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Hybrid Adaptive Peak Load Threshold Controller for Battery Energy Storage System: An Industrial Case Study

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***Abstract*—Battery Energy Storage Systems (BESS) provide a flexible solution for peak load reductions in industrial power management. Industrial facilities face challenges in managing peak power demands due to unpredictable load variations and the limitations of traditional BESS control strategies. To address this, a Hybrid Adaptive Peak Load Threshold (HAPLT) controller is introduced, integrating day-ahead forecasting with real-time 30-minute updates to refine thresholds dynamically. This approach integrates advanced predictive modelling techniques to optimize peak load reduction, enhance energy savings, and ensure reliable operation under real-world conditions. Validation using Daikin R&D power network data showed an average maximum demand reduction factor (K_{MDR}) of 0.89. Real-time analysis demonstrated effective power demand management and optimal State-of-Charge (SOC) control. The system successfully reduced peak loads while preventing early battery depletion. The HAPLT controller minimizes forecasting errors, optimizes battery utilization, and enhances energy savings, proving a robust solution for industrial applications.**

***Index Terms*—battery energy storage system, peak load reduction, dynamic threshold adjustment, real-time control**

I. Introduction

The industrial sector, as depicted in Fig. 1, demonstrates steady growth in energy consumption, solidifying its position as the dominant consumer. Effective energy management in this sector is vital to improve efficiency, reduce operational costs, and lower carbon emissions while sustaining economic growth. One of the major challenges faced by industrial facilities is the substantial cost of maximum demand charges, which often constitute a significant portion of their electricity bills [1, 2]. Utilities impose these charges based on the highest power demand during a billing period, incentivizing industries to manage their energy consumption efficiently [3, 4]. For manufacturing plants and large industrial complexes, peak load events can escalate operational costs, impacting overall profitability [5, 6]. Moreover, with the rising adoption of renewable energy and energy storage systems, managing peak loads effectively is more critical than ever [7, 8].

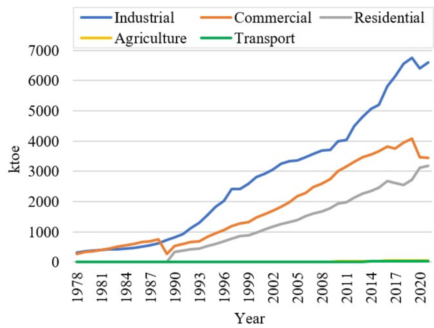

Fig. 1. The energy usage across various sectors in Malaysia from 1978 to 2021 adapted from [9].

Battery Energy Storage System (BESS) has become a key tool for peak demand mitigation, storing excess energy during off-peak hours and discharging it during high-demand periods. This approach flattens demand curves, enhances grid stability, and reduces operational costs [10, 11]. Among the types of batteries used for peak shaving, Lithium-ion (Li-ion) batteries are the most popular due to their high energy density, long cycle life, fast charge/discharge capabilities, and efficiency [12]. These qualities make them ideal for quickly responding to peak demand periods and ensuring grid stability. Lead-acid batteries, though cheaper upfront, have shorter lifespans and lower energy density, making them less efficient for modern applications. Sodium-sulfur and flow batteries offer long cycle lives but are bulkier, making them less suitable for smaller-scale use. Nickel-cadmium batteries, while reliable, have environmental concerns and are more expensive. Lithium-ion's high efficiency, longer lifespan, scalability, and cost reductions over time make it the preferred choice for peak shaving, offering a balance of performance, cost-effectiveness, and versatility for residential and large-scale systems [13, 14].

The integration of smart grid technologies enables dynamic adjustments to energy consumption based on real-time data, with smart meters playing a vital role in peak shaving by providing the necessary information to optimize battery usage [15, 16]. During peak demand times, when electricity costs are higher and the grid is under stress, smart meters enable the Battery Management System (BMS) to determine the most efficient times to discharge stored energy from batteries and reduce reliance on the grid. By continuously monitoring energy usage patterns, smart meters help the system predict and respond to peak periods, ensuring that the battery discharges when it is most cost-effective and beneficial for grid stability. Moreover, the smart meter data allows for precise control of energy flows, ensuring the battery is charged during off-peak times when electricity is cheaper and discharged during peak times to minimize costs. This integration between smart meters and BMS improves overall energy efficiency, supports grid reliability, and reduces operational costs.

Predictive modelling plays a pivotal role in addressing the challenges of peak demand management by enabling accurate forecasts of power consumption and peak load occurrences [17]. Advanced predictive techniques, such as machine learning and deep learning models, analyse historical energy consumption patterns to provide reliable insights into future demand trends [18, 19]. These forecasts empower industries to implement strategies, such as load shifting, optimal BESS utilization, and demand response programs, to mitigate peak demand costs [20, 21]. By integrating predictive models into energy management systems, industries can enhance operational efficiency, improve decision-making, maintain system reliability, and better align their energy usage with cost-saving objectives [22, 23].

Machine learning models are becoming essential for optimizing BESS. Their ability to handle non-linear relationships and temporal dependencies makes them invaluable for real-time peak demand forecasting. XGBoost model is highly effective for structured or tabular data, with fast training and strong predictive performance. As a gradient-boosting algorithm, XGBoost excels in capturing complex feature interactions, non-linear relationships, and handling missing data. These attributes make it particularly well-suited for initial demand predictions, such as predicting power demand in battery energy systems. Several studies have demonstrated XGBoost's ability to accurately predict power demand in these systems [24, 25]. Its scalability and speed make it especially useful for processing large dataset commonly involved in power demand forecasting, ensuring timely and actionable predictions [26, 27]. However, the predictions and forecasts from these studies have not been integrated with BESS to optimize demand response and reduce peak loads.

The Long Short-Term Memory (LSTM) is a deep learning model suitable for sequential data with long-term dependencies. As a type of Recurrent Neural Network (RNN), LSTM is highly effective for modelling temporal dependencies and identifying long-term patterns in time-series data. In the context of battery energy systems, LSTM excels at forecasting dynamic load profiles and predicting battery State-of-Charge (SOC) and State-of-Health (SOH) over time [28]. By learning the sequential relationships in the data, LSTM can accurately capture power fluctuations, leading to improved real-time energy management strategies. This capability ensures optimal utilization of battery under variable load conditions, enabling more efficient energy storage and distribution.

