TRIBHUVAN UNIVERSITY

KHWOPA COLLEGE OF ENGINEERING

DEPARTMENT OF ELECTRICAL ENGINEERING

Libali-2, Bhaktapur, Nepal

A

MID TERM PROGRESS REPORT

ON

“ IMPACT OF TIME OF USE OF ELECTRICITY PRICING IN POWER SYSTEM LOSS AND NODE VOLTAGE ”

(as a partial fullfillment of Bachelor’s Degree in Computer Engineering)

(Course Code: EE755)

Project Members

Mani Niraula	073BEL20
Prabesh Raj Ojha	073BEL26
Sunil Simkhada	073BEL45
Yogesh Layalu	073BEL48

Febraury, 2020

ACKNOWLEDGEMENT

We would like to appreciate **Er. Rakesh Gwachha**, HoD, Department of Electrical Engineering, for providing us an opportunity to do the project and giving us all support and guidance despite of his busy schedule. We are highly obliged to **Er. Ashish Shrestha** who took keen interest on our proposal and guided us all along by providing all the necessary information for moving on our project ahead. We would like to express our deepest gratitude to the entire lecturer for their suggestions and encouragement. We would like to express our gratitude to Khwopa College of Engineering for the opportunity of undertaking the Fourth Year Project.

Abstract

This project proposes an analytical method that incorporates the time of use (TOU) strategy into the reliability evaluation, power system loss and node voltage. Traditional utility prices involve a set rate per kilowatt-hour, which can fluctuate during the summer and winter. A sliding rate scale, however, is structured according to peak and off-peak times of day. It enables the reduction of peak valley difference of a load curve, economizes the electricity cost, and eases energy consumption for the customers. We will use RBTS as test system in our project.
Keywords:*Time of Use electricity, Power system reliabiblity, Power system loss, RBTS*

TABLE OF CONTENTS

List of Figures

1 Intoduction

Traditional utility prices involve a set rate per kilowatt-hour, which can fluctuate during the summer and winter. A sliding rate scale, however, is structured according to peak and off-peak times of day. This is called a “time-of-use” (TOU) rate plan. Under such a plan, your bill will be determined by how much energy you use and when you use it. The prices and peak times vary based on the season and day of the week; for example, many utility companies consider weekends off-peak. The structure often looks different in the summer or winter months, with more tiers to accommodate the increase in HVAC system use as everyone tries to cool off or stay warm.

2 Problem Statement

Every power generation plant can generate a fixed quantity of power. However, energy demand cannot be fixed. It varies from time to time which destabilizes the utility. Demand response (DR) program is designed to cope with the load balancing problem. To minimize the extensive usage of electricity during on-peak hours (i.e., energy demand increases). The DR program encourages the user to shift the load from on-peak hours and get incentives. TOU tariff is the most common pricing scheme among others. The TOU tariff is divided into three blocks: peak, flat and valley hours. Although, TOU tariff can reduce the peak-load of electricity demand. However, almost zero energy consumption is observed during some peak period. Zero energy consumption means no revenue. To achieve the better performance, an energy management controller is required to schedule the load in mean level. The electricity price for load shifting consumer is the same as other consumers and reducing the peak mean improving the reliability of the system and reducing the loss of system.

An equal step length iteration method is used to compute peak, flat and valley period and use analytical method to compute voltage fluctuation and losses of system.

3 Objective of Project

The main objective of this project is to evaluate power system loss percentage and voltage fluctuation before and after considering TOU and compare with our conventional method of tariff system. We have divided objective in two parts.

Major Objective

- To analyze impact of TOU on power system loss and node voltage

Specific Objective

- To draw load curve
- To obtain optimal period partition
- To calculate power loss and node voltage before and after considering TOU

4 Scope of Project

It is one of the best tools for demand side management and its scope is in the reduction of system loss by implementing TOU also play important role.

5 Literature Review

TOU electricity pricing is a relatively new field which has attracted attention from researchers. When firms use dynamic pricing in order to match demand with the inventory or capacity, the creation of price differences between segments may cause consumers to switch (from higher priced segments to lower priced segments).

