

Article

Adaptive Iterative Algorithm for Optimizing the Load Profile of Charging Stations with Restrictions on the State of Charge of the Battery of Mining Dump Trucks

Nikita V. Martyushev ^{1,*} , Boris V. Malozyomov ² , Vitaliy A. Gladkikh ³ , Anton Y. Demin ¹,
Alexander V. Pogrebnoy ¹, Elizaveta E. Kuleshova ¹ and Yulia I. Karlina ³ 

¹ Department of Information Technology, Tomsk Polytechnic University, 634050 Tomsk, Russia; ad@tpu.ru (A.Y.D.); pogrebnoy@tpu.ru (A.V.P.); eek24@tpu.ru (E.E.K.)

² Department of Electrotechnical Complexes, Novosibirsk State Technical University, 630073 Novosibirsk, Russia; borisnovel@mail.ru

³ Scientific Research and Testing Center “Stroytest”, Moscow State University of Civil Engineering, 129337 Moscow, Russia; gladkikh_87@mail.ru (V.A.G.); jul.karlina@gmail.com (Y.I.K.)

* Correspondence: martjushev@tpu.ru

Abstract

The development of electric quarry transport puts a significant strain on local power grids, leading to sharp peaks in consumption and degradation of power quality. Existing methods of peak smoothing, such as generation control, virtual power plants, or intelligent load management, have limited efficiency under the conditions of stochastic and high-power load profiles of industrial charging stations. A new strategy for direct charge and discharge management of a system for integrated battery energy storage (IBES) is based on dynamic iterative adjustment of load boundaries. The mathematical apparatus of the method includes the formalization of an optimization problem with constraints, which is solved using a nonlinear iterative filter with feedback. The key elements are adaptive algorithms that minimize the network power dispersion functionality (i.e., the variance of $P_{grid}(t)$ over the considered time interval) while respecting the constraints on the state of charge (SOC) and battery power. Numerical simulations and experimental studies demonstrate a 15 to 30% reduction in power dispersion compared to traditional constant power control methods. The results confirm the effectiveness of the proposed approach for optimizing energy consumption and increasing the stability of local power grids of quarry enterprises.

Keywords: optimal control; mathematical modeling; load peak smoothing; integrated battery energy storage system; dynamic optimization; iterative algorithms; nonlinear filtering; constrained problem; real-time control; adaptive systems; numerical methods

MSC: 93C10; 93D30; 90C26



Academic Editors: Yuan Cao,
Chunsheng Wang and Liqing Liao

Received: 13 November 2025

Revised: 8 December 2025

Accepted: 9 December 2025

Published: 12 December 2025

Citation: Martyushev, N.V.; Malozyomov, B.V.; Gladkikh, V.A.; Demin, A.Y.; Pogrebnoy, A.V.; Kuleshova, E.E.; Karlina, Y.I. Adaptive Iterative Algorithm for Optimizing the Load Profile of Charging Stations with Restrictions on the State of Charge of the Battery of Mining Dump Trucks. *Mathematics* **2025**, *13*, 3964. <https://doi.org/10.3390/math13243964>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The rapid development of electric transport in the industrial sector, especially in the mining industry, leads to a significant increase in electricity consumption and the emergence of new load profiles that put pressure on the power system [1,2]. In recent years, large mining companies have been switching from diesel mining trucks to electric ones, reducing carbon emissions and operating costs. However, the mass introduction of such vehicles sharply increases peak loads in local power grids that supply charging

stations, deteriorates the quality of electricity, increases losses, requiring modernization of distribution substations and power lines. The problem of smoothing peaks and filling in consumption dips is becoming a key area in the field of smart grids and flexible load management [3].

One of the most obvious ways to solve the problem of compensating peak loads is to regulate generation from energy sources, when power plants change the generated power depending on fluctuations in consumption. Similar approaches were actively used in thermal and hydropower engineering. For example, in [4] the authors proposed an algorithm for controlling thermal power plants to regulate load schedules by changing the modes of turbine generators. In [5], a system for optimizing gas turbine plants in the Shanghai energy system was developed, which reduced peaks by up to 12%. In [6], the authors studied the capabilities of hydroelectric units to compensate for daily load fluctuations and showed that increasing the flexibility of hydroelectric power plants requires significant operating costs. Despite certain successes, generation control methods have a number of drawbacks (long reaction time, low economic efficiency and high capital intensity) when expanding the capacity of plants. In addition, their use is limited in local power grids without generation, and the load is formed exclusively by consumers.

Another area is the use of renewable energy sources in conjunction with storage devices, accumulating excess electricity during periods of low demand and supplying it to the grid during peak consumption. In [7], the authors proposed a model for the market evaluation of energy storage systems taking into account the nonlinear characteristics of batteries, showing that optimizing the storage device parameters could increase the profitability of the project by 8–10%. The authors of [8] investigated the application of pumped storage systems in isolated island networks, where wind energy was used to pump water, providing up to 30% of fuel savings in diesel installations. However, for quarry enterprises remote from large sources of renewable energy, such solutions are not always feasible. The limited availability of wind and solar energy and the need for significant investment in infrastructure make this approach less suitable for off-grid industrial areas.

In recent years, special attention has been paid to virtual power plants (VPPs), which combine distributed energy sources, consumers and energy storage into a single control system. The authors of [9] performed an economic analysis of VPPs with large-scale battery systems and showed that their integration could increase the utilization rate of generating capacity and reduce the cost of electricity by 6–9%. However, the high complexity of prediction algorithms and the need for high-speed communication links limit the practical implementation of VPP in real-time, especially in industrial areas with unstable load profiles. In addition, the efficiency of virtual power plants decreases dramatically in the absence of reliable data on the state of grid elements.

Intelligent load management involving the system of integrated battery energy storage (IBES), which is connected to distribution networks or charging stations and acts as a buffer between the grid and consumers, is considered a promising area. In [10], a tool was developed for technical and economic analysis and optimization of small-scale photovoltaic systems with batteries, showing that the correct selection of the capacity and operating mode of the storage device can reduce peak loads by up to 18% and extend the service life of the battery by 25%. In [11], the authors demonstrated that the joint planning of household appliances and IBES reduced energy costs by up to 15% and load peaks by 20%. Despite these advances, most of the work is focused on the domestic or urban sector, where the load capacity is relatively low and temporary fluctuations in consumption are easily predictable. In the case of industrial charging systems for quarry transport, the load pattern is much more stochastic, and short-term peaks reach hundreds of kilowatts, making traditional strategies ineffective.

In summary, existing approaches show good results in residential or grid-connected environments but demonstrate limited transferability to quarry conditions. Generation control solutions require significant reserve capacity and have response times on the scale of minutes, which is insufficient for short spikes of 200–500 kW typical of haul truck charging [4–6]. VPP-based architectures depend on continuous high-speed communication and accurate forecasting that are difficult to maintain at remote sites with unstable power profiles [9]. Intelligent load-shifting methods with IBES buffers reported 15–20% of peak reduction in household and commercial studies [10,11], whereas quarry stations exhibit irregular multi-megawatt charging waves with poor predictability, reducing the effectiveness of rule-based scheduling. Therefore, the proposed approach specifically targets high-amplitude stochastic load patterns, where dynamic boundary adjustment provides faster response and does not rely on prediction accuracy.

Recent research has started to focus specifically on high-power charging infrastructure in industrial environments. The authors of [3] proposed a sequential decision-making process for the techno-economic operation of grid-connected traction substations with integrated solar PV and IBES, showing that the coordinated scheduling of storage and fast charging could significantly reduce demand peaks at traction nodes in the context of electric transport. In [4], the authors analyzed battery charging from a traction voltage inverter with an integrated charger and demonstrated the importance of matching charging profiles to the upstream network constraints and converter capabilities. For mining applications, the study [5] developed an optimal energy-efficiency control framework for a system of distributed energy-storage-based mining truck. These studies confirm that the electrification of heavy-duty vehicles creates highly concentrated and intermittent charging demand at industrial fast-charging stations, which in turn calls for dedicated peak-shaving strategies coordinated with the local grid. At the same time, a number of recent works have analyzed the use of battery energy storage systems for peak shaving in distribution grids and industrial consumers. The authors of [6] proposed a BESS-based scheme to reduce local and global peak loads in distribution networks, highlighting the role of storage placement and control strategy. The researchers of [7,8] formulated joint optimization problems for storage operation that simultaneously address peak shaving and ancillary services, obtaining super-linear economic benefits compared with independent operation. The scientists of [9] carried out techno-economic assessments of battery storage for peak demand management in smart grids and commercial facilities, while the research of [10] demonstrated that coordinated control of generation and storage could substantially improve reliability and peak-load handling capability in isolated or weak grids. However, most of these approaches rely on day-ahead optimization or model-predictive control with explicit forecasts of the load profile and electricity prices, which may be difficult to obtain in applications of stochastic industrial charging.

IBES distributed control systems based on machine learning algorithms are also of interest. In [12], a distributed control system was developed, using reinforcement learning to mitigate overvoltage during high penetration at solar power plants. The simulation results showed that voltage deviation was reduced by 35% while reducing load peaks. However, the use of such algorithms requires large computing resources and constant access to telemetry data, which makes it difficult to use them in conditions of limited communication channels at remote industrial facilities.

Another approach involves optimizing EV charging schedules based on network conditions and IBES parameters. In [13], the authors proposed a consistent decision-making algorithm for the optimal operation of traction substations integrated with solar photovoltaic systems and storage devices. Their model reduced peak loads by 22% and increased the use of renewable energy by up to 91% during the day. However, the method

requires accurate prediction of the movement profile and consumption of electric dump trucks, which is extremely difficult in quarry conditions, where transportation cycles are irregular and depend on technological downtime.

A number of authors have considered hybrid energy storage schemes that combine lithium-ion batteries with supercapacitors or flywheels. In [13], the authors showed that combining systems can improve primary standby and load smoothing by 25% compared to single battery storage. In [14], the authors proposed a strategy for planning the work schedules of companies operating battery systems in the electricity market, which made it possible to increase the equipment utilization rate and to ensure the economic stability of the system. However, the use of hybrid schemes is associated with the complication of the control system, the need to synchronize the operating modes of various drives and an increase in the cost of installation.

Compared to state-filtered disturbance rejection and multilayer neuro-control algorithms, the proposed method has a simpler computational structure and does not require forecasting models, deep training datasets or high-performance processors. Active disturbance rejection controllers achieve high tracking quality but depend on internal observer tuning and may be sensitive to noise under stochastic load fluctuations. Neuro-control approaches provide strong generalization ability, but their implementation at remote industrial sites is limited by data availability and training stability.

The advantage of the present approach is real-time adaptability using iterative boundary adjustment applying only measurable variables (SOC , $P_{\text{grid}}(t)$, P_{load}), which reduce the variance by 15–30% without predictive models. The main limitation of our method is sub-optimality in long-horizon planning. In contrast to forecast-driven controllers, it operates reactively and does not anticipate future load surges. However, for isolated mine grid conditions with unpredictable duty cycles, this reactive robustness becomes a practical benefit.

In comparison with well-established strategies of energy storage control such as model predictive control (MPC), fuzzy logic controllers, and adaptive filtering approaches, the proposed method does not rely on a predictive model or rule base and does not require solving an optimization problem at each control step. MPC-based BESS controllers achieve high global optimality but require forecasting accuracy, matrix inversion, and horizon tuning, which limits their use in stochastic microgrids with rapidly varying loads. Fuzzy logic schemes ensure robustness to uncertainty but cannot guarantee variance minimization as a formal objective and require expert-defined membership functions. Adaptive filters smooth signals effectively, but do not incorporate physical battery constraints or allow boundary reconfiguration in response to SOC dynamics.

The novelty of the proposed approach lies in the dynamic iterative adjustment of the upper and lower power boundaries of $PH(t)$ and $PL(t)$ directly as a function of real-time energy capacity (E_c , E_d) and SOC, without prediction, rule tables or offline tuning. This makes the algorithm computationally lightweight and scalable for industrial stations where load uncertainty is high and predictive accuracy is limited.

Despite significant progress, all the considered approaches have common limitations. Generation control methods do not provide local load compensation in distribution networks; renewable energy solutions depend on weather conditions and require power redundancy [15]. Virtual power plants are difficult to implement in real time [16,17], and intelligent control algorithms and hybrid systems require high computing power and expensive components [18]. In mining environments where power is often supplied from isolated grids or loosely connected feeders, the greatest potential is to integrate the systems of battery energy storage directly into the charging stations of electric mining trucks. This

approach makes it possible to locally smooth out peak loads [19], increase the stability of power supply and reduce the cost of reconstructing network equipment [20].

In contrast to the solutions considered earlier, this paper proposes using the strategy of direct charge and discharge control of IBES applying dynamic adjustment of load boundaries. This method is based on the continuous redistribution of energy between the grid and the storage device depending on the current consumption capacity [21]. Unlike traditional methods with fixed charging thresholds, the proposed algorithm allows for real-time adaptation of the charging and discharging boundaries. This provides a more accurate match to the load profile and extends the life of batteries by limiting the cycling depth [22]. This approach smooths peaks, fills troughs, increases the utilization rate of electrical equipment, savings in capital costs for the modernization of power grids [23].

The relevance of the chosen direction is conditioned by the combination of technological, economic and environmental significance. On the one hand, the transition of mining equipment to electric traction is a prerequisite for the decarbonization of the industry and is in line with global trends in sustainable development [24]. On the other hand, the increasing load on power systems requires intelligent solutions for adaptive energy flow management. The use of IBES as part of charging stations makes it possible to efficiently use the stored energy during periods of peak demand and create a buffer capacity without increasing transformer capacity. Moreover, the proposed direct control strategy can be implemented at the level of controllers of the local charging station without expensive data centers, which makes it especially attractive for industrial facilities with limited resources [25,26].

