly peak kW reduction was estimated using the methodology that was proposed by Ref. [41] and was based on [45]. By considering $\ln(X_1/X_2) = Z$ as the non-random portion of the regression line and by using simple algebraic manipulation we can write the peak kWh usage (S) as:

$$S = X_1/_X = e^Z/(1+e^Z) \tag{15}$$

where X is equal to X_1+X_2 and represents the daily total consumption. This implies that the peak consumption is given as:

$$X_1 = SX \Rightarrow \ln(X_1) = \ln(S) + \ln(X) \tag{16}$$

Furthermore, the changes in peak consumption can be derived in percentage by using:

$$\begin{aligned} \Delta X_1/X_1 &= \Delta S/S + \Delta X/X \\ &= \textit{load shifting effect} + \textit{Total consumption effect} \end{aligned} \tag{17}$$

However, as indicated by the author of [46], for a "revenue-neutral" time-varying tariff, such as the one developed in our study, the total consumption effect is close to zero. For this reason the total consumption effect was neglected and the peak consumption reduction was based solely on the load shifting effect. Since load shifting depends on the pre-pilot profile and the price-ratio, the $\Delta S/S$ value was estimated by utilizing the regression equation using different price ratios that range from 2:1 to 12:1 for all three seasons (winter, middle, summer).

3. Results

The duration of each ToU block, the respective ToU rates, the results of the sensitivity analysis carried out to evaluate the effect of shifting loads from the peak to lower rate periods as well as the estimated peak kWh reductions are presented in this section. A comparison of the participants' energy behaviour between the the reference year and the ToU implementation year is also explored.

3.1. Developed ToU tariff

The summer, middle and winter season ToU tariffs obtained from the optimization method applied to the seasonal load curves and the average load profile of the participating prosumers are presented in Fig. 5 (a), (b) and (c), respectively. All plots clearly show three distinct segments for the off-peak, shoulder and peak period.

The derived ToU tariffs and periods for each segment for every season are summarized in Table 1.

The value of the peak, shoulder and off-peak price was calculated at 18.85, 14.85 and 10.85 €cents/kWh, respectively, fulfilling in parallel all the set optimization criteria. In addition, the period of each ToU block varied according to the season, with the highest peak duration occurring for the middle season and the lowest for the winter season.

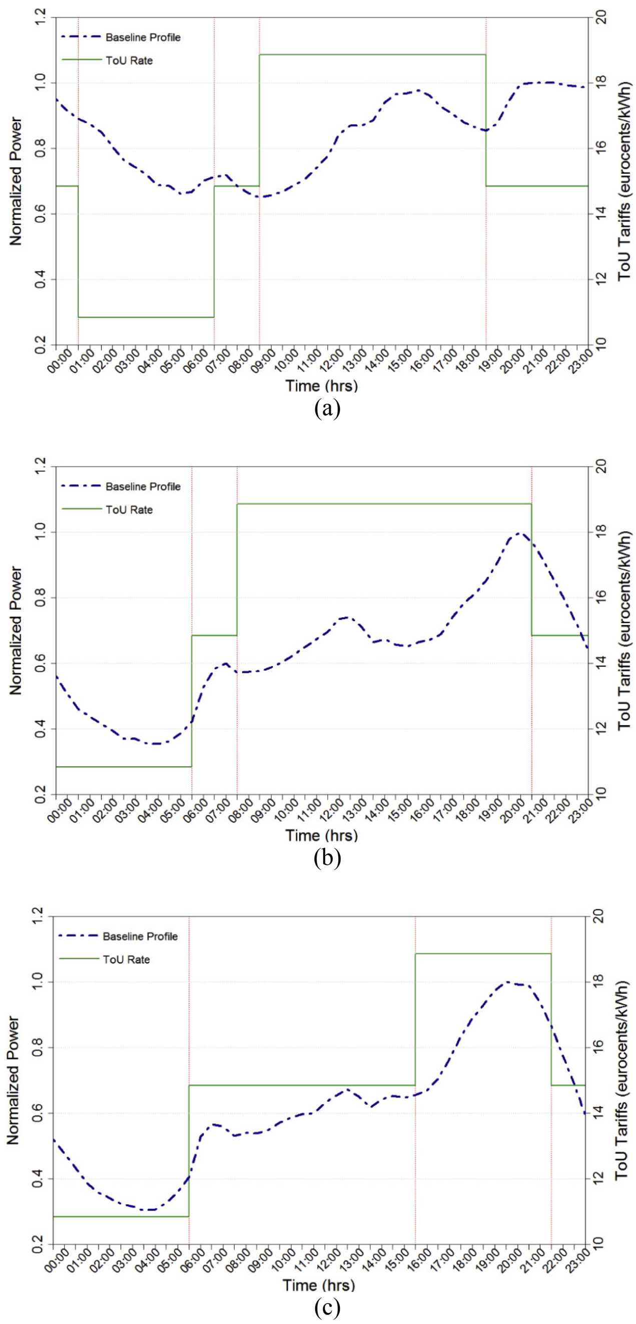

Fig. 5. Derived ToU tariffs and average load profiles of participating prosumers for: (a) summer, (b) middle and (c) winter season.