The demand response (DR) program has a significant influence on improving the reliability of electrical distribution systems and alleviating the electricity shortage during the peak Period [1] [2] [3] [4] . TOU Programme has been widely used in the electrical Power system. After carrying out a TOU electricity price program, the electrical energy consumption behavior of customers will be changed through increasing load demand during the valley period and reducing load demand during the peak period [5] [6] . Thus by the use of TOU programme it helps in economic use of the system and maintain the utilization rate of the electrical equipment. The existing literatures related to TOU strategies primarily focused on two aspects, i.e., the period partitioning and the TOU electricity pricing optimization. Time varying prices by motivating customers to reduce their consumption in peak periods propel the electricity industry towards a higher efficiency compared to that of common flat prices [7]. Traditional k-means algorithm [8] and bisecting k-means algorithm [9] are used for period Partitioning, load forecasting and probabilistic power flow analysis.

Our specific objective is to make an analysis on the impact of TOU strategy on the voltage quality and the power loss of the electrical distribution system. Here in our project the work are divided into the three parts, firstly a period partitioning algorithm based on the moving variable boundary technique is used for overcoming the instability of traditional clustering algorithms and improving the efficiency of the period partitioning. Secondly, an optimal TOU pricing model is proposed by minimizing the peak-valley difference with the help of RMSD (root mean square distance). Thirdly the reliability indices are defined for considering the impact of TOU strategy and improving the power quality and the power loss. Finally, the system is tested on IEEE-6 bus system for the validation of the proposed method.

The price elasticity matrix of the demand is composed of elasticity coefficients which describe the ratio of electrical energy variation and to the price variation. The electricity consumption is not only related to the current period but also to the other periods. Elasticity coefficients of demand are divided into self-Elasticity and Cross-Elasticity coefficient [10] . A self-elasticity coefficient relates the load and price at the same time while cross elasticity coefficients relate the load and price at different times [7]. To capture the elastic behavior of load in response to the time varying prices, a price elasticity matrix with self-elasticity and cross-elasticity coefficients equal to -0.2 and 0.0087 is utilized, respectively [11] .

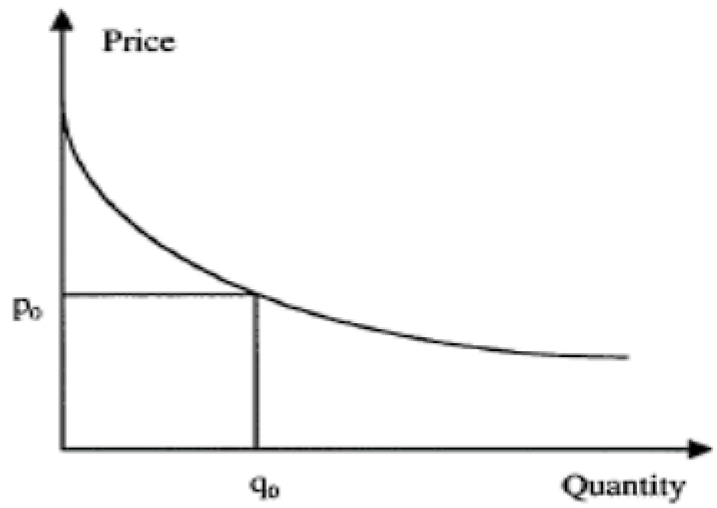

Figure 1: ***Typical Demand Curve***

The demand for most commodities decreases as the price of the commodity increases as illustrated by the demand curve sketched on Fig 1.

The diagonal elements of this matrix represent the self-elasticity and the offdiagonal elements correspond to the cross elasticity. Column of this matrix indicates how a change in price during the single period affects the demand during all the periods. If the only nonzero elements in this column are above the diagonal, the consumers react to a high price by bringing forward their consumption. If they are below the diagonal, they postpone their consumption until after the high price period. If consumers have the ability to reschedule their production over a long period, the nonzero elements will be spread widely over the column. On the other hand, if their flexibility is limited, the nonzero elements will be clustered around the diagonal. Some customers may also decide that, if they have to reschedule their electricity consumption, they might as well take advantage of the hours of lowest prices, which typically are in the early hours of the morning [12].

6 Methodology

Here, we will use RBTS as test system and if required data are unavailable data will be assumed from related research papers and following are the steps to calculate the node voltage and percentage power loss by considering time of use of electricity.

