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Application of Battery Energy Storage Systems for Power Demand Smoothing in Industrial Machinery and Equipment

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Industrial manufacturing processes involve various types of electrical load profile, which can generally be categorized into continuous-operation loads and start–stop operation loads. These load profiles are often highly fluctuating rather than stable, forcing factories to contract demand capacities significantly higher than their average power consumption, thereby increasing basic electricity charges. By installing a small-capacity battery energy storage system at the equipment front end and utilizing its fast charge–discharge characteristics to discharge during heavy-load periods and charge during light-load periods, the total power demand of the supply line can be effectively smoothed, resulting in a substantial reduction in contracted demand capacity. In this study, a sensor-based power monitoring system consisting of current sensors, power transducers, and a programmable logic controller is used to acquire high-resolution electrical load data from industrial machines. The measured sensing data were used as the input for short-term load forecasting and battery energy storage control. We focus on industrial machinery exhibiting pronounced periodic start–stop operating characteristics, in which short-term actions on the order of seconds or minutes frequently generate peak power demands that compel users to increase contracted capacity. Time-series forecasting models, including the autoregressive, autoregressive integrated moving average, and seasonal autoregressive integrated moving average models, are first applied to predict the load behavior of such equipment. On the basis of the forecasting results, a smoothing-baseline-based load smoothing control strategy is proposed to regulate the charge–discharge operation of the energy storage system, thereby stabilizing power demand and enabling an economic benefit analysis. The results verify the feasibility of applying energy storage systems to smooth the power demand fluctuations of industrial machinery and to effectively reduce basic electricity charges.

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1. Introduction

Mechanical power equipment primarily relies on electric motors as the driving source to convert electrical energy into various forms of mechanical energy. From conveyor systems to air compressors and chilled water systems, motors serve as the core power source. However, the power consumption of most industrial equipment is not constant during operation. For example, hydraulic punching machines exhibit highly fluctuating power demand profiles. Owing to these load characteristics, industrial users are often required to contract demand capacities significantly higher than their actual average demand. In general, the average demand utilization rate of factories is only approximately 60% of the contracted demand capacity. If the power consumption during heavy-load periods can be suppressed, the power demand on the grid side can be stabilized and the utilization rate of contracted capacity can be improved.(1,2)

Many industrial machines, such as cutting, punching, and machining equipment, exhibit pronounced periodic or start–stop operational characteristics. Their load profiles frequently generate peak power demands during short actions on the order of seconds or minutes, forcing users to increase their contracted demand capacity. However, these peaks are typically short-duration transient demands rather than sustained load requirements, leading to an overestimation of contracted capacity. Energy storage systems, characterized by fast response and high charge–discharge rates, can release energy during peak periods and recharge during low-load intervals, making them well suited for mitigating load fluctuations.(3,4) When combined with accurate load forecasting models, energy storage scheduling can be better aligned with actual operating conditions, thereby enhancing the effectiveness of demand management.(5,6)

In this study, the proposed power demand smoothing framework is built upon a sensor-based power monitoring system composed of current sensors, power transducers, and a programmable logic controller. The sensing system provides high-resolution electrical load data, which are used as the input for short-term forecasting and battery energy storage control. Thus, the proposed method can be regarded as a sensing-enabled energy management approach for industrial machinery.

Among load forecasting methods, traditional statistical time-series models, such as the autoregressive (AR), autoregressive integrated moving average (ARIMA), and seasonal autoregressive integrated moving average (SARIMA) models, have been widely applied to electrical load forecasting owing to their simple structure, high interpretability, and suitability for time-series data.(7) In this study, these well-established models are adopted and compared for different industrial load characteristics. Although nonlinear forecasting models such as support vector regression, long short-term memory networks, and gated recurrent units have been widely used for load forecasting, these models generally require larger datasets and higher computational resources. For the measured industrial machinery loads in this study, the dominant characteristic was short-cycle periodicity rather than long-term stochastic variation. Therefore, the SARIMA model was selected because it provides sufficient accuracy, physical interpretability, and low computational complexity for controller-level implementation.