Every six months, the developed ToU tariffs were re-evaluated and applied to the selected sample. Consequently, at the end of the implementation year two different ToU price ratios were applied to the selected sample.

3.2. Sensitivity analysis based on the Load Factor

To evaluate the impact of the developed ToU tariffs, a sensitivity analysis based on the LF was carried out. More specifically the seasonal average load profile of the participants was divided into a number of main load type categories. The percentage of each category was estimated by conducting a statistical analysis on the listed appliances included on the questionnaire completed by the participants. A load shifting (LS) technique was applied for percentiles between 5 and 20% (in steps of 5%) exclusively on the category of the listed deferrable loads. The participants should be able to shift the electricity consumption of these appliances from peak periods to lower rate periods, usually through timers, and therefore minimize their electricity cost. The sensitivity analysis included two scenarios: i) shifting deferrable loads mainly to off-peak periods ii) shifting deferrable loads mainly to shoulder periods.

The sensitivity analysis performed to emulate the response of the pilot network of prosumers to the imposed ToU tariffs, yielded important results on the potential improvement of the average residential load profile. The resulting average load profiles of the residential prosumers, after deferring load segments from the peak to the off-peak periods, for the all three seasons, are demonstrated in Fig. 6.

The results highlight that overall the derived load profiles were improved due to the load increase occurring mainly during the off-peak hours, however, this does not apply for the summer season. As shown in Fig. 6a, during the summer season and for the case of shifting 20% of deferrable load, the demand was significantly reduced during the peak hours (15:00 p.m.) and increased on the off-peak hours (00:00 a.m.), which resulted in a transfer of the peak demand from peak period to off-peak period. Additionally, a slight increase in demand during the transition of off-peak to shoulder period (06:00–07:00 a.m.) was observed for all the investigated cases of the summer season. This is more evident during the summer season due to the difference between the peak and the lowest demand being the minimum of all three seasons and thus implying that the summer load profile is flatter compared to the winter and middle seasons. Therefore, shifting a relatively high percentage of consumption load can lead to the displacement of the peak demand. In addition to the summer profile being flatter, the low duration of the shoulder period following-up the off-peak period caused the small increase of the demand during that transition period. This occurred due to the lack of time to potentially shift the usage time of the appliances.

In order to evaluate the impact of shifting segments of deferrable loads to the off-peak period, the average residential LF for each one of the cases was calculated. Table 2 summarizes the LF results for different LS percentages and for each season.

The results demonstrated that the average residential LF was increased in all cases, while the maximum LF improvement occurs during the summer season (highest peak demand season). Likewise, this is more noticeable during that season, due to the fact that the summer load profile was already flatter, before applying DSM, compared to the winter and middle seasons. In this respect, any improvements to the LF, especially for high demand seasons, can benefit the utility.

Table 1
Derived ToU periods for each block period per season.

Block	Price (€cents/kWh)	Winter Period (Dec–Mar)	Summer Period (Jun–Sep)	Middle Period (Apr, May, Oct, Nov)
Peak	18.85	16:00–21:59	09:00–18:59	08:00–20:59
Shoulder	14.85	06:00–15:59	07:00–08:59	06:00–07:59
		22:00–23:59	19:00–00:59	21:00–23:59
Off-peak	10.85	00:00–05:59	01:00–06:59	00:00–05:59

The same approach was conducted to analyze the impact of shifting deferrable loads mainly to the shoulder periods. The resulting average load profiles of the residential prosumers, for the load shifting technique, are demonstrated in Fig. 7.

The sensitivity analysis results showed that shifting loads to the shoulder periods for the summer and middle season can potentially lead to the creation of a second peak demand during a specific period as shown in Fig. 7a and b. This can be considered as an outcome of the low duration of the shoulder period that follows immediately after the off-peak period. However, this is not the case

Table 2
Residential Load Factor (LF) for the load shifting technique (off-peak period scenario) per season.

