National University of Lesotho

Development of Time-of-Use Tariffs

Lebohang Edwin Mohasoa

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Abstract

The electricity consumption profile varies during any 24-hour period, but the electricity pricing policy for Lesotho Electricity Company (LEC) does not reflect this fluctuation as it employs flat-rate tariffs across all customer categories. This fails to adequately capture the costs exerted on the electricity network by each customer at a certain period. To address this problem, time-of-use (ToU) tariffs are determined in this study, while ensuring revenue neutrality for the utility before any load shifting. Implementation of a comprehensive ToU based pricing model could be an effective mechanism to reflect the costs imposed on the network by customers and therefore encourage customers to engage in load adjustment. The Gaussian mixture model has been utilized to determine ToU time-periods and prices. The time-periods are divided into different periods; off-peak, standard, and peak periods. Different customer categories have different durations of time-periods. This is attributed to the observed load profiles of different customer categories. Furthermore, different customer categories have different prices per period resulting in different price ratios. Possible load-shifting scenarios of 5% and 10% have resulted in a reduction in customer energy bills of 2.6% and 5.2%, respectively. While, the LEC bulk energy savings translated to 13 GWh and 30 GWh for the two load-shifting scenarios, respectively.

Key words: Time of Use tariff, Flat-rate tariff, Time-Periods, Price-ratio, Load-shifting

1 Introduction

1.1 Background to the study

The demand for electricity from the national electrical grid varies throughout any 24-hour period. During peak demand periods utility companies face enormous challenges to maintain a balance between the demand from consumers and the need to supply enough generation capacity (Li et al., 2016). On the other hand, during off-peak periods, the use of only a small portion of the installed generation capacity easily meets user demand. This results in the under-utilization of expensive generation and distribution capacity (Di Cosmo et al., 2014a). This situation creates challenges for the utility company in respect of providing adequate capacity and determining fair pricing models. The Time-of-Use (ToU) pricing model has been identified in numerous countries as an effective enabler for influencing user behavior towards shifting their consumption from expensive peak periods to less costly off-peak periods (Kourosh et al., 2016; Reneses et al., 2011a; Torriti, 2014; Yang et al., 2013).

Electricity pricing depends on many factors such as electricity demand, availability of generation sources, fuel costs, and power plant availability. Electricity costs are usually highest during peak times when the total demand is high because normally more expensive generation sources are added to the generation capacity to meet the increased demand (Di Cosmo et al., 2014a). Although the cost of supplying electricity vary from time to time, the electricity prices which end-users face, on the other hand, need some degree of control. This is typically achieved through regulation that aims to maintain price stability to ensure fairness to all stakeholders (Fridgen et al., 2018).

In the process of creating such price stability, the use of the ToU tariff approach is considered to be one of the most attractive ways to influence the reduction of demand during peak periods by shifting as much as possible of the load to periods of low demand (Henley and Peirson, 1994). This would result in better utilization of existing generation facilities and would avoid premature major investments in further power generation capacity (Reneses et al., 2011b). Furthermore, load shifting also has the potential to enable the deployment of renewable energy generation by shifting some demand to periods when variable renewable energy generation is abundant (Grünewald et al., 2015; Philippou et al., 2015)

1.2 Problem Statement

Currently, Lesotho Electricity Company (LEC) employs a flat-rate pricing methodology that does not reflect any variations in network operating costs. Operating a network during peak periods attracts more costs than during off-peak but the current methodology fails to translate a clear signal to end-users to engage in demand management. Moreover, the application of flat-rate pricing does not encourage the deployment of renewable energy technologies such as solar energy. For instance, for Lesotho to derive value from the envisaged 20 MW solar farm in Mafeteng (Department of Energy, 2017), there need to be some incentives of shifting the bulk of the load from current system peak hours (06:00 - 10:00 and 18:00 – 21:00) to during the day when solar energy is abundant. Lastly, more than 50% of Lesotho's power demand needs are met through imports from South Africa and Mozambique, contracted bilaterally with Eskom and Electricidade de Mozambique (EDM) based on Time-of-Use charging centered on the peak, off-peak and standard prices in low and high seasons (Thamae et al., 2015a).

In addressing the above concerns, implementation of the ToU methodology would be important since it provides an incentive for voluntary load shifting from customers' perspectives. Thus, assisting to flatten the load profile which, subsequently reduces network operational costs. It is therefore imperative for the ToU tariffs to be developed for Lesotho because they are country-specific in nature. The determined ToU tariffs in different countries yield different price ratios for off-peak, standard, and peak periods. This is influenced by country-specific factors such as level of industrialization, economy, and consumption per capita.

1.3 Research Objective

The main objective of this study is to develop electricity tariffs for LEC based on the ToU approach using actual electricity demand data for the period 2010 to 2019. This is achieved through the following specific objectives:

- To determine ToU time-periods for different customer categories that maintain revenue neutrality between flat-rate and ToU;

- To determine the ToU tariffs per time-periods.
- To create possible load-shifting scenarios and assess their impact on customer bills and LEC revenue.

1.4 Justification of the study

In Lesotho, the electricity consumption profile varies during any 24-hour period, but the electricity pricing policy does not reflect this fluctuation. Implementation of a comprehensive Time-of-Use based pricing model could be an effective mechanism to encourage consumers to engage in load adjustment. The benefits of such a load shift do not only include a reduction in customer bills and network optimization but also promote renewable energy (RE) adoption and energy security. To promote RE, it is imperative to ensure that the network load is shifted to periods when the RE resources are available. This could be achieved by strategic time-varying pricing mechanisms that entice customers to use power when these RE resources are available. Some scholars have focused on implementing ToU tariffs that optimize the pricing at each time of use period so that one or more market players gets maximum utility (Celebi and Fuller, 2007; Fahrioglu and Alvarado, 2000; Hatami et al., 2011; Henley and Peirson, 1994; Orans et al., 2010; Ou et al., 2010). However, a few studies such as Li et al. (Li et al., 2016) focus on the basic shape design of ToU which can influence the demand response of customers, consequently influencing the load profile. This study employs such an approach in ToU tariff design while maintaining revenue neutrality from flat-rate tariffs. The anticipation is that the application of these tariffs will influence customers to shift their consumption to off-peak periods and hence relieving network stresses thereby saving investment costs on infrastructure expansion. This would also reduce the quantities of imported electricity in the country, thus improving energy security.

1.5 Organization of the Dissertation

The remaining part of this dissertation is divided into four chapters. Chapter 2 provides a critical review of the existing literature on ToU tariffs, whilst Chapter 3 presents a report on the research methodology adopted for conducting this study. Chapter 4 determines and discusses the ToU tariffs. Finally, the last chapter features the conclusion and recommendations.

2 Literature Review

2.1 Introduction

This chapter serves to explore different models and or, methodologies adopted by other scholars and is organized as follows: the first part provides a general background of electricity pricing. The theoretical literature on existing ToU models is then presented and followed by the empirical evidence concerning their determination. It then concludes with a synthesis that summarizes the main points highlighted in the review and a declaration of the author's point of departure.

2.2 Electricity pricing

Studies in power sector tariff design indicate that the overall economic cost of supply for each consumer category should include all costs incurred throughout the entire supply chain of delivering electricity to the customers of that specific category (Malik and Alzubeidi, 2006). It is recommended that one of the first steps in determining a tariff design process involves quantifying the total revenues that have to be achieved through tariffs (Reneses et al., 2011a). These revenues include all costs incurred throughout the entire electricity supply chain − generation, transmission, distribution, and supply to the customers − plus some form of return on investments (Reneses et al., 2011a). The second step involved apportioning these costs among the three cost drivers, namely, peak demand (kW), electricity consumption (kWh), and the number of customers. Consequently, the three cost drivers yield three charges: demand charge, electricity charge, and fixed charge (per customer). The next step would be to allocate these costs to different customer categories following the principle of cost-causality[1] (Passey et al., 2017a). This then serves as the basis for determining an appropriate end-user tariff structure. In determining the end-user tariffs that reflect the cost of supply, it would be required to determine the consumer characteristics

[1] The principle of cost causality dictates that costs should be allocated to the customers who incurred them.

through a responsibility analysis[2] exercise which would yield the responsibility of every customer class in the overall energy demand.

Cost causality is a principle used in defining and classifying costs for supplying an additional unit of electricity (kW or kWh) to a category of customers and ensuring fair allocation of such to the same class that incurred them (Zainudin et al., 2017). This is based on the allocation of costs by voltage level depending on their drivers and the limitation of metering equipment deployed. Costs are classified as specific, shared, and indirect (Mpholo et al., 2020; Passey et al., 2017a). Specific costs refer to direct costs that are incurred as a consequence of customer presence which, include connection costs. Shared costs are network related such as operation and maintenance costs which accrue as a result of energy consumption. Lastly, indirect costs denote those that are not related to either energy consumption or capacity demand but accrue as a consequence of the number and scale of customers. These include administration and commercialization costs.

Once costs are defined, they are consequently allocated in the form of prices to different customer classes following the concept of responsibility analysis. Responsibility analysis is the price allocation concept that follows the load-profiling criteria of customers (Lesotho Electricity and Water Authority, 2018). Under this concept, the load-profiling is used to establish the level of coincidence in peak demand among customers within a class (internal coincidence), and between the customer class peak-demand relative to the overall system peak. Responsibility analysis is critical in facilitating the fair allocation of costs to customers based on their contribution to overall system costs (Zainudin et al., 2017).

Moreover, key parameters of ToU tariffs include the number of price differentiated periods (e.g. on-peak, standard, off-peak), the duration of each period, the potential seasonality of the periods, the coincidence of on-peak periods with peak system demands, and the ratio of prices between periods (Yudong Tang et al., 2005). All of these features can impact customer behavior, acceptance of the tariffs, and the volatility of customer bills (Zainudin et al., 2017). In the design of feasible ToU tariffs, it is essential to reflect the network stress points and high energy cost periods so that the customers' response thereto will naturally lead to peak shaving and cost savings (Li et al.,

[2] Responsibility analysis determines the overall contribution of each customer category to the system peak demand.

2016). The critical elements in the design of a feasible ToU tariff are defining of ToU time-periods and pricing thereof.

2.2.1 Number and duration of ToU time-periods

The basic guideline for the selection of time-periods is based on the load profiles which provide clear indications on the hours depicting different system conditions such as peak and off-peak (Aigner et al., 1994; Aigner and Ghali, 1989). It is further argued that the non-observance of these critical system conditions may lead to poor ToU tariff design that fails to capture the essence of sending proper price signals to end-users (Aigner et al., 1994). The same assertion has been made by Wu and Xia when they purported that variations in energy demand over any 24 hours justify the need for different ToU time-periods to cater for a few hours when the system under stress as a result of high loading and more hours when it is idling due to low loading (Wu and Xia, 2018).

Ferreira et al (2013) pointed out that the time duration of price-differentiated usage periods could sometimes be a two-edged sword. Generally, pricing periods should reflect the underlying costs. Shorter periods, e.g. 2-4 hours, allow more easily for larger price differentiation and closer ties of pricing to utility costs since in this case it would be easier for customers to engage and respond to a price signal (Ferreira et al., 2013). On the other hand, periods of this duration may not appeal to certain customer classes with loads that have to run for a predetermined period before they can be interrupted, like batching plants. In contrast, long periods, generally greater than 5 or 6 hours, would tend to dilute both cost recovery and the price signals and consequently, customers may not respond by making any load adjustments (Ferreira et al., 2013).

2.2.2 Pricing of ToU time-periods

Another important element of ToU tariff design is the pricing of the associated time-periods once defined. On this element, Fan and Hyndman (2011) advocated for pricing that is designed to incentivize customers to avoid usage during highly-priced peak periods without any significant compromises to health, safety, or lifestyle. As outlined in the previous section, there are usually a limited number of hours when the utility's systems are under severe stress. The occurrence of these stressful periods frequently influences utility and wholesale market decisions for triggering additional capital investments in power infrastructure to relieve the stress and ensure grid reliability. However, the stressful periods between generation and distribution systems do not coincide and may thus not correlate with the ToU on-peak periods (Bhattacharyya, 2011; Benali, 2018). This situation demonstrates just how much of balancing role regulators have to play in tariff determination.

ToU rates for peak periods are often designed based on the marginal costs combined with the underlying cost-causation principle. The rationale is that, as the customers respond to the price signals, the need for hasty capital investments to address the situation, decreases. This approach is also expected to result in cost savings for all customers. At the same time, off-peak periods should be priced at rates attractive enough to encourage the shifting of consumption to such periods and the differential in prices should be large enough to support policy objectives (Doukas et al., 2008).

The evolution of the ToU pricing mechanism has been characterized by the development of many models and methodologies used in the determination of charges considered to reflect variations in both price and system demand. These models are discussed below.

2.3 Models of ToU tariffs

The literature indicates that various technical models are used to derive ToU tariffs from bulk energy prices. This subsection discusses a computable equilibrium model, time-of-use price decision model, mathematical model of ToU, proportionality constant approach, and the Gaussian mixture model.

2.3.1 A Computable Equilibrium Model

This is a model for efficient consumer pricing schemes in electricity markets developed by Celebi and Fuller (2007). It is used to determine ToU charges based on the marginal cost principles. Marginal cost pricing dictates that the pricing of a product or commodity must be equal to the cost of producing an extra unit of output of the same product (Boonkham and Leeprechanon, 2015; Chontanawat et al., 2014). The model is designed to estimate ToU prices at both wholesale (supply) and demand-side (consumers) to reconcile their differing time-scales of response to changing prices. Celebi and Fuller (2007) argued in their design that suppliers' response to price changes is much volatile and quicker than consumers who tend to take longer to respond to similar changes. Hence the need to reconcile this difference in their model which, then differentiates it from the rest of the others. The model estimates prices for both the supply and demand sides but, for this study, the main focus will be on the demand side of their model. Therefore, the main advantage of this model is its ability to forecast and reconcile prices between the supply-side and demand-side at any given time-period (Celebi and Fuller, 2007). Moreover, this model has the advantage of being applied to determine both price and load-oriented ToU tariffs using bulk-prices or load profiles as input. Furthermore, this model is set apart from the rest of its rivals because it considers time differentiated response to price changes between the wholesale and end-user sides in an optimization framework. The demand side of the model is formulated as follows;

$$d^{(t)} = a^{(t)}\left(p^{(t)}\right)^{b}\left(d^{(t-1)}\right)^{e} \tag{1}$$

Where; $d^{(t)}$ is the electricity demand in period t

$a^{(t)}$ is a constant representing non-price effects such as weather conditions

$p^{(t)}$ is the price of electricity at period t

$d^{(t-1)}$ is the lagged demand

b is the price elasticity

e is the lag elasticity.

