PLATFORM - A Journal of Engineering

DOI: https://doi.org/10.61762/pajevol9iss1art008

Received: 23 September 2024, Revised: 20 March 2025, Accepted: 22 March 2025, Published: 31 March 2025, Publisher: UTP Press, Creative Commons: CC BY 4.0

BI-LEVEL ENERGY DISPATCH OPTIMISATION FOR PEAK LOAD SHAVING IN MICROGRIDS WITH BATTERY STORAGE

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ABSTRACT

Peak load periods in electrical networks result in significant power losses, straining generation capacity, and increasing operational costs. Strategically optimising electricity supply from battery storage-based distributed generation (DG) during these peak times can mitigate these losses and enhance grid efficiency through peak load shaving (PLS). However, electrical loads vary throughout the day and night. Thus, identifying peak and off-peak loads would be the most challenging task to complete before scheduling operations for batteries. This study presents a bi-level energy optimisation framework to identify the peak and off-peak loads and plan the energy dispatching operations for battery storage. The bi-level energy optimisation framework is developed in such a way that during the first level, peak load times (PLT), off-peak load times (OPLT), and no operation times (NOT) from the daily time-varying load profiles are identified. During the second level, scheduling of energy supply to and from the batteries is performed using a seven-stage battery dispatch controller. Considering the reduction in power losses as a primary objective function, the genetic algorithm (GA) is used to solve the optimisation problem for three time-varying load profiles (industrial, residential, and commercial) using an IEEE 33 bus microgrids network. The numerical results for three case studies have revealed that the proposed method could significantly shave the peak loads by 23.3% in industrial, 18.89% in residential and 10.99% in commercial loads. Due to the shaving of peak loads, the reductions in power loss of 5.73%, 5.44%, and 2.45% in each load profile are also noticed. To further validate the efficacy, the results from the optimisation framework were compared with results using fixed values. The comparison showed that the proposed optimisation approach could achieve maximum peak shaving in microgrids. The PLS, reduction in daily power losses, improvement in load factors, and enhancements in bus voltage profiles for each load confirm that the proposed optimisation approach can be helpful in the future planning of PLS in microgrids.

***Keywords**: Battery energy storage systems, genetic algorithm (GA), microgrids, peak load shaving, power loss minimisation*

INTRODUCTION

The electrical networks of communities mixed with residential and commercial loads ranging from a few kilowatts (kW) to some megawatts (MW) powered by electric power sources are known as microgrids (MGs) [1]. Universities with built-in small power stations are good examples of MGs. According to the literature, diesel gen-sets, gas turbines, solar photovoltaic (PV) modules, wind turbines, and battery energy storage are the primary power sources for MGs [2]. The MGs can operate in islanded and grid-connected modes [3]. In islanded mode, the generators deliver the electricity to the whole network alone.

In contrast, in the grid-connected mode, MGs are connected to national or neighbouring grids to sell and purchase electricity according to specific conditions. Since the electrical loads in communities and universities vary throughout the days and seasons, MGS must schedule the supply from generators to tackle the changes in normal loads and during peak loads. Due to the varying loads, MGs are usually equipped with multiple generators, so some generators, also known as base generators, are installed to deliver the electricity for base loads, while the remaining generators, also known as peaking generators, are installed to generate the electricity for the peak loads. Peaking generators are usually fast, responsive, but expensive sources of electricity, which can take a few seconds to minutes to reach an acceptable power output level [4]-[5]. Usually, peak loads in the grid are observed for a short time, such as turning ON many air conditioners for a few hours during a hot day or turning ON many home appliances during sunset when people return home. An example of an electrical demand curve with a short time load is shown in Figure 1. From this, it is known that peaking generators usually operate fewer times than base generators. Therefore, it is necessary to size peaking expensive generators in MGs appropriately, as undersized generators may result in an imbalanced supply of electricity.

In contrast, oversized generators will require massive investment and incur operation and maintenance costs (O&M). One way to reduce the peaking generator operation is to use the peak load shaving (PLS) technique. The PLS technique helps reduce the peak loads in the network, ultimately reducing the burden on peak generators.

The PLS in the MGs can be achieved in different ways. The most commonly used methods are the use of solar photovoltaic (PV) energy, which usually supplies electricity during peak times, and the use of demand-side management (DSM) or demand response (DR) method, which is done by swapping flexible loads from peak to off-peak load hours and, the use of battery energy storage; which stores the electricity in off-peak load times (OPLTs) and supply the electricity during the peak load times (PLTs) [5].

The use of batteries for PLS in MGs is motivated by recent research about the integration of batteries at the distribution level. Batteries have been widely utilised for various applications in the past. However, in recent years, the use of batteries has started gaining more importance due to the integration of renewable energy sources in electrical networks. In addition to supplying bulk electricity, batteries are suitable for increasing the penetration of renewable energy, enhancing network reliability, improving network power quality, and achieving PLS in MGs [7]. Due to the installations of renewable energy power projects worldwide, batteries are expected to become a primary power source component to deliver reliable electricity for electrical networks. The cost of renewable energy components, such as PV modules, is also expected to decrease in the coming years.

Some recent studies have been reported on using batteries for PLS in MGs. A phase-wise day-ahead dispatch of batteries in [8] has shown positive results in better PLS and load levelling in low-voltage unbalanced distribution networks. The control of battery operation depended on a Characteristic Daily Load Profiles (CDLPs)

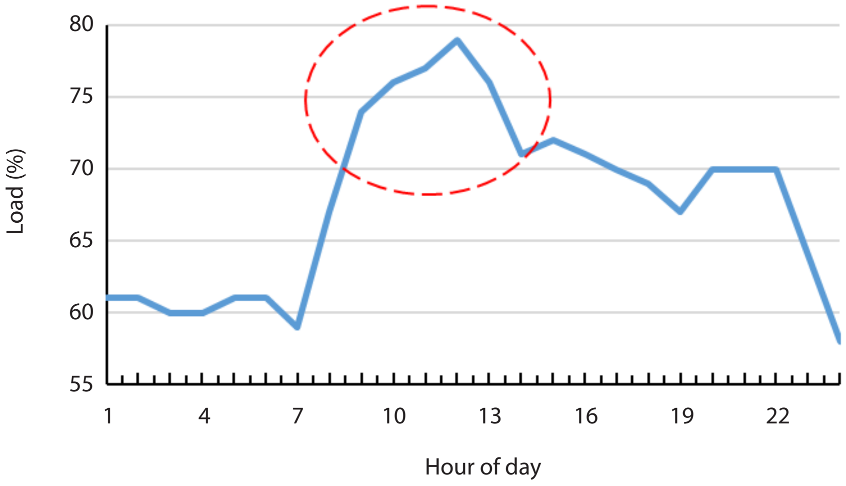

Figure 1 Electrical demand with short time peak [6]

approach. Using a 500 kWh battery energy storage system (BESS) of 10 units helped reduce the peak residential, commercial, and industrial loads from 1.1 p.u to 0.57 p.u.