Therefore, this study is aimed at developing and experimentally testing a method for direct control of charge and discharge of a system of battery energy storage using dynamic adjustment of load boundaries integrated into an electric charging station for mining electric dump trucks. The main goal of this study is to develop and verify a mathematical model and algorithm for direct charge and discharge control IBES, integrated into a charging station for mining electric dump trucks. The algorithm is aimed at minimizing the target functional characterizing the dispersion of network power, while observing the system of differential and algebraic constraints describing the energy balance and physical limits of the storage battery. In what follows, we denote this objective as the dispersion functional DDD. A single mathematical definition of DDD is used throughout the work (see Equation (1) in Section 3, where DDD is given as the time variance of the network power ($P_{grid}(t)$) over the calculation interval TTT).

The algorithmic component is separated here from the general mathematical model to maintain clarity. The following text describes step-by-step boundary update rules, SOC-driven adaptation and convergence properties. The scientific novelty of the work lies in the following:

A new mathematical formalism of the problem of smoothing load peaks is proposed, representing it as a conditional optimization problem in continuous time with dynamically adaptable constraints.

An original iterative algorithm with dynamic adjustment of load boundary values (upper $PH(t)$ and lower $PL(t)$) have been developed, which is interpreted as a nonlinear adaptive filter. Unlike classical methods with fixed thresholds, this algorithm recalculates the boundaries in real time based on the current state of charge (SOC) and integral estimates of the charge/discharge energy (E_c , E_d).

The convergence of the iterative process to a quasi-stationary solution providing minimal power dispersion under conditions of a stochastic load profile is mathematically substantiated and experimentally confirmed.

Compared to existing adaptive BESS controllers, the key novelty of this work lies not in the use of iteration or feedback themselves, but in the mechanism of real-time bound-

any reconfiguration. Traditional strategies rely on fixed charging thresholds, predictive scheduling or model-based foresight, while the proposed method treats the upper and lower power limits ($PH(t)$, $PL(t)$) as continuously adjustable control variables. Their values evolve dynamically based on instantaneous grid power deviation and the integrated charge/discharge availability (Ec , Ed), enabling the controller to redistribute power without forecasting, optimization solvers or long-horizon planning. The system therefore adapts to stochastic load peaks using boundary migration rather than explicit trajectory tracking, which distinguishes the approach from gradient-based MPC, rule-driven battery dispatch and conventional constant-limit BESS operation reported in the literature.

Compared with existing optimization-based and model-predictive control strategies for load profile smoothing, the proposed dynamic boundary algorithm follows a different philosophy. Classical MPC or multi-time-scale optimal control formulations compute the storage power set-point by repeatedly solving a constrained optimization problem over a prediction horizon, which requires accurate forecasts of the load profile and relatively high computational resources. Advanced control schemes for BESS, including adaptive and distributed charge/discharge control, typically rely on detailed system models and communication between multiple agents, and their performance is sensitive to parameter tuning. In contrast, our approach embeds the minimization of network power variance into a nonlinear iterative filter that directly adjusts the admissible power band ($PH(t)$, $PL(t)$) in response to the measured SOC and cumulative charge/discharge energy. As a result, the controller operates without explicit load prediction, uses only local measurements available at the charging station, and can be implemented on low-cost industrial controllers while still providing a 15–30% of reduction in the power variance in the considered industrial fast-charging scenario.

The article structure: The article is organized as follows. Section 2 presents a mathematical formulation of the problem, including a system of power balance equations and constraints, a detailed description of an iterative algorithm for dynamic boundary tuning, illustrated by flowcharts. Section 3 demonstrates the quantification of the method effectiveness based on the introduced optimization criteria (variance, peak/trough difference) and visualizes the results of the algorithm for four typical operating modes. Section 4 provides a comparative analysis of the proposed strategy with the traditional constant-power method, supported by full-scale test data. Section 5 summarizes the main findings and outlines directions for future research.

2. Methods and Materials

The study is based on a combination of theoretical modeling and experimental verification aimed at analyzing the joint operation of an electric charging station for mining electric dump trucks [27] with a system of integrated battery energy storage (IBES). The study was carried out in two consecutive stages: at the first stage, a mathematical model of the interaction of the charging station, the power grid and the battery was created. At the second stage, full-scale tests were carried out on an experimental facility, including a charging module, an energy storage device, and a control system [28].

The experimental stand of the electric charging station was made in the form of a modular installation, including a converter part, a battery pack and a digital control system. To visualize the relationships between the components of the system, Figure 1 shows the structural diagram of the experimental test bench. The diagram shows the power supply network, the AC/DC converter, the battery energy storage system (IBES) with the BMS system, the load in the form of charging system modules for mining dump trucks, and a central controller that implements the proposed algorithm. The arrows show the power flows (P_{grid} , P_{bat} , P_{load}) and information feedback (SOC, power measurements) that

close the control loop [29]. The following subsection formalizes the objective, constraints and stability criteria that define the IBES peak-shaving task. This part focuses strictly on the mathematical representation, without implementation-specific assumptions. The mathematical formulation of the problem was based on the representation of network power as $P_{grid}(t)$, load power as $P_{load}(t)$, and battery power as $P_{bat}(t)$. In this case, the power balance is implemented.

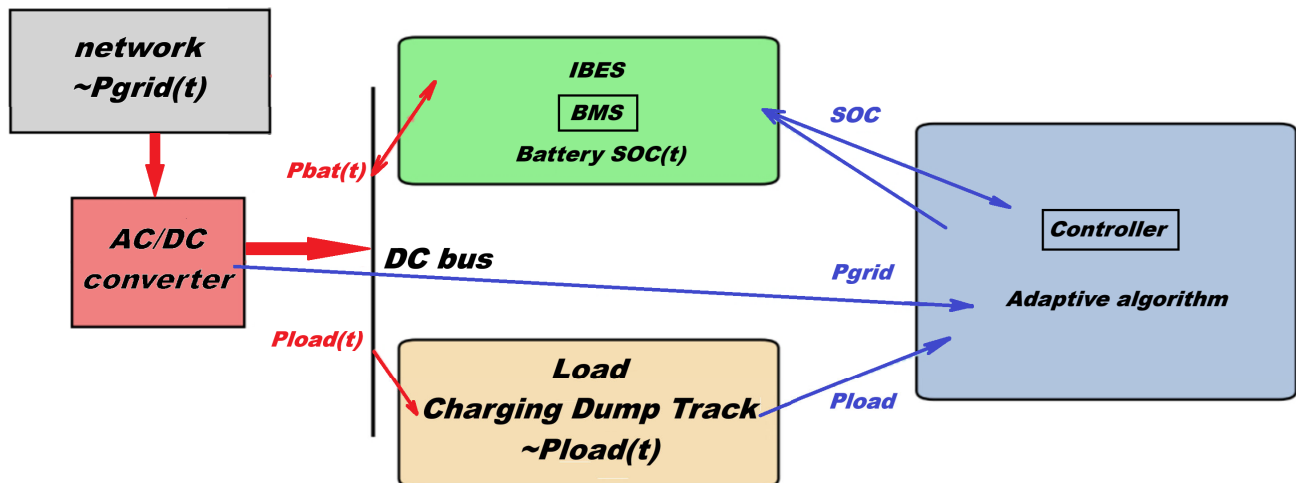


Figure 1. The structural diagram of the charging station system with a system of integrated battery energy storage (IBES).

Dotted lines indicate data flows (feedbacks); solid lines indicate power flows based on measurements of network power (P_{grid}), load power (P_{load}), and state of charge (SOC) of the battery. The main element of the energy part was an AC/DC converter, which provided a bidirectional energy conversion between the AC network and the DC bus. To protect against reverse currents, a diode barrier was used to prevent the flow of energy from the batteries to the grid in abnormal modes [30]. The battery module was a set of lithium-ion cells combined in a configuration with a rated power of up to 40 kW that was controlled by a BMS system that monitored currents, voltage, and state of charge (SOC). To simulate the load of an electric vehicle, a programmable active load was used, which made it possible to reproduce typical charging profiles for mining dump trucks [31]. All elements of the plant were controlled via the industrial CAN bus, which provided synchronization with the central controller and transmission of telemetry data to a personal computer. Using the PC, data were collected, power curves were visualized, and control algorithms were developed within the framework of a mathematical model [32].

For the reader's convenience, the main symbols and notations used in the mathematical formulation are summarized in Table 1.

Table 1. Main symbols and notations used in the mathematical model.

Symbol	Meaning	Units	Representative Values Used in Numerical Examples
$P_{grid}(t)$	Power drawn from the external grid by the charging station at t time	MW	(given by load-flow solution/measurement)
$P_{load}(t)$	Total load power of the fast-charging station (traction converters, auxiliaries, etc.) at t time	MW	Given by the measured load profile in Section 2
$P_{bat}(t)$	Power of the IBES battery at t time; positive for discharge, negative for charge	MW	–
R_{bat}	Sign indicator of the battery operating mode: $R_{bat} > 0$ for discharge, $R_{bat} < 0$ for charge	–	–
$SOC(t)$	State of charge of the battery at t time (the ratio of stored energy to nominal capacity)	p.u.	Typically, within 0.1–0.9 in simulations
SOC_{min}, SOC_{max}	Lower and upper admissible SOC limits	p.u.	$SOC_{min} = 0.1, SOC_{max} = 0.9$
E_{max}	Nominal (maximum) energy capacity of the battery	MWh	100 MWh (200 MWh in Mode 4)
E_0	Initial stored energy in the battery at the beginning of the simulation	MWh	10–40 MWh depending on the scenario
$E_c(t), E_d(t)$	Cumulative charging and discharging energy of the battery over the current control interval	MWh	Reset to 0 at the beginning of each control interval
E_{cmax}, E_{dmax}	Admissible limits for cumulative charge and discharge energy, ensuring compliance with SOC bounds	MWh	Selected according to SOC_{min} and SOC_{max} in Section 2
$P_H(t), P_L(t)$	Dynamic upper and lower boundaries of the admissible network power band used by the algorithm	MW	Adapted iteratively according to the dynamic boundary algorithm
γ	Iterative step coefficient in the dynamic boundary update law	–	Chosen empirically to ensure convergence (see Section 2)
λ	Filtering parameter that determines the smoothing of the dynamic boundaries and the sensitivity to random spikes	–	$0 < \lambda < 10$; the value used in simulations is given in Section 2
D	Variance (dispersion) of the network power of $P_{grid}(t)$ over the observation period	MW ²	Computed according to Equation (1)
ΔP_{load}	Difference between maximum and minimum values of the network power over the observation period	MW	Computed according to Equation (2)
β	Peak–Valley Coefficient characterizing the contrast between peak and valley loads	–	Computed according to Equation (4)
Δt	Time step of the discrete load and control profile	h or s, depending on data resolution)	Given by the sampling interval of the measured load profile
k	Iteration index of the dynamic boundary update algorithm	–	$k = 0, 1, 2, \dots$

The mathematical formulation of the problem was based on the representation of the power system of the charging station in the form of three interacting subsystems: the power supply network, the battery storage and the external load, whose role belongs to the electric car. Let the instantaneous power of load consumption be denoted as $P_{load}(t)$, the power output by the network as $P_{grid}(t)$, and the battery power as $P_{bat}(t)$. In this case, the power balance is achieved.

$$P_{grid}(t) = P_{load}(t) + P_{bat}(t), \quad (1)$$

where $R_{bat} > 0$ corresponds to the discharge of the battery (the transfer of energy to the load), and $R_{bat} < 0$ corresponds to its charge.

$$D = \frac{1}{T} \int_0^T [P_{grid}(t) - \bar{P}_{grid}]^2 dt, \quad (2)$$

where $\bar{P}_{\text{grid}}$ is the average value of the network power for the time interval (T). This expression coincides with the dispersion functional D introduced in Equation (1). Minimization of this functional makes it possible to obtain an optimal distribution of charge and discharge modes, when network power fluctuations are minimal.

For the algorithm to work correctly, it is necessary to take into account the physical limitations of the battery. Firstly, the charging and discharging power is limited by $P_c^{\max}$ and $P_d^{\max}$ values, which is formalized by inequalities

$$-P_c^{\max} \leq P_{\text{bat}}(t) \leq P_d^{\max}. \quad (3)$$

Secondly, the state of charge (the SOQ of the battery must remain within acceptable limits) is

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max}. \quad (4)$$

The dynamics of the SOC change is described by the differential equation

$$\frac{dSOC(t)}{dt} = -\frac{\eta_c P_{\text{bat}}(t)}{E_{\max}}, \quad (5)$$

where η_c is the energy conversion efficiency factor, and $E_{\max}$ is the nominal capacity of the battery. These dependencies form a system of constraints within which the charging and discharging modes are optimized [33].

In the developed model, the key element is the mechanism for dynamic adjustment of load boundary values, which ensures the adaptation of the control algorithm to current fluctuations in consumption [34]. In traditional methods, peak smoothing is carried out using fixed power thresholds, above which the battery charge or discharge is turned on [35]. However, this approach does not take into account the non-stationarity of the load and does not allow using the potential of the storage device efficiently. According to the proposed methodology, the boundary values of $P_H(t)$ and $P_L(t)$ are determined iteratively in the modeling process and change depending on the current levels of peaks and troughs of the consumption curve [36].

In this work, adaptivity means real-time modification of the control boundaries based on instantaneous feedback rather than on fixed thresholds. During every cycle of the Δt duration, the algorithm receives updated values of $P_{\text{load}}(t)$, $P_{\text{grid}}(t)$ and $SOC(t)$ and recalculates E_c and E_d . If the current boundary pair of $(P_H(t)$ and $P_L(t))$ leads to insufficient charge/discharge capability or violates SOC/power limits, the boundaries are shifted by $\pm \Delta P$ until a feasible state is reached. The adaptation therefore does not rely on forecasting or learning-based prediction; instead, it continuously tunes the boundaries according to the measured operating state of the system. In contrast to static tuning, where a fixed pair of $(P_H(t)$ and $P_L(t))$ cannot track rapid fluctuations, the dynamic update compensates stochastic peaks more effectively and prevents battery saturation by tightening or relaxing limits depending on available SOC reserve. This feedback-driven boundary update is the core mechanism that provides adaptability under highly variable industrial load conditions.