	LF-Summer (%)	LF-Middle (%)	LF-Winter (%)
Average load profile	40.65	32.94	32.48
Case 1: 5% LS	41.29	33.34	32.69
Case 2: 10% LS	41.79	33.48	32.90
Case 3: 15% LS	42.30	33.36	33.12
Case 4: 20% LS	42.83	33.21	33.33

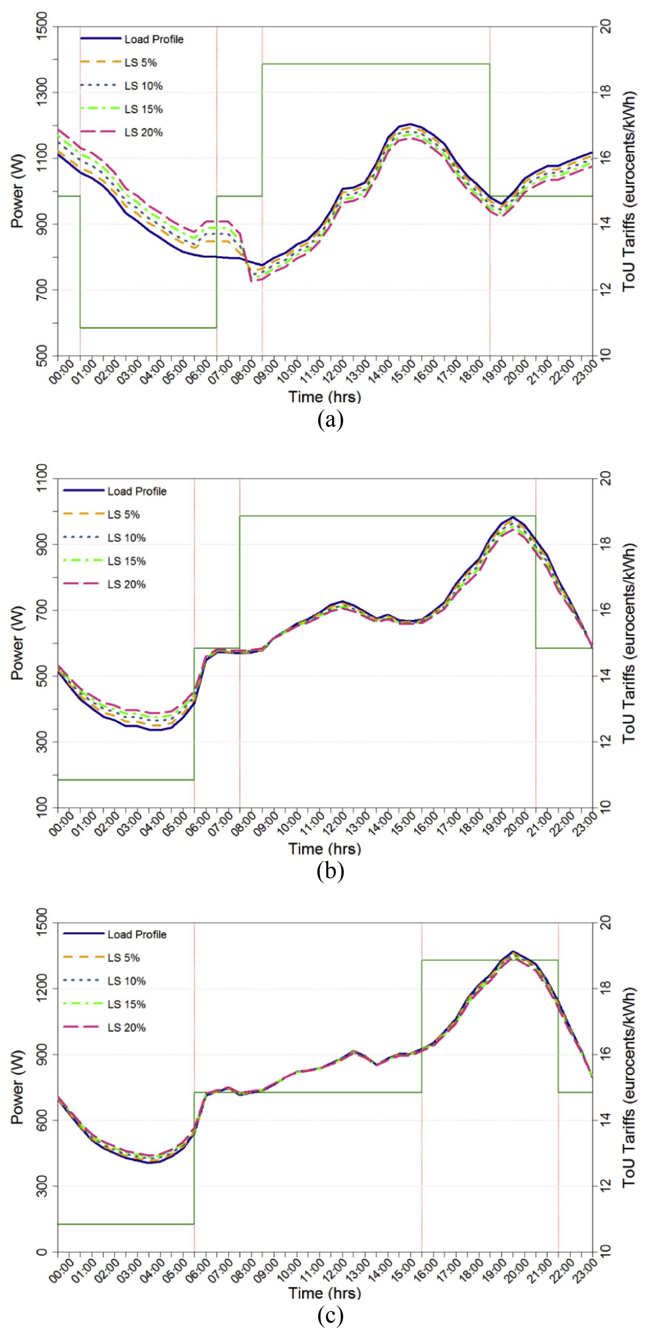

Fig. 6. Load Shifting (LS) of deferrable loads from peak to off-peak periods for: (a) summer, (b) middle and (c) winter season.