Convolutional Neural Networks (CNNs), originally developed for image recognition, have been successfully adapted for time-series analysis, proving especially beneficial for energy systems. Unlike traditional fully connected neural networks, CNNs apply convolutional filters to extract meaningful features, allowing them to identify local dependencies and patterns in complex datasets. This makes CNNs particularly effective for analyzing intricate interactions in battery energy systems, such as load demand fluctuations, environmental influences, and charge-discharge cycles. Their ability to efficiently process high-dimensional data enables significant improvements in energy optimization and system reliability. When combined with other deep learning models, such as LSTM and Gated Recurrent Unit (GRU) networks, CNNs contribute to hybrid frameworks like CNN-LSTM and CNN-GRU [29, 30]. These models leverage CNNs for feature extraction while utilizing LSTM and GRU's ability to capture long-term temporal dependencies. This hybrid approach enhances forecasting accuracy and provides better adaptability to dynamic energy consumption patterns. However, most multi-model approaches have primarily focused on analyzing the battery's SOC and SOH, with limited research on integrating these models with BESS for real-time peak load reduction.

In addition to single-stage controllers, a two-stage controller was found to deliver a more consistent peak demand reduction percentage compared to other control strategies [31]. The controller uses an incremental model called DBeSOINNeR for both day-ahead and 1-hour-ahead load prediction. The controller adjusts the threshold for charging and discharging every five min. The first stage determines the threshold based on a day-ahead load forecast, while the second stage refines the threshold using a 1-hour-ahead load forecast to prevent peak reduction failures. This approach aims to address the limitations of conventional controllers that use rigid parameters derived from long-term historical data. The proposed controller requires only 30 days of historical data and can adapt to evolving load patterns. The performance of the two-stage controller was evaluated against fixed threshold, conventional single-stage, and fuzzy controllers, in the context of a commercial building. However, these controllers were not deployed in an actual BESS implementation, which limits their real-world applicability.

Previous studies often struggle to adapt to rapidly changing industrial load patterns and fail to provide a comprehensive approach to peak demand management within the industrial context. Conventional methods often lack the necessary adaptability to handle fluctuating power demands, whereas advanced predictive models are seldom integrated with BESS for optimizing peak load reduction. This study aims to bridge these gaps by exploring the use of advanced predictive modelling, integrated with BESS and smart grid technologies, to optimize demand management and contribute to a more sustainable energy system.

Industrial load demand is inherently unpredictable due to fluctuations in usage patterns and external factors, making it challenging to determine an optimal threshold for peak load reduction. This study tackles the issue of peak power consumption in industrial settings by utilizing both simulation and real-world case studies to evaluate the effectiveness of the predictive modelling methods. For the real case study, the controller was implemented in the real BESS setup in a factory called Daikin R&D in Sungai Long. The results from the implementation of the HAPLT controller at Daikin R&D from August 2024 to December 2024 demonstrate its significant impact on peak demand reduction. The predictive control strategy achieved a notable 89% average maximum demand reduction factor (K_{MDR}), optimizing battery usage and preventing premature discharges while ensuring sufficient energy for critical periods. By dynamically adjusting peak thresholds every 30 min, the system effectively lowered peak power demand, leading to a total monthly savings of RM 2,445.07, combining both demand reduction and energy consumption optimization. Additionally, the system saved an average of 2342.21 kWh per month, with a Round-Trip Efficiency (RTE) of 70%, further validating its ability to reduce electricity costs and improve operational efficiency. These findings highlight the effectiveness of predictive modelling and real-time threshold adjustments in industrial energy management, providing a robust framework for future peak load reduction strategies.

The structure of this paper is as follows: Section II describes the methodology adopted for the study which focuses on the development of the BESS, the design of the predictive models together with the selection criteria, and the development of the control strategy. Section III presents the results and discusses the simulation and real-word case study, whereas Section V concludes the study.

II. METHODOLOGY

The research is conducted in a real-world industrial environment at Daikin R&D in Sungai Buloh, Malaysia. The methodology begins with a comprehensive site inspection to analyse the facility's demand patterns and identify key factors influencing power usage. Following this, control and monitoring systems for the BESS are installed to facilitate real-time management of power consumption and energy storage. To collect relevant data, power meters and the Battery Management System (BMS) are utilized to monitor power consumption of the building and monitor the BESS performance. This data is essential for evaluating the developed controller, which integrates advanced load prediction models to optimize peak load reductions. The simulation phase tests the controller under controlled conditions to evaluate its functionality and refine its performance. The simulation method allows for assessing the system's response to various load patterns and operational scenarios.

The real-world implementation validates the controller's effectiveness in an operational industrial environment. This phase ensures that the system can handle the complexities and unpredictability of actual factory operations, providing valuable insights into its practical performance. By combining simulation with real-world validation, this dual-phase approach ensures that the proposed methodology is robust, adaptable, scalable, and capable of addressing the uncertainties inherent in factory load demand, ultimately contributing to a more efficient energy management and reduced peak power consumption.

A. BESS Configuration

Fig. 2 shows the external view of the BESS setup, housed within a blue cabin. This cabin is strategically positioned behind the Daikin Research and Development (R&D) building, providing a secure and accessible location for the system's operation.

Fig. 3 depicts the internal setup of the BESS which houses 168 lithium-ion batteries. These batteries are connected to the bi-directional power converter, which facilitates the integration of the battery system with the power distribution board. The Python program and Node-RED are deployed on a dedicated computer. This computer is connected to the Local Area Network (LAN) via a Wi-Fi router, enabling remote control and real-time monitoring of the system's performance.

Fig. 2. The external view of the BESS location.

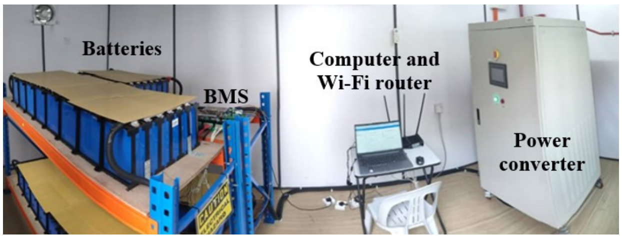

Fig. 3. The internal view of the BESS setup.