To find these limits, an iterative process is used, based on minimizing the discrepancy between the actual and desired charging or discharging capacity. Let E_c and E_d denote the energy stored and delivered by the battery per cycle (P_H^0, P_L^0):

$$P_H^0 = P_{\max} - P_d^{\max}, \quad P_L^0 = P_{\min} - P_c^{\max}. \quad (6)$$

At each step of the iteration, the integral area under the load plot sections above and below these boundaries is calculated, which makes it possible to estimate the current values of E_c and E_d . If the calculated values are outside the permissible range of the

battery's capacity, the boundaries are corrected by stepping ΔP up or down. Therefore, the algorithm tends to achieve a position of boundaries when the charge and discharge energy corresponds to the physical capabilities of the storage device [37], and the variance of network power is minimal.

Mathematically, this process can be considered as a problem of finding a quasi-stationary solution to a system of nonlinear equations that relate instantaneous values of power and accumulated energy [38]. The solution is found by iterative methods until the change in the load variance between adjacent iterations is less than that of the specified threshold (ϵ). To make the mathematical structure explicit, the control task can be written as a constrained optimization problem:

$$\min_{P_{bat}(t)} D = \frac{1}{T} \int_0^T \left(P_{grid}(t) - \overline{P_{grid}} \right)^2 \cdot dt \quad (7)$$

Subject to power constraints:

$$P_{bat}^{\min} \leq P_{bat}(t) \leq P_{bat}^{\max} \quad (8)$$

and SOC feasibility conditions:

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max}, \quad \dot{SOC}(t) = -\frac{\eta_c P_{bat}(t)}{E_{\max}}, \quad (9)$$

The iterative nonlinear filter performs gradient-free adjustment of dynamic load boundaries ($P_H(t)$ and $P_L(t)$) to minimize D while ensuring that all candidate control actions remain inside the feasible domain defined above. At each iteration of k , the boundary is perturbed by $\pm \Delta P$, and the step is accepted only if both power and SOC constraints remain satisfied; otherwise, the change is rejected and the boundary is shifted in the opposite direction.

Convergence in simulation is demonstrated by the fact that for all 4 test modes the iteration count remained finite (10–35 iterations per cycle), and the stopping criterion of $|D_{k+1} - D_k| < 10^{-3}$ was consistently achieved. Numerical experiments and full-scale tests showed no divergence or boundary oscillations, confirming practical stability of the filter under stochastic load conditions.

This approach ensures the convergence of the algorithm even with sharp fluctuations in the consumption profile.

The logic of the proposed adaptive iterative algorithm for dynamic adjustment of the $P_H(t)$ and $P_L(t)$ load boundaries is presented in the form of a flowchart in Figure 2. The algorithm begins by measuring the current values of the load power and the state of IBES charge. Based on this data, the current energy capacitances of E_c and E_d are calculated. The key step is the condition check, which determines one of the four possible modes of operation of the system. Depending on the mode, the upper and/or lower limit of the load is adjusted by the value of ΔP . The iteration process continues until a balance is reached between the charge/discharge energy and capacitive capabilities of IBES, which minimizes the dispersion of network power. Figure 2 shows a flow diagram of an adaptive iterative algorithm for direct charge and discharge control of IBES.

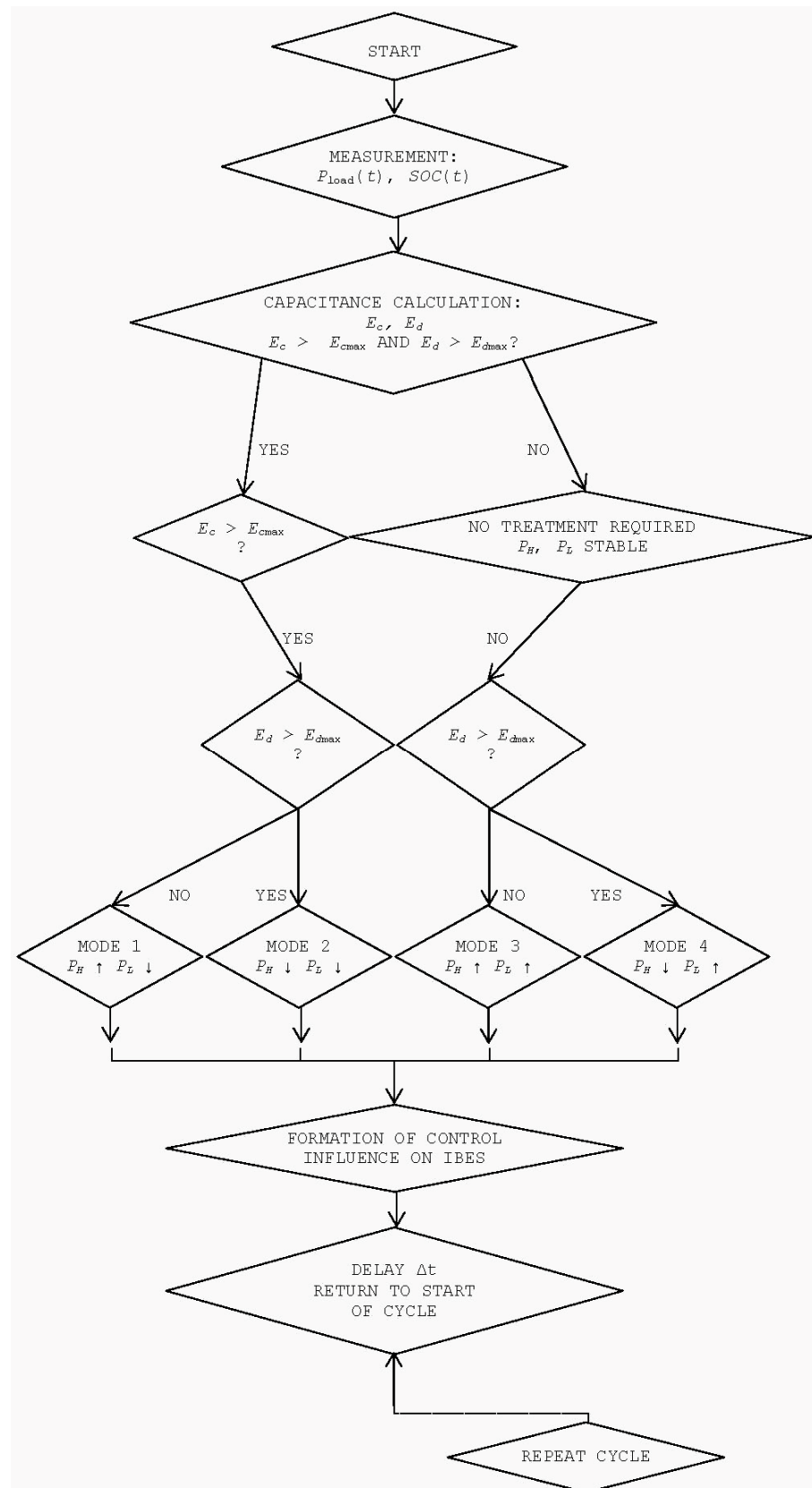


Figure 2. The block diagram of an adaptive iterative algorithm for direct charge and discharge control of IBES.

In real-time operation, the algorithm works as follows. First, the initial load boundaries of P_H^0 and P_L^0 are set based on a predicted or historically observed daily load curve and

on the nominal charging/discharging capabilities of the battery (Equations (5)–(7)). Then, at each control step of the Δt duration (1 s in the numerical experiments), the controller receives updated measurements of the grid power ($P_{\text{grid}}(t)$), the load power ($P_{\text{load}}(t)$) and the battery state of charge ($\text{SOC}(t)$). Using these real-time inputs, the current charge and discharge energies per cycle (E_c and E_d) are recalculated as the areas of the load curve above and below the active boundaries of $P_H(t)$ and $P_L(t)$. If E_c and E_d satisfy the capacity constraints and the instantaneous power and SOC remain within the limits given by Equations (5) and (6), the boundaries are kept unchanged and the IBES charge/discharge power is determined directly from the position of $P_H(t)$ and $P_L(t)$. Otherwise, the algorithm slightly shifts one or both boundaries by a ΔP step up or down and repeats the calculation of E_c and E_d . In this way, each iteration first enforces the hard constraints on battery power and SOC, and it reduces the variance of the grid power (D) only within this feasible region. The cycle of measurement–update–correction is repeated at every time Δt step, which enables the system to track fast stochastic changes in the load without relying on long-horizon forecasts.

The algorithm functions in real time, calculating the current energy capacitances (E_c, E_d) at each step and adapting the load boundaries accordingly; a detailed description of the four operating modes will be provided later in this section.

In Figure 2, the following notations are adopted: $P_H \uparrow$ is an increase in the upper limit of power; $P_H \downarrow$ is a decrease in the upper limit of power; $P_L \uparrow$ is an increase in the lower limit of power. $P_L \downarrow$ is reducing the lower limit of power; E_c is the current energy capacity; E_d is the current energy dissipation; Δt is the time lag between iterations. Figure 2 shows the sequence of steps, logical branching (4 modes) and the closed nature of the algorithm. To clarify the link between the flowchart and the mathematical formulation, each block in Figure 2 directly corresponds to specific expressions introduced in Section 2. The calculation of E_c and E_d is based on integral evaluation of the areas defined in Equations (8) and (9), while SOC evolution follows the dynamic model (6). The decision node in the flowchart maps for the four conditional states is listed in Table 1, where each combination of (E_c, E_d) relative to ($E_c^{\text{max}}, E_d^{\text{max}}$) selects a specific update rule for $P_H(t)$ and $P_L(t)$. The adjustment step of ΔP shown in the diagram reflects the iterative boundary update mechanism formalized in Equations (25)–(27). In view of this, the flowchart is not abstract but represents a compact procedural form of the mathematical algorithm described earlier.

This visualizes the novelty of the proposed solutions: adaptive logic is based on dynamic boundaries rather than on static thresholds or predictions. A description of the characteristics of the operating modes of the above algorithm is given in Table 2.

Table 2. Modes Description.

No. Mode	Mode Options $E_c, E_{c\text{max}}, E_d, E_{d\text{max}}$	Parameters of the PH and PL Power Boundaries
1	$E_c > E_{c\text{max}}, E_d \leq E_{d\text{max}}$	– $P_H \uparrow$: Increasing the upper limit of power – $P_L \downarrow$: Reducing the lower limit of the capacity
2	$E_c > E_{c\text{max}}, E_d > E_{d\text{max}}$	– $P_H \downarrow$: Decreasing the upper limit of power – $P_L \downarrow$: Reducing the lower limit of the capacity
3	$E_c \leq E_{c\text{max}}, E_d \leq E_{d\text{max}}$	– $P_H \uparrow$: Increasing the upper limit of power – $P_L \uparrow$: Increasing the lower limit of the capacity
4	$E_c \leq E_{c\text{max}}, E_d > E_{d\text{max}}$	– $P_H \downarrow$: Decreasing the upper limit of power – $P_L \uparrow$: Increasing the lower limit of the capacity

For numerical modeling, experimental data of the daily consumption schedule of the experimental charging station were used, which are characterized by the presence of two pronounced peak sections and several zones of minimum load. In the considered dataset, the instantaneous load power ($P_{\text{load}}(t)$) varies between approximately 41.7 and 51.8 kW over a 24 h interval, with an average value of 46.9 kW. The most intensive charging

periods correspond to clusters of high-power sessions when one or more dump trucks are connected, during which the power remains close to the upper level for several tens of minutes. Between these clusters, the station operates near the average power level, while shorter step-like changes caused by individual connection and disconnection events are superimposed in this trend. Such pattern reflects the stochastic nature of truck arrival times and leads to a sequence of peaks and troughs on time scales from several minutes up to a few hours.

Based on these data, different modes of IBES operation were compared. The computational experiments were performed in the MATLAB/Simulink R2020b software environment [39], where modules for modeling the network, battery and controller were implemented. In the numerical integration of the differential equations, the fourth-order Runge–Kutta scheme with a discretization step of 1 s was used, which provides stability under rapidly changing power profiles.

Laboratory tests were carried out to verify the adequacy of the model. Experimental data were taken using current and voltage sensors with a sampling rate of 10 Hz built into the converter, and data processing and algorithm implementation were performed in real time using an industrial controller with an ARM microprocessor. The obtained experimental power curves were compared with the results of modeling according to the standard deviation criterion and the peak-trough ratio coefficient. The discrepancy did not exceed 5%, which confirms the reliability of the proposed model and the mathematical transformations used.

From the point of view of the mathematical apparatus, the main transformation used in the study can be considered as the operation of the nonlinear filtering of the power time series [40]. In this case, a nonlinear iterative filter implies a feedback operator that maps the raw grid power signal ($P_{grid}(t)$) to a smoothed signal ($P_{grid}(t)$) by repeatedly updating the control boundaries of $P_H(t)$ and $P_L(t)$ so as to reduce the variance of $P_{grid}(t)$ under the battery constraints. At each time step, the filter computes correction increments for P_H and P_L based on the current power deviation, available charge/discharge energy and SOC limits and applies these corrections until the change in the dispersion measure between successive iterations becomes negligible. In contrast to the standard smoothing methods based on convolution of a signal with a fixed core, adaptive nonlinear filtering is used here, whose parameters are determined by the state of the battery and the dynamic limits of the load feedback and optimization algorithms in continuous time [41]. Essentially, the algorithm implements a discrete-continuum transformation in which the solution of the optimization problem is updated iteratively in time increments (Δt), and the load boundaries are recalculated as a function of the power deviations and the current SOC:

$$P_H^{(k+1)} = P_H^{(k)} + \gamma(E_d^{(k)} - E_d^*), \quad P_L^{(k+1)} = P_L^{(k)} - \gamma(E_c^{(k)} - E_c^*), \quad (10)$$

where γ is the iterative step coefficient, and the asterisks indicate the target capacitance values. This transformation provides a quick approximation to a sustainable solution and allows the system to adapt to any changes in load without the need to predict its profile.