On the basis of the above motivation, in this study, we target industrial equipment with periodic start–stop load characteristics at sub-minute time scales. A small-capacity battery energy storage system (BESS) is installed at the equipment front end to discharge during heavy-load periods and charge during light-load periods, thereby effectively smoothing the total power demand of the supply line and significantly reducing the contracted demand capacity. Load forecasting results are used to estimate future load behavior, and a power smoothing baseline is calculated on the basis of the energy storage capacity, output power limits, and energy balance constraints. This baseline serves as the reference for the charge–discharge scheduling of the energy storage system, enabling the load profile to be smoothed, the peak demand to be reduced, and the contracted capacity to be lowered. An integrated framework encompassing load forecasting, smoothing baseline determination, and energy storage charge–discharge control is proposed and validated using actual industrial equipment data.

The main contribution of this work is the development of a sensing-enabled machine-level power demand smoothing framework for industrial equipment with sub-minute periodic start–stop load characteristics. Unlike previous studies that mainly focused on building-level or grid-level peak shaving, in this work, we use high-resolution sensor data from individual industrial machines to forecast short-cycle load fluctuations and determine a smoothing baseline for small-capacity battery energy storage control.

2. Load Forecasting Models

During the operation of industrial equipment, electrical load varies with machine actions, start–stop patterns, and process cycles. Therefore, load profiles must be obtained using measurement instruments or circuit-based power monitoring systems. On the basis of the measured load data, electrical load forecasting is performed using three time-series forecasting models to support the scheduling and smoothing strategy of the energy storage system. The adopted models include the (1) AR, (2) ARIMA, and (3) SARIMA models. The forecasting performance characteristics of these models are subsequently compared.

(1) AR model

The AR model assumes that the current load value has a linear relationship with several past load values. The mathematical expression of the AR model is given by

$$y_t = C + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t, \tag{1}$$

where y_t denotes the load value at time t, p is the model order, ϕ_i represents the regression coefficients, and ε_t is a white noise term. The AR model is suitable for load profiles with relatively stable variations and without pronounced seasonal characteristics, such as certain types of continuously operated industrial equipment.

(2) ARIMA model

The ARIMA model eliminates trends in time-series data through differencing to obtain a stationary sequence, followed by modeling using autoregressive and moving average components. The ARIMA model is denoted as *ARIMA(p,d,q)*, where p is the order of the autoregressive component, d is the number of differencing operations required to achieve stationarity, and q is the order of the moving average component. The general form of the ARIMA model is expressed as

$$y'_t = c + \phi_1 y'_{t-1} + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t. \tag{2}$$

The ARIMA model is suitable for continuous loads with gradual variations and clear trends but without fixed periodicity, such as industrial equipment operating steadily over long durations or environmentally affected loads. For such load characteristics, differencing effectively stabilizes the time series, allowing the ARIMA model to accurately describe the underlying temporal structure.

(3) SARIMA model

The SARIMA model can be regarded as an extension of the ARIMA model. Its key feature lies in the incorporation of seasonal components to effectively capture periodic fluctuations in time-series data. The SARIMA model is expressed as

$$SARIMA(p, d, q)(P, D, Q)\ m, \tag{3}$$

where (p, d, q) represents the non-seasonal parameters, (P, D, Q)m denotes the seasonal parameters, and m is the number of observations per season or per cycle.

$$B^z y_t = y_{t-z} \tag{4}$$

With the backshift operator, the SARIMA model can compactly represent both seasonal and non-seasonal differencing, autoregressive, and moving average components. Accordingly, the SARIMA model can be rewritten in the form shown in

$$\begin{aligned} &(1-\phi_1 B - \cdots - \phi_p B^p)(1-\phi_1 B^m - \cdots - \phi_p B^{pm})(1-B)^d (1-B^m)^D y_t \\ &= (1+\theta_1 B + \cdots + \theta_q B^q)(1+\theta_1 B^m + \cdots + \theta_q B^{qm})\varepsilon_t. \end{aligned} \tag{5}$$

Owing to its ability to simultaneously account for trend, randomness, and seasonality, the SARIMA model is particularly suitable for industrial equipment loads with fixed periodic operations, such as cutting and punching machines with start–stop characteristics. It is therefore well suited for short-cycle industrial load forecasting.

To comprehensively evaluate the accuracy and robustness of the forecasting models used in this study, three performance metrics are adopted: mean absolute error (*MAE*), mean relative error (*MRE*), and normalized root mean square error (*nRMSE*). The definitions of these metrics are described as follows.