Table I provides the specifications of the lithium-ion batteries and power converter. This table presents the key specifications for the lithium-ion batteries and the associated power converter, detailing their capacities, voltage ranges, and ratings essential for the system's performance and energy management.

TABLE I: THE BESS SPECIFICATIONS

Specifications	Rating
Type of battery	$LiFePO_4$
Battery cell capacity	280 Ah
Depth-of-Discharge (DOD)	90%
Capacity of the batteries	155 kWh
Battery usable energy	139.5 kWh
Battery voltage range per cell	2.8 V–3.6 V
Maximum power rating set	50 kW
Size of the power converter	100 kW
Cable power capacity	68 kW

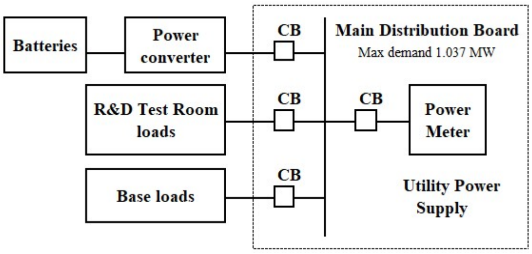

Fig. 4. Single-line diagram of the BESS connection.

Fig. 4 illustrates the single-line diagram of the BESS connection. In this setup, the batteries are connected to the power converter, which is linked to the factory loads through Circuit Breakers (CB). The power converter is connected to the main distribution board, which is equipped with a power meter for monitoring the energy flow. This diagram highlights how the BESS integrates with the factory's electrical infrastructure, enabling energy storage, load management, and real-time power monitoring.

B. Development of Load Profile Prediction Models

The demand profiles collected from the power meter of Daikin R&D building are used to simulate and validate the load profile prediction model. Fig. 5 shows the predictive modelling and deployment framework for peak load reduction. The workflow for peak load reduction consists of three main stages: Data Processing, Feature Selection, and Deployment. Historical power demand data undergoes cleaning and preprocessing to ensure quality.

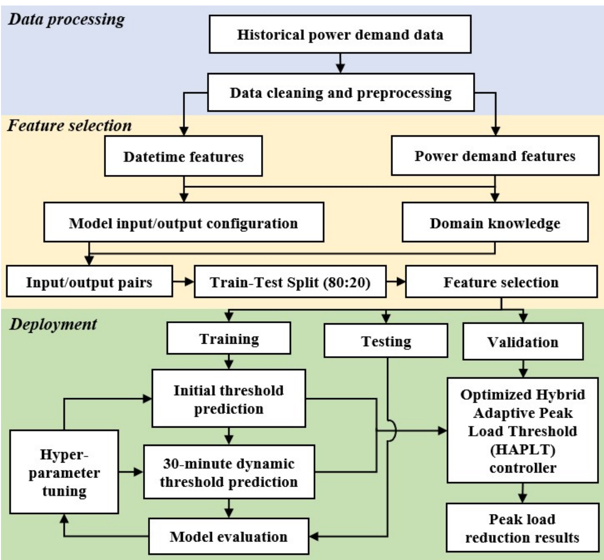

Fig. 5. The HAPLT framework.

In the Feature Selection stage, datetime and power demand features are extracted based on domain knowledge, and model input/output configurations are set before splitting the dataset for training and testing. A two-year dataset from January 2022 to April 2024 is used for training and testing purposes. The training and testing dataset are split into 80% and 20% respectively. Feature selection is applied to optimize model performance. The Deployment stage involves training models for initial threshold prediction, followed by hyperparameter tuning and a 30-minute dynamic threshold prediction to refine the peak reduction strategy. The trained model undergoes testing before being integrated into the Hybrid Adaptive Peak Load Threshold (HAPLT) controller. The validation was carried out from August 2024 to December 2024.

The prediction models and the controller's performance are evaluated based on peak load reduction results. The calculated performances are based on the statistical metrics summarized in Table II.

TABLE II: THE PERFORMANCE METRICS

Performance metrics	Description
$\mathrm{MAE}=\frac{1}{n}\sum_{i=1}^{n}\left\|y_{\mathrm{true},i}-y_{\mathrm{pred},i}\right\|$	Mean Absolute Error (MAE) measures the average absolute difference between actual and predicted values.
$\mathrm{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(y_{\mathrm{true},i}-y_{\mathrm{pred},i}\right)^2$	Mean Squared Error (MSE) measures the average squared difference between actual and predicted values.
$\mathrm{RMSE}=\sqrt{\mathrm{MSE}}$	Root Mean Squared Error (RMSE) is the square root of the MSE, emphasising on larger errors.
$\mathrm{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\left\|\frac{y_{\mathrm{true},i}-y_{\mathrm{pred},i}}{y_{\mathrm{true},i}}\right\|\times 100$	Mean Absolute Percentage Error (MAPE) measures the error as a percentage of the actual value.

Variable control is essential for effective peak load reduction, especially in systems where load behaviour is unpredictable. The preliminary control establishes the initial threshold to trigger peak load reduction, whereas the next stage ensures the battery's SOC remains sufficient to support discharge throughout the 14-hour peak period, from 8 am to 10 pm. If the initial threshold is set too high, the BESS might fail to reduce the peak load effectively. Conversely, if the initial threshold is too low, the battery could be discharged prematurely, leaving insufficient energy to manage peak loads later in the day. To address this, the model needs to predict the next day's power demand and set the initial threshold for peak load reduction. The subsequent stage uses the model to forecast the load demand for the next 30-minute interval. This forecast allows for dynamic adjustment of the threshold every 30 min, ensuring that the battery is neither over-utilized early in the day nor underutilized during critical peak periods.

XGBoost, CNN, LSTM and GRU models are integrated into developing the HAPLT controller. Table III shows the important Hyperparameters used for tuning the models.