By taking natural logarithms of both sides of equation (1), the model is extended to represent electricity demand in different ToU time-periods. This is expressed in the following equation;

$$\ln\left(D^{(t)}\right) = \mathrm{A}^{(t)} + B\ln\left(P^{(t)}\right) + E\ln(D^{(t-1)}) \tag{2}$$

Where; $A^{(t)}$ is the vector of factors for non-price effects

$D^{(t)}$ is the vector of electricity demands in ToU period t (Peak, Standard, or Off-peak)

$P^{(t)}$ is the vector of electricity prices in ToU period t (Peak, Standard, or Off-peak)

B is the square matrix of constant price elasticity

E is the square matrix of constant lag elasticity

Relative to the ToU price decision model 2.3.2, this model seems to have considered that there is some delay in the response of other customer classes to changes in electricity prices thus, introducing the concept of lag elasticity. Lag elasticity measures the delayed response of customer demand to price changes (Celebi and Fuller, 2007). This model can therefore be ideal in situations where a mixer of different customer classes is involved such as residential and industrial categories which exhibit a varied response to price variations. Since the model uses supply-side prices which take care of marginal costs, it can also be ideal in the jurisdiction where end-user prices are regulated, but suppliers offer competitive market prices. This model would therefore be ideal for Lesotho if, LEC became actively involved in the procurement of bulk supply from the Southern African Power Pool.

2.3.2 The time-of-use price decision model

This model is established to derive ToU pricing based on the Monte-Carlo simulation techniques. Monte-Carlo simulation is used to forecast the probability process outcomes which cannot be easily predicted due to the random nature of variables involved in that process (Mosegaard and Sambridge, 2002). This model was established to determine ToU charges with consideration of end-user response to price changes thus, including the estimated price elasticity post ToU implementation (Mosegaard and Sambridge, 2002). Price elasticity in this model is used to demonstrate the economic principle of change in energy demand due to changes in prices. The formulation of the model is represented by equations 4, 5, and 6 for standard, peak, and off-peak prices respectively;

$$\delta i\ (j) = \delta(j)\ \ j \in p \tag{3}$$

$$\delta i\ (j) = \varepsilon \times \delta(j) \times (\frac{\Delta P(f)}{P}) + \delta(j)\ \ j \in f \tag{4}$$

$$\delta i\ (j) = \varepsilon \times \delta(j) \times (\frac{\Delta P(g)}{P}) + \delta(j)\ \ j \in g \tag{5}$$

Where:

- P_f is the peak price
- P_p is the standard price
- P_g is the off-peak price
- J is the time-period
- ε is the price elasticity
- δ is the consumption

The main advantage of the model is its simplicity, making it easy to implement. It also does not have many assumptions except, about price elasticity. The issue of simplicity corroborates the argument advanced by (Charwand and Gitizadeh, 2018)in their development of an optimal TOU tariff design in 2018 when they emphasized it as a key requirement to encourage buy-in from end-users.

One of the limitations of this model is the total reliance of it on price elasticity in the energy industry which, may render the model disadvantageous in economies where such figures are not readily available. Although Ou et al. (2010) argued that the model can be easily adapted in any industry where time-varying pricing is considered, the non-availability of scientifically researched elasticity coefficients will still work against them. Thus, failing to produce results that can be reliably validated. The other limitation of the model is the non-availability of the means to define or validate ToU time-periods. This means the model can only determine the price per period. Hence falling short of providing the second critical element of time-period determination, which is considered critical for feasible ToU pricing as dictated by other authors in this area (Fridgen et al., 2018; Grünewald et al., 2015; Grünewald and Layberry, n.d.; Reneses et al., 2011a). Although the model has taken consideration of elasticity in its computation, it has fallen short of recognizing that some customers may have delayed response to changes in prices. Thus requiring future assessments of their elasticity post price changes. This implies that the results of this model cannot be generalized across customers who respond differently in terms of timing to price changes. This weakness has however been addressed by the computable equilibrium model in section 2.3.1.

2.3.3 Mathematical model of ToU

This model was introduced by Tang et al. (2005) for determining ToU tariffs for the region of Nanjing, China. The objective of the model was to derive ToU prices that would encourage consumers to actively participate in the power sector market transformation by shifting their consumption to periods where the transmission and distribution network was experiencing less pressure due to low demand. The ultimate goal was to determine ToU tariffs that would be mutually beneficial to both consumers and the supply utility by helping to reduce bills for the former while, the latter would cut on bulk energy purchases' costs. Thus, promoting power system efficiency and stability (Yudong Tang et al., 2005). Some of the basic principles underlying this model include; ensuring that the ultimate price ratio yielded does not cause volatility on either customers' bills or the system load-curves, and providing certainty on the sustainability of supply utility.

As input into the model, ToU time-periods and their duration are determined by a comprehensive analysis of the system load profile data for the past period. These are obtained from the system load duration curve from which, inflections are used to identify different time-periods and their respective consumption quantum and durations. Thus the model does not determine its own ToU time-periods and durations thereof. The other input into the model is the bulk purchase price incurred by the supply utility during each time-period. In determining final ToU prices per time-period, the model relies on the following basic equation;

$$p = \frac{\sum_{TT \in T_n}(\int_{TT}^{\cdot} W(t)dt \cdot c(TT))}{\int_{T_n}^{\cdot} W(t)dt} \tag{6}$$

Where:

- P is the ToU price per period
- W is the consumption per ToU period
- *TT* is the time-period for bulk purchase
- C(*TT)* is the bulk purchase price
- T_n is the ToU time-period

The mathematical model seems to be straightforward and much easier to implement where access to data relating to bulk energy prices is not a challenge. Although time-periods are derived outside the model, the emphasis on the use of load duration curves for their derivation makes input data more statistically acceptable for estimating the probabilities of meeting or exceeding specific consumption levels. This provides a fair judgment on how system capacity can be planned to meet demand levels Grünewald et al.(2015). The main disadvantage of this model is the inability to determine its own ToU time-periods and their respective duration. Thus, falling short of providing the second critical element of time-period determination, which is considered critical for feasible ToU pricing as argued by Fridgen et al. (2018) and Reneses et al. (2011). This model is therefore very similar in this respect to the ToU price decision model discussed in section 2.3.2. The model also falls short of providing a mechanism for balancing between conflicting objectives of; ensuring the sustainability of supply utility on one hand, and providing savings on the energy bills for consumers on the other side.

2.3.4 Proportionality constant approach

In their study of ToU design and implementation issues in Brazil, Ferreira et al. (2013) introduced a parameter called proportionality constant through which the flat-rate tariff was translated into off-peak rate under the TOU methodology. This constant which they sometimes referred to as an indifference value was derived from each customer class to ensure that the revenues produced by the ToU rate match those generated through flat rates in order to achieve revenue neutrality prior to any load-shifting. In other words, the indifference value is derived in such a way that the customer's electricity bill under the TOU tariffs remained equivalent to that resulting from the Flat tariff.

The Proportionality Constants were calculated for each customer category, but the final value adopted was based on their weighted average wherein, the weights corresponded to each category's contribution to the total electricity consumption over a specific period. In determining off-peak ToU prices, the model applies the following basic equation;

$$P_o = \frac{K_i}{\sum_{i=1}^{n} K_i} \times \sum P_{ratio} \times K_i \times F_r \tag{7}$$

Where:

- P_o is the off-peak price
- K_i is the consumption per customer category
- n is the number of customer categories
- P_{ratio} is the price ratio for bulk supply
- F_r is the flat rate end-user price

Although this approach may seem simple and easy to implement, it remains very inconclusive where there are many bulk suppliers involved, and each having own price ratio. For instance, in the case of LEC where bulk supply is procured from more than one supplier. Moreover, this method has a weakness of applying a blanket bulk price ratio across different customer categories which implies that there is a coincidence between individual peaks with system peaks. This contradicts the phenomenon of cost allocation based on the causality principle as advanced by Passey et al. (2017) who argued that costs are allocated to customers who incur them.

Similar to price decision and mathematical ToU models discussed in sections 2.3.2 and 2.3.3, the proportionality constant approach does not derive its time-periods and their respective durations. This weakness, therefore, renders it inadequate for feasible ToU tariff determination as argued by Reneses et al. (2011) and Fridgen et al. (2018).

2.3.5 Gaussian Mixture Model

This is an approach that has widely been adopted in TOU tariff designs due to its nature of delivering validated results even where future demand levels are not known and, can capture the uncertainty inherent in load and price variations. As result, a mixer model utilizes the probability density function (PDF) for observations, described as the weighted sum of finite PDFs where each represents a cluster (Zhang et al., 2019; Wang et al., 2014). This is called the Gaussian mixture model (GMM). For a given data set (y) of *n* energy demand observations, the GMM is specified by the following equation;

$$L(\theta_1, \dots, \theta_G; W_1, \dots, W_G) = \prod_{j=1}^{n} \sum_{g=1}^{G} W_g f_g(y_j|\theta_g) \tag{8}$$

Where:

- L is the Gaussian mixture model
- θ Defines the mean and covariance (width) of each cluster
- n is the number of observations
- f_g is a density function of the g^th^ component
- W_g is the weight of the g^th^ component which, represents the probability of an observation

Since its adoption in the design of ToU tariffs, the GMM has been advantageous due to its capability of handling large amounts of data (distributions) (Li et al., 2016). Secondly, GMM's other advantage is in its ability to cater to the consideration of uncertainties, such as weather and economic meltdown, affecting the variations of electricity load and price. This is achieved through a specific condition built within the model which iteratively generates constants for non-price effects without applying general estimates across different ToU periods based on assumptions (Li et al., 2016). Furthermore, GMM features a very flexible clustering model when one can easily use predefined clusters. This means, in situations where cluster parameters are known such as duration of ToU time-periods, those can be input into the model for clustering purposes. Thus, the model can be easily adapted in any situation. The other advantage of GMM is its ability to measure the probability of how much a data point belongs to a particular cluster. Furthermore, GMM has the advantage of being able to determine either price or load-oriented ToU tariffs depending on which variable is provided as input. Moreover, the weakness of the mathematical model of ToU with respect to non-availability of a mechanism for balancing conflicting objectives between energy suppliers and consumers has however, been addressed by the GMM through the introduction of revenue neutrality principle. On the contrary, the application of GMM where only small amounts of data are involved, has proved to produce unreliable results which tend to distort the reality on the ground. For instance, clustering of energy demand that covers a short duration like a few hours where the number of observations is highly limited. This is due to the model configuration that uses the amount of data available to calculate GMM parameters (covariance, mean and mixing probability) used in the application thus, the lesser the data, the more the inaccuracy.

Like all the other models, GMM has its limitations. The model struggles in determining the optimal number of clusters. Therefore, for successful estimation, the number of required clusters should be identified first. The computation of GMM employ the expectation-maximization, which estimates missing data values using the mean of a cluster. When the data set becomes large, the algorithm can take a very long time to converge depending on the number of the missing values

The GMM, despite its limitations, has several advantages over other models described. If the Mathematical model for ToU is considered, it has been found that one of it’s greatest limitation for this study is its inability to determine the ToU periods and and durations. Considering the ToU price decision model, its drawback is that it uses price elasticities in the energy industry. Lack of scientifically research elasticity coefficients, couple with lack of detailed ener consumption data in Lesotho makes this model unsuitable. The Computable equilibrium model on the other hand uses supply-side prices, which would only be ideal in Lesotho if LEC procured power from the Southern African Power Pool. Similarly, the Proportionality constant will not be appropriate for the case of LEC with multiple suppliers, each offering power according to their bilateral agreements. Given the above, to effectively design ToU for LEC, the demand-side is considered. A model that estimates the ToU time-periods and their duration accurately is desired. The GMM effectively estimates the ToU time-periods and their durations. This is especially easy as the number of time periods had been clearly defined before. Thus, this nullifies the limitation that the GMM fails to determine the optimal number of clusters or time-periods.

2.4 Empirical evidence

This section provides a systematic review of the empirical evidence on ToU tariffs determination and adoption in other economies. Its main objective is to discuss how each of the models presented in section 2.3 performs in real life when determining ToU tariffs.

2.4.1 Model evidence on ToU tariff determination

Firstly, the Computable Equilibrium Model has been applied by Celebi and Fuller (2007) to determine ToU using historical demand data for the period 2004 for Ontario’s Independent Electricity System Operator in the United States of America. The market elasticity parameters were also obtained for the same period. In the final analysis, the model yielded a price ratio of 1:0.89:1.2 for standard to off-peak and peak periods respectively. This implies that ToU prices reduced by 11% from standard to off-peak periods whilst they increased by 20% from standard to peak periods. This denotes considerably moderate volatility in customers’ bills with a saving potential of 11% when the load is shifted from standard to off-peak periods. On the other hand, shifting consumption from standard to peak periods denotes a 20% increase in energy prices for consumers.

Secondly, ToU Price Decision Model was adopted by City Planning and management in China to determine ToU tariffs in the natural gas market (Ou et al., 2010). The objective of that application was to propose ToU prices that would ensure a balance between supply and demand of natural gas throughout different seasons, thereby improving system efficiency by avoiding unnecessary capital investments. Similarly, past consumption data and elasticity coefficients were used as inputs into the model. The model produced a price ratio of 1:0.12:5 for standard to off-peak and peak periods respectively. This implies that the prices reduced by 88% from standard to off-peak periods whilst they increased by 400% from standard to peak periods. This denotes very high volatility in customer bills when transitioning from standard to peak periods thereby, discouraging consumption during peak times and vice-versa.

Compared with the computable equilibrium model, the ToU Price Decision Model seems to cause more volatility in customer bills during the transition from standard to peak periods. This is so since the price increases by 5 and 1.2 times for the price decision and computable equilibrium models respectively. On the other hand, the price decision model has a weakness of assuming that different customer categories respond to price changes in a similar manner concerning timing, whereas that may not be the case and thus, require evaluation post new price implementation to cater for the delayed response (Celebi and Fuller, 2007). That weakness has however been addressed by the computable equilibrium model by making use of lag elasticity which makes consideration of delayed consumer response to price changes.