The study in [9] employed a 1100 kWh / 1 MW BESS, charged by PV generation, for PLS and load smoothing of an actual distribution circuit on the island of Maui, Hawaii. Load forecasting was performed using Complex-Valued Neural Networks (CVNN) and series-parallel to filter the peak and off-peak loads. A control mixed with a non-linear programming method was applied to charge the batteries in the morning and discharge them at night. Since the charging and discharging operation follows the predetermined load values, the limitation of this study was reliable forecasting of daily load, which was required to utilise the BESS system effectively.

A data-driven forecasting method based on fuzzy logic (FL) for optimised peak load reduction in [10] was performed using a PV-BESS hybrid system. The energy generated by PV determines the size of the BESS capacity. An adaptive neuro-fuzzy inference system (ANFIS) was performed for the load forecasting.

The research in [11] considered a 500 Ah/600 V lithium batteries-based BESS for peak load shaving in a grid-connected MG using linear programming for problem-solving. The study suggested the benefits of using BESS when applied in a grid with a time-of-use tariff scheme. However, battery charge and discharge operation mainly depended on time-of-use (TOU) pricing.

Furthermore, a 1 MWh BESS in [12] was used for peak load reduction in a feeder. The distribution of peak load hours took place using probability from the load profiles. An MG study using three power units with a cumulative battery energy storage of 1.1 MWh was proposed for the distribution networks [13]. A bi-level multi-objective optimisation was performed using a hybrid approach. Their study adopted the TOU pricing strategy for charging and discharging batteries to perform PLS. The summary of literature for similar works used for PLS in MGs is provided in Table 1.

The batteries can be charged and discharged at any time; however, proper charge and discharge of batteries can provide better results such as PLS, minimisation of power losses, and reduction in the cost of electricity. Efficient discharging of batteries during peak load could turn off peaking generators. Similarly, efficient controlled charging of batteries during low load hours can help operate electrical generators to run efficiently. The main problem in PLS studies is identifying peak and off-peak load hours. The literature review of several studies reveals that the operation of PLS mainly depends on load forecasting and TOU pricing. Load forecasting can normalise the historical load to predict following-day load curves. However, this technique cannot identify a threshold between peak and off-peak loads. In most studies, batteries are charged and discharged in a fixed condition. On the other hand, TOU pricing varies with time and geographical location, so the TOU of one region cannot be applied to the different areas.

Battery is an effective and reliable solution for several power system applications. Batteries can also help in PLS and MGs. However, an effective PLS operation is limited to prior information about the timings of

Table 1 Methods for PLS using batteries in MGs

Ref	BESS size	System Network	Peak shaving approach
[8]	500 kWh	IEEE 37 node	Characteristic Daily Load Profiles (CDLPs)
[9]	1100 kWh	Island of Maui in Hawaii (unknown buses)	Load forecasting using two methods; Complex-Valued Neural Networks (CVNN) and series-parallel
[10]	54 kWh	Single node-based load	Load forecasting using adaptive neuro-fuzzy inference system (ANFIS)
[11]	300 kWh	Single node-based load	Using time-of-use pricing (TOU)
[12]	1 MWh	University of California MG	Distribution of peak load hour using probability from load profile
[13]	1.1 MWh	Modified IEEE-33 bus	Minimising the variance of net load

peak and off-peak loads. The existing literature about determining the peak and off-peak load timings for PLS in MGs reveals serious loopholes, resulting in charging and discharging batteries inappropriately. Such approaches have limited the efficient use of batteries to achieve maximum benefits from PLS in MGs. The loopholes in identifying peak and off-peak load hours necessitate finding suitable methods that can easily be used for PLS in MGs in any region.

Existing approaches primarily rely on load forecasting techniques, such as CDLPs, neural networks, and fuzzy logic, or depend on TOU pricing strategies to determine charging and discharging schedules. However, these methods often lack adaptability to different microgrid settings, as TOU-based strategies are region-specific, and forecasting models require accurate historical data. Additionally, most prior studies implement fixed conditions for battery dispatch, limiting their effectiveness in dynamic microgrid environments. This study introduces a bi-level optimisation framework that autonomously identifies peak and off-peak load periods based on real-time demand variations to address these limitations. Moreover, the proposed seven-stage battery dispatch controller enhances flexibility by dynamically adjusting battery charge and discharge operations, improving peak shaving efficiency and minimisation of power loss. This novel approach ensures a more generalised and adaptable PLS strategy, making it suitable for diverse microgrid configurations.

METHOD AND MATERIALS

This research aims to develop a method to determine PLT, OPLT, and no operation time (NOT) to perform an efficient peak load PLS in microgrids MGs. An optimisation framework is developed to determine the discharge threshold value (DTV) and charge threshold value (CTV) for the charging, discharging, and resting battery energy storage. The batteries are charged, discharged, and taken in rest mode to minimise the power losses in MGs.

The values of DTV and CTV are a percentage of the total load connected to MGs. The value of DTV and CTV ranges between 0 to 1. Since batteries are charged during the off-peak load hours and are discharged during the peak load hours, the value of CTV is always lower than that of DTV.

An example for PLT, OPLT, and NOT for a time-varying load using DTV=0.75 p.u. and CTV=0.5 can easily be understood in Figure 2. The batteries will be discharged at any hour when the load becomes equal to or higher than 0.75 p.u of the total connected load. Similarly, the batteries will be charged at any hour when the load becomes equal to or less than 0.5 p.u of the total connected load. Also, any hour with a load between 0.75 p.u and 0.5 p.u shall be considered NOT. Hence, no operation shall be performed on the batteries.

Several studies have widely used the power loss minimisation technique to optimise DG size and location in distribution networks [14]-[30]. As peak

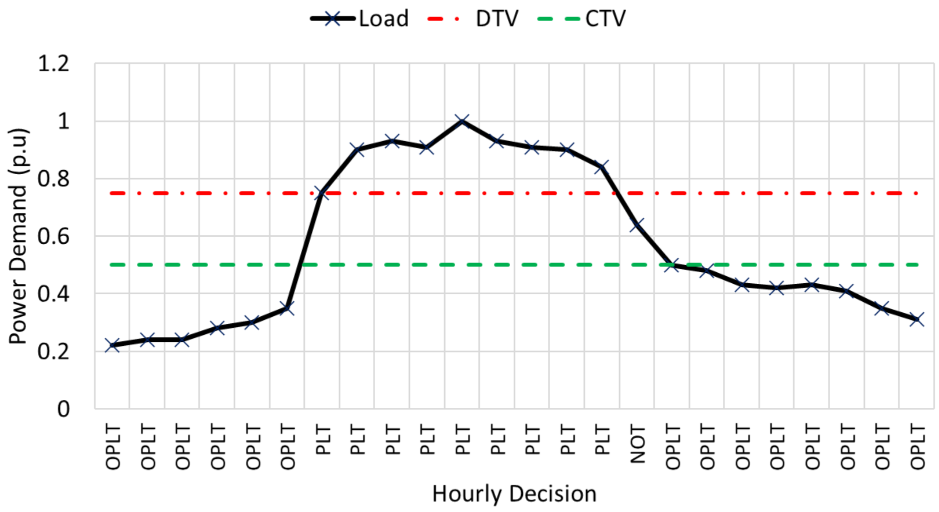

Figure 2 Example of DTV and CTV for OPLT, PLT and NOT

loads result in more power losses, the battery can store energy during low-load hours and supply energy during peak-load hours. Besides reducing power losses, this method can also help reduce peak loads. For example, MG at Universiti Teknologi PETRONAS (UTP) is equipped with two gensets with a maximum capacity of 8.4 MW to supply a peak load of 6 MW [6]. At specific periods, the grid load is as low as 4.2 MW, which is slightly higher than the capacity of one genset. However, two gensets are required to operate continuously. An efficient PLS strategy would be helpful in reducing the operation of the second genset in UTP and worldwide for similar cases.