TABLE III: SUMMARY OF MODEL HYPERPARAMETERS

Model	Important Hyperparameters
XGBoost	n_estimators, max_depth, min_child_weight, subsample, colsample_bytree, gamma, lambda, alpha, scale_pos_weight, tree_method
CNN	num_layers, filters, kernel_size, strides, pool_size, activation_function, dropout_rate, early_stopping
LSTM	num_layers, units, dropout, recurrent_dropout, activation_function, early_stopping
GRU	num_layers, units, dropout, recurrent_dropout, activation_function, early_stopping

TABLE IV: SUMMARY OF HYPERPARAMETERS TO IMPROVE MODEL PERFORMANCE

Hyperparameter	Settings
Optimizer	learning_rate, batch_size, epochs
Attention mechanism	attention_size, attention_type
Loss function	mean_squared_error, mean_absolute_error, quantile_loss
Regularisation	l2_regularisation, l1_regularisation
Data preprocessing	MinMaxScaler, StandardScaler

Table IV provides an overview of key hyper-parameters used to optimize the machine learning models. The learning rate, batch size, and epochs hyperparameters influence how quickly the model learns, how much data is processed at once, and how many times the model iterates over the dataset. The attention mechanism category includes parameters such as attention size and attention type, which are crucial for models which processes sequential data, enabling the model to focus on different parts of the input. Loss Functions, such as mean squared error and mean absolute error, measure the difference between predicted and actual values, guiding the optimization process. Regularization techniques are used to prevent over-fitting by penalizing complex models. Data preprocessing methods, such as scaling and normalization ensure that input features are properly standardized, improving model convergence and performance.

C. Development of the BESS Control Strategy

Python is used to compute the peak load predictions for the threshold adjustment, this information is then passed to Node-RED for the peak load reduction operation. The data processing involves establishing a connection to the PostgreSQL server as shown in Fig. 6. Configuration details, such as the server address, login credentials, and database selection, are specified within the Node-RED program. The system retrieves data from the PostgreSQL server, which may include timestamped records and the state of the battery stored in the database. This data is then passed through subsequent stages of processing.

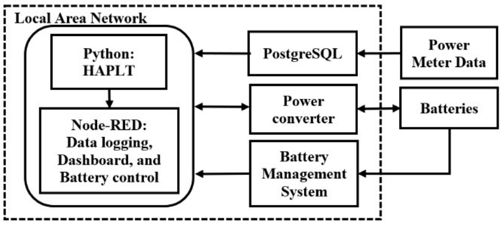

Fig. 6. Communication framework for the BESS.

The filtered dataset is directed to a data logging module, where essential information is stored for analytical purposes. This logging process makes use of dedicated nodes within Node-RED. The processed data is sent to the Node-RED dashboard for real-time monitoring and visualization.

Fig. 7 to Fig. 9 illustrate the Graphical User Interfaces (GUIs) developed for monitoring and controlling the BESS. These interfaces provide real-time insights into the performance and status of key system components. Fig. 7 displays the battery monitoring interface, which shows detailed information on individual battery cells, including their voltages, temperatures, and state of charge. This allows for effective health tracking and balancing of the cells, essential for maintaining battery efficiency and longevity. Fig. 8 presents the interface for the power converter, monitoring the operational parameters such as phase voltage, frequency, battery voltage and current, and the output active power. It also includes manual and automatic control options for managing power flow between the battery system and the grid. Fig. 9 shows the power meter interface, which tracks total power demand and accumulated energy consumption over time. This information is crucial for load profiling, energy auditing, and peak demand management. Collectively, these user interfaces form an integrated monitoring and control platform that enhances the reliability, safety, and operational efficiency of the BESS for real-time application.

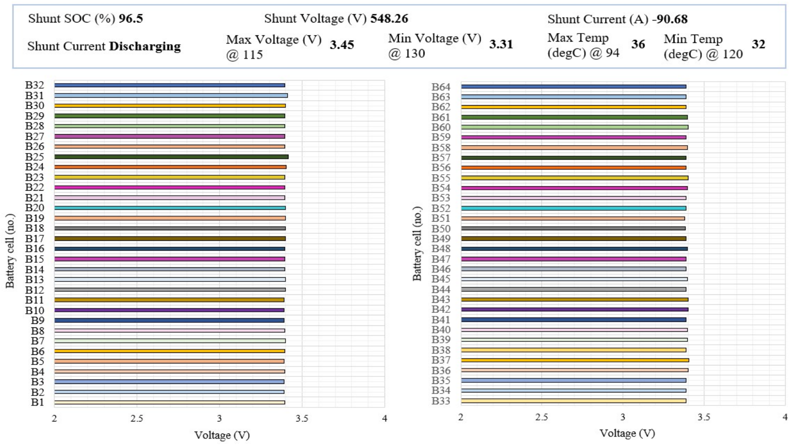

Fig. 7. User interface for the batteries (showing cell no. 1 to cell no. 64 out of the total 168 cells).

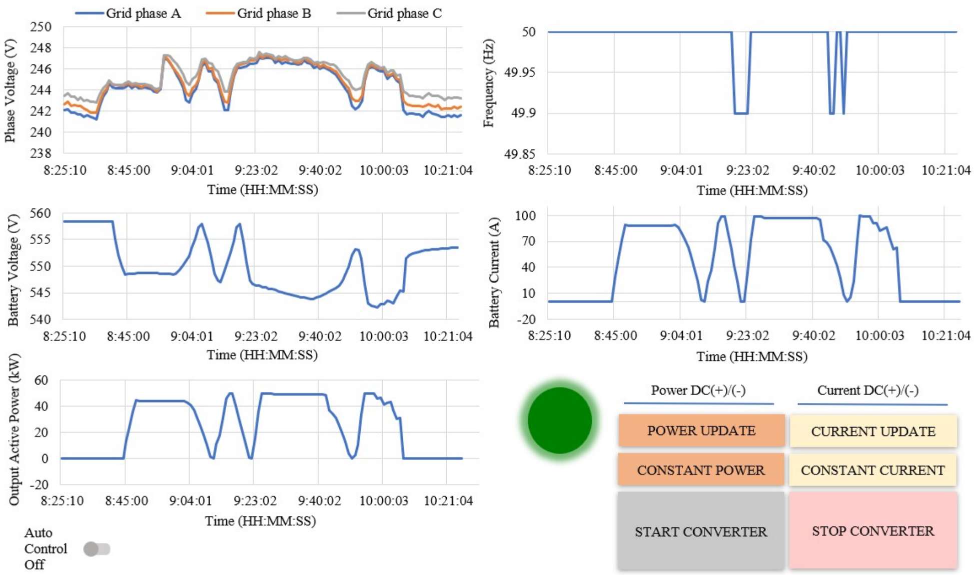

Fig. 8. User interface for the power converter.