This subsection summarizes real-time execution settings, controller parameters, and a communication structure. Numerical examples remain in Sections 3 and 4 for separation between method and results. The developed algorithm was tested for four typical operating modes, differing in initial SOC values and battery power [42]. These four operating modes correspond exactly to the conditional branches shown in Figure 2, confirming that the flowchart reflects the executable control logic used in modeling and experiments. In each mode, the dispersion indicators, peak and trough differences, and a smoothing coefficient were evaluated. The results confirmed that the application of dynamic configuration of load boundaries could reduce the network power variance by 15–30% compared to traditional

constant power management. This demonstrates the mathematical efficiency of an iterative approach that combines energy constraints with the principle of minimizing the functional of the variational type.

For clarity, the reported 15–30% reduction corresponds to measured decreases in the variance of $P_{grid}(t)$ over a 24 h operating cycle reproduced on a full-scale charging station test bench. The load profiles were derived from real operating data of mining haul trucks and replayed using a programmable active load to emulate quarry charging dynamics. The DDD variance was calculated according to (1) based on time-series measurements sampled at 10 Hz, and the baseline for comparison was the conventional constant-power charging strategy used in industrial charging stations. The experimental campaign covered four representative operating modes differing in initial SOC and power capacity, each evaluated in both baseline and adaptive-control configurations. In all modes, the adaptive method consistently yielded lower dispersion values, which confirms the quantitative improvement reported above.

It should be noted that the algorithm was implemented using numerical differentiation and integration methods that are resistant to measurement noise [43]. To eliminate the drift of the power signal, sliding averaging with exponential attenuation was used, which can be written as a recurrence relation:

$$\bar{P}_{grid}(t + \Delta t) = \lambda P_{grid}(t) + (1 - \lambda)\bar{P}_{grid}(t), \quad (11)$$

where λ is the filtering parameter that determines the degree of averaging. This made it possible to ensure the stability of calculations and reduce the sensitivity of the algorithm to random load spikes.

Therefore, the proposed method combines the mathematical modeling of the dynamic processes of charge and discharge of IBES with experimental verification of the results. The central element of the study is the use of adaptive iterative transformations, which make it possible to adjust the boundaries of control in real time depending on the current state of the system [44]. From a mathematical point of view, this is a solution to the constraint optimization problem implemented by means of a nonlinear iterative feedback filter. Such formulation ensures high accuracy and stability of the algorithm, and experimental data confirm its applicability for industrial charging stations of mining electric dump trucks operating under conditions of variable load and limited power of the supply network [45].

3. Results and Discussion

In continuation of the presented method of modeling and experimental analysis, special attention is paid to the assessment of quantitative characteristics that make it possible to objectively determine the effectiveness of the proposed algorithm for direct control of the charge and discharge of the battery energy storage system. Since the developed approach is aimed at reducing dynamic fluctuations in power consumption and leveling the load profile, it is necessary to formalize the parameters that characterize the degree of power smoothing after the implementation of IBES. This section provides a mathematical basis for assessing the compensating properties of the energy storage device in various modes of operation of the charging station.

The basic idea is to compare the initial load profile without the drive and the corrected profile after applying a dynamic load boundary strategy. At the same time, the analysis is carried out not only for local fluctuations (within short time intervals), but also for the global trend of power change during the entire calculation period. The efficiency of IBES is evaluated by a number of indicators reflecting the degree of reduction of peaks and the leveling of thickness troughs [46].

The time series of network power ($P_{grid}(t)$), corresponding to the power mode of the charging station, and the power of the storage battery ($P_{bat}(t)$), which describes the energy exchange between the grid and the storage device, are used as initial data. The combination of these dependencies makes it possible to form a resultant load graph of the system with compensation, which serves as the basis for calculating integral estimates. The description of the degree of vibration compensation, four complementary indicators are introduced, covering the statistical and extreme properties of the power signal [47].

In what follows, we treat the variance of the series of grid power time as the dispersion functional of the network power. The first indicator is the dispersion (deviation) of power fluctuations, i.e., a value that characterizes the degree of dispersion of instantaneous power values relative to the average level. This parameter reflects the stability of energy consumption and is sensitive to short-term fluctuations. Mathematically, this dispersion functional (DDD) is expressed as:

$$D = \frac{1}{T} \int_0^T [P_{grid}(t) - \bar{P}_{grid}]^2 dt, \quad (12)$$

where $P_{grid}(t)$ is the power coming from the grid at t time; $\bar{P}_{grid}$ is its average value for the design period (T). The lower the value of D , the higher the system's ability to compensate for peak fluctuations and the more evenly the load is distributed over time.

The following indicator is the absolute difference between load peaks and troughs, defined as the difference between the maximum and minimum values of network power during the observation period:

$$\Delta P_{load} = P_{max} - P_{min}, \quad (13)$$

where P_{max} and P_{min} are the extreme values of the load graph, respectively. This parameter characterizes the total amplitude of oscillations and makes it possible to assess the efficiency of peak smoothing at the level of the power system [48].

For additional analysis of the relationship between local maximums and load minimums, the coefficient of the relative difference between peaks and bottoms is used:

$$\alpha = \frac{P_{max} - P_{min}}{P_{max}}, \quad (14)$$

which shows the relative magnitude of the uneven power distribution. When $\alpha \rightarrow 0$, the load is almost uniform, while an increase in α indicates a significant power variation and the need to adjust the IBES modes.

The Peak–Valley Coefficient is defined as

$$\beta = \frac{P_{min}}{P_{max}}. \quad (15)$$

This parameter is inversely proportional to the contrast of the load graph and allows conveniently comparing the simulation results between different charging and discharging modes. The higher the β value, the closer the network load becomes to a constant one.

These indicators are used together, forming a mathematical system of criteria for quantitative analysis. Minimization of the D variance and the ΔP_{load} difference in combination with an increase in β serves as an indicator of successful compensation for fluctuations in consumption. In view of this, the developed estimation methodology integrates both integral statistical characteristics (variance) and extreme values that determine the real limits of the load. For the initial (uncompensated) daily profile of the experimental charging

station these indicators take the following values: $D = 50.7866$ kW, $\Delta P_{load} = 159.1481$ kW, $\alpha = 0.6798$ and $\beta = 0.3202$. The corresponding standard deviation of the network power is $\sqrt{D} \approx 7.1$ kW, which is about 15% of the average load of 46.9 kW. These numerical characteristics quantify the stochastic high-power load of the quarry charging station and serve as a reference for assessing the performance of the proposed optimization strategy.

However, formal minimization of these parameters is impossible without taking into account the physical limitations of the battery system. The charging and discharging power of the battery is limited by limit values depending on its design and operating conditions. These limits are described by the ratio:

$$-P_c^{\max} \leq P_{bat}(t) \leq P_d^{\max}. \quad (16)$$

where $P_c^{\max}$ is the maximum charging power (with $P_{bat} < 0$), and $P_d^{\max}$ is the maximum discharge power (with $P_{bat} > 0$). To prevent the accelerated aging of batteries, charge efficiency factors (η_c) and discharge (η_d) are introduced, which are taken into account when calculating the energy balance. In future, we denote these bounds by $P_c^{\max}$ (maximum charging power) and $P_d^{\max}$ (maximum discharging power). These symbols are used consistently in all subsequent equations. For brevity, in the configuration of Table 2 below, the same quantities are shown as P_c and P_d , i.e., $P_c = P_c^{\max}$ and $P_d = P_d^{\max}$.

In addition to power limitation, the battery is characterized by a finite capacity that determines the range of change in the state of charge (SOC). To ensure safe and long-term operation, the SOC must remain within

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max}. \quad (17)$$

where $SOC_{\min}$ and $SOC_{\max}$ are the lower and upper limits of the charge level. These limits prevent deep discharge and the overcharging of the battery, which lead to the degradation of electrochemical cells and a decrease in service life.

As part of the developed strategy for direct control of battery charge and discharge, dynamic power and capacity limits are used as active boundaries involved in the formation of the load profile. For this purpose, variable upper P_H and lower P_L load boundaries are introduced, which change over time depending on the current values of $P_{grid}(t)$, $SOC(t)$ and the maximum power of the battery [49]. In this context, the term *load boundaries* refers to two time-varying reference levels ($P_H(t)$ and $P_L(t)$) that delimit the admissible range of grid power. When the instantaneous load ($P_{load}(t)$) tends to exceed $P_H(t)$, IBES switches to a discharge mode to keep $P_{grid}(t)$ close to the upper boundary. Conversely, when $P_{load}(t)$ falls below $P_L(t)$, IBES is charged to prevent the grid power from dropping below the lower boundary. Therefore, $P_H(t)$ and $P_L(t)$ act as dynamic control thresholds shaping the effective load profile seen by the grid.

The initial values of these boundaries are determined based on the predicted load curve characteristic. Let the $\hat{P}_{\max}$ $\hat{P}_{\min}$ predicted consumption extremes be described; then the initial boundaries are chosen as

$$P_H^0 = \hat{P}_{\max} - P_d^{\text{nom}}, \quad P_L^0 = \hat{P}_{\min} - P_c^{\text{nom}}, \quad (18)$$

where P_d^{nom} and P_c^{nom} are the nominal discharge and charging powers, respectively. These parameters determine the initial limits of the area within which vibration compensation is carried out [50].

We denote these nominal powers by P_c^{nom} (nominal charging power) and P_d^{nom} (nominal discharging power). Together with $P_c^{\max}$ and $P_d^{\max}$ introduced after Equation (5), this provides a unique and unambiguous set of symbols used in the subsequent derivations.

Direct control of the IBES charge/discharge power is realized by means of dynamic load boundary control. In order to take full advantage of the effects of compensation for load peaks and consumption dips of battery energy storage systems, a strategy for direct control of the IBES charge/discharge power using dynamic adjustment of load boundaries is proposed. The strategy is presented below.

Initial parameter setting. As shown in Figure 3, the maximum load (P_{load}) and the minimum load (P_{max}) can be determined as P_{min} from the predicted characteristic load curve, and the initial upper load limit (P_{H-init}) and the initial lower load limit (P_{L-init}) can be defined as

$$\begin{cases} P_{H-init} = P_{max} - P_d \\ P_{L-init} = P_{min} + P_c \end{cases} \quad (19)$$

where P_d and P_c are the rated discharge power and charge of the battery, respectively.

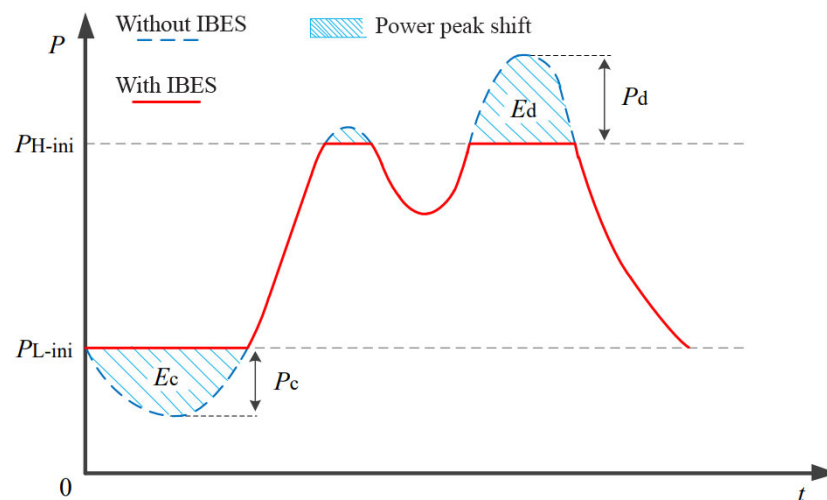


Figure 3. The diagram of initial load power time.

In addition, the area below P_{L-init} bounded by P_{load} is defined as the initial charging capacity of E_{c-init} . And the area above P_{H-init} limited by P_{load} is defined as the initial discharge capacity of E_{d-init} , E_{c-init} and E_{d-init} and can be expressed as

$$\begin{cases} E_{c-init} = \int (P_{L-init} - P_{load}(t))dt \\ E_{d-init} = \int (P_{load}(t) - P_{H-init})dt \end{cases} \quad (20)$$

The charge management strategy. Using the iterative process described above, it is possible to determine the time and power of charge and discharge. When the IBES power is low, areas of peaks and dips can be compensated. With high IBES power, using the maximum power, charging and discharging power of IBES, it is possible to improve the efficiency of compensation for load peaks and consumption dips.

A typical mode of operation of IBES for load power compensation is shown in Figure 4, where $E_c > E_{cmax}$ and $E_d > E_{dmax}$. The upper limit of the load of P_H needs to be iterated up and the lower limit of the load of P_L needs to be iterated down. This operating mode is suitable for scenarios with low IBES power, where the load curve is stable at the peak and trough points.

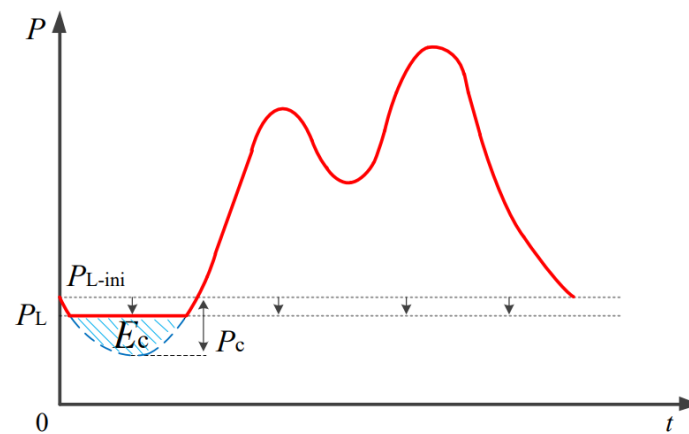


Figure 4. The iteration diagram when $E_{c-init} > E_{cmax}$.

When the initial charging capacity of E_{c-init} exceeds the maximum rechargeable capacity of the E_{cmax} battery, then the capacity limit cannot be met. If E_{c-init} is less than E_{cmax} , the battery capacity cannot be fully utilized.