(1) *MAE*

MAE is a commonly used metric for quantifying the magnitude of errors between predicted and observed values. A smaller *MAE* indicates that the predicted values are closer to the actual measurements.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{6}$$

Here, n is the total number of samples, y_i is the ith observed value, $\hat{y}_i$ is the ith predicted value, and $|y_i - \hat{y}_i|$ denotes the absolute error.

(2) *MRE*

MRE measures the average relative ratio between predicted and observed values. A smaller *MRE* indicates a higher forecasting accuracy.

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{7}$$

(3) *nRMSE*

nRMSE is a relative error metric obtained by normalizing the root mean square error. It represents the proportion of prediction error relative to the range or mean of the actual data. A smaller *nRMSE* indicates a higher model accuracy.

$$nRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\bar{y}} \times 100\% \tag{8}$$

Here, $\bar{y}$ denotes the mean of the observed values.

In general, for periodic start–stop loads, the SARIMA model is more suitable owing to its ability to capture short-term and periodic load variations.

3. Smoothing-baseline-based Power Demand Smoothing Control Strategy

In this study, we proposed a load smoothing control strategy based on a smoothing baseline to stabilize the power demand of industrial machinery. The primary objectives of the smoothing control strategy are as follows: (1) to suppress instantaneous peak demand and prevent abrupt load spikes, (2) to store surplus energy during low-load periods in the energy storage system for subsequent redistribution, and (3) to shape the overall load profile into a smoother curve that approaches a constant power level.[8–10]

In this study, short-term load forecasting results obtained from the AR, ARIMA, and SARIMA models are first used to estimate the load variations of industrial equipment for the subsequent operating period. On the basis of the forecasted load profile, a smoothing baseline is determined by considering the capacity of the energy storage system, the rated power of the power conversion system (PCS), and the energy balance constraints. The smoothing baseline serves as the reference for controlling the charge–discharge scheduling of the energy storage system.

The core control logic of the smoothing baseline strategy is described as follows. (1) When the predicted load exceeds the smoothing baseline, the energy storage system discharges to shave the load peak. (2) When the predicted load falls below the smoothing baseline, the energy storage system charges to replenish the discharged energy in preparation for the next operation cycle.

Accordingly, the smoothing baseline must satisfy the following constraints: (1) the discharge energy must not exceed the usable capacity of the energy storage system, thereby extending its service life; (2) sufficient charging energy must be reserved during low-load periods to compensate for previous discharging; and (3) the charging and discharging power must not exceed the rated power of the PCS.

The design procedure of the smoothing baseline for start–stop periodic loads at sub-minute time scales is illustrated in Fig. 1. This type of load is characterized by fixed operation cycles at the second or minute level with high repeatability and pronounced periodic peaks. A complete daily load profile is first forecast using the selected load prediction model. The total available energy capacity of the energy storage system is then evenly allocated across all operation cycles, and the average power level is defined as the smoothing baseline. If the calculated smoothing