The industrial, residential, and commercial load profiles in Figure 3 have widely been used in distribution and MG studies [13],[17]-[18],[21]. Also, some studies have used the IEEE test distribution network as MG [8],[13]. The simulations are performed for three case studies using IEEE 33 bus data to test the proposed approach's effectiveness.

The size of battery energy storage is of concern for power operators due to its higher costs. The size of the battery energy storage in this study is considered fixed and takes 10% of the daily energy usage of the MG; however, optimisation for an optimum size of battery energy storage shall be of interest and will be investigated in future studies.

Heuristic methods are generally considered robust and provide optimal solutions for large and complex problems [31]. Among the various heuristic methods, the genetic algorithm (GA) is well recognised for solving complex optimisation problems due to its powerful search and optimisation capabilities [32]-[33]. GA is adopted for the optimisation of parameters in several studies as a dynamic electrical battery model in [34], sizing of Flexible AC Transmission Systems (FACTS) devices in [35], and the size of DGs in [24],[36]-[39]. GA is considered more efficient in finding the best solutions than other optimisation techniques. The numerical comparison of results in a recent study using GA in [40] demonstrates that GA is a promising and suitable algorithm and has been adopted for optimisations in this research.

MODELING OF SYSTEM PARAMETERS

PLS strategy in this study is performed using minimisation of the power losses. The power losses in distribution networks are calculated with the help of the Back-Forward Sweep (BFS) load flow method [41]-[43]. The total power losses in MGs without and with PLS can be calculated as [44],

$$P_{loss\_total}(t)=\sum_{i=1}^{no.\,of\,branches} P_{loss(i)}(t) \tag{1}$$

$$P_{loss\_total}^{PLS}(t)=\sum_{i=1}^{no.\,of\,branches} P_{loss(i)}^{PLS}(t) \tag{2}$$

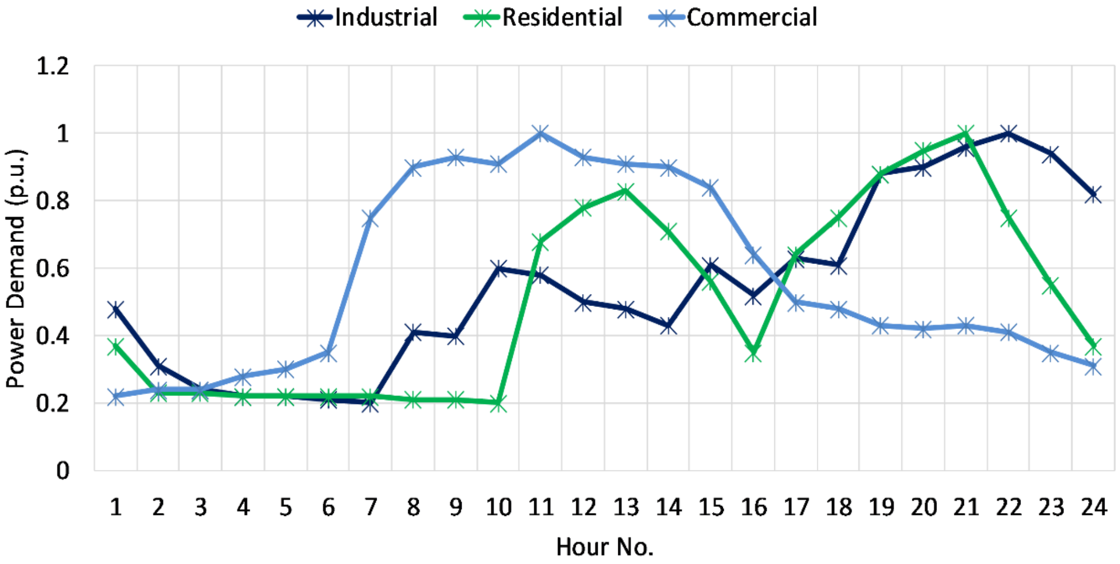

Figure 3 Load profiles for the proposed study [21]

Similarly, the deviation in power losses due to the use of PLS can be observed using [44],

$$Power\ loss\ index = \sum \frac{real\left(P_{loss\_total}^{PLS}(t)\right)}{real\left(P_{loss\_total}(t)\right)} \tag{3}$$

Load factor (LF) is the average electrical load divided by the maximum electrical load in a specific period [5]. It is a valuable indicator for describing characteristics of electricity consumption over time. A low LF value means that the load is highly variable. Practically, the value of LF is always less than 1, unless for those networks with a constant load throughout the day. Because peak loads put more pressure on power generation, the consumers put efforts into improving LF by reducing peak loads to save on their monthly bills. The performance of the PLS strategy can also be evaluated by measuring the load factor of MG, which is given by,

$$Load\ factor\ (LF) = \frac{P_{average}}{P_{peak}} \tag{4}$$

where $P_{average}$ is the average load, and P_{peak} is the peak load in MG load profiles.

The electrical output from the MG power station at any hour can be calculated using [45],

$$MG_{pout}(t) = PD(t) + BES_{pout} \tag{5}$$

PD is the power demand and BESpout is the output power from battery energy storage (BES). The value of BES_{pout} is positive; when batteries are charged, the demand for MG increases. The value of BES_{pout} is negative when batteries are discharged; this will decrease the demand for MG. The capacity of battery energy storage used is 10% of daily energy demand and is presented as,

$$BES = \sum_{t=1}^{t=24} PD(t) \times 10\% \tag{6}$$

For safety purposes, batteries are allowed a maximum depth of discharge (DoD) of up to 70%; therefore, the minimum state of charge (SoC) for batteries is set at 30%. SoC of batteries at any hour can be calculated as [46],

$$SoC(t) = \frac{E_{Store}}{BES} \times 100 \tag{7}$$

where Estored_BES is the cumulative energy stored in batteries in kWh. The initial value of Estored_BES is assumed to be 30% of the total capacity of BES, which is the minimum value set for SoC (SoC_{min}). Batteries can be charged to a maximum value of SoC ranging from 80% - 100%. Since this value affects the replacement life of batteries, it is considered 100% in this study.

$$E_{Free}(t) = E_{Store} - SoC_{min} \tag{8}$$

where E_{free} is the maximum amount of energy available to discharge at any hour.

The amount of energy to charge (E_{char}) in batteries at any time usually depends on energy availability. However, the size of the battery charger plays a vital role in this situation. The size of the charger used in this study is 185.75 kW, which is equal to the specifications of a commercial EV charger as provided in [47].