E_{cmax} can be expressed as:

$$E_{cmax} = E_{max} - E_0 \quad (21)$$

where E_{cmax} is the maximum capacity of the battery, and E_0 is the initial capacity of the battery:

$$E_{c-init} > E_{cmax}$$

In order to reduce the charging capacity, E_c as the lower limit value of the load of P_L is repeated downwards. The iterative process is as follows:

$$\begin{cases} P_L = P_{L-init} - k\delta P \\ k = k + 1 \end{cases} \quad (22)$$

Using δP in Figure 4, we determine the updated value of E_c according to Equations (9) and (11) and compare it to E_{cmax} . If $E_c > E_{cmax}$ at this point, we continue the iteration until the condition of $E_c < E_{cmax}$ is met. We determine the number of iterations when $k = k_n$ in order to determine the dynamically adjusted lower limit value of the load of P_L .

$$P_{load}(t) < P_L P_{bat}(t) = P_{load}(t) - P_L \quad (23)$$

When $E_{c-init} < E_{cmax}$, a load curve is used to facilitate the calculation of the battery's rechargeable capacity. $P_{load}(t)$ shifts upwards by the amplitude of P_c and the auxiliary curve of $P_{net-c}(t)$ is plotted as shown in Figure 5.

$$P_{net-c}(t) = P_{load}(t) + P_c y \quad (24)$$

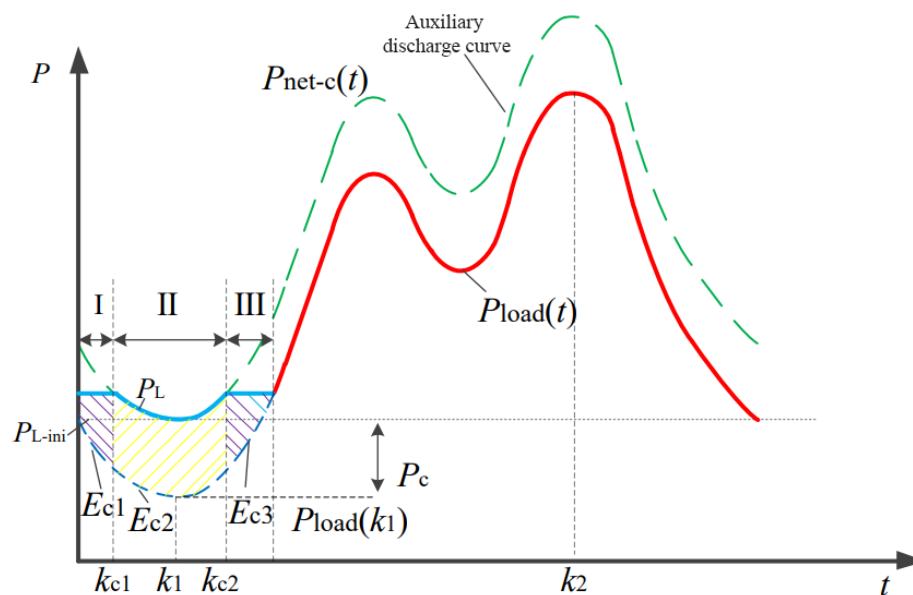


Figure 5. The iteration diagram when $E_{c-init} < E_{cmax}$.

At the same time P_{min} is defined as $P_{load}(k_1)$, which means that the sampling time corresponding to P_{min} is k_1 . It is possible to define the initial power separation time as $k_{c1} - k_{c2} = k_1$. Then k_{c1} and k_{c2} will participate in the left and right iterations, respectively, depending on the size of the charging capacity, thereby dividing the charging area into three areas, as shown in Figure 5, namely:

- Domain I: When $t \in [0, k_{c1}]$, simultaneously satisfying $P_{load}(t) < P_{net-c}(k_{c1})$ and $P_{net-c}(t) > P_{net-c}(k_{c1})$.
- Domain II: When $t \in (k_{c1}, k_{c2})$ and $P_{net-c}(t) \leq P_{net-c}(k_{c2})$.
- Domain III: $t \in [k_{c2}, T]$, satisfying $P_{load}(t) < P_{net-c}(k_{c2})$ and $P_{net-c}(t) > P_{net-c}(k_{c2})$.

The charging capacities in the above three areas are E_{c1} , E_{c2} and E_{c3} accordingly, and they can be calculated as

$$\begin{cases} E_{c1} = \int_0^{k_{c1}} (P_{load}(k_{c1}) - P_{load}(t)) dt \\ E_{c2} = \int_{k_1}^{k_{c2}} P_c dt \\ E_{c3} = \int_{k_{c2}}^T (P_{load}(k_{c2}) - P_{load}(t)) dt \end{cases} \quad (25)$$

Therefore, the total charging capacity will be equal to

$$E_c = E_{c1} + E_{c2} + E_{c3} \quad (26)$$

By increasing E_c , the maximum power load can be fully utilized, and the power sharing points must be iterated as k_{c1} k_{c2} both left and right, respectively. The iterative process is as follows:

$$\begin{cases} k_{c1} = k_1 - k \\ k = k + 1 \\ P_{load}(k_{c2}) = P_{load}(k_{c1}) \end{cases} \quad (27)$$

When $E_c < E_{cmax}$, we continue to repeat the iterations. When $E_c > E_{cmax}$, we stop the iterations. Next, we will fix the points of power sharing of k_{c1} and k_{c2} during the end of the iteration to obtain a dynamically adjusted lower k_{c1} limit value of the load of P_L

$$P_L = \begin{cases} P_{load}(k_{c1}) + P_c \\ P_{load}(t) + P_c \end{cases} \quad (28)$$

Therefore, the charging power of a battery is defined as:

$$P_{bat}(t) = P_{load}(t) - P_L \quad (29)$$

The strategy for controlling the discharge. The maximum discharge capacity is defined as E_{dmax} :

$$E_{dmax} = E_{max} - E_{min} \quad (30)$$

where E_{min} and E_{max} are the capacity of the battery at the minimum and maximum SOC levels, respectively.

Similar to the charging management method, the discharge methods must be considered: $E_{d-init} > E_{dmax}$ $E_{d-init} < E_{dmax}$.

- (1) Under the $E_{d-init} > E_{dmax}$ condition, it is necessary to reduce the capacity of E_d to meet the capacity limitation, so it is necessary to repeat the upper limit value of the load of P_H . The iterative process is as follows:

$$\begin{cases} P_H = P_{H-init} + k\delta P \\ k = k + 1 \end{cases} \quad (31)$$

As shown in Figure 6, we calculate and update the E_d value according to Equations (9) and (20). If $E_d > E_{dmax}$, we continue the iteration, and when $E_d < E_{dmax}$, we stop the iteration. We record the number of iterations of $k = k_{f2}$ to determine the dynamically adjusted upper G limit value of the P_H load. In view of this, the partial power of the battery when $P_{load}(t) > P_H$ is:

$$P_{bat}(t) = P_{load}(t) - P_H \quad (32)$$

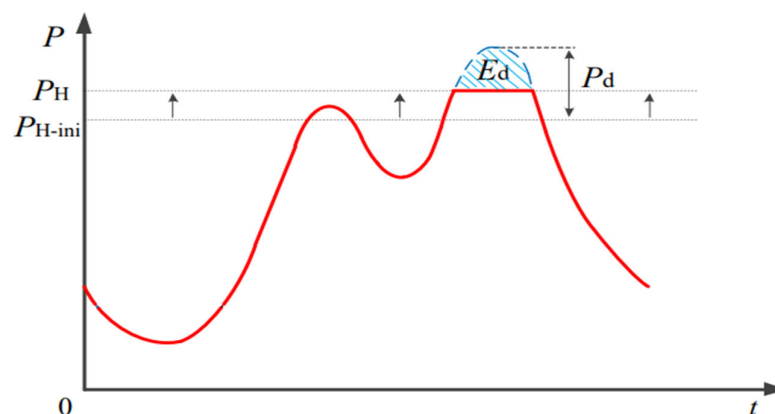


Figure 6. The iteration diagram when $E_{d-init} > E_{dmax}$.

- (2) When $E_{d-init} < E_{dmax}$, the curve of $P_{load}(t)$ shifts down by the amplitude of P_d and plot an auxiliary charging curve of $P_{net-d}(t)$ as shown in Figure 5. P_{net-d} can be expressed as:

$$P_{net-d}(t) = P_{load}(t) - P_d \quad (33)$$

Here, P_{max} is defined as $P_{load}(k_2)$, which means that the sampling time corresponding to P_{max} is k_2 . We define the initial power sharing time as $k_{d1} = k_{d2} = k_2$. Among them, k_{d1} and k_{d2} will iterate left and right depending on the size of the charging capacity, thereby dividing the charging area into three domains, as shown in Figure 7, namely:

- Domain IV: when $t \in [0, k_{d1}]$, and it satisfies $P_{load}(t) > P_{net-d}(k_{d1})$ and $P_{net-d}(t) < P_{net-d}(k_{d1})$;
- Domain V: when $P_{net-d}(t) \geq P_{net-d}(k_{d2})$;
- Domain VI: when $t \in [k_{d2}, T]$, and it satisfies both $P_{load}(t) > P_{net-d}(k_{d2})$ and $P_{net-d}(t) < P_{net-d}(k_{d2})$.

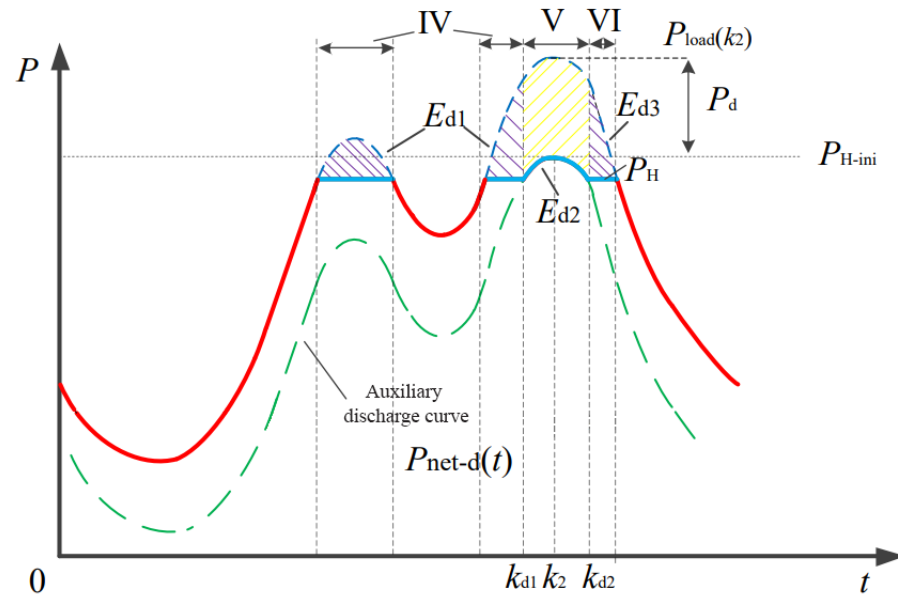


Figure 7. The iterative diagram for selecting the charging capacity of a battery pack.

The discharge capacity of the battery in the above three domains is E_{d1} , E_{d2} and E_{d3} , accordingly, and can be calculated as:

$$\begin{cases} E_{d1} = \int_0^{k_{d1}} (P_{load}(t) - P_{load}(k_{d1}))dt \\ E_{d2} = \int_{k_{d1}}^{k_{d2}} P_d dt \\ E_{d3} = \int_{k_{d2}}^T (P_{load}(t) - P_{load}(k_{d2}))dt \end{cases} \quad (34)$$

Total Discharge Energy:

$$E_d = E_{d1} + E_{d2} + E_{d3} \quad (35)$$

When increasing E_d in order to fully utilize the maximum power load, it is necessary to iterate the power sharing points of k_{d1} and k_{d2} , left and right, respectively, to dynamically adjust the upper limit value of the load of P_H . The iterative process is

$$\begin{cases} k_{d1} = k_2 - k \\ k = k + 1 \\ P_{load}(k_{d2}) = P_{load}(k_{d1}) \end{cases} \quad (36)$$

If $E_d < E_{dmax}$, it is still running; if we continue the iteration until $E_d > E_{dmax}$, it stops. By defining the power separation points of k_{d1} and k_{d2} at this time, the dynamically adjusted upper limit value of the load of P_H can be obtained as

$$P_H = \begin{cases} P_{load}(k_{d1}) - P_d \\ P_{load}(t) - P_d \end{cases} \quad (37)$$

Therefore, charging power can be expressed by the expression:

$$P_{bat}(t) = P_{load}(t) - P_H \quad (38)$$

When the IBES power is low, the peak and trough parts can be “filled”; when the IBES power is large, the peaks and troughs are converted into a “circular ring” in (k_{c1}, k_{c2}) and (k_{d1}, k_{d2}) intervals and “filled” in the remaining parts.

To program the IBES automatic control system, the algorithm shown in Figure 8 was synthesized. In the above algorithm, there are two iterative methods for dynamically adjusting the boundary value of the charging and discharging load [51] at the charging and discharging stage, based on the relationship between the initial value of the load and discharge and the maximum charging and discharging capacity of the load. Four charging and discharging control modes were proposed, as shown in Figure 9.