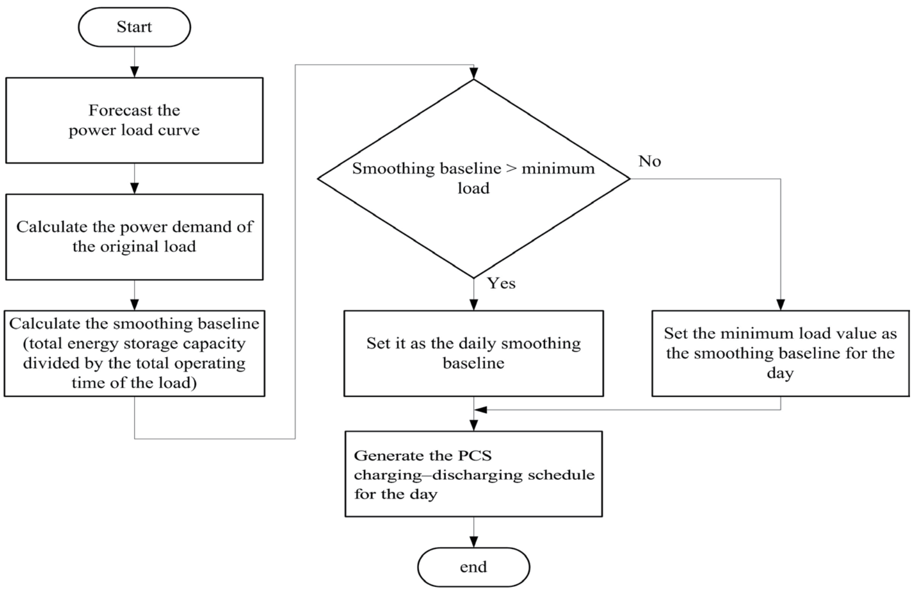


Fig. 1. Flowchart of the smoothing baseline design for start–stop periodic loads at the minute level.

baseline is lower than the minimum load, the minimum load is adopted as the baseline. On the basis of this baseline, a PCS discharge schedule is generated.

By applying this strategy, peak demand within each operating cycle can be effectively shaved, transforming the original sawtooth-like load profile into a smoother curve and suppressing excessive power demand on the grid side. Consequently, the proposed smoothing baseline strategy enhances load smoothness and reduces the contracted demand capacity required by industrial users.

In this study, we presented an integrated power demand smoothing control framework that incorporates multiple load forecasting models, energy storage system constraints, and an adaptive baseline adjustment mechanism. The effectiveness of the proposed baseline strategy in reducing periodic peak demand and improving load smoothness is demonstrated, with the expected demand reduction of approximately 50% for the tested equipment. The feasibility of the proposed control strategy is further validated in the following section through experimental results obtained from actual industrial machinery.

The smoothing baseline used in this study was determined on a daily basis because the tested industrial machines exhibited highly repeatable operation cycles. This static baseline approach is computationally simple and suitable for implementation in industrial controllers. However, for production lines with variable operating schedules or multiple interacting loads, the baseline can be adaptively updated using recent sensing data and BESS state-of-charge information. A model predictive control framework may also be incorporated in future work to dynamically optimize charge–discharge scheduling under time-varying load and tariff conditions.

4. Experimental Results and Discussion

In this study, we conducted on-site power measurements on two representative cutting machines used in a footwear manufacturing factory. The first machine is a manual energy-saving gantry cutting machine, and the second machine is a fully automated turret-type cutting machine. Photographs of the two machines are shown in Figs. 2 and 3, respectively. Both machines exhibit highly periodic start–stop load characteristics. Each operation cycle consists of multiple actions, including downward motion, cutting, upward motion, and horizontal movement, resulting in significant fluctuations in power demand.

The power measurement and data acquisition system consists of a current sensor (CS), a power transducer (PT), and a programmable logic controller, as illustrated in Fig. 4. The current sensor is clamped on the power supply line of the tested machine to measure the time-varying load current during each operation cycle. The power transducer converts the measured voltage and current signals into instantaneous power signals. The programmable logic controller is used as the data acquisition and control interface to record high-resolution power data and provide the input dataset for load forecasting and smoothing baseline determination. The CS used in this study is a Hall-effect type with a conversion ratio of 50/5 A, an accuracy class of ±0.5 %, a bandwidth of 1 kHz, and an installation method of the current sensor used for noninvasive current measurement on the power supply lines. The PT converts measured voltage and current signals into a proportional analog output of 0–10 V_{dc} with a measurement range of 0–5 kW and a

Fig. 2. (Color online) Energy-saving gantry cutting machine.

Fig. 3. (Color online) Turret-type automatic cutting machine.