LOAD SHAVING APPROACH

It is essential to note that, despite the DTV and CTV, the amount of power charged and discharged to and from batteries shall depend on the status of the EStore. For instance, in an example given in Figure 2, the total load in many hours is less than 0.5 p.u., which indicates charging the batteries. However, charging cannot be done if the batteries are fully charged; $E_{Store=}$BES. Also, the total load in many hours is higher than 0.75 p.u., indicating the batteries' discharge. Similarly, discharging cannot be done if the batteries are already at a minimum state of charge; SoC = SoC_{min}. A similar study was conducted for battery-coupled solar photovoltaic plants in [48], where batteries were charged and discharged using a multi-stage battery dispatch controller.

The same control model has been adopted and is further extended with some essential modifications for this study. The seven-stage battery dispatch controller is shown in Figure 4.

The energy management for batteries in a seven-staged battery dispatch controller occurs through seven stages.

Stage 1: PD(i)>=DTV && SoC(i)<= SoCmin

When PD(i)>=DTV, it means this is PLT, and batteries need to discharge. Because SoC(i)<= SoCmin, no discharge operation can be performed as the battery is at its minimum level.

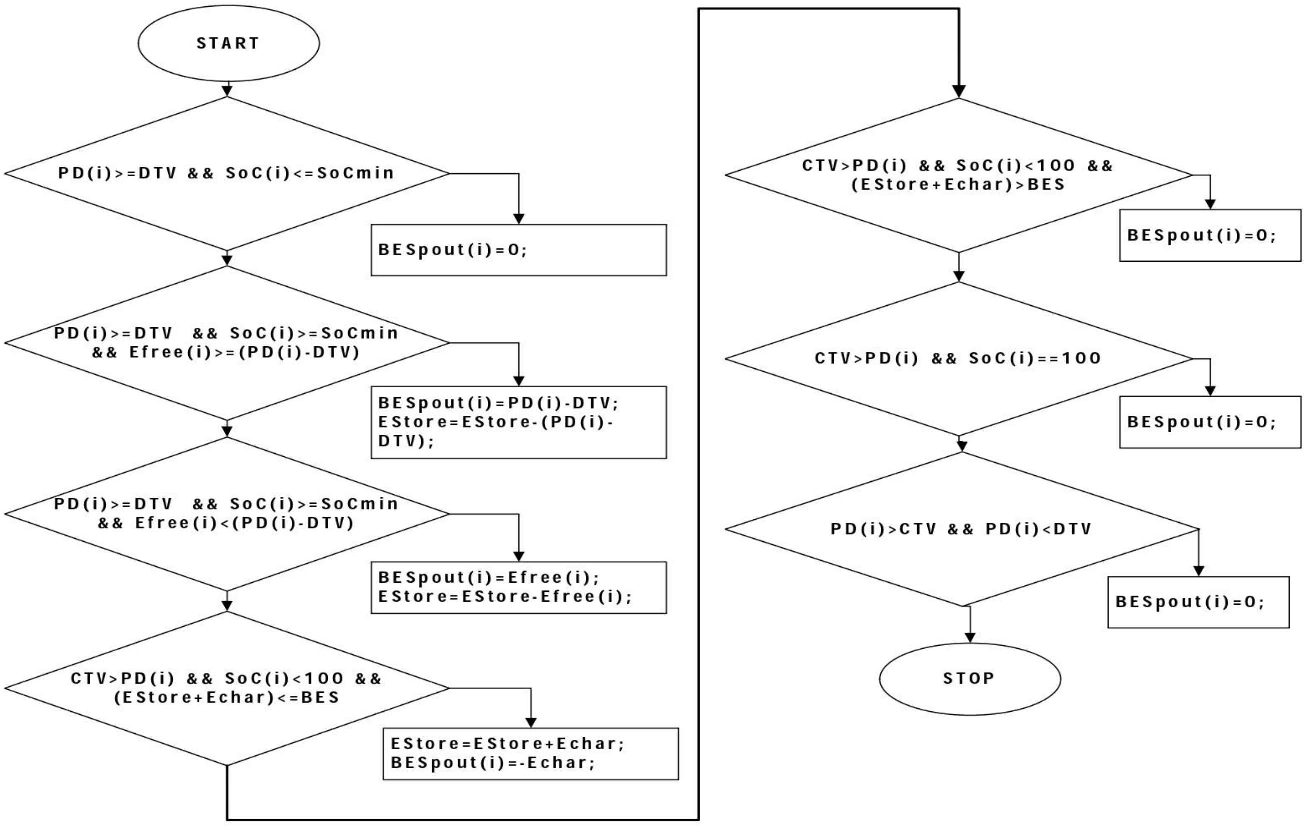

Figure 4 Seven-stages battery dispatch controller

Stage 2: PD(i)>=DTV && SoC(i)>=SoCmin && Efree(i)>=(PD(i)-DTV)

When PD(i)>=DTV, it means this is PLT, and batteries need to discharge. During this stage, the battery SoC level is higher than SoCmin and enough to supply the total required energy for the current hour. The BESpout(i) is set to PD(i)-DTV and the net energy at the battery is calculated using EStore=EStore-(PD(i)-DTV).

Stage 3: PD(i)>=DTV && SoC(i)>=SoCmin && Efree(i)<(PD(i)-DTV)

When PD(i)>=DTV, it means this is PLT, and batteries need to discharge. During this stage, the battery SoC level is higher than SoCmin, which is enough to supply the total required energy for the current hour. BESpout(i) is set to Efree(i), and net energy at the battery is calculated using EStore=EStore-Efree(i).

Stage 4: CTV>PD(i) && SoC(i)<100 && (EStore+Echar)<=BES

When CTV>PD(i), it means this is an OPLT, and batteries need to charge. As SoC< 100 means not fully charged and EStore+Echar)<=BES, batteries are set to EStore=EStore+Echar, and BESpout(i) is set –Echar. Echar is the chargeable amount to batteries and a load value for the grid.

Stage 5: CTV>PD(i) && SoC(i)<100 && (EStore+Echar)>BES

When CTV>PD(i), it means this is an OPLT, and batteries need to charge. As SoC< 100 means not fully charged but (EStore+Echar)>BES, no charge operation can be performed as the battery is almost at its maximum.

Stage 6: CTV>PD(i) && SoC(i)==100

When CTV>PD(i), it means this is an OPLT, and batteries need to charge. Because SoC(i)== 100, no charge operation can be performed as the battery is at its maximum level.

Stage 7: PD(i)>CTV && PD(i)<DTV

When PD(i)>CTV && PD(i)<DTV, it means there is NOT. During this period, no charge or discharge operation will take place.

The charging and discharging of batteries mainly depend on the values of DTV and CTV. We have used a GA using a step-by-step approach to determine the values for DTV and CTV, as provided in Figure 5.

The GA works based on natural selection, which drives biological evolution and repeatedly modifies a population of individual solutions. At each step, the GA selects individuals from the current population to be parents. It uses them to produce children for the next generation to achieve an optimal solution successfully. The GA has adapted to solve various optimisation problems that are not well suited for standard optimisation algorithms, including problems in which the objective function is discontinuous, nondifferentiable, stochastic, or highly non-linear. Details on the operation of the GA can be found in [49] and [50].