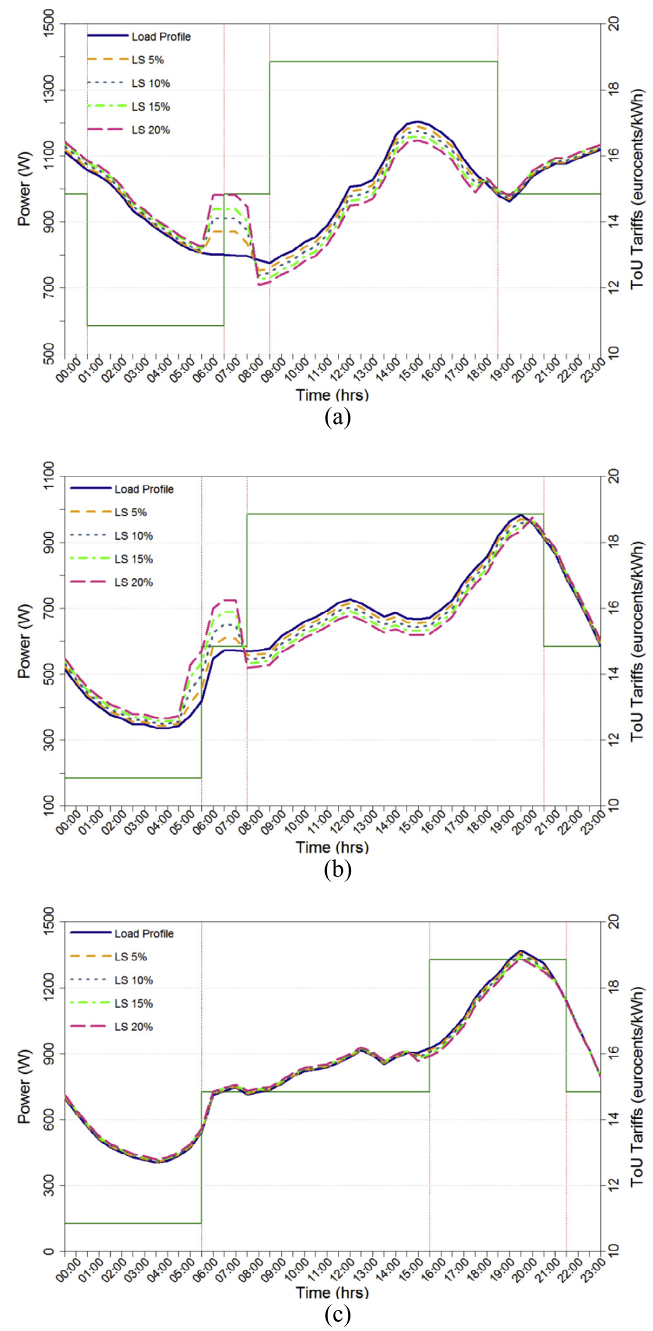

Fig. 7. Load Shifting (LS) of deferrable loads from peak to shoulder periods for: (a) summer, (b) middle and (c) winter season.

Table 3
Residential Load Factor (LF) for the load shifting technique (shoulder period) per season.

	LF-Summer (%)	LF-Middle (%)	LF-Winter (%)
Average load profile	40.65	32.94	32.48
Case 1: 5% LS	41.15	33.25	32.64
Case 2: 10% LS	41.51	33.56	32.80
Case 3: 15% LS	41.88	33.88	32.97
Case 4: 20% LS	41.92	34.21	33.13

for the winter season as shown in Fig. 7c, where the respective shoulder period is longer compared to the one of summer and middle season and therefore participants are able to disperse the usage time of their appliances in a more convenient way.

Finally, the changes that occurred on the LF by shifting loads due to the ToU tariffs to the shoulder segments, are summarized in Table 3. The obtained results indicated that the average residential load profile can benefit from the specific DSM technique as the LF is increased in all cases.

The comparative assessment of the LF results, when shifting load segments to the shoulder or off-peak periods, further showed that there is a slight improvement in the LF when shifting loads mainly to off-peak periods compared to shoulder periods. Additionally, the sensitivity analysis proved that the application of the developed ToU tariffs can benefit the electricity utility by improving the LF for all the investigated cases.

3.3. Real implementation of the developed ToU tariffs in a pilot network

The proposed DSM price-based scheme was approved by both the local Distribution System Operator (DSO) which is the Electricity Authority of Cyprus (EAC) and the Cyprus Energy Regulatory Authority (CERA) for one year of real pilot-implementation. Before the pilot application of the developed ToU tariffs, the candidate participants were informed about the scope and objectives of testing the tariffs on residential prosumers and had the option to either participate voluntarily or entirely “opt-out” and thus stay on the prevailing flat tariff.

Prosumers who chose to participate in the pilot application were provided bill protection. In this respect, for each bimonthly period the participants paid the lower of the two calculated bills — the bill they would have paid had they stayed on the prevailing tariff or the bill they would pay on the ToU tariffs. In addition to the calculation of the two bills, each bimonthly period the DSO examined if the participants were “active” by comparing their energy profiles with the baseline of the respective period.

A prosumer can be considered “active” if at least one of the following rules apply:

- Load percentage recorded during the peak period was reduced compared to the one of the baseline profile for the respective bimonthly period;
- Load percentage recorded during the off-peak period was increased while the load percentage recorded during the peak-period remained the same, compared to the baseline profile for the respective bimonthly period.

The aforementioned criteria successfully eliminated any unintended revenue loss caused by free riders (consumers with below average peak consumption shares who will experience bill decreases without load shifting).

The derived ToU tariffs were applied to the prosumers of the pilot network, for the year of 2016 (implementation year), in order

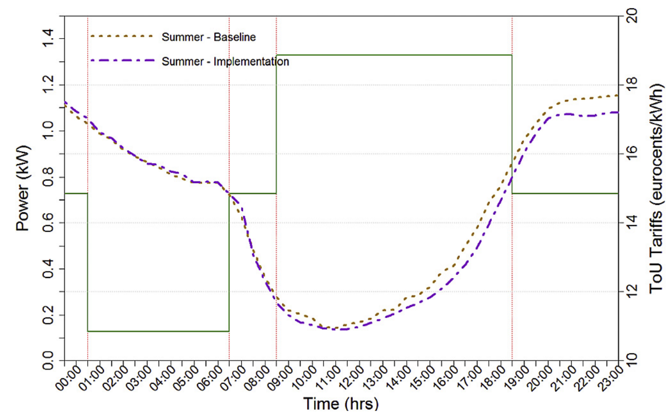

Fig. 8. Comparison of the average load profile of all the participant prosumers between the summer season of the reference year (2015) and the respective season of the implementation year (2016).

to provide insight into the prosumers' ability to adjust their demand timing as a result of the time varying rates. The plot of Fig. 8 demonstrates that over the implementation period, the application of the ToU tariffs created incentives for the prosumers to shift their energy demand from the peak to off-peak periods, driven by the price variations.