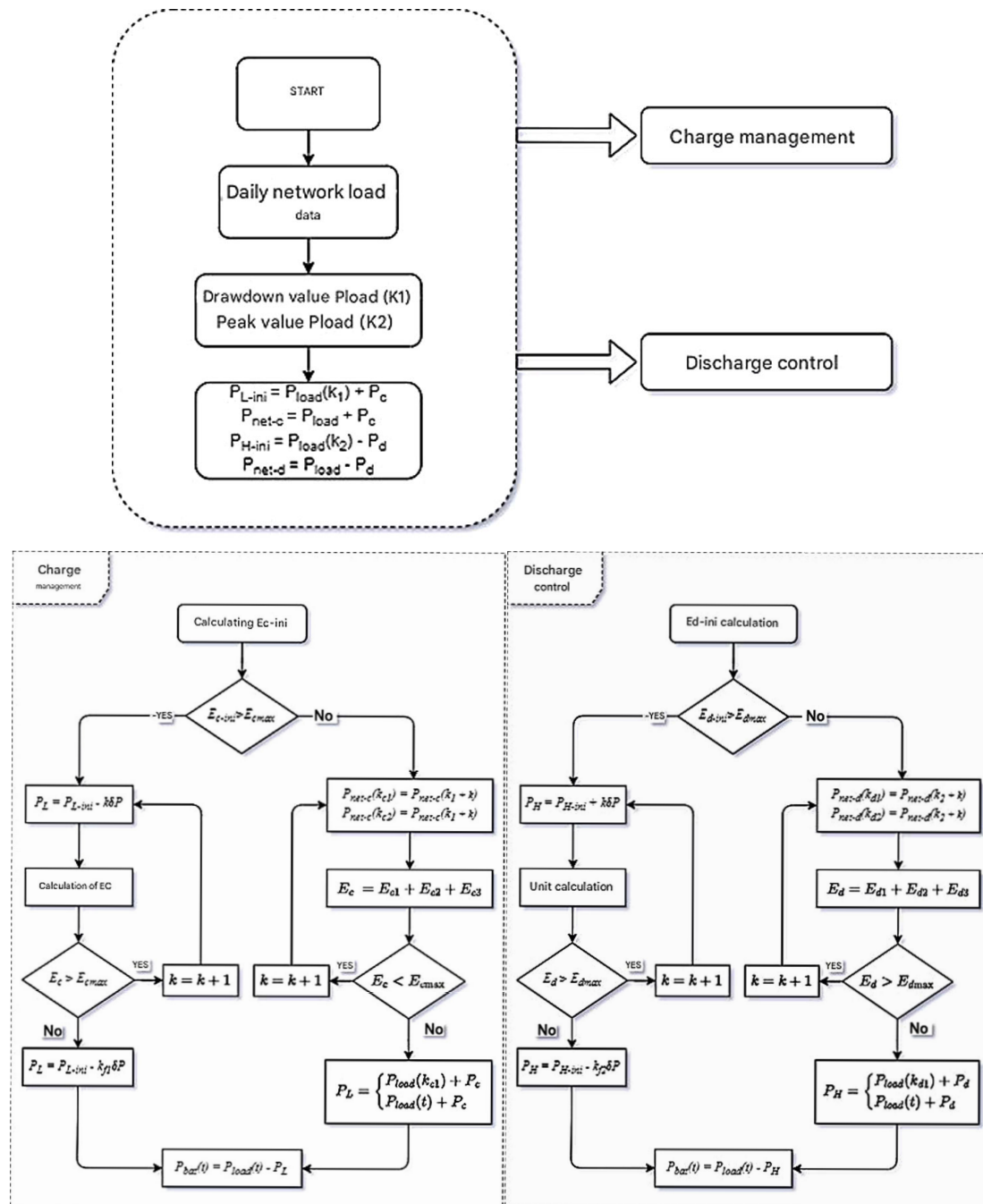


Figure 8. The charge–discharge algorithm for IBES automatic control system programming.

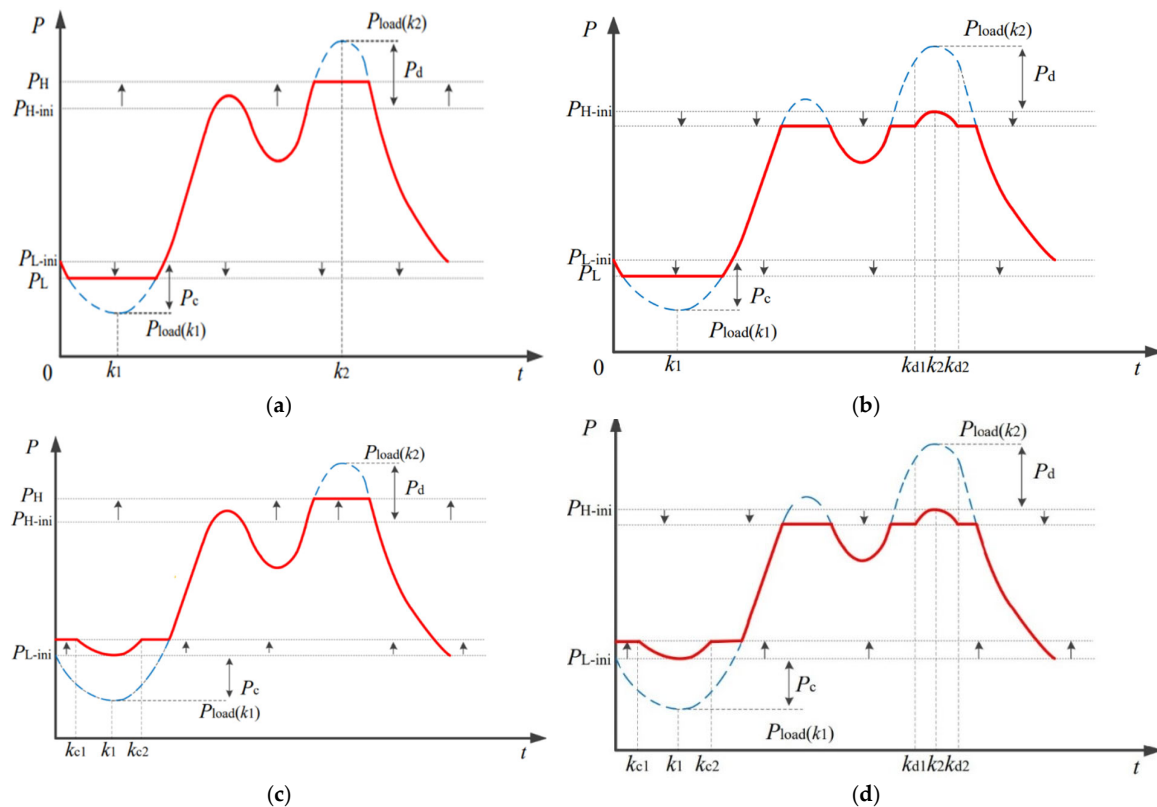


Figure 9. The temporary diagram of load power compensation using IBES of four types of charging/discharging modes: (a) mode 1, (b) mode 2, (c) mode 3, (d) mode 4.

Mode 1: As shown in Figure 9, when $E_c > E_{cmax}$ and $E_d > E_{dmax}$, the upper limit of the PH load needs to be iterated up and the lower bound of the PL load needs to be iterated down. This operating mode is suitable for scenarios with low IBES power where the load curve is stable at the peak and trough points.

Mode 2: As shown in Figure 9b, when $E_c > E_{cmax}$ and $E_d \leq E_{dmax}$, both the upper bounds of the PH load and the lower bound of the PL load need to be iterated down. This mode of operation is suitable for scenarios with high initial battery capacity in IBES. Due to the low E_{cmax} , the lower limit of the load can be shifted down to reduce the charging capacity. The discharge occurs at rated power, while other parts will be reduced to “flat-top waves”.

Mode 3: As shown in Figure 9c, when $E_c \leq E_{cmax}$ and $E_d > E_{dmax}$, the upper limit of the PH load needs to be iterated up, and the lower limit of the PL load needs to be iterated up. This mode is suitable for high battery scenarios of SoC_{min} . At this point, the battery cannot fully release the stored energy at the peak, so it is necessary to perform an upward iteration of the PH.

Mode 4: As shown in Figure 9d, when $E_c \leq E_{cmax}$ and $E_d \leq E_{dmax}$, the upper limit of the PH load needs to be iterated down, and the lower limit of the PL load needs to be iterated up. This mode is suitable for scenarios with high battery capacity and low SoC_0 capacity. In this way, it is possible to fully charge the IBES during the decline and release of the entire energy stored in the IBES at the peak.

4. Experimental Research and Analysis

As shown in Figure 10, using the example of the daily load curve of the consumption of an experimental charging station for charging an electric vehicle for a daily time interval.

At the same time, the maximum, minimum and average load values are 51.8, 41.7 and 46.9 kW, respectively.

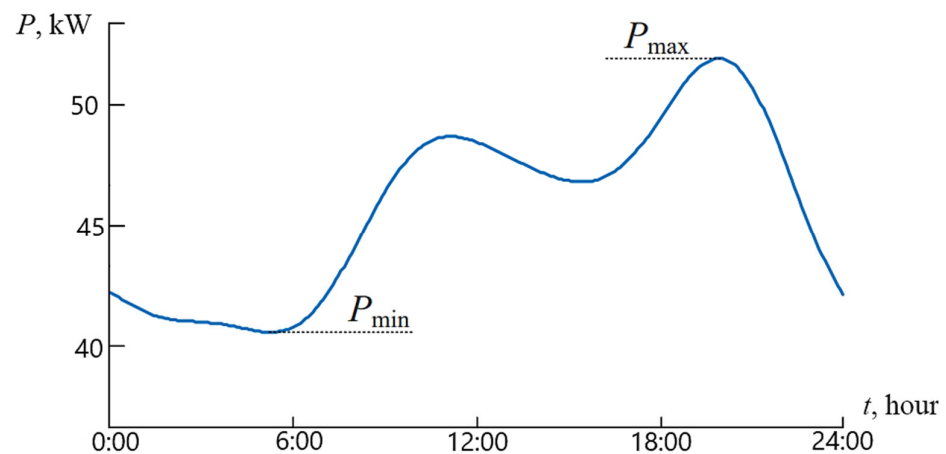


Figure 10. The daily load graph of the case under consideration.

In Table 3, E_{max} denotes the energy capacity of the storage system; P_c and P_d correspond to the maximum charging and discharging power limits introduced in Equation (5). $P_c \equiv P_c^{max}$ and $P_d \equiv P_d^{max}$, and E_0 are the initial energy content of the battery.

Table 3. The diagram of the energy storage configuration for four modes of operation.

Estimates	Mode 1	Mode 2	Mode 3	Mode 4
E_{max} , MWh	100	100	100	200
P_c , MW	20	20	15	20
P_d , MW	40	20	40	40
SOC, Range	0.1–0.9	0.1–0.9	0.1–0.9	0.1–0.9
E_0 , MWh	40	10	10	20

Figure 11 shows the waveform for simulating battery charging and discharging control modes. Both dynamically adjustable upper and lower load boundary lines are horizontal lines. The basic waveform shown in Figure 9a corresponds to that in Figure 11. Table 2 presents the characteristics of the indicators for assessing the compensation of load peaks and consumption dips in comparison with the traditional constant power method.

To visually assess the effectiveness of the proposed method, Figure 12 shows the time power plots for mode 1. The graph allows one to directly compare the initial load profile ($P_{load}(t)$), the network power profile using the traditional constant power method, and the profile obtained using the developed adaptive algorithm and $P_L(t)$ during the day.

In Figure 12, the gray area shows the initial load profile. The dashed black line represents the operation of the system with the traditional constant power method. The solid blue line shows the network power profile using the proposed adaptive algorithm. The red and green dashed lines illustrate the dynamic adjustment of the top (P_H) and bottom (P_L) load limits, respectively. Visually, it is noticeable that the proposed method provides a significantly better smoothing of peaks and the filling of dips. Figure 12 demonstrates direct, visual evidence of the superiority of the new algorithm over the traditional approach. The figure shows how dynamic boundaries “trim” peaks and “raise” troughs. At the same time, the work of dynamic boundaries is visualized in real time, which is adapted to the shape of the load, in contrast to the static line of the traditional method.

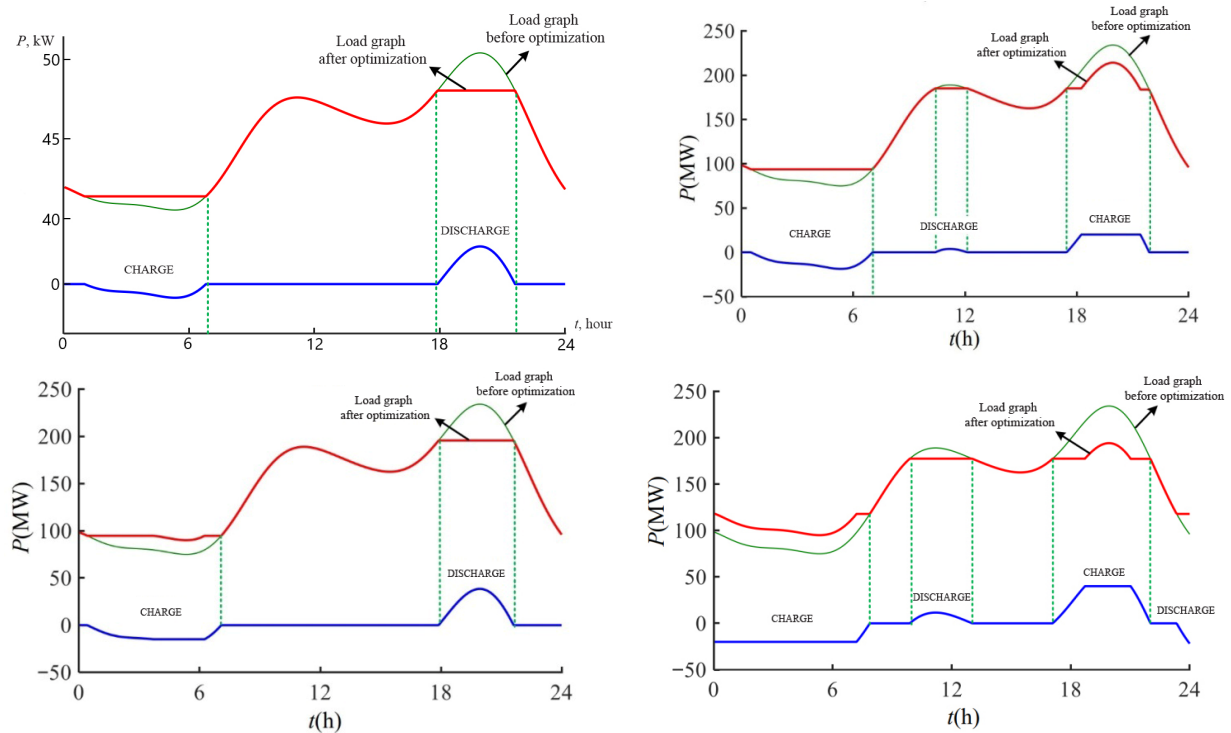


Figure 11. Results of simulation of charging/discharging modes.