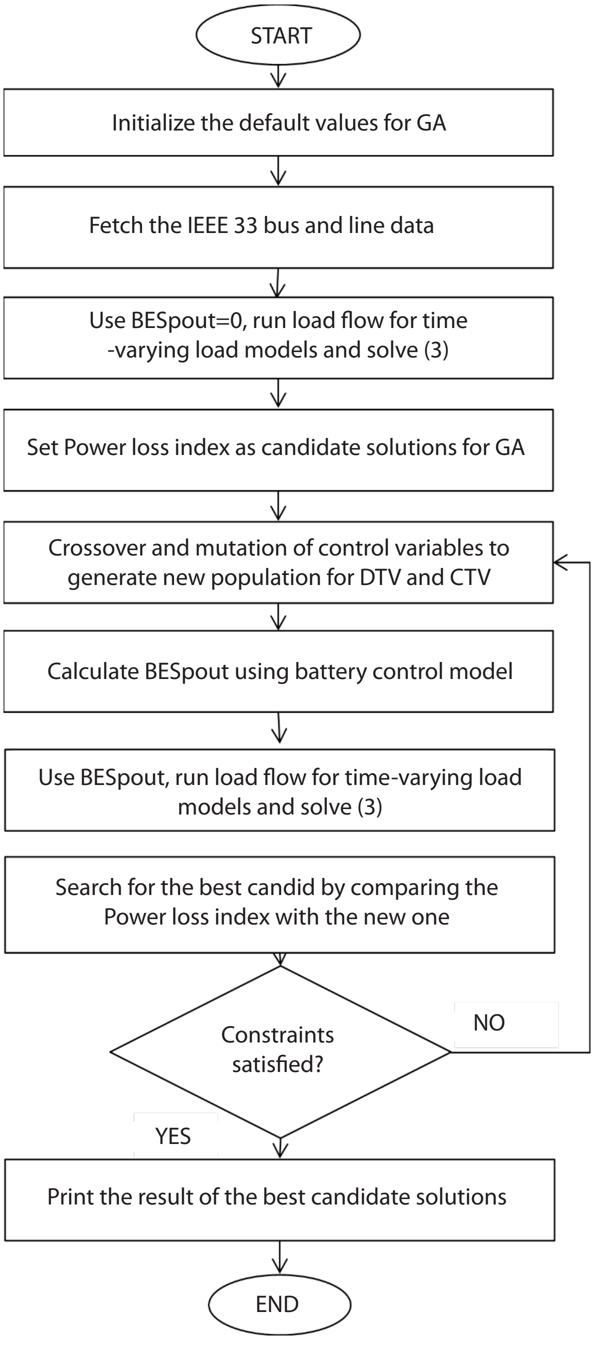

Figure 5 Step-by-step approach for peak load shaving

SIMULATION RESULTS

For the three load profiles, battery energy storage with fixed sizes of 4885.22 kWh, 4506.30 kWh, and 5078.4 kWh, respectively, are installed at bus no. 6. It is mainly because bus no. 6 is the most optimum bus in IEEE 33 bus test networks for the installation of power sources [23],[52], and therefore, is considered for the installation of battery energy storage in this study. The amount of battery energy storage chosen in this study is 10% of the total daily energy requirements for each load profile. Based on the simulation performed, the DTV and CTV for the three networks determined by GA optimisation are provided in Table 2. The impact of using this amount of battery energy storage concerning PLS in MGs for each case is provided in Table 3 and discussed as follows:

Table 2 DTV and CTV using optimisation

Parameters	Load Profile		
	Industrial	Residential	Commercial
Total Battery Size (kWh)	4885.22	4506.30	5078.4
Discharge Threshold Value (DTV)%	76.66	78.299	88.99
Charge Threshold Value (CTV)%	69.08	36.709	30.546

Impact on Peak Loads

The proposed approach is seen to identify the peak load time (PLT), off-peak load time (OPLT), and no operation time (NOT) for each load profile. The PLT, OPLT and NOT and their impact on power demand for each load profile, are plotted in Figures 6 to 8. The batteries are charged and discharged in the respective hours according to OPLT, PLT, and NOT. The results and plotting show that the proposed method reduced the peak load from 3715 kW to 2849.41 kW, 3012.98 kW, and 3306.57 kW for industrial, residential, and commercial loads. In terms of percentage, this is a peak shaving of 23.3% for industrial, 18.90% for residential, and 10.14% for commercial loads. The proposed method helped

Table 3 Summary of simulation results

Parameters	Load Profile					
	Industrial		Residential		Commercial	
	Without	With PLS	Without	With PLS	Without	With PLS
Peak Load (MW)	3.71	2.85	3.71	3.01	3.71	3.30
Reduction in Peak loads (%)		23.3		18.89		10.99
Min Load (MW)	0.74	0.93	0.74	0.93	0.81	1.0
Load Factor (%)	54.79	71.44	50.54	62.32	56.96	63.99
Daily Energy Losses (MWh)	1.77	1.67	1.61	1.52	1.95	1.90
Total Energy Demand (MWh)	48.85	48.85	45.06	45.06	50.78	50.78

shave 3343.5 kWh, 1857.5 kWh, and 928.75 kWh during peak load hours for each load profile.

Impact on Load Factor

The reduction of peak loads in each load profile also helped improve the load factors (LF). The LF for the industrial load was improved from 54.79% to 71.44%, the residential load from 50.54% to 62.32%, and the commercial load from 56.96% to 63.99%. This comparison of LF with and without PLS is plotted in Figure 9.