The percentage of the total normalized consumption, corresponding to each ToU block, for the reference year (2015) and the year of the implementation of the developed ToU tariffs (2016) is depicted in Table 4.

It can be clearly seen that the percentage of consumption during the peak hours of the implementation year is reduced by 3.19%, 1.03% and 1.40%, compared to the reference year, for the summer, middle and winter season, respectively. This indicates that the ToU tariffs led the participating prosumers to apply DSM techniques. Furthermore, an increase of the LF from 40.65% (reference year) to 41.43% (implementation year) was observed, which can also be considered as another benefit of the applied ToU tariffs. This appears to be similar to the sensitivity analysis' LFs that were estimated for the case 1 and case 2 of the off-peak and shoulder scenarios respectively. Based on the conducted sensitivity analysis, the developed ToU tariffs can achieve a LF up to 42.83%, leading to the conclusion that further training might be required in order to exploit the full benefits of the applied ToU tariffs. Continuous energy performance behaviour feedback and information (through a dedicated website, tablet application etc.) should be provided to the participants for effective and correct use of the applied ToU tariffs, in the scope of their successful implementation for both utility and prosumer benefit.

3.4. Estimation of the peak kWh reduction due to possible various ToU price ratios

For the regression model, the two ToU tariff schedules (original and re-evaluated) were utilized for estimating the regression coefficients while the sample size was equal to 109,500 (300 prosumers $\times$ 365 days). The OLS method has the drawback of being very sensitive to the presence of outliers or high-leverage points [47] and therefore outliers were removed when using this method. Although this led to a reduction of the sample size by approximately 0.07%, it is in line with the approach followed in similar studies [41,43].

The *p-value* for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A low *p-value* ($<$0.05) indicates that the null hypothesis can be rejected. In other words, a

Table 4
Comparison of the consumption percentage between the year 2015 and 2016.

	Summer (%)		Middle (%)		Winter (%)	
Time Block	2015	2016	2015	2016	2015	2016
Peak	42.70	39.51	36.11	35.08	61.02	59.62
Shoulder	24.01	25.66	15.12	16.87	22.89	23.33
Off-peak	33.29	34.82	48.77	48.05	16.08	17.05

coefficient that has a low *p-value* is likely to be a meaningful addition to a model because changes in the coefficient's value are related to changes in the response variable. The regression results, based on the model (14) that is described in the methodology section, for the winter, middle and summer season are presented in Tables 5–7 respectively. The *p-value* for each coefficient is included in the parenthesis.

The low R^2 value indicates that the estimated regression explains 6.89, 4.17 and 6.91% of the variance in the natural logarithm of the consumption ratio for the winter, middle and summer period respectively for the OLS method. Similar observations are obtained when CRSE were included in the regression. Additionally, the obtained results highlight that all coefficients are statistically significant ($p\text{-}value < 0.05$) with one exception: the coefficient estimates yielded from the panel-data analysis with fixed effects were statistically insignificant ($p\text{-}value > 0.05$), even with the use of the CRSE.

As depicted, the coefficient for $\ln(P_{1kt}/P_{2kt})$ is negative and relatively high for all seasons and methods, implying that participant responsiveness to the time-varying prices is adequate and that the developed ToU tariff structure is a major driver in the reduction of the consumption ratio. Similarly, the coefficient estimates of θ that correspond to $\ln(Q_{kt})$ are negative, supporting that total consumption has a compelling role in the peak kWh reduction.

The coefficient estimates for the daily HDH $\ln(H_{kt})$ are negative, thus indicating that falling temperatures tend to reduce the participants' consumption ratio. However, the coefficient estimates for the daily CDH $\ln(C_{kt})$ are positive, supporting that rising temperatures tend to increase the participants' consumption ratio. This is understandable as the results from the questionnaire showed that space-cooling units and swimming pool pumps are two of the most commonly used major electric loads during the summer period. This can also be verified by the month-of-the-year binary indicators. The coefficient estimates revealed that during the warmest month of each investigated season, the participants' consumption ratio is the highest.

Furthermore, the day-of-the-week indicators (W_{dt}, W_{et}) demonstrate that during the weekdays the ratio of peak to off-peak consumption is higher. This was expected as the participants spent more time at their residence during the weekends and therefore it is easier to shift the usage-time of their appliances from peak to either shoulder or off-peak periods.

Using the regression coefficient estimates shown in Table 5 through 7, the percentage kWh reductions by price ratio were computed. The mean percentage kWh reduction by price ratio and the lower and upper bounds (=mean ± 2.5 standard deviations) for the three seasons are illustrated in Fig. 9. The results confirm the percentage peak reductions estimated by the average seasonal profiles (Table 4).