Furthermore, the mathematical model of ToU pricing was applied to the historical consumption data provided by the power supply corporation of Nanjing, China, which resulted in the price ratio of 1:0.49:1.28 for standard to off-peak and peak periods respectively (Yudong Tang et al., 2005). This implies that the final end-user price reduced by 79% when transitioning from standard to off-peak periods whereas, it increased by 28% from standard to peak periods. The levels of customer bill volatility during the transition from standard to off-peak period appeared to be very comparable with that of the ToU price decision model. However, the price differentials for standard to peak periods differ very drastically with an increase of 28% and 400% for the mathematical and price-decision models respectively.

Likewise, the proportionality constant approach was adopted by Ferreira et al. (2013) when determining ToU tariffs in Brazil to enable the transition from flat-rate to ToU pricing as part of the energy reforms. The result in terms of the price ratio was 1:0.33:1.67. This implies that the end-user price reduced by 67% for shifting from standard to off-peak periods, while it increased by 67% for the transition from standard to peak periods. The final price differential of more than 50% for shifting from standard to off-peak period for this model compares very well with that of price-decision and the mathematical ToU models, and that implies an emphasis on encouraging customers to shift their load to off-peak times.

Lastly, GMM was applied by Li et al. (2016) in the United Kingdom to determine both price and load-oriented ToU tariffs following clustering of bulk-price variations and load profiles respectively. The bulk price variations represented changes in prices from suppliers, while load profiles denoted variations in consumption levels (Li et al., 2016). The final price ratios obtained were 1:0.75: 1.13 and 1:0.78:1.4 for load-oriented and price-oriented respectively. This implies that under the load-oriented approach, the end-user prices decreased by 25% from standard to off-peak period whereas, they increased by 13% from standard to peak periods. Under a price-oriented arrangement, the prices decreased by 22% from standard to off-peak periods, while they increased by 40% from standard to peak periods. It was observed that under the two approaches, the price differential for transitioning from standard to off-peak periods compared very well with a decrease of 25% and 22%. On the contrary, the price differentials from standard to the peak were much higher at 40% for the price-oriented approach relative to 13% under the load-oriented method. This indicates that under-price-oriented method, GMM resulted in higher customer bill volatility during the transition from standard to peak periods, while the price change remained moderate under the load-oriented approach for the same transition.

The GMM seems to be very comparable with the price equilibrium model in so far as minimal bill volatility is concerned when transitioning from standard to off-peak and peak periods. Although the two models were able to arrive at closely comparable price ratios, the GMM went further to address a weakness identified in the latter of not being able to determine own ToU time-periods.

2.4.2 Evidence on the adoption of ToU tariffs

Although ToU tariffs have been developed and implemented in many countries, their yields in terms of final charges, price-ratios, and the levels of adoption have not been the same. This is so mainly because of their country-specific nature that tends to be influenced by factors such as level of economic activity, the main objectives behind setting up of such tariffs, and assumptions made in adopted models (Nicolson et al., 2018). For example, Yang et al. (2013) used real electricity consumption data from a case study of Ontario in Canada to compare the results produced by the use of ToU and flat rate approaches. In this study, they considered a vertically integrated electricity company that sought to determine the optimal generation capacity and price levels required to meet the demand during peak and off-peak periods under-price-cap regulation[3]. The objective of this study was to maximize the electricity company's profits by optimally determining the capacity requirements under ToU and flat-rate Pricing methodologies. They concluded that the implementation of ToU can create a win-win situation for both the utility company and consumers.

The basic assumption in the study by Yang et al. (2013) was that the demand in each period is only sensitive to a change in unit price in the same period and that when price increases, the reduction in demand in that period was greater than the increased demand in the other period. This means some load will be load shed thus, the assumption may only hold under circumstances where the partial load shifting occurred as a result of a change in price signals. This is considered a limitation of this approach as it remains inconclusive about what will happen in cases of full-load shifting. It however goes to confirm that the choice of assumptions has an influence on the outcome of ToU models and may differ from one author to the other consequently, leading to different results. The argument on assumptions based on the country-specific situation has also been corroborated by other authors including Cosmo et al. (2014) and Ferreira et al. (2013) who advanced that, assumptions should be carefully considered where ToU pricing is being proposed in economies where there is lack of empirical data on customer response to electricity price change.

Ferreira et al. (2013) added by advocating that the implementation of ToU should be piloted first in situations where no prior empirical data exists about the expected response of the customers to the introduction of the ToU-based tariffs. They argued that the pilot would assist in gauging customer buy-in and thus provide a solid foundation for the deployment plans. Their study differed from other similar studies in respect of how ToU rates were designed─in comparison with existing flat rates─to achieve revenue neutrality.

Moreover, the quest for the determination of ToU charges has been characterized by price ratios that differ considerably from country to country. For example, Table 1 presents the ToU pricing chargeable to Lesotho Electricity Company (LEC) by Eskom in South Africa and EDM in Mozambique. It is clear that the pricing during Peak periods was higher than those during standard and off-peak periods with EMD at 132.38 c/kWh whilst, Eskom was 91.96 c/kWh. The pricing during Off-Peak periods was set at 40.15 c/kWh and 52.95 c/kWh by Eskom and EDM,

[3] Price-cap regulation sets upper limits on the Electricity Company's price, below which there is full pricing freedom.

respectively. Of paramount importance to note is the pricing ratios from Off-Peak to Standard and Peak periods which were set at 1:1.6:2.3 and 1:1.8:3.3 by Eskom and EDM, respectively. This implies that Eskom's price increased by 2.3 times from Off-Peak levels during Peak-periods while EDM's price increased by 3.3 times during the same periods.

Large price differentials between on-peak and off-peak periods greatly increase bill levels and bill volatility. Therefore, in designing rates to reflect marginal costs and cost causation, careful consideration should be made regarding the impacts on affordability and bill volatility (Di Cosmo et al., 2014b; Faruqui and Sergici, 2009). The goal should be to adopt price differentials that motivate consumers to shift their load to time-periods when there is no network pressure without causing too much bill volatility. This could be achieved through a customer-friendly approach that offers incentives for voluntary demand response to ToU rates via the different attractive characteristics.

Table 1: ToU pricing for Eskom and EDM chargeable to LEC

	Eskom-Mega Flex (Cents/kWh)	**EDM (Cents/kWh)**
Peak	91.96	132.38
Standard	63.29	92.66
Off-Peak	40.15	52.95
Price Ratio (Off-Peak : Std : Peak)	**1 : 1.6 : 2.3**	**1 : 1.8 : 3.3**

On the other hand, another argument advanced by Ferreira et al. (2013) on high price differentials between off-peak and peak is to achieve the objective of totally discouraging consumption during peak periods. For instance, their study based on the proportionality constant approach depicted a price ratio of 1:3:5 for off-peak, standard, and peak periods. Ferreira et al. (2013) argued that the larger the differences in the price ratios, the more the customers would be incentivized to shift their consumption to off-peak periods to take advantage of the cost-saving opportunities due to the lower rates during those time frames. This view, however, contradicted that of Yang et al. (2013) who argued that larger price differentials lead to bills' volatility which, customers tend to be uncomfortable with, consequently leading to lack of adoption. The phenomenon of larger price differentials among time-periods can work best in countries where the supply of electricity is characterized by massive load-shedding initiatives throughout the day to balance demand with generation capacity. It, therefore, confirms that the main objectives for the development of ToU charges will vary depending on prevailing circumstances. Hence justifying different price ratios from country to country due to specific factors.

The determination of ToU tariffs remains an academic exercise if not implemented thus, calling for buy-in from customers. ToU tariffs that appeal to customers are those characterized by simplicity, clear terms, and emphasis on customer benefits such as cost-saving. These tend to promote ease of adoption and deployment without compromising end-use production (Fahrioglu and Alvarado, 2000). According to some studies including Wang and Li (2015) and Wang et al. (2014), customer participation is even more critical where the market transition from flat-rate to ToU approach is being considered. In the study which sought to measure the appetite of industrial customers for ToU pricing, Wang and Li (2015) reported that approximately 84% of their surveyed electricity utilities in the United States of America voluntarily opted for ToU (Wang and Li, 2015). This was mainly due to the following reasons; firstly, the tariffs were easily accessible to customers via utility websites. Secondly, the tariff terms were simple to understand. Lastly, the ToU tariff sheets were able to identify and communicate customer benefits without any ambiguity. Wang and Li (2015) further make an inference to the effect that customers who stand to benefit more from time differentiated pricing are those that will optimally align their production schedule to match ToU methodologies closely. This assertion is corroborated by Grunewald et al. (2015b) who emphasize that simplicity and customer knowledge of the ToU terms remain key factors for their adoption.

Finally, one of the barriers to the adoption of ToU as identified by several studies including Ferreira et al. (2013) and Eid et al (2016) is the volatility of customers' bills during the transition from a flat rate. Bill volatility can negatively impact customers by increasing their bills when they opt for ToU and is, therefore, one area that requires careful consideration during the design stage. Hence the need to maintain revenue neutrality during tariff transition. In their study on mandatory ToU, Jessoe and Rapson (2015) purported that the issue of increased bill volatility has been overly exaggerated for commercial and industrial customers whose consumption remains constant throughout the day and emphasized consideration on residential-class only. This was corroborated by Li et al. (2016) in their design of ToU tariffs based on the Gaussian mixture model. They emphasized the need to ensure revenue neutrality for economies considering a transition from a flat rate to ToU charges as that can take care of human behavior which tends to affect electricity load and price profiles, hence promoting customer buy-in.

2.5 Synthesis of the literature

As outlined in the literature review, many approaches have been adopted in developing ToU tariff charges with each having strengths and weaknesses depending on different conditions facing the utility companies or regulators wishing to introduce them. Such conditions include, but are not limited to: the need to enforce load-shifting to reduce peak loads, the country-specific factors, and, finally, the need to balance the demand with the available generation capacity to reduce the costs of energy. Furthermore, the effect of the introduction of ToU has to be carefully considered to manage the volatility of the customers' bills, as excessive volatility can lead to the customers not supporting the new tariff approaches. The volatility of the prices is reflected in the final price-ratios among different time-periods. In cases where load shifting has not been implemented by the customers, higher price ratios can result in higher volatility in the customer bills (Ferreira et al., 2013; Li et al., 2019).

It is, therefore, clear that there is no "one-size fits all" as far as ToU methodologies are concerned. Key factors such as transparency and ease of implementation need to be considered whenever a utility contemplates the development of ToU charging especially when it is transitioning from flat-rate charging (Torriti, 2014). Following this argument, this study adopted the Gaussian mixture model to determine ToU tariffs for the LEC. This choice is motivated by the GMM's ability to fully cater for the three basic requirements for the determination of feasible ToU charges namely; derivation of own time-periods, the establishment of the duration of time-periods, and determination of price per time-period (Grünewald et al., 2015; Li et al., 2019; Reneses et al., 2011b; Yang et al., 2013). The other important factor considered in the choice for GMM was the principle of maintaining revenue neutrality on customer bills when transitioning to ToU tariffs. This is key since, LEC is currently applying flat-rate tariffs to its customers, and therefore revenue neutrality will encourage customers to easily support the proposed ToU approach as it will not negatively impact their cost before any load-shifting.

3 Methodology

3.1 Introduction

This chapter discusses the methodology that is used in this study. Typical load profiles of customer categories are discussed and how they contribute to the overall observed system peaks. Further, the clustering method, Gaussian mixture model (GMM), used in the study is outlined. Moreover, the chapter continues by specifying how the ToU tariffs are determined. The chapter is concluded by creating possible load-shifting scenarios to assess the impact of ToU tariffs on customer bills and LEC revenue.

3.2 Data Description

Electricity consumption data was obtained from LEC covering the period 2010-2019. This data was disaggregated in 30 minutes intervals, which covered 8760 hours for each year and result in 48 data observations in a day. These are herein referred to as 48 settlement periods. Typical load profiles were generated for different customer types. There are six customer types within LEC, and these are low and high voltage commercial, low and high voltage industrial, residential, and general-purpose customer types. Figure 1 and Figure 2 illustrate load profiles for consolidated residential and low voltage industrial customer types, respectively. Load profiles for other customer categories have been provided in the appendix to maintain the current flow of this paper and, are depicted in Figure 14, Figure 15, and Figure 16 for high voltage industrial, high voltage commercial, and low voltage commercial customer types, respectively. It is observed that the residential profile experiences two peaks within 24 hours; morning and evening. It should be noted though, that the data used here is for high-end residential customers such as high-ranking government officials' residences because they are on post-paid meters with the capability of storing consumption profiles. Otherwise, typical residences are on prepaid meters without data storing capabilities. This data set covers approximately 10% of all customers on post-paid meters and exhibits the same consumption pattern with the rest of the residential category although, it differs with them on the energy quantities or volumes consumed.

The low voltage industrial profile exhibits a morning and an afternoon peak, although the latter is a bit lower in magnitude.

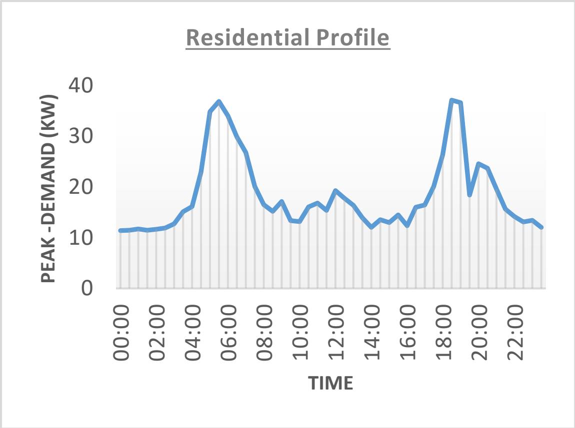

Figure 1: Average residential load profile

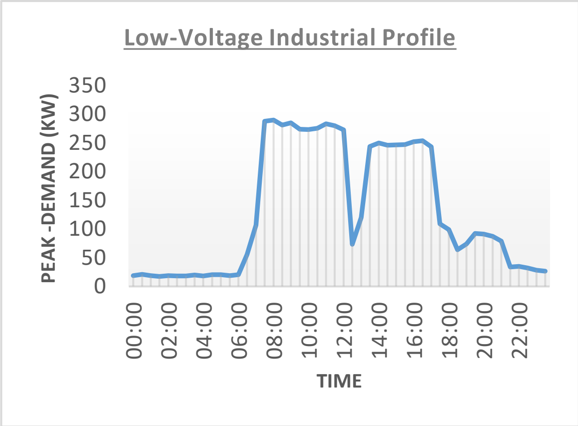

Figure 2: Average industrial low voltage load profile

Figure 3 illustrates a typical daily load profile of the whole LEC system. Similarly, it is noted that the system also experiences a morning and an evening peak. It is further noted that the system morning peak coincides with the industrial profile morning peak. There is no clear influence on the system's morning peak from the residential load profile. However, there seems to be a correlation between the system evening peak and the residential evening peak. This observed behavior shows that ToU tariffs need to be applied across all customer types as each customer category may influence the peak one way or the other.