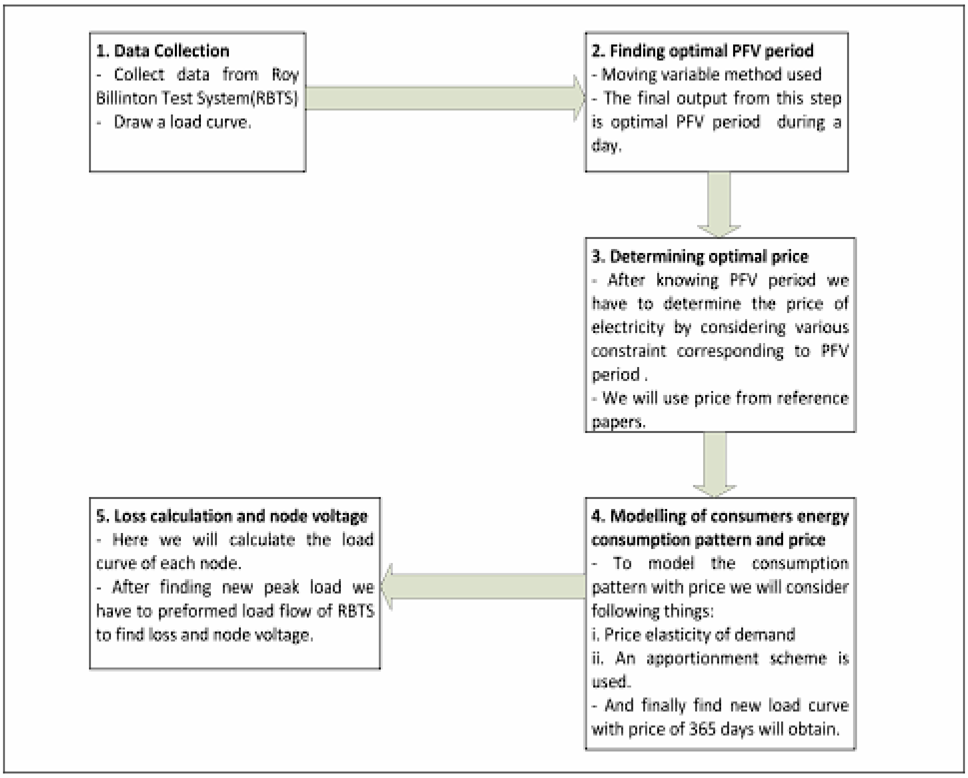

Figure 2: ***Block diagram of proposed project***

6.1 Optimal Period Partition

Hourly load curve of a day can be divided into peak flat and valley period [13] .Equal step length iteration algorithm is used to optimize the period partitioning [14] is used in our project. Optimized period partition is divided into two parts.

6.1.1 Peak flat valley period partition

Let $\{Pt,t = 1,2...24\}$ be the hourly load sequence for a day. t = 1 denotes the hour period from midnight to 1 am. The subsequent hour periods are defined ac- cordingly. P_{min} denotes the minimum of the sequence and P_{max} the maximum. Assume that m_1, m_2, and, m_3, which belong to the interval $[P_{min}, P_{max}]$ repre- sent three moving variables related to the peak, the flat, and the valley periods, respectively.

let m_j (j = 1, 2 , 3) be the decision variables and the root mean square distance (RMSD) between P_t and m_j as the objective function [15]. An optimal period partition model of a typical day can be established by the following optimization problem:

$$MinRMSD = \sqrt{\frac{1}{24}\sum_{t=1}^{24}(P_t - \sum_{j=1}^{3}(\theta_j m_{j|P_t \varepsilon G_j}))^2} \tag{1}$$

where,

$$\left\{ \begin{array}{c} m_1 - m_2 > 0 \\ m_2 - m_3 > 0 \\ P_{min} \leq m_j \leq P_{max} \end{array} \right\} \tag{2}$$

Where, $j = 1, 2, and 3$ represent the peak, flat, and valley periods, respectively, and G_j is the load set of the j^{th} period; if $4p_t$ is the element of $G_j, \theta_j = 1$, otherwise $\theta_j = 0$.

6.1.2 Optimization of peak flat valley period partition

This section presents an optimization method for the PFV partition model based on an equal step length iteration technique.Let the moving variables m_1, m_2 and m_3 gradually move from $P_{min} to P_{max}$ with an equal step length, and keep $m_3 < m_2 < m_1$. The interval $[P_{min}, P_{max}]$ is divided into N equal parts.