Both of the applied ToU tariff ratios lie within the range of 1.5 and 2 (in particular 1.73 for the first and 1.6 for the re-evaluated design) and it is obvious that higher ratios can potentially lead to higher peak reductions. However, applying a higher ratio to the selected sample is not an easy task due to the fact that the off-peak price is close, and in some periods equal, to the lowest price that the power utility can provide electricity. Consider the two following cases that result in higher price ratios:

a) The off-peak rate remains constant while the peak rate increases: This will have two potential outcomes. Firstly, consumers will not be willing to participate in the optional ToU tariffs due to the high peak rate and therefore they will tend to stay on the flat tariff. Secondly, consumers will voluntarily participate on the optional ToU tariffs and in their attempt to reduce their electricity bills they will shift a relatively high percentage of peak kWh either to the shoulder or the off-peak period thus moving the peak consumption to these periods.
b) The off-peak rate increases and the peak rate increases: In this case, the off-peak rate will be close to the prevailing flat rate while the peak rate will be too high compared to the flat rate. Therefore, since at this early stage of introducing ToU tariffs it is optional for the consumers to participate, they will prefer to stay on the current flat tariffs.

For the aforementioned reasons, at this moment it is difficult to investigate a ratio that is higher than 2.

Table 5
Regression results based on the developed tariffs for the Winter period. The p-value for each coefficient is included in the parenthesis.

Winter Period	Ordinary Least Squares (OLS)		Clustered Robust Standard Errors (CRSE)		Fixed Effects with CRSE		Random Effects with CRSE	
R^2	0.0689		0.0666		–		–	
Intercept: γ	3.0539	(<0.0001)	2.8939	(<0.0001)	2.8974	(<0.0001)	2.9657	(<0.0001)
$\ln(Q_{kt})$: θ	−0.0788	(0.0230)	−0.0770	(0.0180)	−0.0769	(0.0702)	−0.0773	(0.0140)
$\ln(P_{1kt}/P_{2kt})$: β	−0.1646	(0.0350)	−0.1628	(0.0120)	−0.1618	(0.0310)	−0.1499	(<0.0001)
$\ln(H_{kt})$: φ_1	−0.0047	(0.0087)	−0.0049	(0.0082)	−0.0027	(0.0456)	−0.0156	(0.0115)
$\ln(C_{kt})$: φ_2	0.0037	(0.0030)	0.0031	(<0.0001)	0.0042	(0.0690)	0.0015	(0.0266)
$M_{12t} = 1$ if t in December; 0, otherwise: μ_{12}	0.0584	(0.0048)	0.0563	(<0.0001)	0.0561	(0.0687)	0.0537	(<0.0001)
$M_{01t} = 1$ if t in January; 0, otherwise: μ_{01}	0.0552	(0.0034)	0.0597	(<0.0001)	0.0545	(0.0368)	0.0529	(<0.0001)
$M_{02t} = 1$ if t in February; 0, otherwise: μ_{02}	0.0468	(0.0050)	0.0414	(<0.0001)	0.0482	(0.0209)	0.0530	(<0.0001)
$M_{03t} = 1$ if t in March; 0, otherwise: μ_{03}	0.0761	(0.0027)	0.0732	(<0.0001)	0.0766	(0.0234)	0.0698	(<0.0001)
$W_{dt} = 1$ if t in weekdays; 0, otherwise: ω_1	0.0397	(<0.0001)	0.0318	(<0.0001)	0.0235	(0.0650)	0.0326	(<0.0001)
$W_{et} = 1$ if t in weekends; 0, otherwise: ω_2	0.0312	(<0.0001)	0.0248	(<0.0001)	0.0128	(0.0753)	0.0278	(<0.0001)

Table 6
Regression results based on the developed tariffs for the Middle period. The p-value for each coefficient is included in the parenthesis.