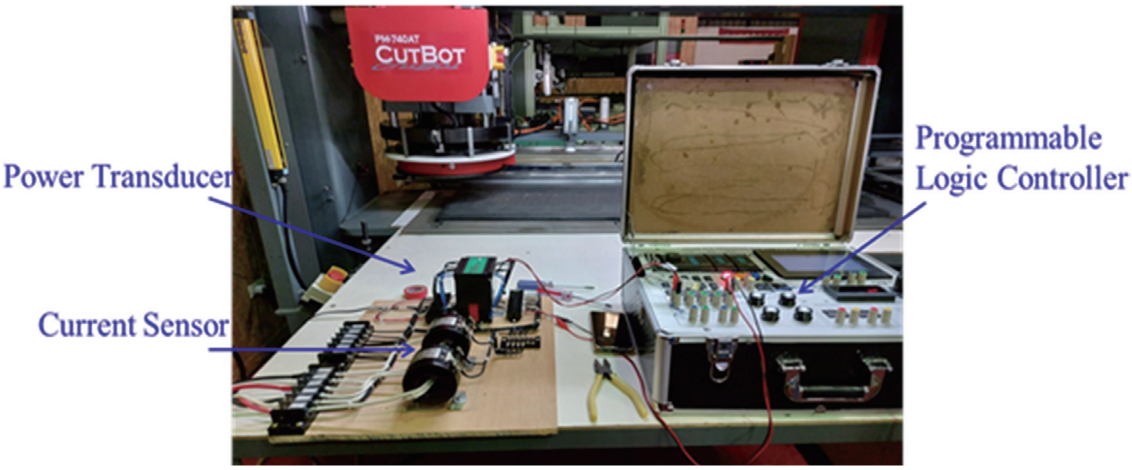


Fig. 4. (Color online) Power measurement and data acquisition system.

measurement accuracy of ±1 %. The system is capable of recording power data with millisecond-level resolution, which serves as input data for subsequent load forecasting modeling and smoothing baseline determination.

The BESS used in this study was a small-capacity machine-level energy storage unit. Its main electrical characteristics included a rated PCS power of 1 kW and usable energy capacities of 8.9 and 10.7 kWh for the tested cases. The BESS was operated within a predefined state-of-charge range to prevent over-charge and over-discharge. The maximum charge and discharge powers were limited by the PCS rating. The main parameters of the small-capacity machine-level energy storage unit are shown in Table 1.

Table 1
Main parameters of small-capacity machine-level energy storage unit.

Parameter	Value
Battery type	$LiFePO_4$
Rated PCS power	1 kW
Usable capacity	8.9 kWh/10.7 kWh
Nominal DC voltage	48 V
AC output voltage	220 V
Maximum charge power	1 kW
Maximum discharge power	1 kW
Round-trip efficiency	0.98
SOC operating range	0.1–0.9

4.1 Load forecasting results

For the energy-saving gantry cutting machine, the measured power waveform of a single operation cycle is shown in Fig. 5. The cycle duration is approximately 3.6 s and consists of three primary actions: the leftward movement of the cutting head, downward pressing and cutting, and the rightward movement of the cutting head. The power demand exhibits clear periodic characteristics.

Similarly, the measured power waveform of a single operation cycle for the turret-type automatic cutting machine is shown in Fig. 6. The cycle duration is approximately 3.5 s and includes four actions: cutting head descent, cutting operation, cutting head ascent, and horizontal movement. As observed in Figs. 5 and 6, the power demand varies significantly across different operation stages for both machines.

The three load forecasting models were applied to predict the load profiles of the energy-saving gantry cutting machine. The forecasting results and performance evaluation metrics are presented in Fig. 7, where the red curve represents the predicted load and the blue curve represents the measured load. Among the three models, the SARIMA model achieved the highest performance, with an *MAE* of 60.74 W, an *MRE* of 2.4%, and an *nRMSE* of 4.18%. These results indicate that the SARIMA model provides the highest accuracy and stability for short-term periodic load forecasting.

The forecasting results and evaluation metrics for the turret-type automatic cutting machine are shown in Fig. 8. Consistent with the previous case, the SARIMA model outperformed the AR and ARIMA models, achieving an *MAE* of 18.87 W, an *MRE* of 0.69%, and an *nRMSE* of 0.9%. These results further confirm the suitability of the SARIMA model for the short-term forecasting of periodic start–stop industrial loads.