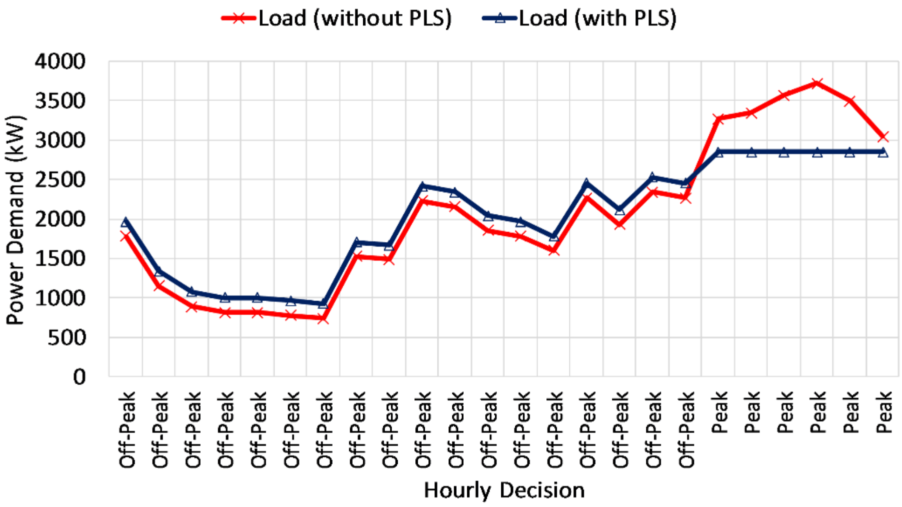

Figure 6 Power demand in industrial load

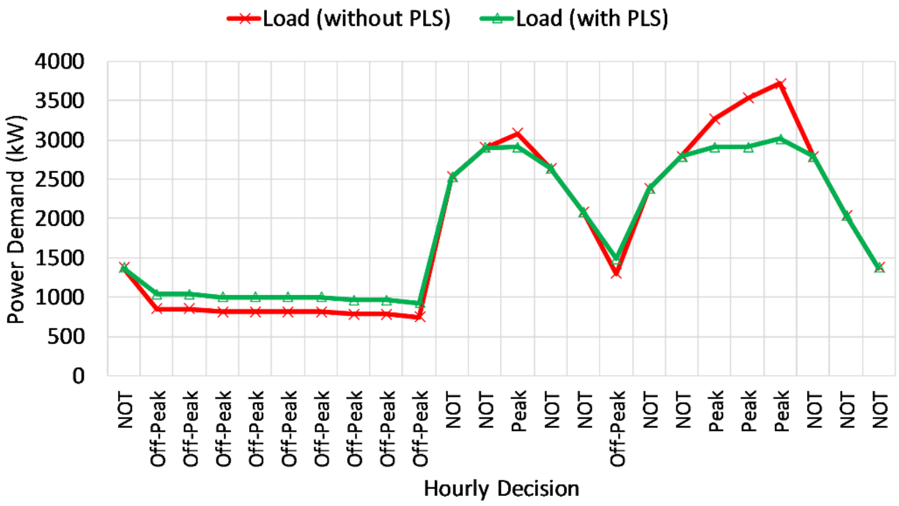

Figure 7 Power demand in residential load

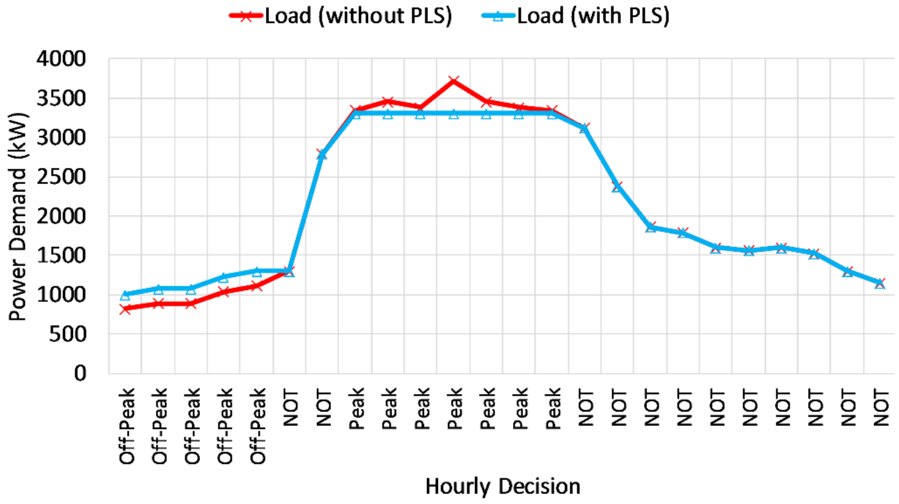

Figure 8 Power demand in commercial load

Impact on Power Exchange with the Grid

Based on PLT, OPLT, and NOT with the battery control model, the electricity supply from and to the grid is shown in Figures 10 to 12. For further understanding of the charging and discharging of batteries, the SoC for each hour is also plotted. In the figures, positive values show the power supply to the grid during the discharging of batteries; therefore, SoC is seen reduced during this time. The negative values show the supply of power from the grid to the batteries during the charging of batteries; ultimately, SoC is seen to increase during this time. Charging batteries during off-peak load hours increased the load from 743 kW to 928.75 kW in both industrial and residential loads, whereas it increased from 817.3 kW to 1003.1 kW in commercial loads. However, this shifting of energy from peak load hours to off-peak load hours did not affect the daily energy requirements in each load profile.

Impact on Power Losses

The primary objective function for optimising DTV and CTV was based on the reduction in power losses; therefore, the impact of PLS on the reduction of power losses in each load is investigated. The comparison of the hourly power losses with and without PLS for each load profile is plotted in Figures 13 to 15. The simulation results show that the proposed method for PLS helped reduce industrial load's daily power losses from 1.77 MWh to 1.67 MWh, from 1.61 MWh to 1.52 MWh in residential from 1.95 MWh to 1.90 MWh in commercial load. This shows that the proposed method for PLS helped reduce power losses of 5.73%, 5.44%, and 2.45%