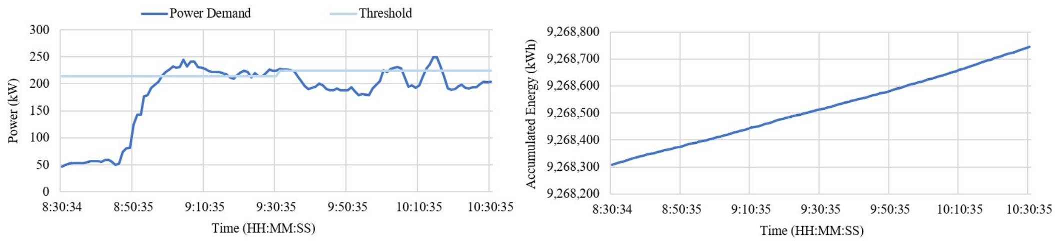

Fig. 9. User interface for the power meter.

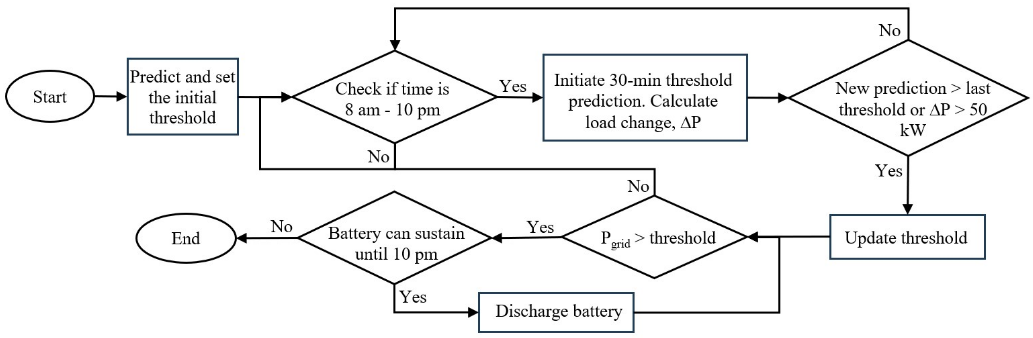

Fig. 10. Flow chart of the peak load reduction control strategy.

Fig. 10 shows the flow chart for the control system of the BESS. The system starts by initiating the initial threshold prediction and setting the threshold value by the HAPLT controller as shown in (1).

$$P_{\text{HAPLT}}(t) = P_{\text{pred\_int}}(t)(1-\alpha) + \beta P_{\text{pred\_30min}}(t) + \delta \Delta P(t) \quad (1)$$

where $P_{\text{pred\_int}}$ is the initial predicted peak power demand in kW, α is the prediction error factor between 0 and 1, $P_{\text{pred\_30min}}$ is the predicted peak power demand in kW for the next 30 minutes, β is the smoothing factor between 0 and 1 that controls the rate at which the threshold adjusts toward the predicted value, and δ is the weight applied to the real-time adjustment factor, which responds to instantaneous changes, ΔP in the load.

The peak load reduction process begins by setting the initial threshold, after which the system checks whether the current time falls within the peak period of 8 am to 10 pm. If it is within the peak period, the system initiates the 30-minute load prediction and calculates the change in load, ΔP. The checking of load change is implemented to overcome the problem of sudden power surges, which are often unpredictable and common in industrial loads. If the new prediction exceeds the previous threshold or if $\Delta P >$ 50 kW, the threshold is updated. This ensures the BESS can respond effectively to fluctuations in load demand.

The BESS starts managing peak load by discharging if the power demand exceeds the predicted threshold.

The load power is found from the following condition:

$$P_{\text{load}}(t) = \begin{cases} P_{\text{grid}}(t) + P_{\text{discharge}}(t), & \text{if } P_{\text{load}}(t) > P_{\text{Th}}(t) \\ P_{\text{grid}}(t), & \text{if } P_{\text{load}}(t) \le P_{\text{Th}}(t) \end{cases} \quad (2)$$

where P_{load} is the power demand in kW, $P_{\text{discharge}}$ is the power discharging from the battery in kW, and P_{grid} is the grid power measured at the power meter in kW.

The system throttles the BESS output based on the battery capacity and predicted demand, ensuring the battery operates efficiently and conserves energy for critical periods. The system also emphasizes safety through continuous SOC monitoring, ensuring the battery operates within safe limits. If the SOC falls below 10%, the system transitions to idle mode or charge mode (depending on the time), whereas SOC levels above 100% trigger the system to halt charging to prevent overcharging. Additionally, at any point, the system will stop operation to protect the battery if under-voltage or over-voltage conditions occur. The total energy consumed in kWh is calculated over 30 minutes by summing up the power for each minute. Table V shows the equations related to the energy calculations with the power information obtained from the data logging.

The performance indicator of the BESS is evaluated based on maximum demand reduction factor (K_{MDR}) which measures the percentage reduction in the overall maximum demand of the electrical system, while peak demand reduction factor (K_{PDR}) specifically measures the reduction in demand during critical peak periods when the grid is under the most stress [32].

TABLE V: ENERGY CALCULATIONS

Energy equation	Description
$E_{\text{peak hour}} = \sum_{i=480}^{1320} P_{\text{load}}^{i} \times \frac{1}{60}$	The energy consumed in kWh during peak hours.
$E_{\text{saved}} = \sum_{i=480}^{1320} P_{\text{discharge}}^{i} \times \frac{1}{60}$	The energy saved in kWh during peak hours.

III. RESULTS AND DISCUSSIONS

Fig. 11 shows the daily maximum, minimum, and average load power in kW during peak hours from January 2022 to December 2024.There was a system maintenance at Daikin R&D from 1st May 2024 to 26th May 2024, during which the power profile was unavailable. The data from January 2022 to April 2023 is used as the training dataset, while the period from August 2024 to December 2024 is used for validation. This dataset is used to train and test the hybrid adaptive peak load threshold controller for the BESS, enabling the controller to learn historical demand patterns and optimize real-time peak load management.