Steps:

1. Setting equal step length

$$\Delta_m = \frac{P_{max} - P_{min}}{N}$$

2. Initializing the moving variable as:

   $m_3 = P_{min}, m_2 = P_{min} + \Delta_m, m_1 = P_{min} + 2\Delta_m. Let, K_3 = 0, K_2 = 1, K_1 = 2$

3. Calculating moving variables as:

$$m_3 = P_{min} + K_3\Delta_m \;\; or \;\; m_2 = P_{min} + K_2\Delta_m \;\; or \;\; m_1 = P_{min} + K_1\Delta_m$$

4. Form the period sets for peak:

   Form the sets for the peak ,the valley and the flat period.Calculate the distance between each hourly load (t=1,2,3..24) and moving variable m_1, m_2 and m_3 respectively. Classify the t^{th} hour into peak period sets G_1, the flat period sets G_2 and the valley period sets G_3 according to the shortest distance principle.

$$\left\{t\varepsilon\left\{G_1\right\}, if \mid P_t - m1 \mid = min \;\; \left\{\mid P_t - m_j \mid j = 1,2,3\right\}\right\}$$
$$\left\{t\varepsilon\left\{G_2\right\}, if \mid P_t - m2 \mid = min \;\; \left\{\mid P_t - m_j \mid j = 1,2,3\right\}\right\}$$
$$\left\{t\varepsilon\left\{G_3\right\}, if \mid P_t - m3 \mid = min \;\; \left\{\mid P_t - m_j \mid j = 1,2,3\right\}\right\}$$

5. Calculation of the RMSD iteratively

6. Termination criterion of iteration if

   $m_3 = P_{min} + (N-2)\Delta m, m_2 = P_{min} + (N-1)\Delta m, and m_1 = P_{max}$

$$Let, k_1 = k_1 + 1 \;\; or \;\; k_2 = k_2 + 1 \;\; or \;\; k_3 = k_3 + 1$$

7. Output the optimal period partitioning results The partition that has minimum RMSD is the optimal PFV period partition. Let G_1, G_2, G_3 be peak partitioned peak, flat and valley respectively.