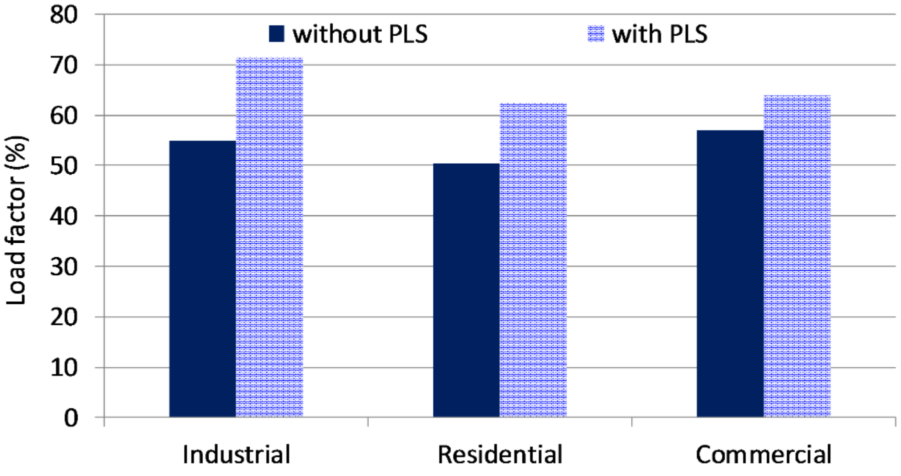

Figure 9 Impact of PLS on load factor

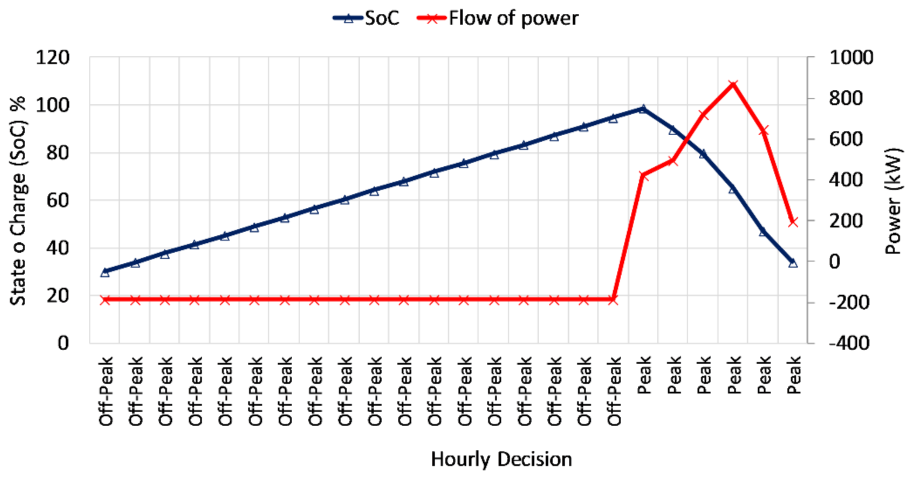

Figure 10 Power exchange with grid and battery SoC in industrial load

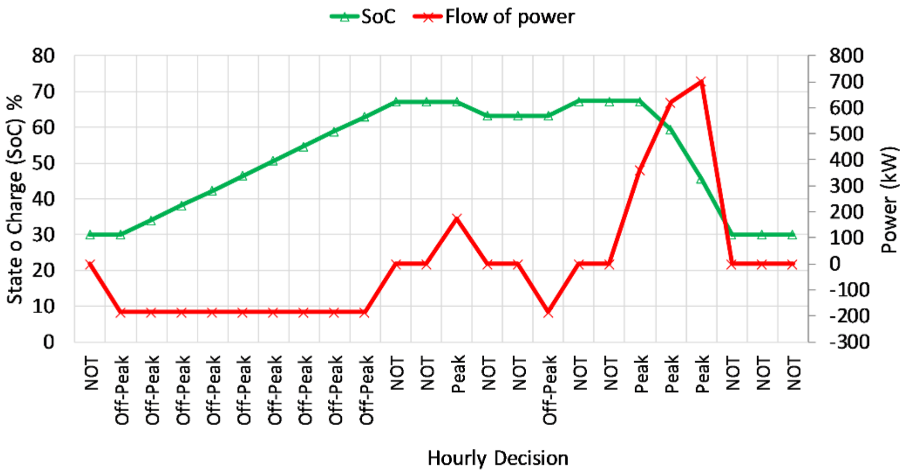

Figure 11 Power exchange with grid and battery SoC in residential load

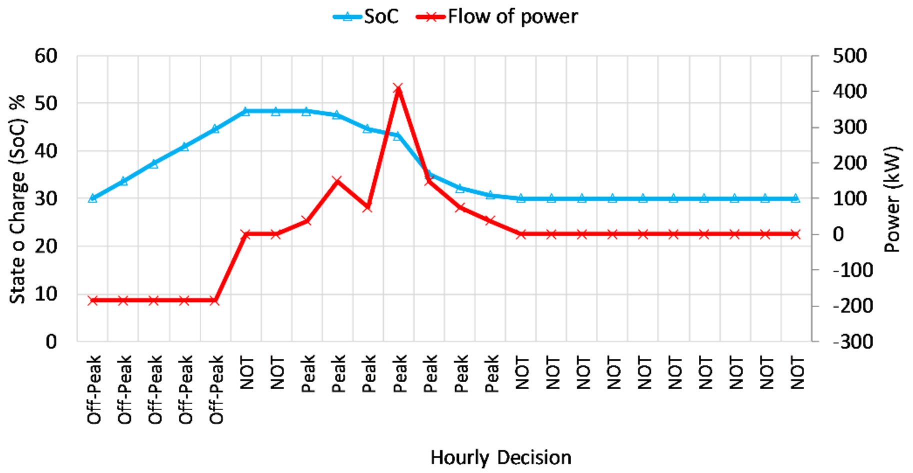

Figure 12 Power exchange with grid and battery SoC in commercial load

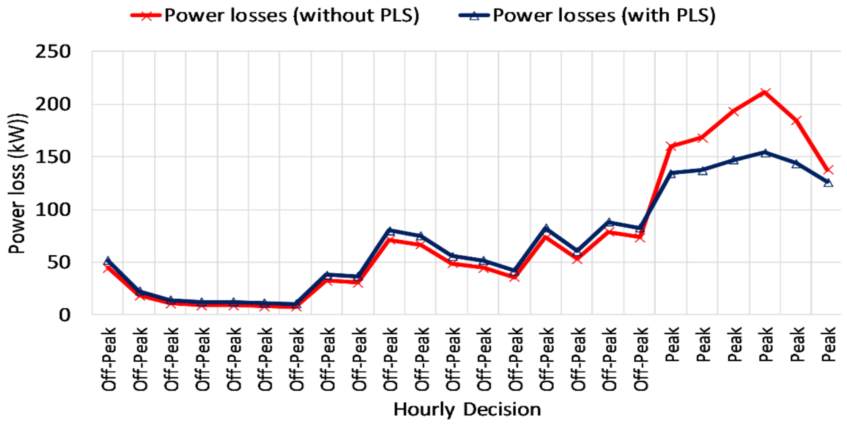

Figure 13 Power losses in industrial load

for the respective load. This electrical saving in terms of reductions in daily power losses is significant while keeping the daily energy needs at the same level.

Impact on Bus Voltages

The impact of PLS on bus voltages in each load profile is investigated for further verifications on the quality of MGs. Buses in MGs and distribution networks usually

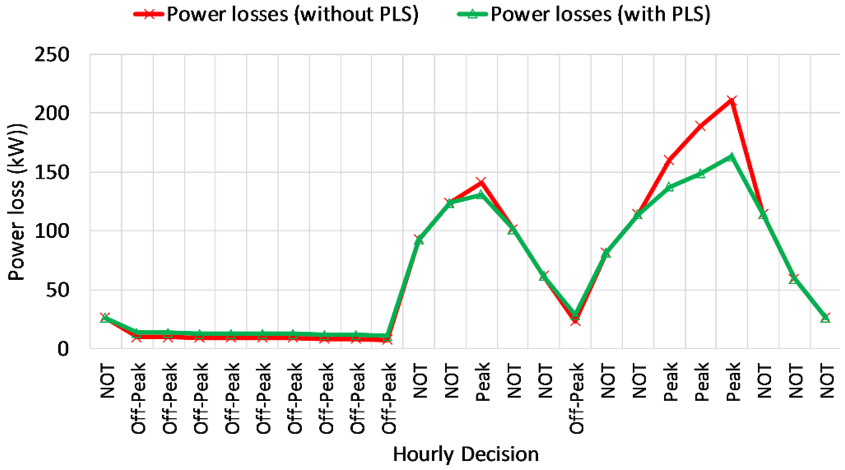

Figure 14 Power losses in the residential load

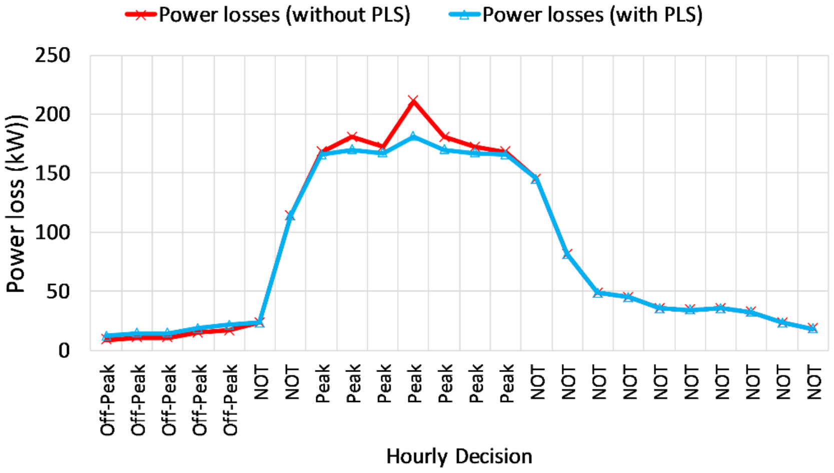

Figure 15 Power losses in the commercial load

experience low voltages during peak load times. However, this study's efficient use of battery energy storage helped improve bus voltages in each load profile. The bus voltages for the weakest bus in each hour with and without the PLS method are plotted in Figures 16 to 18.