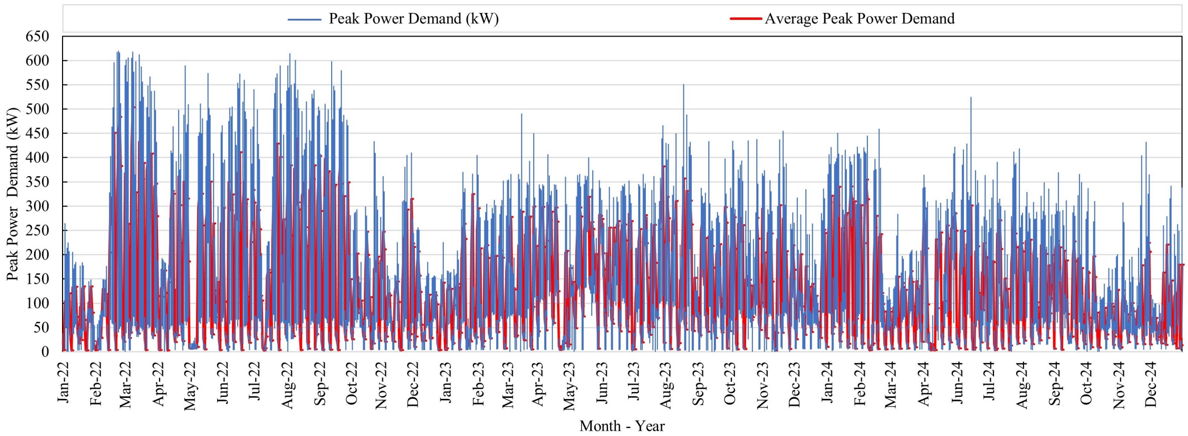

Fig. 11. Time series of daily peak power demand and average peak power demand from 2022 to 2024.

TABLE VI: SUMMARY OF THE MODELS' PERFORMANCE FOR INITIAL AND 30-MINUTE THRESHOLD PREDICTIONS THROUGH SIMULATION

Model	Initial Threshold Prediction				30-minute Dynamic Threshold Prediction			
	MAE (kW)	MAPE (%)	MSE (kW^2)	RMSE (kW)	MAE (kW)	MAPE (%)	MSE (kW^2)	RMSE (kW)
XGBoost	20.30	31.59	4401.14	66.34	170.71	81.71	192.19	13.86
CNN	350.98	65.76	152206.31	390.14	11.99	2.72	196.38	14.01
LSTM	131.18	239.10	30908.11	175.80	21.63	20.82	1594.87	39.94
GRU	123.70	299.27	28270.31	168.14	23.44	33.78	1842.78	42.93
CNN-LSTM	252.35	47.61	82167.39	286.65	23.52	5.36	632.59	25.15
CNN-GRU	131.17	23.61	30037.53	173.31	44.70	10.21	2154.58	46.42
LSTM-GRU	506.26	99.73	303971.38	551.36	24.91	5.68	711.55	26.67
CNN-LSTM-GRU	507.26	100.26	305729.94	552.93	6.33	1.44	66.74	8.17

Table VI compares the performance of various machine learning and deep learning models in two stages of power demand forecasting: initial threshold prediction and 30-minute dynamic threshold prediction. For the initial threshold, XGBoost outperforms all other models with the lowest MAE (20.30 kW), MAPE (31.59%), MSE (4401.14 kW^2) and RMSE (66.34 kW), making it the most reliable for day-ahead forecasting. In contrast, deep learning models such as CNN, LSTM, and GRU variants perform poorly in this stage, showing higher errors and variability. However, in the dynamic threshold prediction, the CNN-LSTM-GRU hybrid model significantly outperforms all others, achieving the lowest MAE (6.33 kW), MAPE (1.44%), MSE (66.74 kW^2) and RMSE (8.17 kW), indicating its strength in short-term, high-resolution forecasting. This demonstrates that while XGBoost is best suited for long-term predictions, hybrid deep learning models excel in short-term dynamic adjustments.

Fig. 12 to Fig. 16 show the distribution of power demand before and after implementing of the HAPLT controller in peak load reduction from August 2024 to December 2024.

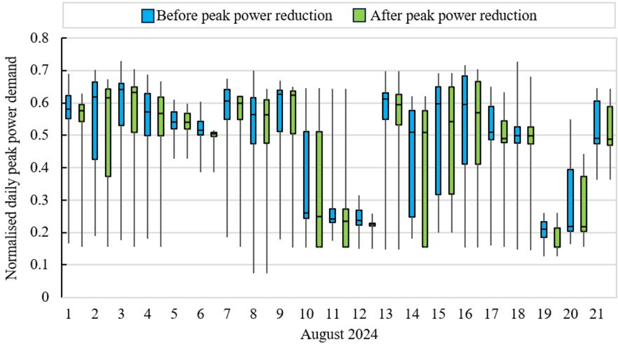

Fig. 12. Comparison of the peak load reduction for August.

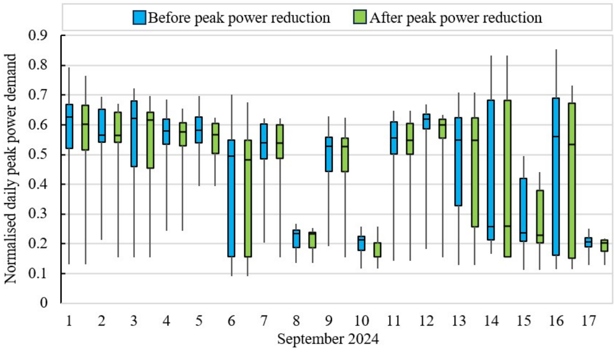

Fig. 13. Comparison of the peak load reduction for September.

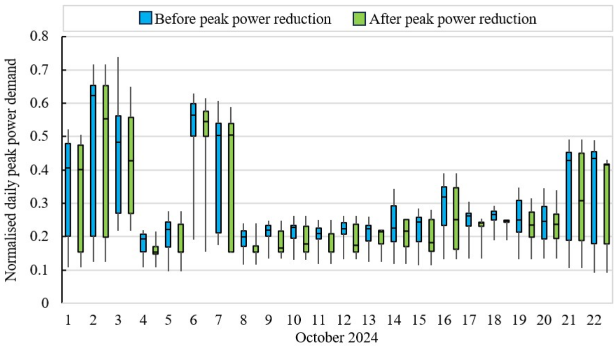

Fig. 14. Comparison of the peak load reduction for October.