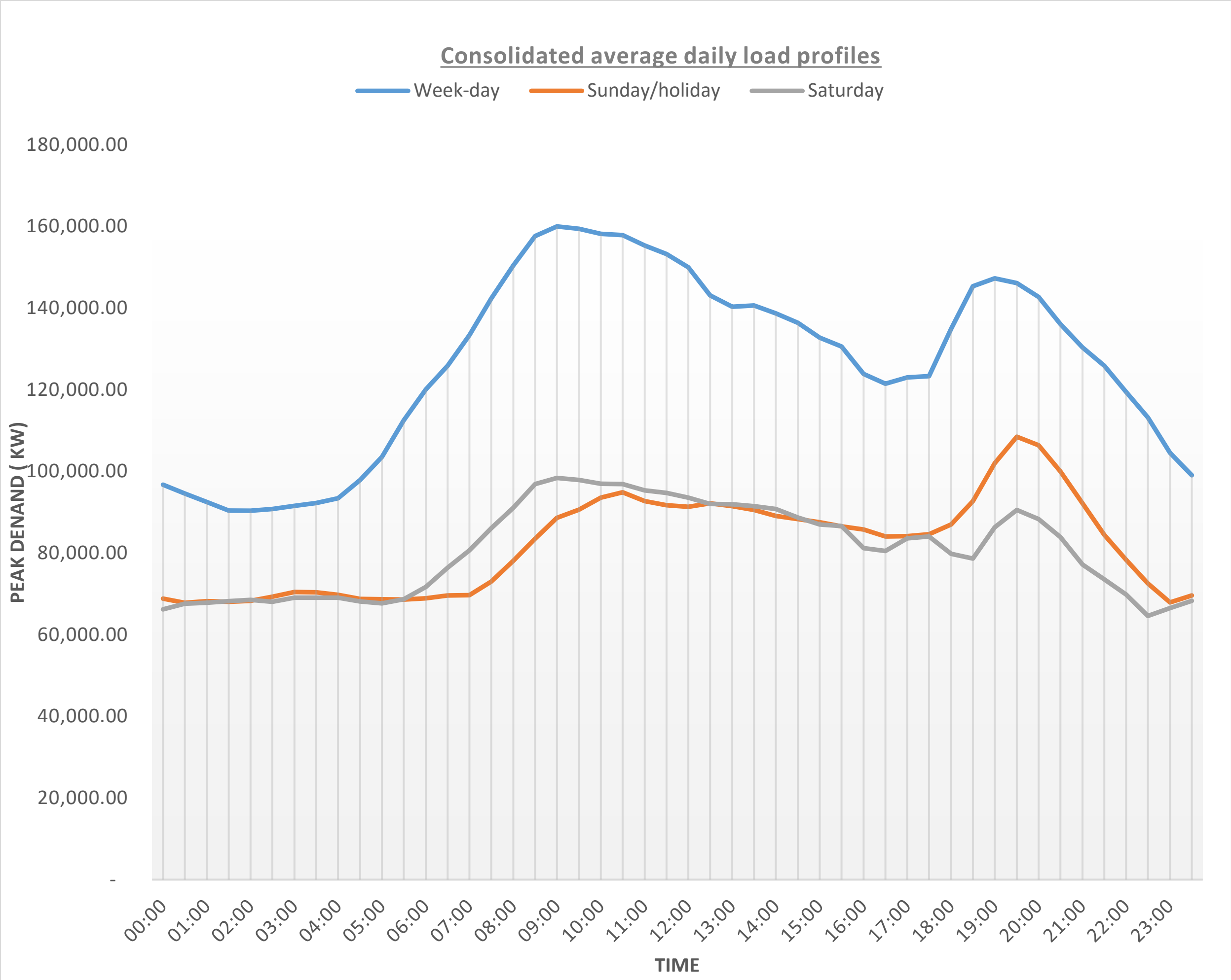

Figure 3: Consolidated average daily load profile

Based on Figure 3, a table of tentative time-periods was deduced as depicted in Table 2. It is observed that during a weekday, peak periods range from 06:00 am to 10:00 am and 18:00 hours to 21:00 hours for morning and evening, respectively, due to the start of business activities in the morning and increased residential loading in the evening whilst, standard period ranges from 10:00 am to 18:00 hours may be due to stable business operations leading to a smooth decline in consumption profile. Accordingly, the off-peak period runs from 21:00 hours to 06:00 am due to a very low consumption as there is no significant business or residential activity. On the other hand, weekends or holidays are observed to be exhibiting very low consumption as a result of inactivity in most sectors of the economy. Thus, being classified under the off-peak period.

Table 2: Tentative time-periods

Tentative LEC Time-Periods			
Day	**Peak**	**Standard**	**Off-Peak**
Weekday			21:00-06:00
	06:00-10:00		
		10:00-18:00	
	18:00-21:00		
Saturday/ Sunday/ Holiday			00:00-00:00

3.3 Model Specification

The data provided by LEC gives energy consumption in 24 hours. To design a ToU regime, it is necessary to have load profiling such that energy demand over 24 hours can be divided into latent classes. These latent classes are called clusters and they capture the variations in load between them and anticipated prices. To achieve this clustering, a GMM from Li et al. (2016) is adopted. Its choice over other models is motivated by the following aspects. Firstly, GMM offers the opportunity to ensure revenue neutrality when transitioning from flat-rate to ToU methodology. This is vital since LEC is currently applying the former approach to derive customer prices. Thus, maintaining revenue neutrality will be a win-win position for both LEC and its customers. Secondly, GMM can define its time-periods and their respective pricing, which other models fail to deliver. This means it can come up with a different version from that shown in Table 2. The GMM model is then specified in equation (8). Since this equation is a function of mean and weight, each data set applied to it will be assigned a specific mean and covariance which, represents the width of each cluster. Therefore, data points with similar mean and covariance will be allocated to one cluster.

For a typical day, the energy prices or loads during all predefined 48 settlement periods are clustered based on the GMM where each period is assigned to a distribution model with different probabilities signifying tariff stages, e.g. peak, standard and off-peak. The individual weights in equation (8) should lie between 0 and 1 because they represent settlement periods that occur within 24-hours such that the total summation of all the weights must be unity as shown by equations (9) and (10) below, respectively. Each data set is assigned a weight based on its magnitude and contribution to the total weight over the 24 hours.

$$0 \leq W_g \leq 1 \tag{9}$$

$$\sum_{g=1}^{G} W_g = 1 \tag{10}$$

The GMM approach also caters for uncertainties such as the probability that a certain consumption level may belong within a particular cluster. Products of ToU with uncertainties are therefore modeled as specified by Equation (11). This equation generates probabilities of each data set belonging to each cluster and assigns it to a cluster with the highest probability.

$$U = \prod_{j=1}^{48} \{U_{jg}\}_{g=1}^{G} \tag{11}$$

Where:

- U_{jg} is the clustering uncertainty in settlement period j belonging to model g.

Since the above clustering process sets the time windows of the ToU with a respective duration of the time block, this is followed by the determination of price ranges for each cluster and the final consumer bill as shown by Equation (12). This equation is used to calculate the price for each cluster while maintaining revenue neutrality with the flat-rate tariff.

$$\sum_{t \in k} (T_t \times L_t) = \sum_{t \in k} (F \times L_t) \tag{12}$$

Where:

- t is a set of settlement periods within-cluster k
- T_t is the tariff rate of ToU in time t
- L_t is the demand level during period t
- F is the flat rate
- C is the electricity bill under ToU
- B_t is the charging rate during period t

3.4 Possible load-shifting scenarios

This study further creates possible load-shifting scenarios to assess the impact of the proposed ToU tariffs on customer bills and LEC bulk costs. It is assumed that load-shedding from peak to off-peak periods is enabled by the availability of different types of loads at the customer level such as interruptible appliances, shiftable-loads, and thermostatic loads. Interruptible loads refer to electricity appliances whose energy supply can be interrupted on the condition that it will be supplied at some point, whereas shiftable load is one whose energy supply cannot be interrupted once initiated. Thermostatic loads are those fitted with thermal controllers to switch on and off their energy supply based on temperature set-points (Soares et al., 2019).

The availability of technology such as smart metering, which provides access for consumers to monitor their consumption from time-to-time, has been identified as a key enabler for load-shifting in markets that have adopted ToU tariff structures (Gottwalt et al., 2011). Shifting of loads from peak to off-peak periods also depends on factors such as flexibility and availability of the load involved, together with the requirements of the business at a particular point (Orans et al., 2010). Thus, this makes it practically not possible to achieve a 100% load-shifting. Gottwalt et al. (2011) assert that the practical load-shifting ranges between 5 and 10%. In this study, load-shifting scenarios of 5 and 10% from peak to off-peak periods have been assumed across all customer categories within LEC.

4 Results

This section presents the results. Firstly, the results of the ToU time-periods are presented. Based on these time-periods, their respective tariff charges are determined. This section is concluded by the presentation of the results of 5 and 10% load-shifting scenarios.

4.1 ToU time-periods

The electricity consumption varies from hour to hour on any 24-hour day. However, there are periods where the consumption profile is similar. Given that LEC procures electricity from Eskom based on ToU tariffs with three time-periods, the time-periods in this study have been fixed to align with those of Eskom. LEC data is recorded in 30 minutes interval and when this data is fit with the GMM model specified in Equation (8), periods with similar consumption patterns are clustered together into three classes. The clustering of the 48 observations into classes (time-periods) is shown in Table 3, for each customer category. For instance, in the Industrial HV customer category, observations 22 to 30 are around the same mean and have been assigned to Class 1, Class 2 is made of observations 31 to 48 while the last Class 3 is made up of observations 1 to 21.

Table 3: Observations per cluster determined by GMM

Customer category	Class 1	Class 2	Class 3
Industrial HV	Obs22 – Obs30	Obs31 – Obs48	Obs1 – Obs21
Commercial HV	Obs1 – Obs19	Obs41 – Obs48	Obs20 – Obs40
Commercial LV	Obs1 – Obs14	Obs31 – Obs48	Obs15 – Obs30
Industrial LV	Obs1 – Obs15, 26	Obs27, 36 – Obs48	Obs16 – Obs15 Obs28 – Obs35
Residential	Obs1 – Obs10 Obs16 – Obs25	Obs26 – Obs37 Obs40 – Obs48	Obs11 – Obs15 Obs38 – Obs39

Notes: Class 1 = Off-Peak Period, Class 2 = Standard Period, Class 3 = Peak Period, HV = High-Voltage, LV = Low-Voltage, Obs = Observation

As a way of confirming the level of confidence in the clustering depicted in Table 3, posterior probabilities of an observation belonging to a particular class were determined using Equation (11). The results of these probabilities for every customer category are shown in the Appendix in order not to disturb the flow of this paper as a result of their large size. A snapshot of posterior probabilities for the residential customer category is shown in Table 4. The row that is highlighted in yellow shows that observation 10 has 65.5%, 1.2%, and 33.3% chances of belonging to classes 1, 2, and 3, respectively. Ultimately, this observation is assigned to Class 1. On the other hand, the row highlighted in green shows that observation 11 has a 100% probability of belonging to Class 3. These results imply that there is confluence in the outcome of Equations (8) and (11). Therefore, the level of confidence in the clustering determined by GMM is high.

Table 4: Posterior probabilities for residential customer category

Observation	1	2	3	Class
Obs1	0.995	0.005	0.000	1
Obs2	0.994	0.006	0.000	1
Obs3	0.993	0.007	0.000	1
Obs4	0.991	0.009	0.000	1
Obs5	0.988	0.012	0.000	1
Obs6	0.986	0.014	0.000	1
Obs7	0.983	0.017	0.000	1
Obs8	0.981	0.019	0.000	1
Obs9	0.978	0.022	0.000	1
Obs10	0.655	0.012	0.333	1
Obs11	0.000	0.000	1.000	3

Notes: Obs = Observation, Class 1 = Off-Peak Period, Class 2 = Standard Period, Class 3 = Peak Period

These classes are based on the consumption mean for each period. To obtain the ratio for each class, these are calculated as weights to the sum of the three classes. These weights sum up to 1 as required by equations (9) and (10). The means per class per customer category are shown in Table 5.

Table 5: Mean by class determined by GMM

Customer category	Class 1	Class 2	Class 3
Industrial HV	0.305	0.344	0.350
Commercial HV	0.204	0.269	0.526
Commercial LV	0.190	0.360	0.450
Industrial LV	0.083	0.189	0.727
Residential	0.231	0.256	0.514

Notes: Class 1 = Off-Peak Period, Class 2 = Standard Period, Class 3 = Peak Period, HV = High-Voltage, LV = Low-Voltage

The classes are categorized in increasing weights such that class 1 has the lowest weight and class 3 has the highest weight to represent the period of lowest consumption and the period of highest consumption, respectively. Class 1 has been taken to represent the off-peak period, Class 2 represents the standard period while Class 3 represents the peak period. By normalizing the ratios and taking the Class 2, standard period, as the base, Table 6 is obtained.

Table 6: Normalized mean by class

Customer category	Class 1	Class 2	Class 3
Industrial HV	0.89	1.00	1.02
Commercial HV	0.76	1.00	1.95
Commercial LV	0.54	1.00	1.26
Industrial LV	0.44	1.00	3.85
Residential	0.90	1.00	2.01

Notes: Class 1 = Off-Peak Period, Class 2 = Standard Period, Class 3 = Peak Period, HV = High-Voltage, LV = Low-Voltage

The base class has been chosen as Class 2 because it lies between the two extreme consumption periods. Replacing Class 1, Class 2, and Class 3 with Off-peak, Standard, and Peak, respectively, and replacing the observations with the actual time of occurrence, Table 7 is obtained.