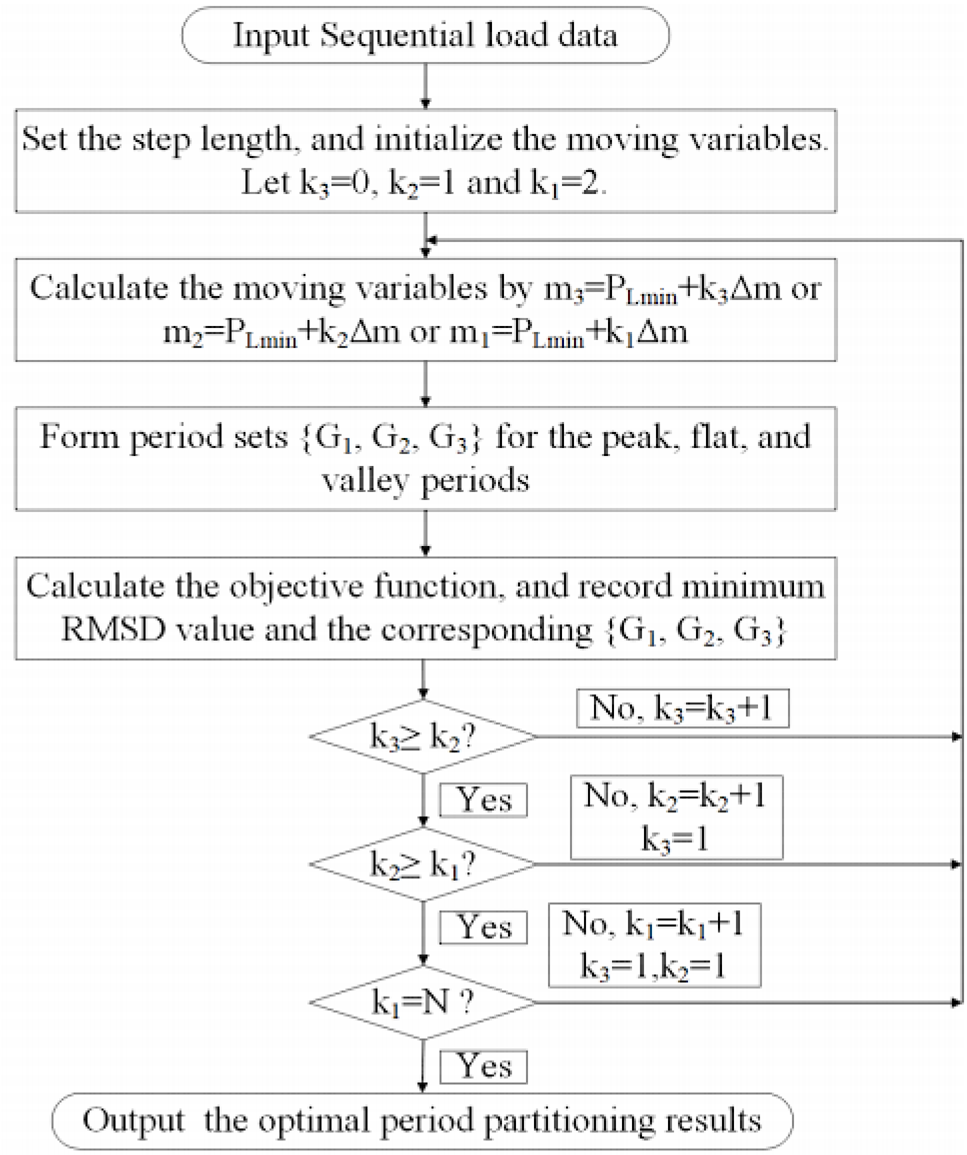

Figure 3: ***Flowchart of Peak Flat Valley period partition***

7 Results

The RTS and RBTS systems are used for the required data. The proposed method was implemented in MATLAB software.

7.1 Draw Load Curve

Hourly sequential data to draw load curve is taken from RTS system which is shown in Table 1 below.

Table 1: Sequential Data

S.N.	Hour	Load in per unit	S.N.	Hour	Load in per unit
1	12-1 am	0.67	13	Noon-1 pm	0.95
2	1-2 am	0.63	14	1-2 pm	0.95
3	2-3 am	0.6	15	2-3 pm	0.93
4	3-4 am	0.59	16	3-4 pm	0.94
5	4-5 am	0.59	17	4-5 pm	0.99
6	5-6 am	0.6	18	5-6 pm	1
7	6-7 am	0.74	19	6-7 pm	1
8	7-8 am	0.86	20	7-8 pm	0.96
9	8-9 am	0.95	21	8-9 pm	0.91
10	9-10 am	0.96	22	9-10 pm	0.83
11	10-11 am	0.96	23	10-11 pm	0.73
12	11-Noon	0.95	24	11-12 pm	0.63

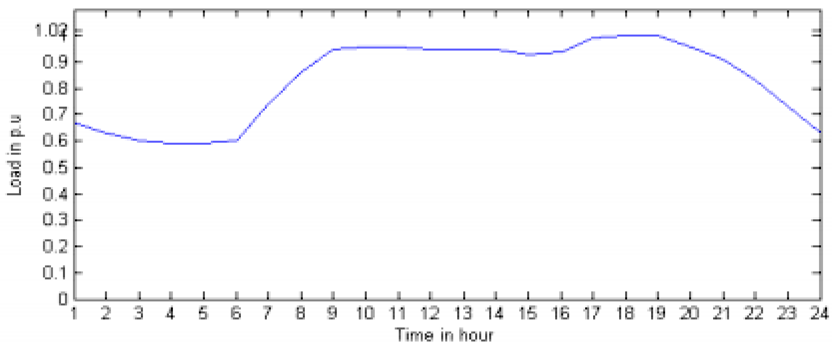

Figure 4: ***Load Curve***

7.2 Period Partition

The normalized sequential load data are provided from the RTS system to construct the period partition. After drawing load curve, we used equal step length iteration for peak, flat, valley period partition. The partitioned load curve is shown below:

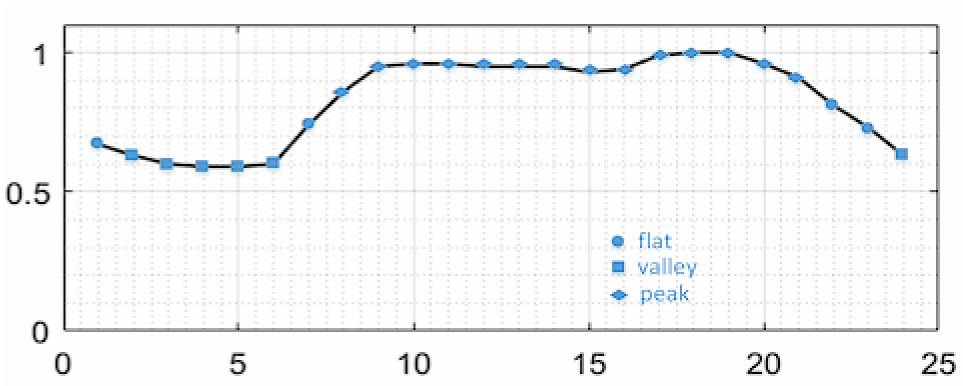

Figure 5: ***Partitioned load curve in peak, flat and valley period***

8 Conclusion

We took the data from the RBTS and plotted the load curve before implementing Time of Use Of electricity (TOU) and after drawing load curve, we used equal step length iteration for peak, flat, valley period partition.

References

[1] P. Yang, G. Tang, and A. Nehorai, "A game-theoretic approach for optimal time-of-use electricity pricing," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 884–892, 2012.

[2] J.-N. Sheen, C.-S. Chen, and J.-K. Yang, "Time-of-use pricing for load management programs in taiwan power company," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 388–396, 1994.

[3] B. Zhou, R. Yang, C. Li, Y. Cao, Q. Wang, and J. Liu, "Multiobjective model of time-of-use and stepwise power tariff for residential consumers in regulated power markets," *IEEE Systems Journal*, vol. 12, no. 3, pp. 2676–2687, 2017.

[4] B. Zeng, X. Wei, D. Zhao, C. Singh, and J. Zhang, "Hybrid probabilistic-possibilistic approach for capacity credit evaluation of demand response considering both exogenous and endogenous uncertainties," *Applied energy*, vol. 229, pp. 186–200, 2018.

[5] R. Li, Z. Wang, S. Le Blond, and F. Li, "Development of time-of-use price by clustering techniques," in *2014 IEEE PES General Meeting— Conference & Exposition*. IEEE, 2014, pp. 1–5.

[6] E. Celebi and J. D. Fuller, "Time-of-use pricing in electricity markets under different market structures," *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1170–1181, 2012.

[7] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "A medium-term decision model for discos: Forward contracting and tou pricing," *IEEE Transactions on Power Systems*, vol. 30, no. 3, pp. 1143–1154, 2014.

[8] Z. Ren, K. Wang, W. Li, L. Jin, and Y. Dai, "Probabilistic power flow analysis of power systems incorporating tidal current generation," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 3, pp. 1195–1203, 2017.

[9] X.-Z. Liu and G.-C. Feng, "Kernel bisecting k-means clustering for svm training sample reduction," in *2008 19th International Conference on Pattern Recognition*. IEEE, 2008, pp. 1–4.

[10] H. Yang, L. Wang, and Y. Ma, "Optimal time of use electricity pricing model and its application to electrical distribution system," *IEEE Access*, vol. 7, pp. 123 558–123 568, 2019.

[11] D. S. Kirschen, "Demand-side view of electricity markets," *IEEE Transactions on power systems*, vol. 18, no. 2, pp. 520–527, 2003.

[12] D. S. Kirschen, G. Strbac, P. Cumperayot, and D. de Paiva Mendes, "Factoring the elasticity of demand in electricity prices," *IEEE Transactions on Power Systems*, vol. 15, no. 2, pp. 612–617, 2000.

[13] Y. Cao, S. Tang, C. Li, P. Zhang, Y. Tan, Z. Zhang, and J. Li, "An optimized ev charging model considering tou price and soc curve," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 388–393, 2011.

[14] H. Yang, L. Wang, Y. Zhang, H.-M. Tai, Y. Ma, and M. Zhou, "Reliability evaluation of power system considering time of use electricity pricing," *IEEE Transactions on Power Systems*, vol. 34, no. 3, pp. 1991–2002, 2018.

[15] I. H. Witten and E. Frank, "Data mining: practical machine learning tools and techniques with java implementations," *Acm Sigmod Record*, vol. 31, no. 1, pp. 76–77, 2002.