Middle Period	Ordinary Least Squares (OLS)		Clustered Robust Standard Errors (CRSE)		Fixed Effects with CRSE		Random Effects with CRSE	
R^2	0.0417		0.0358		–		–	
Intercept: γ	3.2568	(<0.0001)	3.2725	(<0.0001)	3.2678	(<0.0001)	3.2304	(<0.0001)
$\ln(Q_{kt})$: θ	−0.0891	(0.0212)	−0.0874	(0.0097)	−0.0871	(0.0460)	−0.0867	(0.0101)
$\ln(P_{1kt}/P_{2kt})$: β	−0.0704	(0.0110)	−0.0732	(0.0021)	−0.0729	(0.0661)	−0.0726	(0.0270)
$\ln(H_{kt})$: φ_1	−0.1051	(0.0081)	−0.1086	(<0.0001)	−0.1058	(0.0674)	−0.1149	(<0.0001)
$\ln(C_{kt})$: φ_2	−0.0523	(0.0013)	−0.0502	(<0.0001)	−0.0602	(0.0460)	−0.0585	(0.0360)
$M_{10t} = 1$ if t in October; 0, otherwise: μ_{10}	0.0213	(0.0035)	0.0197	(<0.0001)	0.0185	(0.0510)	0.0192	(0.0197)
$M_{11t} = 1$ if t in November; 0, otherwise: μ_{11}	0.0264	(0.0022)	0.0255	(<0.0001)	0.0325	(0.0590)	0.0320	(0.0296)
$M_{04t} = 1$ if t in April; 0, otherwise: μ_{04}	0.0297	(0.0029)	0.0303	(<0.0001)	0.0343	(0.0420)	0.0281	(0.0173)
$M_{05t} = 1$ if t in May; 0, otherwise: μ_{05}	0.0465	(0.0011)	0.0420	(<0.0001)	0.0510	(0.0421)	0.0421	(<0.0001)
$W_{dt} = 1$ if t in weekdays; 0, otherwise: ω_1	0.0302	(<0.0001)	0.0310	(<0.0001)	0.0312	(0.0243)	0.0317	(<0.0001)
$W_{et} = 1$ if t in weekends; 0, otherwise: ω_2	0.0271	(<0.0001)	0.0284	(<0.0001)	0.0254	(0.0187)	0.2444	(<0.0001)

Table 7
Regression results based on the developed tariffs for the Summer period. The p-value for each coefficient is included in the parenthesis.

Summer Period	Ordinary Least Squares (OLS)		Clustered Robust Standard Errors (CRSE)		Fixed Effects with CRSE		Random Effects with CRSE	
R^2	0.0691		0.0625		–		–	
Intercept: γ	2.7782	(<0.0001)	2.7375	(<0.0001)	2.7342	(<0.0001)	2.2888	(<0.0001)
$\ln(Q_{kt})$: θ	−0.0345	(0.0247)	−0.0380	(0.0126)	−0.0389	(0.0650)	−0.0412	(0.0045)
$\ln(P_{1kt}/P_{2kt})$: β	−0.1385	(0.0190)	−0.1309	(0.0030)	−0.1302	(0.0521)	−0.1298	(<0.0001)
$\ln(H_{kt})$: φ_1	0.0000	(0.0000)	0.0000	(0.0000)	0.0000	(0.0000)	0.0000	(0.0000)
$\ln(C_{kt})$: φ_2	0.0769	(0.0046)	0.0720	(<0.0001)	0.0530	(0.0360)	0.0697	(0.0210)
$M_{06t} = 1$ if t in June; 0, otherwise: μ_{06}	0.0533	(0.0041)	0.0569	(<0.0001)	0.0497	(0.0502)	0.0521	(0.0002)
$M_{07t} = 1$ if t in July; 0, otherwise: μ_{07}	0.0598	(0.0038)	0.0611	(<0.0001)	0.0552	(0.0471)	0.0578	(<0.0001)
$M_{08t} = 1$ if t in August; 0, otherwise: μ_{08}	0.0528	(0.0072)	0.0510	(<0.0001)	0.0567	(0.0688)	0.0564	(<0.0001)
$M_{09t} = 1$ if t in September; 0, otherwise: μ_{09}	0.0317	(0.0065)	0.0349	(<0.0001)	0.0298	(0.0428)	0.0335	(<0.0001)
$W_{dt} = 1$ if t in weekdays; 0, otherwise: ω_1	0.0355	(<0.0001)	0.0375	(<0.0001)	0.0315	(0.0587)	0.0368	(0.0160)
$W_{et} = 1$ if t in weekends; 0, otherwise: ω_2	0.0246	(<0.0001)	0.0267	(<0.0001)	0.0235	(0.0535)	0.0253	(0.0005)

Furthermore, when evaluating ToU tariff schemes it is crucial to investigate how a change in the electricity prices affects the household welfare. By utilizing the CES unit expenditure function (14), the welfare improvement indicator I is equal to:

$$I = \frac{CES\ expenditure\ fucntion_{ToU\ rates}}{CES\ expenditure\ fucntion_{Flat\ rate}} \tag{18}$$

where for the flat rate, $P_{1kt} = P_{2kt}$.

When applying (18) the results highlight that the cost index I is less than one, for the whole sample, thus proving that the developed ToU tariff is welfare improving [48].

4. Conclusions

The methodology followed to develop optimal Time of Use (ToU) tariffs for residential prosumers in order to promote effective Demand Side Management (DSM) practices is presented in this paper. In support of this work, the load profiles of three hundred prosumers comprising a pilot network in Cyprus were recorded for one year (reference year). Using the collected datasets, the initial and baseline scenarios were defined in order to verify that an improvement on the participants' consumption profile will benefit the total aggregate consumption.