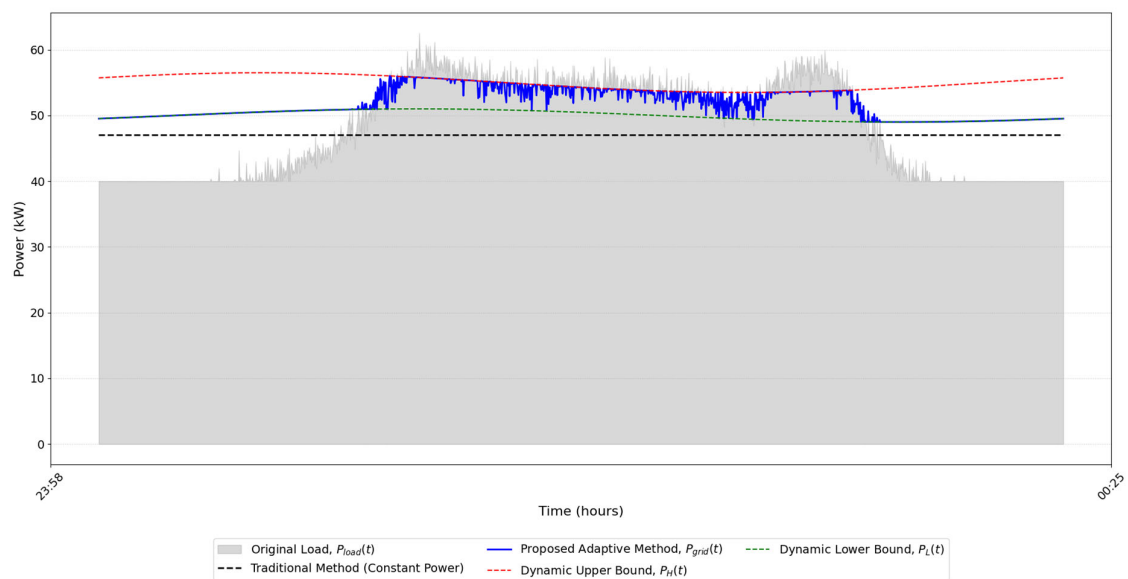


Figure 12. Comparative analysis of daily power profiles for mode 1.

The operation of the control algorithm is directly related to the state of the battery [52]. Figure 13 shows the dynamics of the IBES state of charge (SOC) for the same time interval as in Figure 12. The graph clearly demonstrates how energy is stored in the battery during periods of low load (when P_{grid} is close to P_L) and released to the grid during peak periods (when P_{grid} is limited by P_H).

Horizontal dotted lines indicate the permissible operating range of the SOC (20–90%). Charge cycles (SOC increase) in night and day hours with low power consumption and discharge cycles (SOC decrease) to compensate for morning and evening load peaks are clearly visible [53]. The algorithm ensures efficient use of IBES capacity within the set limits. Figure 13 demonstrates energy balance of the system and shows that the algorithm not

only smooths the power but also does so while remaining within the safe and operational constraints of IBES. Therefore, it is emphasized that the adaptive strategy intelligently manages the energy buffer, preventing it from being overcharged or deeply discharged, which is critical for the longevity of the system [54].

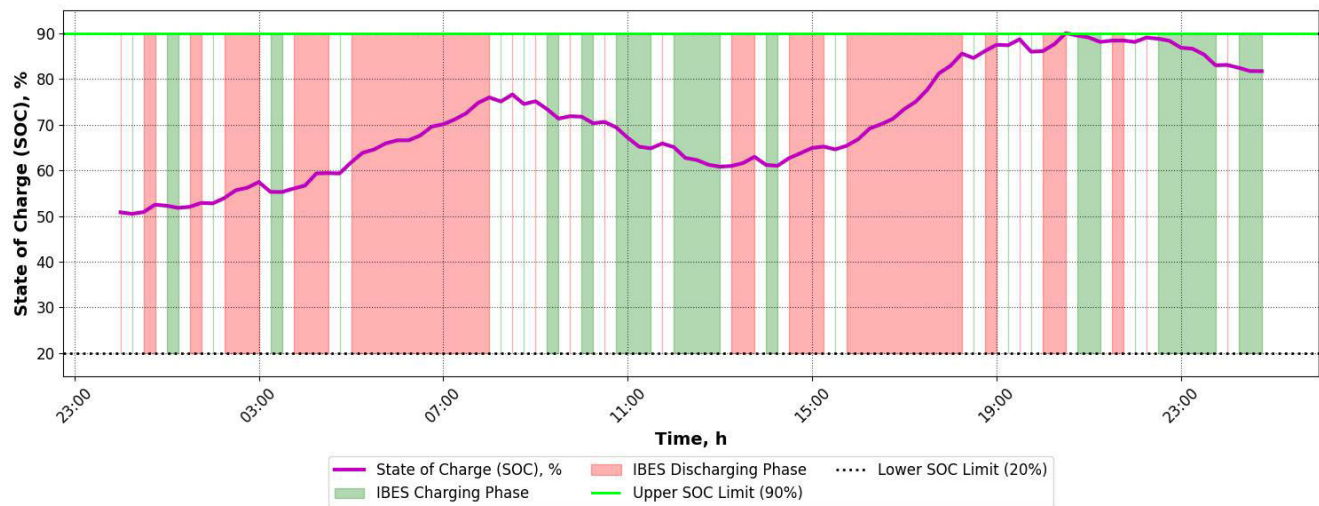


Figure 13. Dynamics of the state of charge (SOC) of the battery during the day when operating according to the proposed algorithm (Mode 1).

Both methods have specific features to compensate for load peaks and consumption dips. However, compared to the four deflection indicators, peak trough difference, a coefficient of peak trough difference and a peak trough coefficient in the charge and discharge mode, the proposed direct control strategy is significantly superior to the traditional constant power method, thus having better peak performance in the ability to compensate for load peaks and consumption dips (Table 4).

Table 4. Comparison of indicators in mode 1.

Estimates	Before Optimization	Power Control (Electricity Meter)	Suggested Method
D	50.7866	43.5259	42.8439
ΔP_{load}	159.1481	140.2782	107.1481
α	0.6798	0.6376	0.5467
β	0.3202	0.3624	0.4533

As shown in Figure 7, in mode 2, the upper limit of the PH load needs to be iterated down, and the lower bound of the PL load needs to be iterated down. The method of controlling the charge is the same as in mode 1 during load drop. However, at the peak end of the load, according to power constraints and iterative methods, there is a partially curved arc segment at the upper limit of the load, which will be discharged at rated power, and the rest will be flat-top waves. This feature is fully consistent with the basic waveform shown in Figure 7. Table 5 shows the characteristics of the peak smoothing and trough fill evaluation values compared to the traditional constant power method. It can be seen that the proposed strategy of direct power charging and discharging control can achieve less variance, peak trough difference, and a peak trough difference rate, but the peak trough coefficient is slightly higher. Therefore, the effect of peak smoothing and trough filling in mode 2 is still better than the traditional constant power method.

Table 5. Comparison of indicators in mode 2.

Estimates	Before Optimization	Power Control (Electricity Meter)	Suggested Method
D	50.7866	42.1240	42.0056
ΔP_{load}	159.1481	132.3654	120.4281
α	0.6798	0.6182	0.5624
β	0.3202	0.3818	0.4376

As shown in Figure 9c, in mode 3, the upper bound of the PH load must be iterated up, and the lower bound of the PL load must be iterated up. At this point, the peak load discharge management method is the same as in mode 1. When the load drops, based on power constraints and iterative methods, the lower boundary line is iteratively adjusted upwards. Therefore, at the lower limit of the load, there is a partially curved arc section that will be charged at rated power, and the rest will be flat-top waves and charged in the same way as in modes 1 and 2. Table 6 shows that the proposed strategy of direct power charge and discharge control can provide less dispersion, peak trough difference, and peak trough difference compared to the traditional constant power method. However, the peak trough ratio is slightly higher, so the effect of peak smoothing and trough filling in mode 3 is still better than the traditional constant power method.

Table 6. Comparison of indicators in mode 3.

Estimates	Before Optimization	Power Control (Electricity Meter)	Suggested Method
D	50.7866	41.9054	41.1882
ΔP_{load}	159.1481	134.3060	105.7481
α	0.6798	0.6084	0.5403
β	0.3202	0.3916	0.4597

As shown in Figure 9d, in mode 4, the upper bound of the PH load must be iterated down, and the lower bound of the PL load must be iterated up. The charging method in this mode in the minimum load area is completely similar to mode 3, and the discharge method in the peak load area is completely similar to mode 2. Table 7 shows that the proposed strategy of direct power charge and discharge control has less variance in load fluctuations compared to the traditional constant power method, indicating that this method is still superior to the traditional constant power method in convergence peaks and trough fills of Mode 4.

Table 7. Comparison of indicators in mode 4.

Estimates	Before Optimization	Power Control (Electricity Meter)	Suggested Method
D	50.7866	34.5819	33.9679
ΔP_{load}	159.1481	99.1481	99.1481
α	0.6798	0.5107	0.5107
β	0.3202	0.4893	0.4893

For a comprehensive comparison of the effectiveness of the management strategy proposed across all regimes, Figure 14 shows a summary bar chart showing the key indicator, i.e., network power variance (D). Although the performance comparison in this study is made relatively conventional constant power control, this reference baseline is relevant because it represents the default strategy currently implemented in industrial charging stations and thus reflects the real operational practice. More complex predictive and rule-based controllers are not used in quarry-grid environments due to communication restrictions and absence of reliable stochastic forecasting. The proposed approach is therefore positioned not only as theoretically novel, but as immediately deployable under current infrastructure limitations. The graph compares the variance values for the initial

load profile, the system with traditional constant power management, and the system with the proposed adaptive algorithm for all four IBES modes of operation.

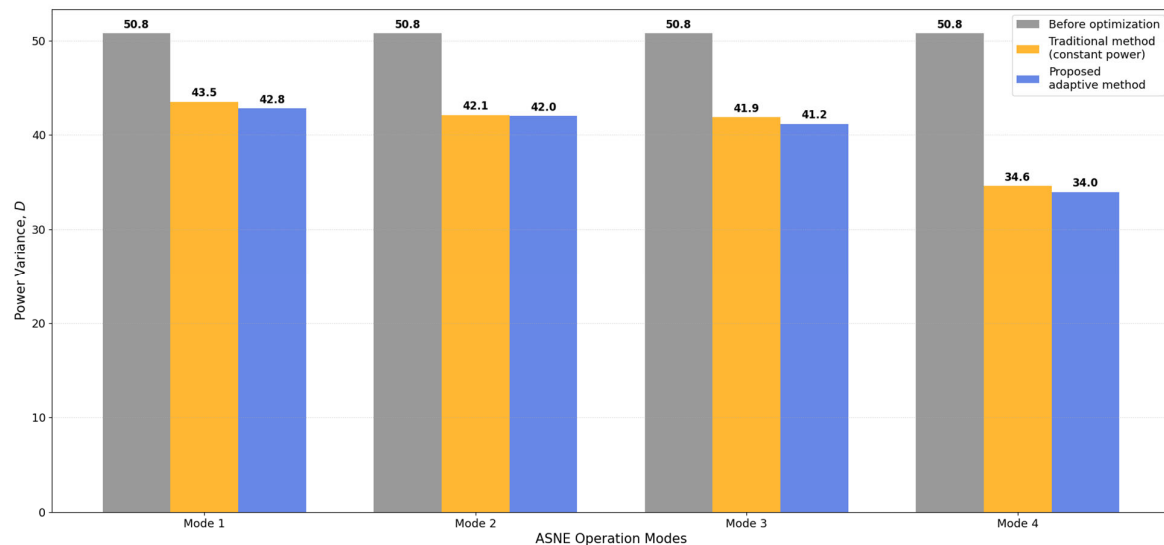


Figure 14. Comparative analysis of network power dispersion for different control methods and IBES operating modes.

In Figure 14, the columns clearly demonstrate that the proposed adaptive algorithm (dark blue) provides the least variance and, therefore, the best smoothing of the load profile in all four modes compared to the traditional method (orange) and the original profile (gray). The greatest relative efficiency is observed in Mode 4, where the capabilities of IBES are used to the fullest. Therefore, a summarized, quantitative picture of the effectiveness of the new method under various initial conditions (capacity, power) was obtained. The universality and robustness of the proposed algorithm is visually confirmed. It performs better in one scenario and consistently delivers superior performance in different system configurations.

5. Conclusions

In this paper, a new strategy for direct charge and discharge control of the system of integrated battery energy storage (IBES) based on dynamic iterative adjustment of load boundaries is proposed and investigated. The mathematical foundation of the method is the formalization of the problem of minimizing the dispersion of network power in the presence of nonlinear constraints related to the power and state of charge (SOC) of the battery. The developed adaptive algorithm demonstrates high efficiency for smoothing peaks and filling load dips in the power grids of industrial charging stations.

The results of theoretical analysis, numerical modeling, and experimental verification allow us to formulate the following main conclusions:

1. Mathematical efficiency and robustness. The proposed iterative algorithm with dynamic boundaries of $P_H(t)$ and $P_L(t)$ provides a steady reduction in network power dispersion by 15–30% compared to the traditional constant-power control method.
2. Optimal control and increased reliability. Dynamic adjustment of the load limits allows the charge and discharge energy to be optimally distributed in strict accordance with the current capacitive availability of the battery. This not only maximizes the utilization of IBES capacitance but also extends its lifespan by actively limiting the depth and number of charge–discharge cycles, thereby improving the overall reliability of the system.