Table 7: Time-periods determined

Customer category	Off-peak	Standard	Peak
Industrial HV	10:30 – 14:30	15:00 – 23:30	00:00 – 10:00
Commercial HV	00:00 – 09:00	20:00 – 23:30	09:30 – 19:30
Commercial LV	00:00 – 06:30	15:00 – 23:30	07:00 – 14:30
Industrial LV	00:00 – 07:00 12:30	13:00 17:30 – 23:30	07:30 – 12:00 13:30 – 17:00
Residential	00:00 – 04:30 07:30 – 12:00	12:30 - 18:00 19:30 – 23:30	05:00 – 07:00 18:30 – 19:00

Notes: HV = High-Voltage, LV = Low-Voltage

It is observed from Table 7 that, off-peak in the industrial HV customer category occurs from 10:30 up to 14:30, lasting around 4 hours. This is followed by an increase in consumption to the standard settlement period. The standard period goes from 15:00 to 23:30, and then the peak time-period from 00:00 to 10:00. A transition can occur from any settlement period to the other due to the abrupt change in consumption patterns that is observed across different customer categories. Furthermore, a time-period may occur more than once within a day as is shown in Table 7. For example, under the industrial LV category, the off-peak time occurs from 00:00 to 07:00 and 12:30.

4.2 ToU tariffs determination

Based on the observed time-periods as shown in Table 7, and the normalized weights from Table 6, ToU tariffs were determined as shown in Table 8, using Equations (12) and **Error! Reference source not found.**.

Table 8: ToU tariffs for each customer category

Customer Category	**Current Flat rate tariff (M)**	**Price-ratio**	**Off-peak (M)**	**Standard (M)**	**Peak (M)**
Industrial HV	0.1936	0.89: 1 : 1.02	0.1740	0.1955	0.1994
Commercial HV	0.1936	0.76 : 1 : 1.95	0.0943	0.1241	0.2420
Commercial LV	0.2144	0.54 : 1 : 1.26	0.1114	0.2063	0.2600
Industrial LV	0.2144	0.44 : 1 : 3.85	0.0300	0.0682	0.2627
Residential	1.4000	0.9 : 1 : 2.01	1.0192	1.1324	2.2762

Notes: M= Maloti (Lesotho currency), HV = High-Voltage, LV = Low-Voltage

The normalized weights have subsequently been used as price-ratio among the three time-periods. The LEC flat-rate tariff was used to calculate the standard-period tariff while maintaining revenue neutrality by applying Equation (12). From the estimated standard-period tariff, the price-ratio was used to determine off-peak and peak periods' tariffs. The tariffs have been designed such that revenue neutrality is maintained across all customer categories. For the Industrial HV customer category, the off-peak price is 89.9% of the flat rate, while the standard and peak are at 100.9% and 103% of the flat rate, respectively. The ToU tariffs for this category are not very much different from the flat-rate tariffs. This is because the load profile of the industrial HV category is relatively flat, as shown in Figure 4, offering a good load factor. A good load factor is desirable on the network as it reduces the strain and hence lowers the operational costs of the network. The ToU tariffs reflect this limited strain on the network as they are not very much different from the flat-rate tariffs. Off-peak is at 89.9% of the flat rate to encourage a little load shifting to the off-peak period, although it will not be a significantly huge load. The price ratio of 0.89:1:1.02 for off-peak – standard – peak further confirms that there is little difference in terms of consumption levels between the individual settlements.

The commercial HV ToU pricing is 48.7%, 64.1%, and 125% of the flat rate for off-peak, standard, and peak prices, respectively. The low pricing at off-peak is such that it persuades the customer to shift some of the load from the peak period to the off-peak. Similarly, the peak period costs much more than the off-peak, relative to the flat rate. This should provide an incentive to the commercial HV to shift the load from the peak period. Figure 5 shows that a slight change in consumption, at around 15:00 hours, can result in substantial changes in the tariff charge. The price ratio of 0.76:1:1.95 for off-peak-standard-peak shows that the consumption levels between off-peak and peak are very much different. The low off-peak prices should provide an incentive to shift some of the load from the peak period to the off-peak.

For the Commercial LV customer category, the off-peak, standard, and peak pricing are 52.0%, 96.2%, and 121% of the flat rate, respectively. Amongst the settlement periods, this results in a price ratio of 0.54:1:1.26 for off-peak-standard-peak. The percentages and the price ratios show that the peak is charge at a much higher rate than the off-peak. The off-peak tariff is very low, lower than the flat rate tariff. So shifting the load to the off-peak periods for this category implies that customers will be charged a tariff lower than what is currently prevailing. This behavior is shown in Figure 6. Higher consumption results in higher charges while the opposite is true. The industrial LV category has a price ratio of 0.44:1:3.85, while the comparison of off-peak, standard, and peak pricing are 14.0%, 31.8%, and 122.5% of the flat rate, respectively. This shows that there is a substantial difference in the energy demand in off-peak versus peak periods. This is further shown in Figure 7. Huge fluctuations in consumption patterns cause a lot of strain on the network as this results in a poor load factor. The pricing is such that it encourages load shifting to off-peak and standard settlement periods.

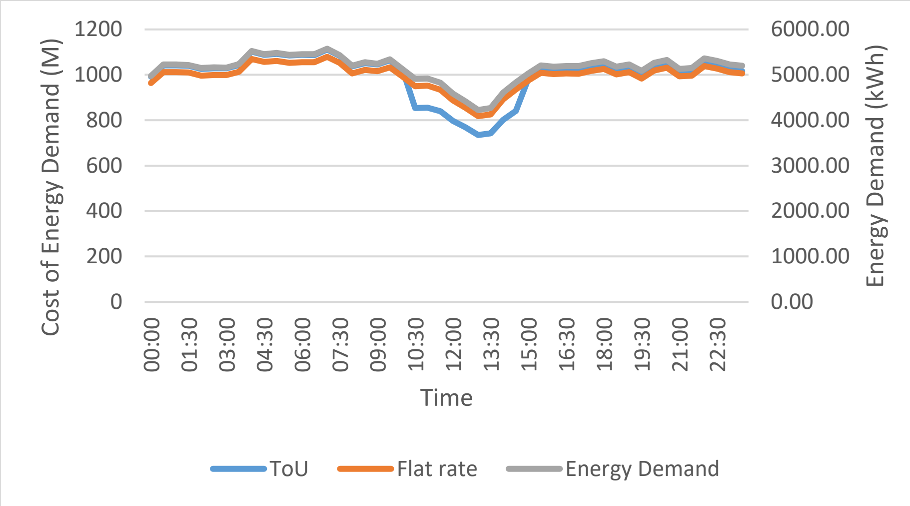

Figure 4: Industrial HV energy demand and its cost under ToU and flat rate

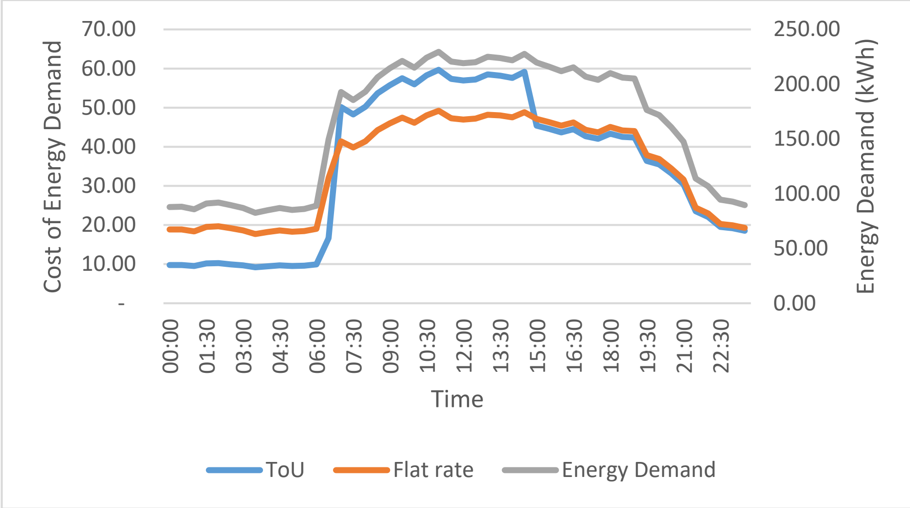

Figure 5: Commercial HV energy demand and its cost under ToU and flat rate

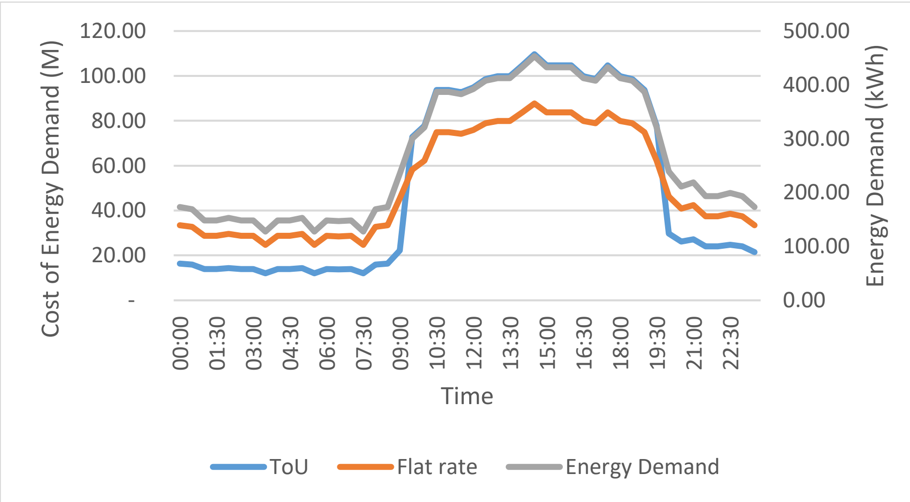

Figure 6: Commercial LV energy demand and its cost under ToU and flat rate

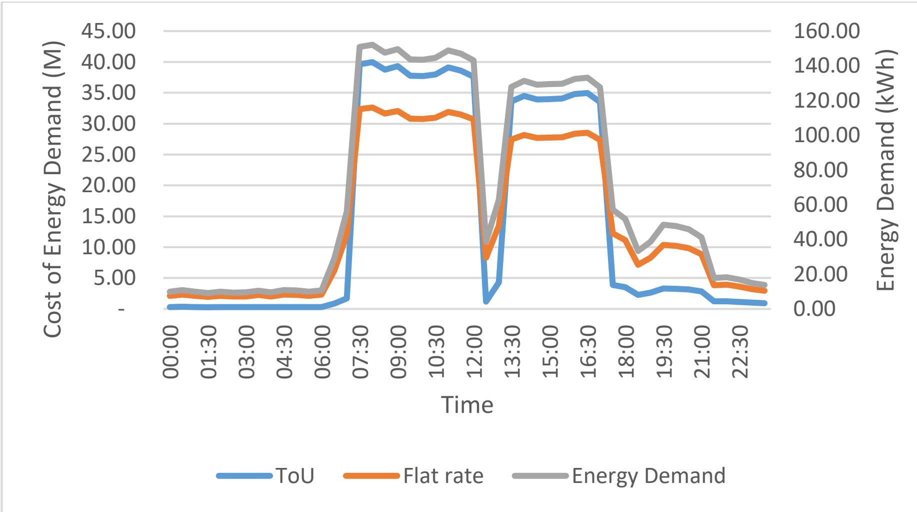

Figure 7: Industrial LV energy demand and its cost under ToU and flat rate

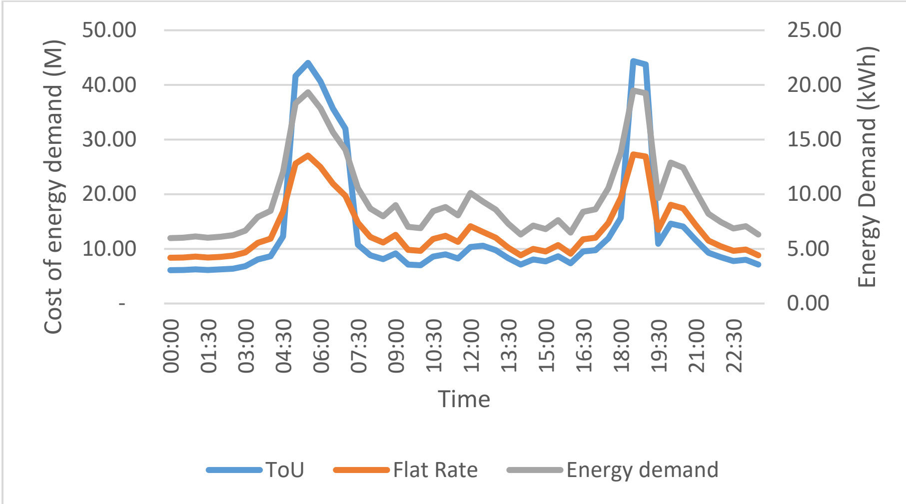

Figure 8: Residential energy demand and its cost under ToU and flat rate

The residential sector is characterized by a morning peak and an evening peak. The pricing of the settlement periods is 72%, 80.9%, and 162.6% of the flat-rate tariff for off-peak, standard, and peak periods, respectively. The price ratio is 0.9:1:2.01 for off-peak-standard-peak. These imply that there is a great difference in energy demand between the off-peak and peak periods. The energy demand during the peak period is above two times the consumption during the off-peak period as is shown by Figure 8. The tariff has been designed such that this behavior is reflected in the pricing. Although the peak periods occur in short bursts, with consumption rising over two times as much as in off-peak, the cost of energy demand rises around four times. The lower tariff that is in line with lower demand periods is an incentive for residential customers to shift their load from peak to standard period and off-peak periods.