4.2 Benefit analysis of power demand smoothing

It is assumed that the footwear factory operates for 12 h per day. During the working hours, the energy storage system discharges uniformly to reduce the power drawn from the utility grid by the cutting machines. During the remaining 12 non-operating hours, the energy storage system is charged uniformly to prepare for the next day’s operation. For the energy-saving

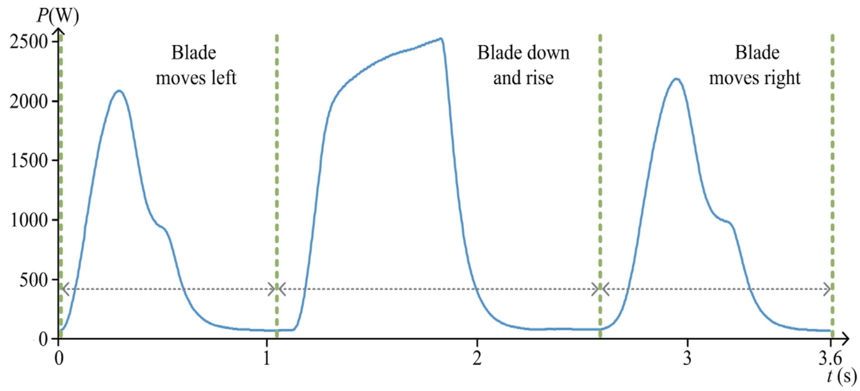


Fig. 5. (Color online) Illustration of a single operation cycle of the energy-saving gantry cutting machine.

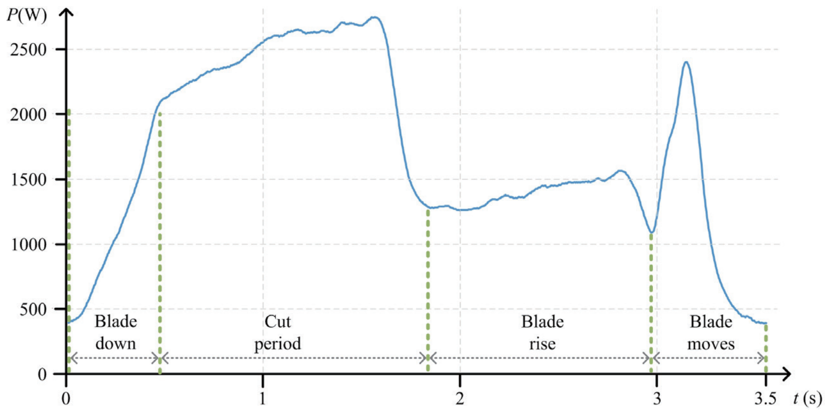
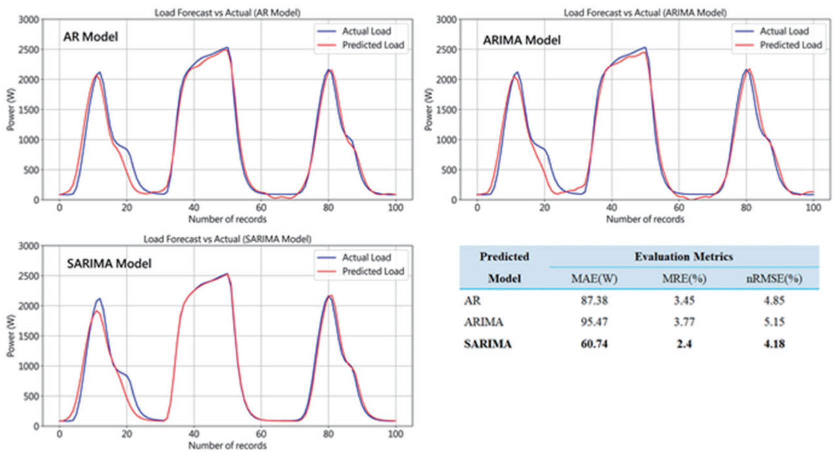
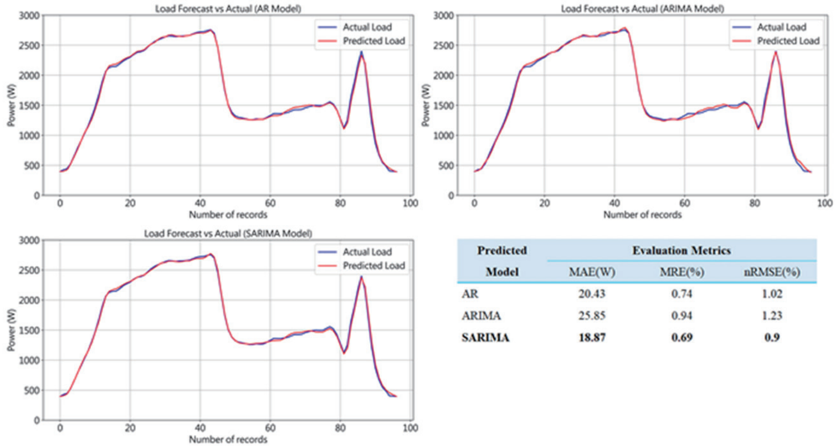


Fig. 6. (Color online) Illustration of a single operation cycle of the turret-type automatic cutting machine.