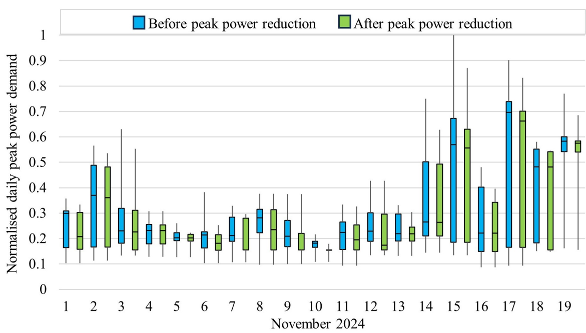

Fig. 15. Comparison of the peak load reduction for November.

Fig. 17 illustrates a comparative box plot of the monthly power demand distributions before and after the implementation of the HAPLT controller from August 2024 to December 2024. The figure complements the detailed monthly trends shown in Fig. 12 to Fig. 16 by summarising the overall impact across the evaluation period. Each pair of box plots represents the demand spread for a given month, highlighting the shift in peak demand values. A noticeable reduction in both the median and the interquartile range of power demand can be observed in the post-implementation data. This result validates the effectiveness of the HAPLT controller in reducing peak load and flattening demand variability.

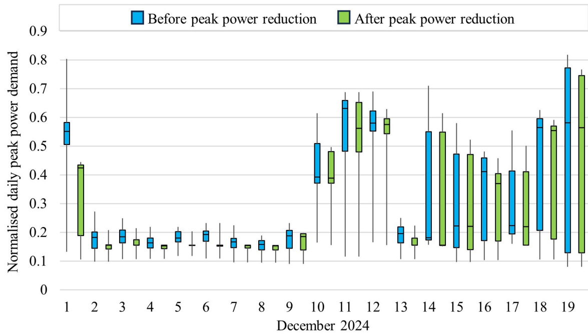

Fig. 16. Comparison of the peak load reduction for December.

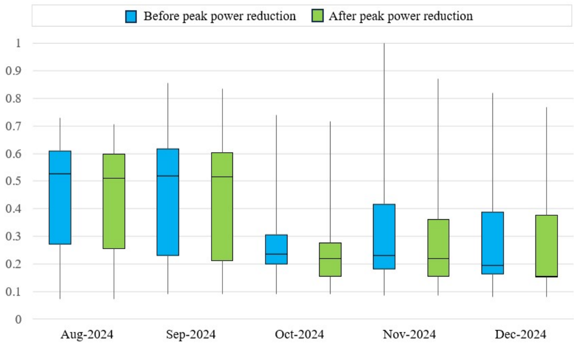

Fig. 17. Monthly power demand distribution before and after HAPLT implementation from August to December 2024.

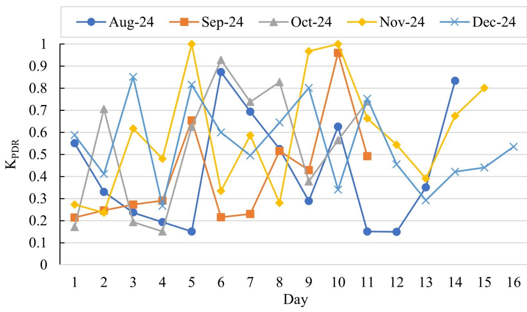

Fig. 18. K_{PDR} validation results of the HAPLT controller.

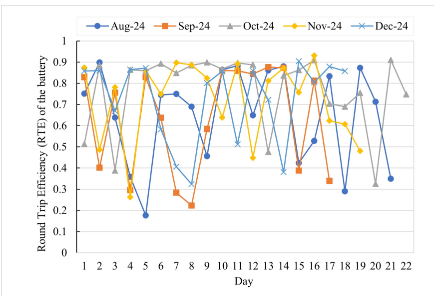

Fig. 19. RTE validation results of the HAPLT controller.

Table VII shows the performance of HAPLT for both initial threshold prediction and 30-minute dynamic threshold prediction. For the initial threshold prediction, the model performs the best in August 2024 with a MAPE of 30.78% and RMSE of 74.25 kW. The average MAPE is 58.43% and RMSE is 93.98 kW. For 30-minute dynamic threshold prediction, the model achieves better overall accuracy. The lowest error is in August 2024, with a MAPE of 18.04% and RMSE of 32.02 kW. The average MAPE is 34.68% and RMSE is 38.16 kW.

TABLE VII: SUMMARY OF THE HAPLT PERFORMANCE FOR INITIAL AND 30-MINUTE THRESHOLD PREDICTIONS THROUGH VALIDATION

Month	Initial Threshold Prediction				30-minute Dynamic Threshold Prediction			
	MAE (kW)	MAPE (%)	MSE (kW2)	RMSE (kW)	MAE (kW)	MAPE (%)	MSE (kW2)	RMSE (kW)
Aug-2024	54.67	30.78	5513.97	74.25	25.31	18.04	1059.82	32.02
Sep-2024	67.55	39.90	6470.45	80.43	26.37	21.29	1219.35	33.99
Oct-2024	87.45	76.49	10854.46	104.18	32.70	37.25	1483.40	37.79
Nov-2024	79.22	45.96	7875.54	88.74	35.49	41.57	1992.18	43.49
Dec-2024	102.72	99.01	14958.75	122.30	38.87	55.25	2069.43	43.52
Average	78.32	58.43	9134.63	93.98	31.75	34.68	1564.84	38.16

Fig. 18. illustrates the values of K_{PDR} of the HAPLT controller across five months. It is noticed that K_{PDR} varies from 0.1 to 0.9 in August 2024 and December 2024, while K_{PDR} being relatively stable in September and October.

Fig. 19 presents the round-trip efficiency (RTE) of the battery across different days from August 2024 to December 2024. November 2024 shows the highest overall efficiency, with RTE consistently near 0.9.