4.2.1 Results for possible load-shifting scenarios

Following a study by Gottwalt et al. (2011), on average, customers are only able to manually shift 5 to 10% of their load, hence possible load-shifting scenarios of 5% and 10% of the load across all customer categories based on the proposed settlement periods; off-peak and peak periods have been created. The scenarios are defined such that the peak period consumption is reduced by 5% and 10% while, the off-peak one is increased by the same percentages. The standard period profile remains unchanged. The behavior of the load profile associated with each customer category remains unchanged, and only the consumption levels for peak and off-peak periods are adjusted by 5% and 10% accordingly. For example, off-peak in the industrial HV customer category still occurs from 10:30 up to 14:30. The standard period goes from 15:00 to 23:30, and then the off-peak period from 00:00 to 10:00. The total daily consumption under flat-rate is 246 770 kWh (consolidated), while it is 243 283 kWh and 239 795 kWh under 5 and 10% load shifting scenarios, respectively. These represent energy savings of 1% and 3% for the two scenarios, respectively for the industrial HV customer category. Conversely, for the residential customer, the total daily consumption under flat-rate is 463.25 kWh while it is 464.91 kWh and 466.58 kWh under 5 and 10% load shifting scenarios, respectively. These represent an increase in consumption of 0.4% and 1% for the two load shifting scenarios, respectively. The increase in consumption comes as a result of shifting a percentage of load from shorter peak-periods to longer off-peak ones that characterize the residential consumption pattern. Hence, these are represented as negative energy savings. The results of the total energy savings or gains due to load shifting for every customer category are shown in Table 9.

Table 9: Total energy savings

Customer category	**5% Load shifting**	**10% Load shifting**
Industrial HV	1%	3%
Commercial HV	2%	4%
Commercial LV	1.4%	3%
Industrial LV	3%	7%
Residential	-0.4%	-1%

Notes: HV = High-Voltage, LV = Low-Voltage

Based on the results shown in Table 9, it is observed that across all customer categories, energy savings were noted. For Commercial HV, Commercial LV and Industrial LV customers experienced energy savings of 2%, 1.4%, and 3% respectively under a 5% load shifting scenario. The energy savings for the same customer categories under the 10% load shifting scenario are 4%, 3%, and 7%, respectively. It appears that the Industrial LV category experiences the highest energy savings from the rest of the categories because the majority of its consumption occurs during peak periods. Therefore, moving energy consumption to an off-peak period results in significant energy savings. On the contrary, the residential customer category exhibited an increase in energy consumption under load-shifting due to its characteristics of long off-peak hours with very little consumption. Thus, shifting consumption from shorter peak to longer off-peak periods will result in an energy increase.

Based on the energy movements observed in Table 9, the proposed ToU tariffs were applied to explore their impact on customer bills. For example, the total daily bill under flat-rate for industrial HV customers is M47 774.84, while it is M47 026.66 and M46 278.48 under 5 and 10% load shifting scenarios, respectively. These represent energy bill savings of 2% and 3% for the two scenarios, respectively for the industrial HV customer category. Similarly, for the residential customer, the total daily bill under flat-rate is M648.55 while it is M642.46 and M636.36 under 5 and 10% load shifting scenarios, respectively. These represent an energy bill reduction of 1% and 2% for the two load shifting scenarios, respectively. Under the residential customer category, it is observed that load shifting has resulted in higher average electricity consumption and reduced bill amounts. The results of the impact on all customer category energy bills are shown in Table 10.

Table 10: ToU tariffs impact on customer bills

Customer Category	**5% Load shifting**	**10% Load shifting**
Industrial HV	-2%	-3%
Commercial HV	-3%	-7%
Commercial LV	-2%	-5%
Industrial LV	-5%	-9%
Residential	-1%	-2%

Notes: HV = High-Voltage, LV = Low-Voltage

As depicted in Table 10, 5% and 10% of load-shifting from peak to off-peak periods results in varied customer bill savings across different categories. Industrial LV customers experienced the highest energy bill saving of 5% and 9% under 5% and 10% load shifting scenarios, respectively. The rest of the customer categories exhibit savings of 3%, and 2% for Commercial HV, and Commercial LV under 5% load shifting scenario, respectively. On the other hand, the energy bill savings under 10% load shifting are 7% and 5% for Commercial HV and Commercial LV, respectively. Since the off-peak tariff is much lower than the peak one, shifting load from these highly-priced periods results in lower energy costs for customers. This provides an incentive for customers to schedule their consumption following how time-periods are arranged to take advantage of the pricing differentials.

The behavior of load-shifting for the two scenarios from peak to off-peak periods by Industrial HV, Commercial HV, Industrial LV, Commercial LV, and Residential customers is depicted in Figure 9, Figure 10, Figure 11, Figure 12, and Figure 13 respectively. Please note that “L-Sht” in these figures denotes “ Load-shifting”. As illustrated in these figures, the substantial difference in energy consumption between off-peak and peak periods for all the categories, with exception of Industrial HV, implies that significant saving opportunities are available as a result of load-shifting from highly-priced peak to low priced off-peak periods. It is further observed that the two load shifting scenarios result in similar load profiles although, they differ in quantities of energy savings or gains across all customer categories.

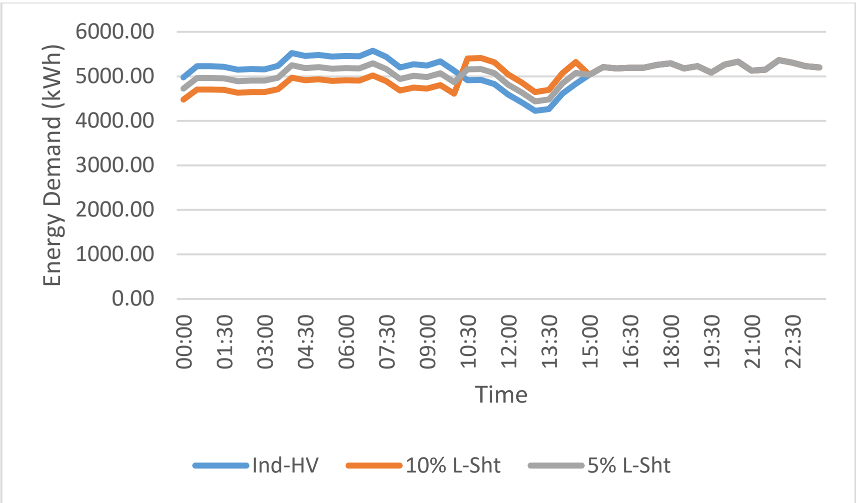

Figure 9: Industrial HV load shifting

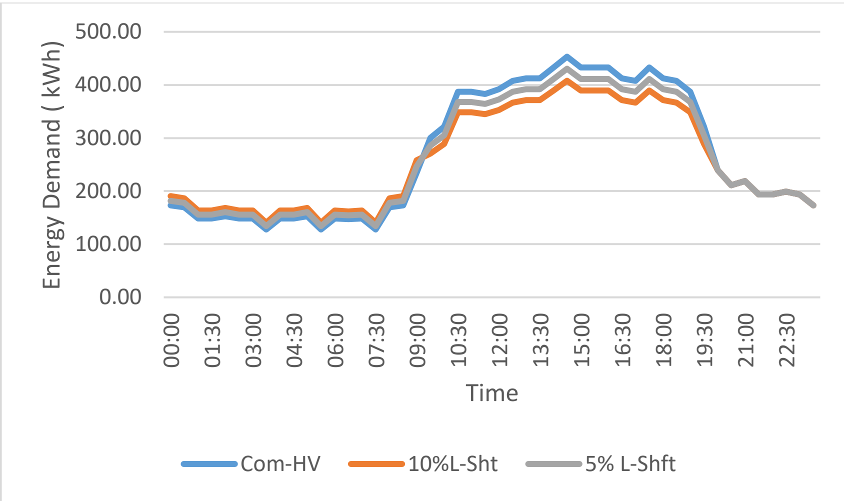

Figure 10: Commercial HV load shifting

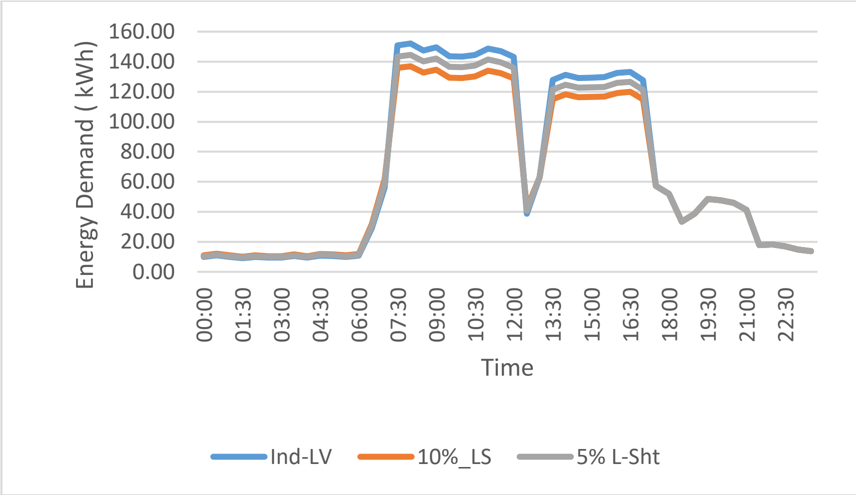

Figure 11: Industrial LV load shifting

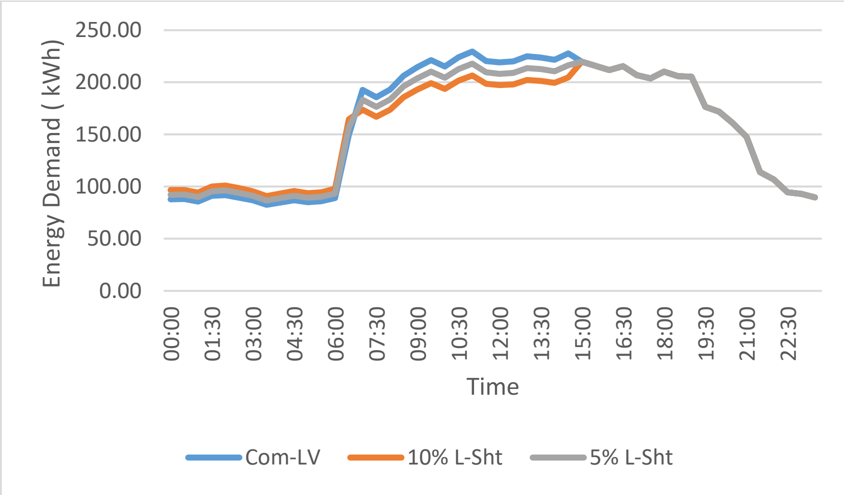

Figure 12: Commercial LV load shifting

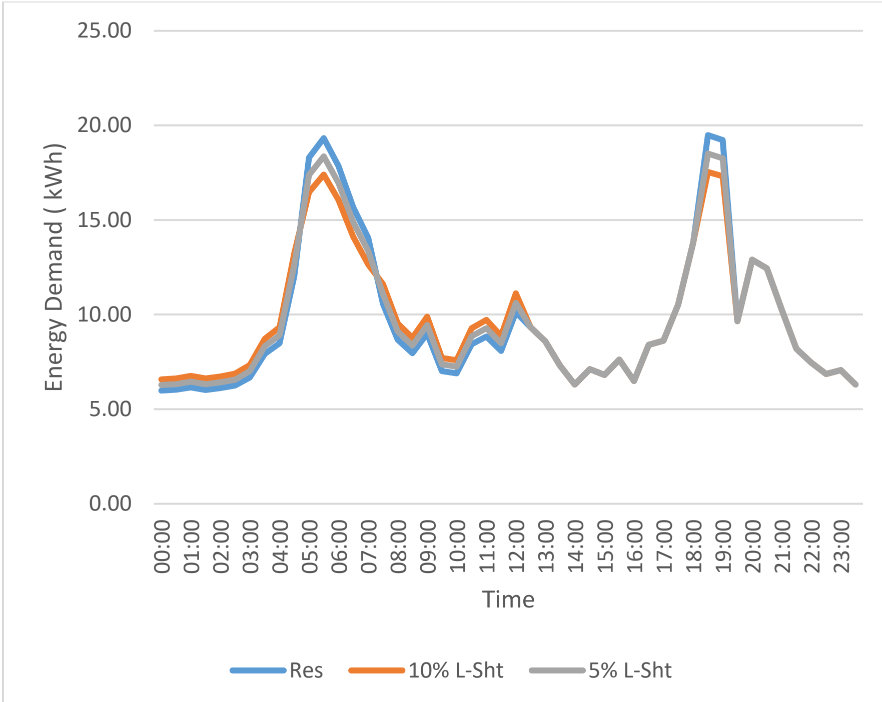

Figure 13: Residential load shifting

The behavior of the Industrial HV category as depicted in Figure 9 does not exhibit significant energy consumption differential between peak and off-peak periods as demonstrated by its flatter profile. Although it does not present many load-shifting opportunities, it is characterized by a very stable consumption profile that exhibits no random fluctuations. Hence, demonstrating the positive effect of high load-factor on the electricity network (Chang and Lu, 2002).

According to the aforementioned results, the cumulative energy savings from the two load shifting scenarios were used to estimate their impact on LEC costs based on the bulk energy data for the financial year 2019-2020. The recorded total energy of **899 GWh** was procured by LEC at an average cost of 63 cents/kWh and 115 cents/kWh with and without Muela local generation, respectively, (Lesotho Electricity Company, 2020). Based on the average savings of 1.4% and 3.2% as depicted in Table 9 for the 5% and 10% load shifting scenarios, respectively, the LEC bulk energy savings results in approximately 13 GWh for the 5% load shifting scenario while it ranges around 30 GWh for the other load shifting scenario. These, in monetary terms, compare to approximately M8.9 Million and M18.7 Million for the 5% and 10% load shifting scenarios, respectively, when Muela local generation is available. Conversely, when LEC relies exclusively on imports without local generation, the bulk energy cost savings translate to approximately M16.3 Million and M34.1 Million for the 5% and 10% load shifting scenarios, respectively.

5 Discussions

This section presents discussions on the results of the determination of ToU tariffs and possible load shifting scenarios. It starts with the discussion on the determined ToU tariffs and concludes with a sub-section presenting an argument for ToU as an enabler for load shifting.

5.1 ToU tariffs

In their study, Ferreira et al (2013), pointed out that shorter time-periods between 2-4 hours allow for larger price ratios and are closely tied to utility costs whilst, longer ones beyond 5-6 hours tend to dilute cost recovery. But shorter time-periods may not be appealing to larger consumers who run batching processes since they cannot be interrupted. In line with this argument, the determined duration of time-periods is customer class-specific, allowing longer periods for industrial and commercial HV customers and shorter duration for residential type. These time-periods allow for voluntary manual or automated load-shifting to avoid higher prices as advised by Fan and Hyndman (2011).