Predicted Model	Evaluation Metrics		
	MAE(W)	MRE(%)	nRMSE(%)
AR	87.38	3.45	4.85
ARIMA	95.47	3.77	5.15
SARIMA	**60.74**	**2.4**	**4.18**

Fig. 7. (Color online) Load forecasting results and forecasting accuracy evaluation for the energy-saving gantry cutting machine.



Predicted Model	Evaluation Metrics		
	MAE(W)	MRE(%)	nRMSE(%)
AR	20.43	0.74	1.02
ARIMA	25.85	0.94	1.23
SARIMA	**18.87**	**0.69**	**0.9**

Fig. 8. (Color online) Load forecasting results and forecasting accuracy evaluation for the turret-type automatic cutting machine.

gantry cutting machine, which has an operation cycle duration of 3.6 s, approximately 12000 operation cycles occur within a 12 h working period.

The optimal smoothing baseline for the energy-saving gantry cutting machine is determined on the basis of the forecasted load generated by the highest-performing forecasting model. The energy storage system is configured with a capacity of 1 kW/8.9 kWh, and the resulting smoothing baseline is shown as the red line in Fig. 9. The green line represents the original power demand of the machine. The smoothing baseline reduces the peak demand by approximately 0.445 kW compared with the original demand, indicating that energy storage discharging can effectively reduce the power demand of the machine.

In terms of economic benefits, a demand reduction of 0.445 kW corresponds to an approximate reduction of 50.17% in contracted demand capacity. This reduction results in annual basic electricity charge savings of approximately NT$ 1017.41. A detailed comparison of the benefits with and without energy storage is provided in Table 2.

For the turret-type automatic cutting machine, the energy storage system is configured with a capacity of 1 kW/10.7 kWh. The resulting smoothing baseline is shown as the red line in Fig. 10. Compared with the original power demand (green line), the smoothing baseline reduces the demand by approximately 0.846 kW. This corresponds to an approximately 50% reduction in contracted demand capacity and annual basic electricity charge savings of approximately NT$ 1934.21. The detailed comparison is summarized in Table 3.

The economic analysis in this study focuses on the reduction in contracted demand capacity and the corresponding annual basic electricity charge savings. In actual industrial applications, battery round-trip efficiency, PCS efficiency, depth of discharge, cycle life, thermal management, maintenance cost, and replacement cost should be incorporated into a lifecycle cost analysis. Moreover, when the proposed method is extended to a factory-wide energy management system, the aggregated load behavior of multiple machines and their operation schedules should be considered.

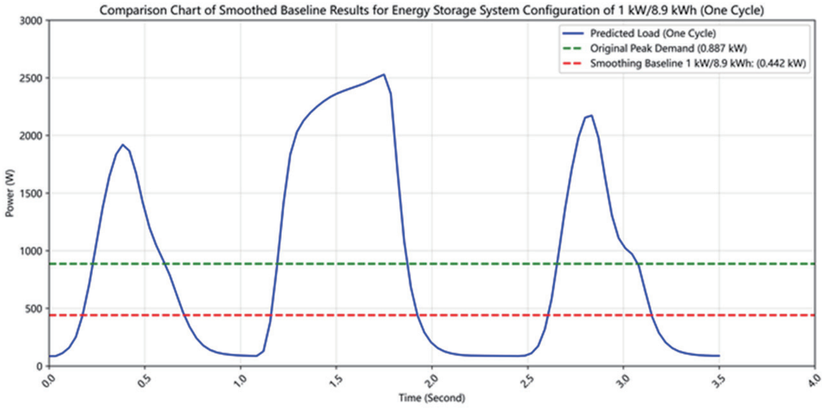


Fig. 9. (Color online) Comparison of smoothing baseline results with a 1 kW/8.9 kWh energy storage system.