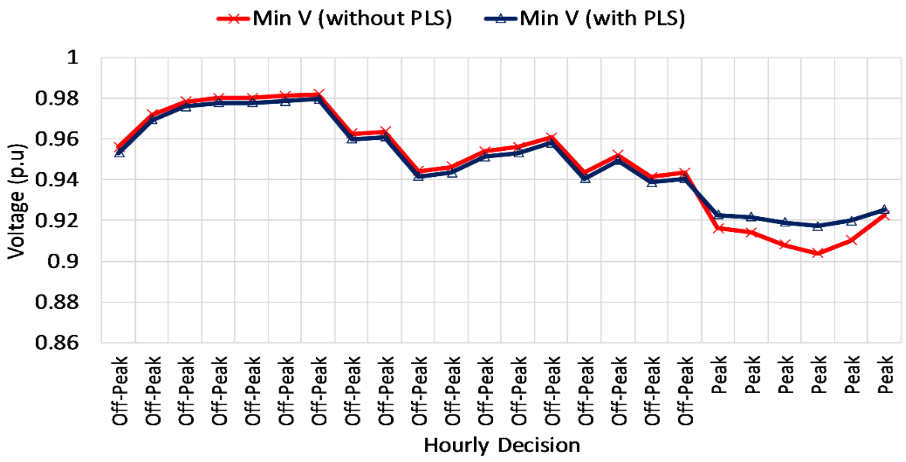

Figure 16 Hourly minimum bus voltage in industrial load

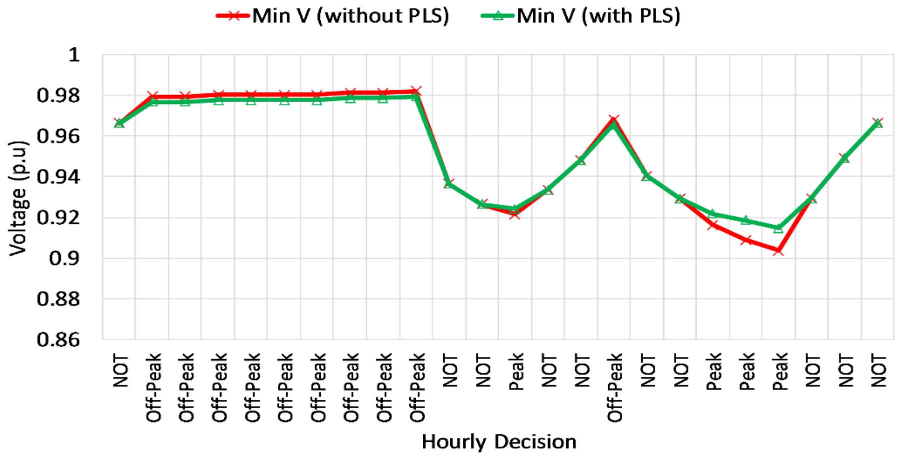

Figure 17 Hourly minimum bus voltage in residential load

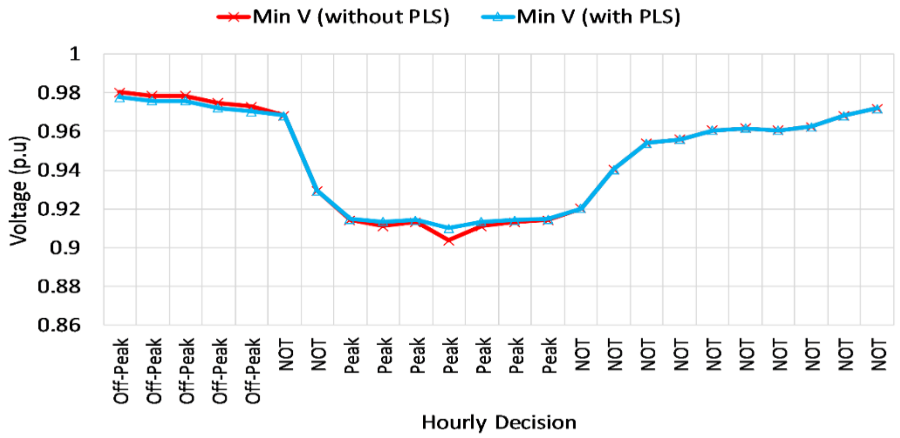

Figure 18 Hourly minimum bus voltage in commercial load

Furthermore, it is imperative to see the bus voltages during the peak loads to investigate a contrasting impact from the PLS. During the investigation, it was found that the PLS strategy has helped to improve bus voltages during the peak load hours for each load profile.

VALIDATION OF THE PROPOSED STUDY

In validating the efficacy, the results from the proposed bi-level energy optimisation framework were compared with results using fixed values for DTV=0.75 p.u. and CTV=0.5, as provided in Figure 2. The comparison of DTV and CTV and peak shaving results for the two cases are provided in Table 4. This comparison showed that the proposed bi-level optimisation approach could achieve maximum peak shaving in microgrids as compared to fixed values for DTV and CTV. The peak shaving using the proposed bi-level optimising approach is 17.30%, 7.90%, and 10.99%, higher than the peak shaving using fixed values for DTV and CTV.

Table 4 Comparison of results using fixed and optimised values for DTV and CTV

Load	Case	DTV (%)	CTV (%)	Peak load (MW)	Peak shaving (%)
Industrial	Optimisation	76.66	69.08	2.85	23.30
	Fixed	75	50	3.5	6
Residential	Optimisation	78.30	36.71	3.01	18.90
	Fixed	75	50	3.3	11
Commercial	Optimisation	88.99	30.55	3.30	10.99
	Fixed	75	50	3.18	0

CONCLUSION

This study proposes a method for determining the peak and off-peak load hours for efficient peak load shaving (PLS) in microgrids (MGs). The PLS was performed by selecting a discharge threshold value (DTV) and a charge threshold value (CTV). The values for DTV and CTV were found through optimisation by a genetic algorithm (GA). Considering three different load profiles, a simulation was performed on an IEEE 33 bus MG network. The results from each case study revealed the robustness of the proposed approach in reducing the peak loads, improving the load factor, minimising power losses, and enhancing bus voltages. In summary, the proposed PLS approach has helped reduce 23.3% of peak load in industrial, 18.90% in residential, and 10.14% in commercial loads, which could result in considerable bill savings for the utilities for using peaking loads. To further validate the efficacy, the results from the optimisation framework were compared with fixed values of DTV=0.75 p.u. and CTV=0.5. Compared to fixed values, the proposed bi-level energy optimisation approach could achieve maximum peak shaving in microgrids. Besides the efficiency, the proposed approach is a quick and easy way to solve significant obstacles associated with PLS in MGs. The proposed framework can be deployed in real-world microgrid applications, including industrial, commercial, and innovative city scenarios.

ACKNOWLEDGMENT

The authors acknowledge Petroleum Research Fund Board of Trustees (Grant number 0153AA-H25) (PRF-BOT) and Yayasan Universiti Teknologi PETRONAS (YUTP) for providing the research grant YUTP-FRG 2017 to perform this research.

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