The price ratios for off-peak-standard-peak for Eskom and EDM are 0.63:1:1.44 and 0.56:1:1.83, respectively (Lesotho Electricity Company, 2020). This implies that the transition from off-peak to standard is 59% and 98% for Eskom and EDM, respectively. Furthermore, a transition from standard to the peak is 44% and 83% for Eskom and EDM, respectively. From Table 8, the proposed transition for LEC is 53% and 100% for off-peak to peak and standard to peak respectively. This shows that for the transition from off-peak to standard, LEC compares very well with Eskom whilst, for the transition from standard to peak, LEC compares with EDM. This is very important considering that LEC imports electricity from Eskom and EDM. The electricity Regulator requires that LEC passes the bulk supply costs onto the customer (Thamae et al., 2015b). Therefore, the observed tariff increase between time-periods reflects the regulator's requirement, which the flat-rate failed to do due to lack of time-specific marginal cost pricing.

The average increase in the price of 100% from standard to the peak provides adequate motivation for customers to shift their load to off-peak. Consequently, the shift in the load from peak demand can result in a better load factor and thus better load management (Sheen et al., 1994). An accurately designed tariff should reflect the cost of supply electricity to the customer, and since operating at peak puts more stress on the network and might force the utility to invest in premature network expansion, therefore, the price increase of 100% is a good indicator to the customer. Under a flat rate, the long-run marginal costs of the utility are not taken into account, which implies that the utility engages in networks expansion but prices electricity at a rate that is not adequate to recover the sunk cost of the network expansion (Passey et al., 2017b; Rhys, 2018)

5.2 Load shifting scenarios

The increase in energy consumption for the Residential customer category as a consequence of load-shifting has the potential to address the existing challenge of declining average household consumption in Lesotho as identified by Mpholo et al. (2020). The decline in household average consumption became a concern that implied a very poor allocation of resources in the electricity sector wherein, electrification efforts were in high gear and, the number of customers was increasing yet, consumption volumes at the household level were on a decline. This situation further implied that return on investments from electrification projects could not be easily realized, making it difficult for the universal access fund to be easily resourced to facilitate further access to electricity by rural communities. Thus, in line with Torriti (2012), ToU tariffs can bring about increased electricity consumption and lower payments by consumers as they encourage a significant load shifting from highly-priced peak periods to longer and lower-priced off-peak times.

The load-shifting scenarios depicted in this study, demonstrate a clear potential for savings for both customers and the supply utility in Lesotho. Through automation of load-shifting activities, Lesotho can achieve even higher savings especially, from the industrial customer categories whose consumption according to the data used in this study, seem to be dominating the rest of the categories. This position is further complemented by the existence of an investment plan in Lesotho that seeks to support and promote initiatives on load management and energy efficiency (Department of Energy, 2017).

The need for implementation of ToU tariffs as an enabler for voluntary load-shifting, which subsequently leads to better network management and reduction in system demand cannot be over-emphasized. Through the adoption of the ToU pricing approach, the Nordic Council of Ministers in 2017 reported a feasible load reduction of 8 MW in Sweden, and possible load-shifting flexibility of 1520 MW within the Nordic market (International Renewable Energy Agency., 2017). Another study conducted in Cyprus reported a reduction of 3.19% in summer consumption during peak periods as a result of the adoption of ToU tariffs (Venizelou et al., 2018). These results are comparable with the findings of this study where the proposed ToU tariffs have shown a feasible potential saving of approximately 3.2% in energy consumption when consumers shift 10% of their load from peak to off-peak periods, while 5% of load shifting has a potential to save 1.4% of bulk energy purchases.

6 Conclusion and recommendations

The study has been undertaken to determine ToU tariffs for the Lesotho Electricity Company to reflect correct pricing signals from bulk suppliers to end-users. The study employs the Gaussian mixture model to determine ToU time-periods and their respective prices. The time-periods are divided into off-peak, standard, and peak periods. Different customer categories have different durations of time-periods. This is attributed to the observed load profiles of different customer categories. For example, the duration of the peak period for HV-Industrial customers is from 00:00 – 10:00 a.m. while for Residential customers is from 05:00 – 07:00 and 18:30 – 19:00. Furthermore, different customer categories have different prices per period resulting in different price ratios. For example, price ratios for commercial and industrial LV customers are 0.54 : 1 : 1.26 and 0.44 : 1 : 3.85, respectively.

The study further carried 5% and 10% load-shifting scenarios, which resulted in the average energy saving of 1.4% and 3.2%, respectively. The average saving on customer bills under the two load shifting scenarios resulted in 2.6% and 5.2%, respectively. The resultant LEC bulk energy savings were 13 GWh and 30 GWh for the 5% and 10% load shifting scenarios, respectively. This amounted to LEC's bulk energy cost savings of M8.9 Million and M18.7 Million if Muela local generation is included in the energy mix for the two load shifting scenarios, respectively. On the contrary, if LEC procured bulk energy from imports only, without bulk Muela local generation, the energy cost savings would be M16.3 Million and M34.1 Million for two load shifting scenarios, respectively. The difference in LEC energy cost savings is due to the Muela energy prices which, are highly subsidized.

These determined ToU tariffs have the following implications; firstly, they provide an incentive for customers to engage in voluntary load-shifting by transferring their consumption from highly-priced peak-periods to standard and off-peak ones. This benefits the supply utility by helping to defer capital investment on the costly generation and supply infrastructure to meet short-term peak demand. On the other hand, customers are also able to take advantage of shifting their consumption to lower-priced periods. Thus, saving on the energy bills. Furthermore, the adoption of ToU tariffs will benefit LEC by aligning with its bulk suppliers and thereby sending correct pricing signals to end-users.

If the results of this study can be implemented, that will be able to generate empirical data which, will enable further research on the actual impact of ToU tariffs on customer load profiles considering Lesotho's country-specific factors such as, the declining average household consumption observed over the past decade. Furthermore, the generated data can facilitate studies on the impact of ToU tariffs on the LEC revenues.

Moreover, the findings in this study will guarantee long-term incentives for energy users to emabark on voluntary load-shifting, thereby, reducing unnecessary pressure on the national grid. This, clearly support the objectives of the Lesotho energy policy of 2015 that seeks to come up with interventions to promote energy efficiency and demand-side management.