Table 2
Comparison of benefits with and without a 1 kW/8.9 kWh energy storage system.

Item	Energy storage configuration	
	0 kW	1 kW/8.9 kWh
Original contract capacity	0.887 kW	0.887 kW
Smoothing baseline (contract capacity)	0.887 kW	0.442 kW
Total discharge energy/per day	0 kWh	8.9 kWh
Total discharge energy/per cycle	0 Wh	0.742 Wh
Discharging power during the first 12 h	0 kW	0.742 kW
Discharging power during the last 12 h	0 kW	0.742 kW
Benefit (compared with no storage)	0 kW (0%)	0.445 kW (50.17%)
Annual basic electricity charge	NT$ 2027.95	NT$ 1010.54
Cost savings (compared with no storage)	NT$ 0	NT$ 1017.41

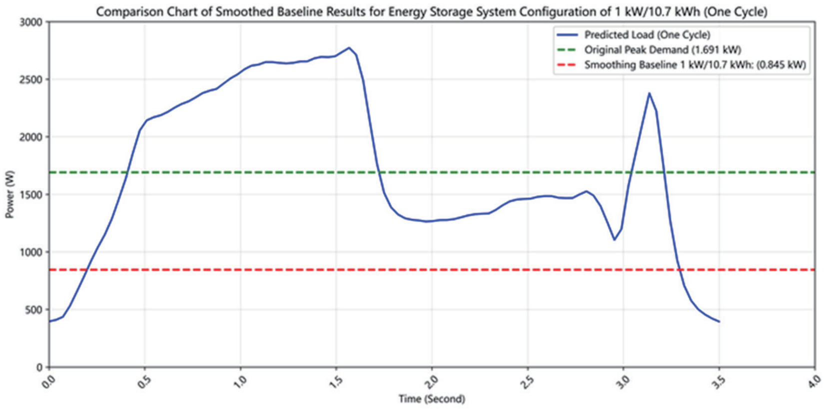


Fig. 10. (Color online) Comparison of smoothing baseline results with a 1 kW/10.7 kWh energy storage system.

Table 3
Comparison of benefits with and without a 1 kW/10.7 kWh energy storage system.

Item	Energy storage configuration	
	0 kW	1 kW/10.7 kWh
Origin	1.691 kW	1.691 kW
Smoothing baseline (contract capacity)	1.691 kW	0.845 kW
Total discharge energy/per day	0 kWh	10.7 kWh
Total discharge energy/per cycle	0 Wh	0.867 Wh
Discharging power during the first 12 h	0 kW	0.892 kW
Discharging power during the last 12 h	0 kW	0.892 kW
Benefit (compared with no storage)	0 kW (0%)	0.846 kW (50%)
Annual basic electricity charge	NT$ 3866.13	NT$ 1931.92
Cost savings (compared with no storage)	NT$ 0	NT$ 1934.21

5. Conclusions

In this study, we investigated the application of battery energy storage systems for the power demand smoothing of industrial machinery. A smoothing-baseline-based load smoothing control strategy was proposed to regulate the charge–discharge operation of the energy storage system and to reduce peak power demand. The effectiveness of the proposed strategy was evaluated through an economic benefit analysis.

Two representative cutting machines used in the footwear industry, namely, an energy-saving gantry cutting machine and a turret-type automatic cutting machine, were selected for experimental validation. Power consumption measurements, load forecasting, and optimal energy storage sizing were conducted for both machines. For the energy-saving gantry cutting machine, an energy storage configuration of 1 kW/8.9 kWh achieved a 50.17% reduction in power demand. For the turret-type automatic cutting machine, an energy storage configuration of 1 kW/10.7 kWh resulted in a 50% reduction in power demand.

The results confirm that sensor-based load monitoring plays a key role in identifying transient power fluctuations and enabling forecasting-assisted BESS control. Therefore, the proposed method provides a practical sensing-enabled energy management approach for industrial machinery. The selected energy storage capacities and maximum charge–discharge power ratings represent a reasonable balance between performance and system constraints. Overall, the feasibility of applying energy storage systems to stabilize industrial machinery power demand and to reduce basic electricity charges is verified.

Acknowledgments

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