Table VIII shows the K_{MDR} validation results of the HAPLT controller to demonstrate its effectiveness in reducing monthly maximum demand (MD). The initial reduction target (MDR_i) was set at approximately 49 kW each month, with the actual reduction achieved (MDR_a) averaging 43.57 kW. The K_{MDR} values, representing the percentage of the intended reduction successfully achieved, are in the range of 0.72 and 0.99, with an average of 0.89, indicating high effectiveness in peak demand reduction. The controller achieved the highest K_{MDR} (0.99) in November 2024, nearly meeting the full reduction target. The controller performed well in September 2024 and December 2024 because K_{MDR} are 0.96 and 0.93, respectively. On the other hand, the controller delivered K_{MDR} of 0.72 in October 2024.

Overall, the HAPLT controller consistently achieved over 89% of its reduction targets, making it an effective strategy for peak demand management.

TABLE VIII: THE K_{MDR} VALIDATION RESULTS OF THE HAPLT CONTROLLER

Month	Monthly MD before reduction (kW)	MDR_i (kW)	MDR_a (kW)	K_{MDR}
Aug-2024	349.23	49.00	40.86	0.84
Sept-2024	369.87	49.00	47.07	0.96
Oct-2024	336.92	49.00	35.36	0.72
Nov-2024	386.93	49.50	49.00	0.99
Dec-2024	316.52	49.00	45.55	0.93
Average	351.89	49.10	43.57	0.89

TABLE IX: THE VALIDATION RESULTS OF THE HAPLT CONTROLLER

Month	Average Load Factor	Average RTE	Total Energy Saved (kWh)
Aug-2024	0.78	0.65	2344.59
Sep-2024	0.77	0.63	1841.29
Oct-2024	0.79	0.77	2910.35
Nov-2024	0.66	0.72	2378.67
Dec-2024	0.71	0.72	2241.18
Average	0.74	0.70	2342.21

Table IX shows the results from August 2024 to December 2024, demonstrate the effectiveness of the HAPLT controller in reducing peak load and optimizing energy savings. The overall average load factor of 0.74, indicating efficient power usage despite varying peak demands. The total average RTE ranged of 0.70, reflecting the system's efficiency in minimizing energy losses during storage and retrieval. The total energy saved is at an average of 2342.21 kWh over the five months.

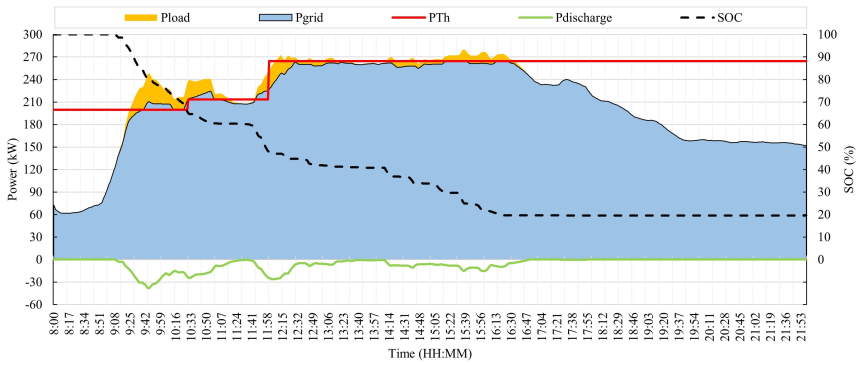

Fig. 20. Peak load reduction profile with BESS at Daikin R&D on 21st August 2024.

Fig. 20 illustrates the power flow dynamics and battery SOC throughout the day under the HAPLT controller. The load demand fluctuates over time, with noticeable peaks occurring in the morning and early afternoon. Grid power consumption increases as the SOC gradually depletes, indicating a shift in power source as the battery discharges. The threshold power limit is maintained at a relatively stable level, ensuring peak demand control. The battery discharge occurs primarily during peak hours, reducing dependence on grid power. The SOC starts at a high level in the morning and steadily declines throughout the day, reaching lower levels after mid-afternoon. This indicates strategic battery utilization, ensuring energy availability during high-demand periods. The figure demonstrates that the HAPLT controller effectively optimizes battery discharge to manage peak loads while maintaining a suitable SOC profile to sustain system operation.

IV. Conclusion

The validation results demonstrate that the HAPLT controller effectively manages peak load reduction and optimizes battery energy storage utilization. For the initial threshold prediction, the model achieved an average Mean Absolute Error (MAE) of 78.32 kW, Mean Absolute Percentage Error (MAPE) of 58.43%, Mean Squared Error (MSE) of 9134.63 kW², and Root Mean Squared Error (RMSE) of 93.98 kW. The 30-minute dynamic threshold prediction exhibited improved accuracy, with an average MAE of 31.75 kW, MAPE of 34.68%, MSE of 1564.84 kW², and RMSE of 38.16 kW. The peak demand reduction performance, represented by K_{MDR} values, averaged 0.89. The Round-Trip Efficiency (RTE) of the battery varied across months but remained stable in most cases, ensuring effective energy utilization. The power flow analysis confirms that the controller strategically discharges the battery to reduce peak grid consumption while maintaining a sustainable SOC. Overall, the HAPLT controller proves to be a reliable and adaptive solution for peak power demand reduction, dynamically adjusting thresholds to optimize battery usage while effectively reducing grid dependency. By implementing the HAPLT controller, the estimated annual cost savings for Daikin R&D is RM29,340.84, demonstrating its economic benefits in reducing peak demand and optimizing energy consumption.

While the HAPLT controller demonstrates strong performance in peak load reduction and battery optimization, several areas for improvement can enhance its effectiveness. Incorporating more advanced deep learning models, such as transformer-based architectures, or integrating external factors like weather and production schedules may further refine accuracy. The current model does not explicitly account for battery degradation over time. Implementing a degradation model to adjust charging and discharging cycles dynamically can enhance long-term efficiency and reduce maintenance costs. The system could be enhanced by integrating renewable energy sources such as solar or wind, reducing grid dependency further while optimizing battery storage. By addressing these aspects, the HAPLT controller can be refined to provide even more accurate, efficient, and cost-effective peak demand reduction solutions in industrial settings.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Huoy Lih Bong: software development, methodology, investigation, and writing, Kien Huat Chua: writing original draft, and supervision, Yun Seng Lim: review, editing, and supervision, Xie Cherng Miow: methodology, and software validation, Wai Meng Chin: Project administration; all authors had approved the final version.

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