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Appendix

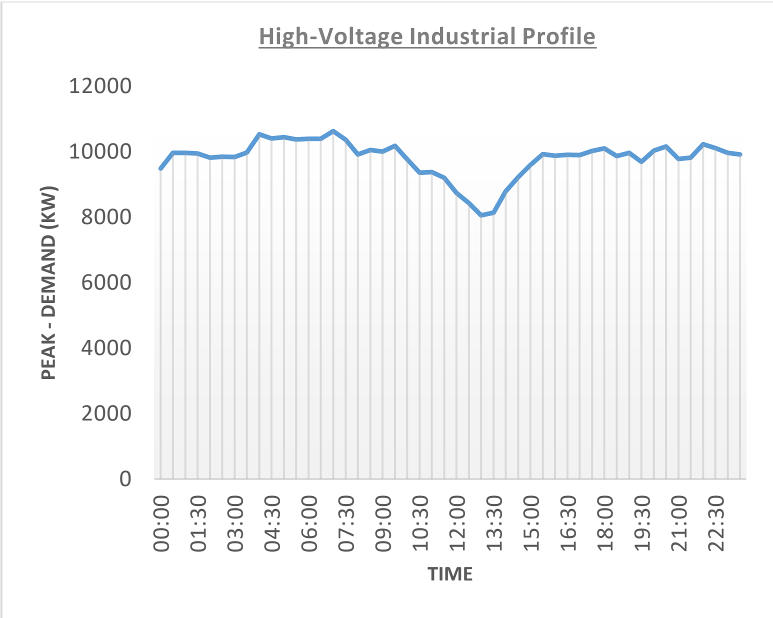

Figure 14: Average industrial high voltage load profile

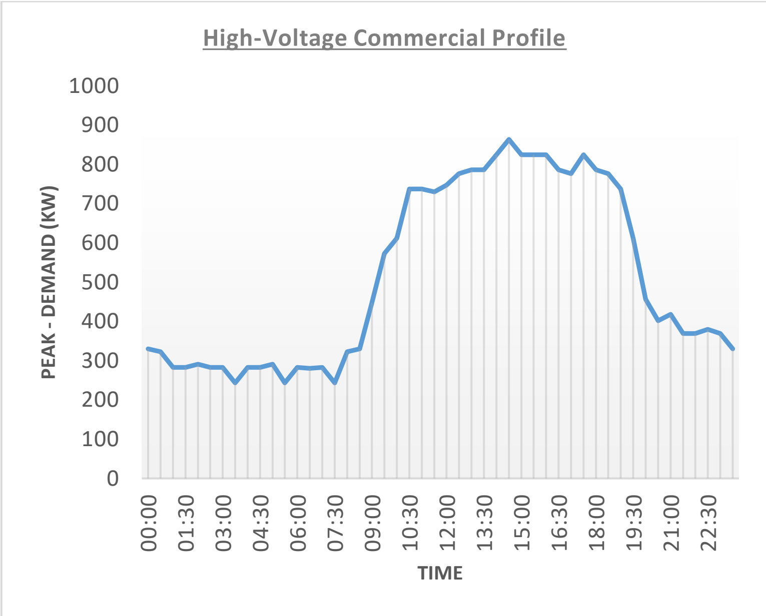

Figure 15: Average high voltage commercial load profile

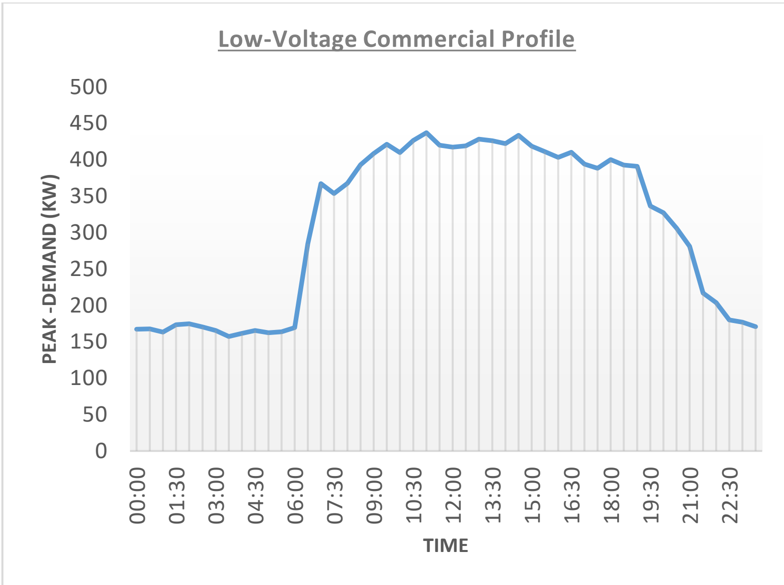

Figure 16: Average low voltage commercial load profile

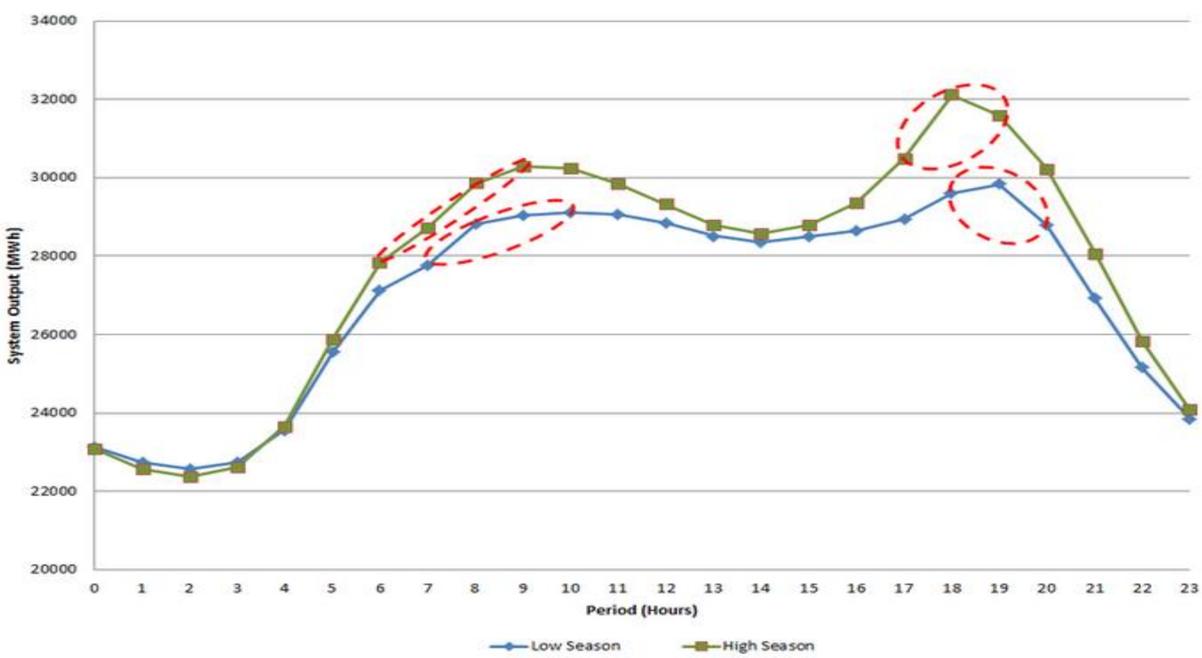

Figure 17: Typical Eskom load profile

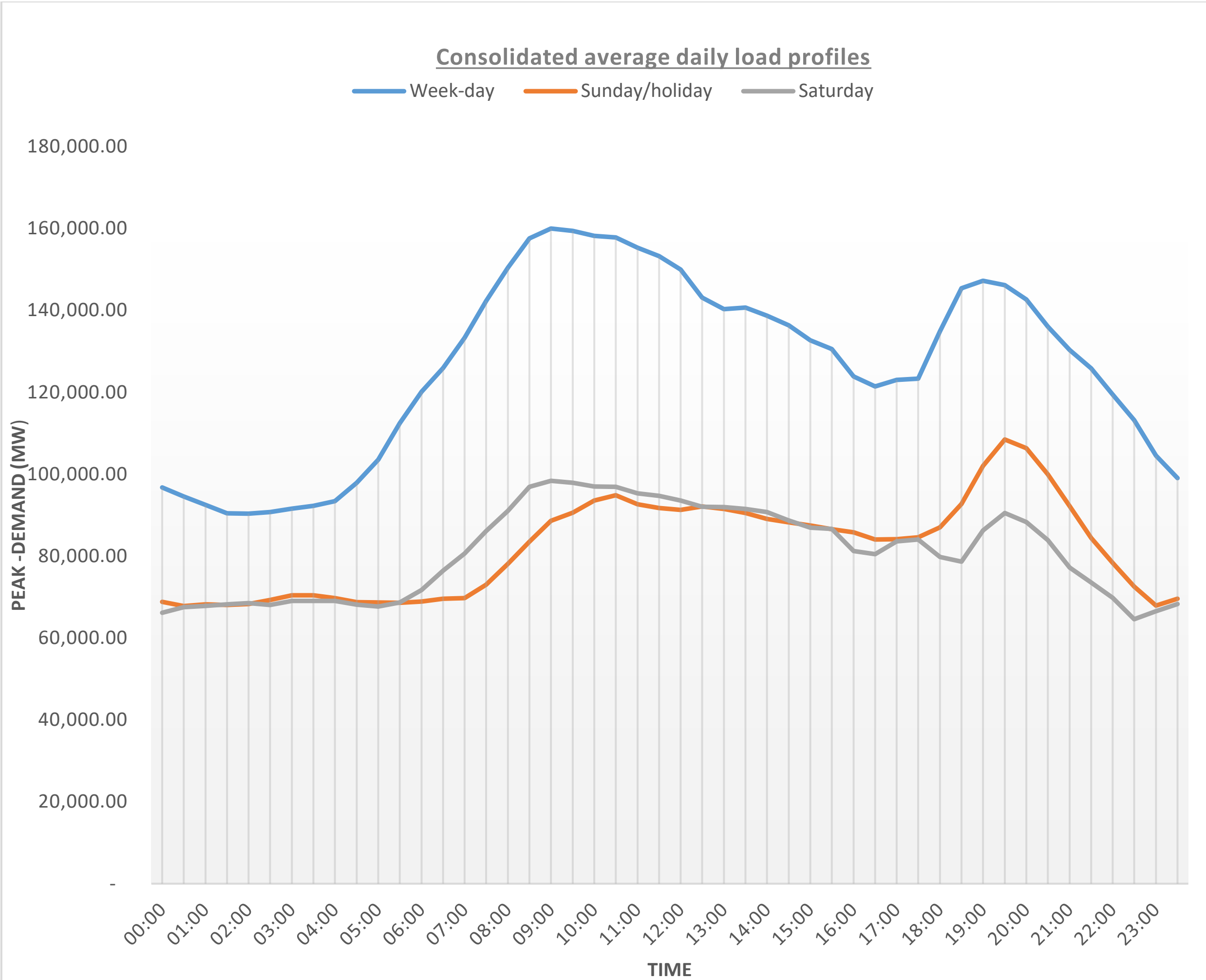

Figure 18: Consolidated Lesotho load profile

Table 11: Residential posterior probabilities

Observation	1	2	3	Class
Obs1	0.995	0.005	0.000	1
Obs2	0.994	0.006	0.000	1
Obs3	0.993	0.007	0.000	1
Obs4	0.991	0.009	0.000	1
Obs5	0.988	0.012	0.000	1
Obs6	0.986	0.014	0.000	1
Obs7	0.983	0.017	0.000	1
Obs8	0.981	0.019	0.000	1
Obs9	0.978	0.022	0.000	1
Obs10	0.655	0.012	0.333	1
Obs11	0.000	0.000	1.000	3
Obs12	0.000	0.000	1.000	3
Obs13	0.000	0.000	1.000	3
Obs14	0.000	0.000	1.000	3
Obs15	0.013	0.001	0.986	3
Obs16	0.908	0.086	0.006	1
Obs17	0.869	0.131	0.000	1
Obs18	0.828	0.172	0.000	1
Obs19	0.811	0.189	0.000	1
Obs20	0.727	0.273	0.000	1
Obs21	0.674	0.326	0.000	1
Obs22	0.662	0.338	0.000	1
Obs23	0.619	0.381	0.000	1
Obs24	0.538	0.462	0.000	1
Obs25	0.540	0.460	0.000	1
Obs26	0.457	0.543	0.000	2
Obs27	0.378	0.622	0.000	2
Obs28	0.291	0.709	0.000	2
Obs29	0.223	0.777	0.000	2
Obs30	0.199	0.801	0.000	2
Obs31	0.159	0.841	0.000	2
Obs32	0.141	0.859	0.000	2
Obs33	0.101	0.899	0.000	2
Obs34	0.101	0.899	0.000	2
Obs35	0.083	0.917	0.000	2
Obs36	0.083	0.917	0.000	2
Obs37	0.058	0.551	0.391	2
Obs38	0.000	0.000	1.000	3
Obs39	0.000	0.000	1.000	3
Obs40	0.030	0.970	0.000	2

Obs41	0.035	0.951	0.015	2
Obs42	0.026	0.971	0.003	2
Obs43	0.016	0.984	0.000	2
Obs44	0.010	0.990	0.000	2
Obs45	0.007	0.993	0.000	2
Obs46	0.005	0.995	0.000	2
Obs47	0.004	0.996	0.000	2
Obs48	0.003	0.997	0.000	2

Table 12: Industrial LV posterior probabilities

Observation	1	2	3	Class
Obs1	1.000	0.000	0.000	1
Obs2	1.000	0.000	0.000	1
Obs3	1.000	0.000	0.000	1
Obs4	1.000	0.000	0.000	1
Obs5	1.000	0.000	0.000	1
Obs6	1.000	0.000	0.000	1
Obs7	1.000	0.000	0.000	1
Obs8	1.000	0.000	0.000	1
Obs9	1.000	0.000	0.000	1
Obs10	1.000	0.000	0.000	1
Obs11	1.000	0.000	0.000	1
Obs12	1.000	0.000	0.000	1
Obs13	1.000	0.000	0.000	1
Obs14	1.000	0.000	0.000	1
Obs15	1.000	0.000	0.000	1
Obs16	0.000	0.000	1.000	3
Obs17	0.000	0.000	1.000	3
Obs18	0.000	0.000	1.000	3
Obs19	0.000	0.000	1.000	3
Obs20	0.000	0.000	1.000	3
Obs21	0.000	0.000	1.000	3
Obs22	0.000	0.000	1.000	3
Obs23	0.000	0.000	1.000	3
Obs24	0.000	0.000	1.000	3
Obs25	0.000	0.000	1.000	3
Obs26	0.962	0.038	0.000	1
Obs27	0.049	0.951	0.000	2
Obs28	0.000	0.000	1.000	3
Obs29	0.000	0.000	1.000	3
Obs30	0.000	0.000	1.000	3

Obs31	0.000	0.000	1.000	3
Obs32	0.000	0.000	1.000	3
Obs33	0.000	0.000	1.000	3
Obs34	0.000	0.000	1.000	3
Obs35	0.000	0.000	1.000	3
Obs36	0.000	1.000	0.000	2
Obs37	0.000	1.000	0.000	2
Obs38	0.000	1.000	0.000	2
Obs39	0.000	1.000	0.000	2
Obs40	0.000	1.000	0.000	2
Obs41	0.000	1.000	0.000	2
Obs42	0.000	1.000	0.000	2
Obs43	0.000	1.000	0.000	2
Obs44	0.000	1.000	0.000	2
Obs45	0.000	1.000	0.000	2
Obs46	0.000	1.000	0.000	2
Obs47	0.000	1.000	0.000	2
Obs48	0.000	1.000	0.000	2

Table 13: Commercial LV posterior probabilities

Observation	1	2	3	Class
Obs1	1.000	0.000	0.000	1
Obs2	1.000	0.000	0.000	1
Obs3	1.000	0.000	0.000	1
Obs4	1.000	0.000	0.000	1
Obs5	1.000	0.000	0.000	1
Obs6	1.000	0.000	0.000	1
Obs7	1.000	0.000	0.000	1
Obs8	1.000	0.000	0.000	1
Obs9	1.000	0.000	0.000	1
Obs10	1.000	0.000	0.000	1
Obs11	1.000	0.000	0.000	1
Obs12	1.000	0.000	0.000	1
Obs13	1.000	0.000	0.000	1
Obs14	0.999	0.000	0.001	1
Obs15	0.006	0.000	0.994	3
Obs16	0.023	0.000	0.977	3
Obs17	0.008	0.000	0.992	3
Obs18	0.002	0.000	0.998	3
Obs19	0.001	0.000	0.999	3
Obs20	0.001	0.000	0.999	3

Obs21	0.001	0.000	0.999	3
Obs22	0.000	0.000	1.000	3
Obs23	0.000	0.001	0.999	3
Obs24	0.000	0.000	0.999	3
Obs25	0.000	0.002	0.998	3
Obs26	0.000	0.006	0.994	3
Obs27	0.000	0.018	0.982	3
Obs28	0.000	0.053	0.947	3
Obs29	0.000	0.186	0.814	3
Obs30	0.000	0.222	0.778	3
Obs31	0.000	0.808	0.192	2
Obs32	0.000	0.983	0.017	2
Obs33	0.000	0.999	0.001	2
Obs34	0.000	0.999	0.001	2
Obs35	0.000	1.000	0.000	2
Obs36	0.000	1.000	0.000	2
Obs37	0.000	1.000	0.000	2
Obs38	0.000	1.000	0.000	2
Obs39	0.000	1.000	0.000	2
Obs40	0.000	1.000	0.000	2
Obs41	0.000	1.000	0.000	2
Obs42	0.000	1.000	0.000	2
Obs43	0.000	1.000	0.000	2
Obs44	0.000	1.000	0.000	2
Obs45	0.000	1.000	0.000	2
Obs46	0.000	1.000	0.000	2
Obs47	0.000	1.000	0.000	2
Obs48	0.000	1.000	0.000	2

Table 14: Commercial HV posterior probabilities

Observation	1	2	3	Class
Obs1	1.000	0.000	0.000	1
Obs2	1.000	0.000	0.000	1
Obs3	1.000	0.000	0.000	1
Obs4	1.000	0.000	0.000	1
Obs5	1.000	0.000	0.000	1
Obs6	1.000	0.000	0.000	1
Obs7	1.000	0.000	0.000	1
Obs8	1.000	0.000	0.000	1
Obs9	1.000	0.000	0.000	1
Obs10	1.000	0.000	0.000	1

Obs11	1.000	0.000	0.000	1
Obs12	1.000	0.000	0.000	1
Obs13	1.000	0.000	0.000	1
Obs14	1.000	0.000	0.000	1
Obs15	1.000	0.000	0.000	1
Obs16	1.000	0.000	0.000	1
Obs17	1.000	0.000	0.000	1
Obs18	1.000	0.000	0.000	1
Obs19	1.000	0.000	0.000	1
Obs20	0.003	0.000	0.997	3
Obs21	0.000	0.000	1.000	3
Obs22	0.000	0.000	1.000	3
Obs23	0.000	0.000	1.000	3
Obs24	0.000	0.000	1.000	3
Obs25	0.000	0.000	1.000	3
Obs26	0.000	0.000	1.000	3
Obs27	0.000	0.000	1.000	3
Obs28	0.000	0.000	1.000	3
Obs29	0.000	0.000	1.000	3
Obs30	0.000	0.000	1.000	3
Obs31	0.000	0.000	1.000	3
Obs32	0.000	0.000	1.000	3
Obs33	0.000	0.000	1.000	3
Obs34	0.000	0.000	1.000	3
Obs35	0.000	0.000	1.000	3
Obs36	0.000	0.000	1.000	3
Obs37	0.000	0.000	1.000	3
Obs38	0.000	0.000	1.000	3
Obs39	0.000	0.000	1.000	3
Obs40	0.000	0.086	0.914	3
Obs41	0.000	1.000	0.000	2
Obs42	0.000	1.000	0.000	2
Obs43	0.000	1.000	0.000	2
Obs44	0.000	1.000	0.000	2
Obs45	0.000	1.000	0.000	2
Obs46	0.000	1.000	0.000	2
Obs47	0.000	1.000	0.000	2
Obs48	0.000	1.000	0.000	2

Table 15: Industrial HV posterior probabilities

Observation	1	2	3	Class
Obs1	0.000	0.000	1.000	3
Obs2	0.000	0.000	1.000	3
Obs3	0.000	0.000	1.000	3
Obs4	0.000	0.000	1.000	3
Obs5	0.000	0.000	1.000	3
Obs6	0.000	0.000	1.000	3
Obs7	0.000	0.000	1.000	3
Obs8	0.000	0.000	1.000	3
Obs9	0.000	0.000	1.000	3
Obs10	0.000	0.000	1.000	3
Obs11	0.000	0.000	1.000	3
Obs12	0.000	0.000	1.000	3
Obs13	0.000	0.000	1.000	3
Obs14	0.000	0.000	1.000	3
Obs15	0.000	0.000	1.000	3
Obs16	0.000	0.000	1.000	3
Obs17	0.000	0.000	0.999	3
Obs18	0.000	0.000	1.000	3
Obs19	0.000	0.001	0.998	3
Obs20	0.000	0.002	0.998	3
Obs21	0.045	0.036	0.919	3
Obs22	0.971	0.015	0.015	1
Obs23	0.964	0.026	0.010	1
Obs24	0.993	0.006	0.000	1
Obs25	1.000	0.000	0.000	1
Obs26	1.000	0.000	0.000	1
Obs27	1.000	0.000	0.000	1
Obs28	1.000	0.000	0.000	1
Obs29	1.000	0.000	0.000	1
Obs30	0.938	0.062	0.000	1
Obs31	0.166	0.834	0.000	2
Obs32	0.004	0.996	0.000	2
Obs33	0.005	0.995	0.000	2
Obs34	0.003	0.997	0.000	2
Obs35	0.002	0.998	0.000	2
Obs36	0.000	1.000	0.000	2
Obs37	0.000	1.000	0.000	2
Obs38	0.001	0.999	0.000	2
Obs39	0.000	1.000	0.000	2
Obs40	0.003	0.997	0.000	2

Obs41	0.000	1.000	0.000	2
Obs42	0.000	1.000	0.000	2
Obs43	0.000	1.000	0.000	2
Obs44	0.000	1.000	0.000	2
Obs45	0.000	1.000	0.000	2
Obs46	0.000	1.000	0.000	2
Obs47	0.000	1.000	0.000	2
Obs48	0.000	1.000	0.000	2