Initially the ToU block periods were derived by applying statistical analysis on the Load Duration Curve (LDC) of the seasonal load profiles of the participants. The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) metrics between the derived ToU block periods and the seasonal total residential power demand were 8.65% and 19.95% respectively. The MAPE and RMSE metrics were reduced to 2.43% and 7.63%, respectively, by combining the results of the statistical analysis with a hybrid optimization function that utilizes Simulated Annealing and Pattern Search algorithms. The ToU rates were calculated by exploiting an optimization function that maintained a neutral electricity bill in the case where the load profile remained unchanged.

Before applying the developed ToU tariffs to the participants located within the pilot network, a sensitivity analysis was conducted in order to estimate their potential impact. The main objective was to maximize the Load Factor (LF) of the seasonal residential load profile. For the summer and winter season, the maximum LF was 42.83% and 33.33% respectively and occurred when load was shifted mainly to the off-peak period.

The developed ToU tariffs were approved by both the Electricity Authority of Cyprus and the Cyprus Energy Regulatory Authority and were applied to the prosumers of the pilot network for one year (implementation year). The results obtained, highlight that the ToU tariffs applied to the pilot network are effective to persuade the participants to shift loads from the peak to off-peak and shoulder periods. This was verified by observing the variation of the LF as well as the percentage of total consumption during peak hours when compared to the year before the real implementation of the derived ToU tariffs. More specifically, with respect to the reference year, the LF was increased from 40.65% to 41.43%, while the percentage of total consumption measured during peak hours was reduced by 3.19%, 1.03% and 1.40% for the summer, middle and winter season respectively. In the end, the impact of various ToU price ratios on the peak kWh usage was investigated. Higher price

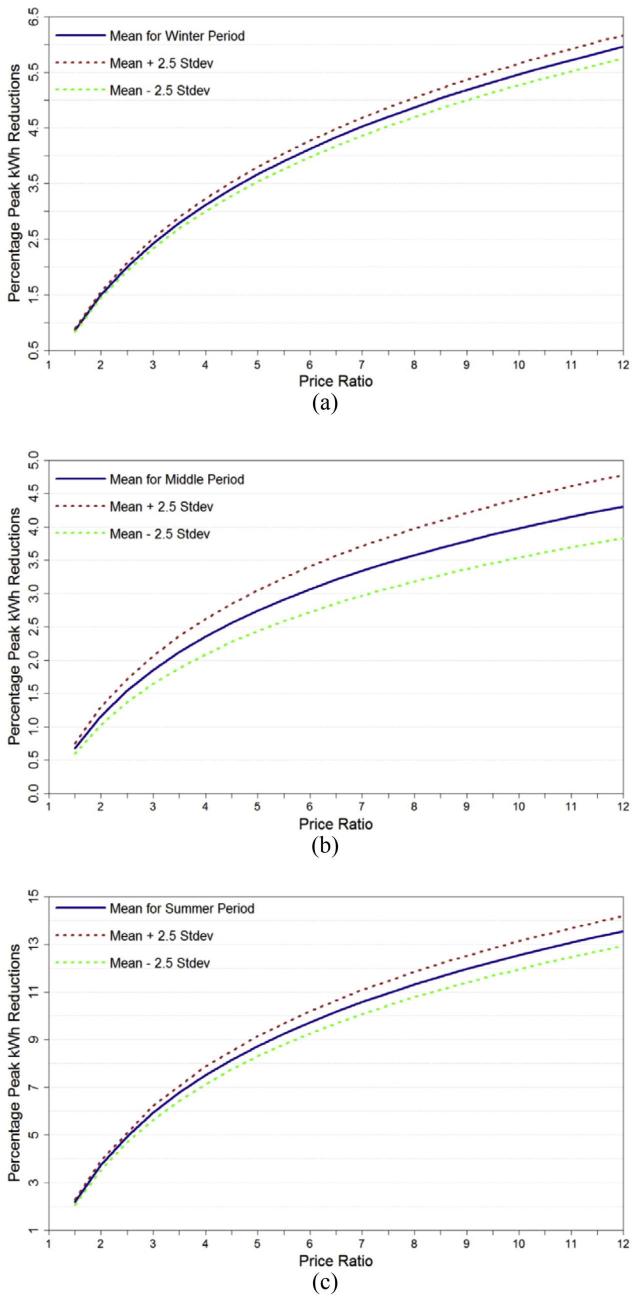

Fig. 9. Estimation of peak kWh reduction due to various ToU price ratios for the: (a) winter, (b) middle and (c) summer season.

ratios, than the one used, indicated higher peak kWh reductions. However, increasing the ratio for the case of Cyprus is difficult at the moment. Nevertheless, as the PV penetration levels increase and the aggregate consumption profile changes then the fixed electricity cost will change. This will result in different off-peak prices and a greater selection of feasible price ratios. The methodology followed in this work can achieve this by adapting the ToU tariff structure (block periods and rates) based on the fixed electricity cost and the system's profile.

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