3. Practical applicability. The algorithm is computationally simple, does not require complex predictive models, and can be implemented on local controllers with limited resources. This makes the proposed strategy particularly attractive for use at remote and isolated industrial sites, such as quarry plants.

Despite its advantages, several limitations should be acknowledged for realistic deployment. First, under tight SOC boundaries, the feasible region for boundary updates (P_H , P_L) becomes narrow, which may reduce smoothing performance in long-duration peak clusters. Second, the current implementation assumes observed rather than forecasted truck arrivals; therefore, large uncertainty in charging events can increase iteration count and delay convergence. Finally, although the iterative algorithm remains computationally lightweight, scaling to fleets with tens of chargers may require controller hardware with sufficient processing margin to maintain the 1 s update cycle. These aspects do not diminish the method's applicability but highlight conditions under which performance may degrade and where further research could be directed.

In terms of scalability, the proposed control approach can be extended to multi-charger configurations by assigning a shared IBES pool and applying the boundary update procedure independently for each charging port. Since the algorithm relies only on real-time measurements of $P_{load}(t)$, $P_{grid}(t)$ and $SOC(t)$, computational complexity grows linearly with the number of chargers, while the control step of $\Delta t = 1$ s remains sufficient for practical deployment. Increasing IBES capacity improves peak-shaving capability proportionally, as a larger energy buffer widens feasible ranges of $P_H(t)$ and $P_L(t)$, reducing boundary saturation and iteration count.

From an engineering perspective, the controller operates with modest communication requirements (10 Hz of telemetry exchange already validated in experiments) and reacts within one control cycle without the need for long-horizon forecasting. The integration into systems of quarry energy management may be achieved through standard CAN/MODBUS protocols, allowing the IBES controller to function as a supervisory layer above existing dispatch logic. These aspects support the applicability of the method to large-scale multi-vehicle charging stations and industrial operation scenarios.

Prospects for further research are seen in the following areas: an integration of stochastic load forecasting models for the implementation of predictive control, an extension of the mathematical model for the control of hybrid energy storage systems (IBES + supercapacitors), the development of multi-criteria optimization algorithms that simultaneously consider technical and economic indicators.

Author Contributions: Conceptualization, B.V.M. and N.V.M.; methodology, V.A.G. and Y.I.K.; software, E.E.K.; validation, A.Y.D. and A.V.P.; formal analysis, A.Y.D. and A.V.P.; investigation, A.Y.D. and A.V.P.; resources, E.E.K.; data curation, V.A.G. and Y.I.K.; writing—original drafting, B.V.M. and N.V.M.; writing—review and editing, V.A.G. and Y.I.K.; visualization, E.E.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Zahedmanesh, A.; Muttaqi, K.M.; Sutanto, D. A Sequential Decision-Making Process for Optimal Techno-Economic Operation of a Grid Connected Electrical Traction Substation Integrated with Solar PV and IBES. *IEEE Trans. Ind. Electron.* **2021**, *68*, 1353–1364. [\[CrossRef\]](#)
2. Nan, X.; Zhang, G.; Liu, W. Effects of typical energy storage systems participating in power grid peak-shaving on economy of power market: From multiple perspectives. *Therm. Power Gener.* **2019**, *48*, 13–21.
3. Liao, S.; Cheng, C.; Cai, H.; Cai, J.; Wu, D. Improved algorithm of adjusting discharge peak by thermal power plants. *Autom. Electr. Power Syst.* **2006**, *30*, 89–93.
4. Zhang, S.; Yan, M. Systematic planning and optimization for GAS turbine plants in Shanghai power system. *Power Syst. Technol.* **1996**, *20*, 27–32.
5. Wang, R.; Wang, J.; Zhang, H.; Bai, X. A cost analysis and practical compensation method for hydropower units peaking service. *Autom. Electr. Power Syst.* **2011**, *35*, 41–46.
6. Nguyen, T.A.; Copp, D.A.; Byrne, R.H.; Chalamala, B.R. Market Evaluation of Energy Storage Systems Incorporating Technology Specific Nonlinear Models. *IEEE Trans. Power Syst.* **2019**, *34*, 3706–3715. [\[CrossRef\]](#)
7. Matienko, O.I.; Kukartsev, V.V.; Antamoshkin, O.A.; Karlina, Y.I. Mathematical Model for the Study of Energy Storage Cycling in Electric Rail Transport. *World Electr. Veh. J.* **2025**, *16*, 357. [\[CrossRef\]](#)
8. Kaldellis, J.K.; Kapsali, M.; Kavadias, K.A. Energy balance analysis of wind-based pumped hydro storage systems in remote island electrical networks. *Appl. Energy* **2010**, *87*, 2427–2437. [\[CrossRef\]](#)
9. Yan, T.; Qu, Z.; Hui, D.; Liu, B.; Hu, J.; Jia, P. Economic analysis of the virtual power plants with large-scale battery energy storage systems. *Autom. Electr. Power Syst.* **2014**, *38*, 98–104.
10. Mohamed, A.A.; Best, R.J.; Liu, X.; Morrow, D.J. A Comprehensive Robust Techno-Economic Analysis and Sizing Tool for the Small-Scale PV and IBES. *IEEE Trans. Energy Convers.* **2022**, *37*, 560–572. [\[CrossRef\]](#)
11. Setlhaolo, D.; Xia, X. Optimal scheduling of household appliances with a battery storage system and coordination. *Energy Build.* **2015**, *94*, 61–70. [\[CrossRef\]](#)
12. Pryalukhin, A.F.; Daus, Y.V.; Konyukhov, V.Y.; Oparina, T.A.; Dubrovin, R.G. Simulation Modeling of Energy Efficiency of Electric Dump Truck Use Depending on the Operating Cycle. *World Electr. Veh. J.* **2025**, *16*, 217. [\[CrossRef\]](#)
13. Sigrist, L.; Lobato, E.; Rouco, L. Energy storage systems providing primary reserve and peak shaving in small isolated power systems: An economic assessment. *Int. J. Electr. Power* **2013**, *53*, 675–683. [\[CrossRef\]](#)
14. Al-Saffar, M.; Musilek, P. Reinforcement Learning-Based Distributed IBES Management for Mitigating Overvoltage Issues in Systems With High PV Penetration. *IEEE Trans. Smart Grid* **2020**, *11*, 2980–2994. [\[CrossRef\]](#)
15. Zhang, S.; Mishra, Y.; Ledwich, G.; Xue, Y. The operating schedule for battery energy storage companies in electricity market. *J. Mod. Power Syst. Clean. Energy* **2013**, *1*, 275–284. [\[CrossRef\]](#)
16. Garttan, G.; Alahakoon, S.; Emami, K.; Jayasinghe, S.G. Battery Energy Storage Systems: Energy Market Review, Challenges, and Opportunities in Frequency Control Ancillary Services. *Energies* **2025**, *18*, 4174. [\[CrossRef\]](#)
17. Chen, P.; Cui, W.; Shang, J.; Xu, B.; Li, C.; Lun, D. Control Strategy of Multiple Battery Energy Storage Stations for Power Grid Peak Shaving. *Appl. Sci.* **2025**, *15*, 8656. [\[CrossRef\]](#)
18. Eghtedarpour, N.; Farjah, E. Distributed charge/discharge control of energy storages in a micro-grid. *IET Renew. Power Gener.* **2014**, *8*, 498–506. [\[CrossRef\]](#)
19. Pogrebnoy, A.V.; Efremenkova, E.A.; Valuev, D.V.; Boltrushevich, A.E. Improving the Reliability of Current Collectors in Electric Vehicles. *Mathematics* **2025**, *13*, 2022. [\[CrossRef\]](#)
20. Kucevic, D.; Semmelmann, L.; Collath, N.; Jossen, A.; Hesse, H. Peak Shaving with Battery Energy Storage Systems in Distribution Grids: A Novel Approach to Reduce Local and Global Peak Loads. *Electricity* **2021**, *2*, 575–588. [\[CrossRef\]](#)
21. Nasir, N.N.; Hussin, S.M.; Hassan, M.Y.; Rosmin, N.; Md Rasid, M. Battery Energy Storage System in Peak Shaving Application. *Appl. Model. Simul.* **2018**, *2*, 84–88.
22. Wu, J.; Chen, Y.; Zhou, J.; Jiang, C.; Liu, W. Multi-timescale optimal control strategy for energy storage systems. *Front. Energy Res.* **2023**, *11*, 1240764. [\[CrossRef\]](#)
23. Hemmati, R.; Azizi, N. Advanced control strategy on battery energy storage system for bidirectional power control and stability improvement. *Appl. Energy* **2017**, *219*, 189–201.
24. Nussipali, R.; Konyukhov, V.Y.; Oparina, T.A.; Romanova, V.V.; Kononenko, R.V. Combined Power Generating Complex and Energy Storage System. *Electricity* **2024**, *5*, 931–946. [\[CrossRef\]](#)
25. Tang, Q.; Hu, M.; Bian, Y.; Wang, Y.; Lei, Z.; Peng, X.; Li, K. Optimal energy efficiency control framework for distributed energy-storage-based mining truck system. *Appl. Energy* **2024**, *350*, 121367.
26. Bao, H.; Knights, P.; Kizil, M.; Nehring, M. Energy Consumption and Battery Size of Battery Trolley Mining Truck Fleets. *Energies* **2024**, *17*, 1494. [\[CrossRef\]](#)

27. Shi, Y.; Xu, B.; Wang, D.; Zhang, B. Using Battery Storage for Peak Shaving and Frequency Regulation: Joint Optimization for Superlinear Gains. *IEEE Trans. Power Syst.* **2017**, *32*, 4469–4479.
28. Langenmayr, U.; Wang, W.; Jochem, P. Peak Demand is Shaved for Photovoltaic Battery Systems: Central Planner—Decentral Operator Approach. *Appl. Energy* **2020**, *266*, 114723.
29. Kirli, D.; Kiprakis, A. Techno-economic potential of battery energy storage systems in smart grids. *IET J. Energy Storage* **2020**, *1*, 103–112.
30. Martyushev, N.V.; Malozyomov, B.V.; Demin, A.Y.; Pogrebnoy, A.V.; Efremenko, E.A.; Valuev, D.V.; Boltrushevich, A.E. Modeling the Reliability of an Electric Car Battery While Changing Its Charging and Discharge Characteristics. *Mathematics* **2025**, *13*, 1832. [\[CrossRef\]](#)
31. Mazumdar, J. All electric operation of ultraclass mining haultrucks. In Proceedings of the Conference Record—IAS Annual Meeting, Lake Buena Vista, FL, USA, 6–11 October 2013; pp. 1–5.
32. Khekert, E.V.; Chetverikova, V.V.; Golik, V.I.; Tynchenko, V.S. Improving the Reliability of the Protection of Electric Transport Networks. *World Electr. Veh. J.* **2025**, *16*, 477. [\[CrossRef\]](#)
33. Feng, Y.; Dong, Z.; Yang, J. Performance modeling and cost-benefit analysis of hybrid electric mining trucks. In Proceedings of the 12th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA), Auckland, New Zealand, 29–31 August 2016; IEEE: Piscataway, NJ, USA, 2016; Volume 11, pp. 1–6.
34. Zou, Y.; Hu, X.; Ma, H.; Li, S. Combined State of Charge and State of Health estimation over lithium-ion battery cell cycle lifespan for electric vehicles. *J. Power Sources* **2016**, *273*, 793–803. [\[CrossRef\]](#)
35. Sarybayev, Y.Y.; Balgayev, D.Y.; Tkachenko, D.Y. Reliability-Oriented Modeling of Bellows Compensators: A Comparative PDE-Based Study Using Finite Difference and Finite Element Methods. *Mathematics* **2025**, *13*, 3452. [\[CrossRef\]](#)
36. Luo, X.; Wang, J.; Dooner, M.; Clarke, J. Overview of current development in electrical energy storage technologies and the application potential in power system operation. *Appl. Energy* **2015**, *137*, 511–536. [\[CrossRef\]](#)
37. Carlo, F.D. *Reliability and Maintainability in Operations Management*; Massimiliano, S., Ed.; InTech: London, UK, 2013.
38. Amy, H. What Is Equipment Reliability and How Do You Improve It? Available online: <https://nonstopreliability.com/equipment-reliability/> (accessed on 15 October 2020).
39. Valuev, D.V.; Boltrushevich, A.E. Mathematical Modeling of Signals for Weight Control of Vehicles Using Seismic Sensors. *Mathematics* **2025**, *13*, 2083. [\[CrossRef\]](#)
40. Norris, G. The True Cost of Unplanned Equipment Downtime. Available online: <https://www.forconstructionpros.com/equipment-management/article/21104195/the-true-cost-of-unplanned-equipment-downtime> (accessed on 3 December 2019).
41. Kumar, U. Reliability Analysis of Load-Haul-Dump Machines. Ph.D. Thesis, Lulea Tekniska Universitet, Lulea, Sweden, 1990.
42. Nazarychev, A.N.; Dyachenok, G.V.; Sychev, Y.A. A reliability study of the traction drive system in haul trucks based on failure analysis of their functional parts. *J. Min. Inst.* **2023**, *261*, 363–373.
43. Yelemessov, K.; Baskanbayeva, D.; Sabirova, L. Algorithmic Optimal Control of Screw Compressors for Energy-Efficient Operation in Smart Power Systems. *Algorithms* **2025**, *18*, 583. [\[CrossRef\]](#)
44. Collins, E.W. Safety Evaluation of Coal Mine Power Systems. In Proceedings of the Annual Reliability and Maintainability Symposium, Philadelphia, PA, USA, 27–29 January 1987; Sandia National Labs.: Albuquerque, NM, USA, 1987.
45. Ivanov, V.V.; Dzyurich, D.O. Justification of the technological scheme parameters for the development of flooded deposits of construction sand. *J. Min. Inst.* **2022**, *253*, 33–40. [\[CrossRef\]](#)
46. Roy, S.K.; Bhattacharyya, M.M.; Naikan, V.N. Maintainability and reliability analysis of a fleet of shovels. *Min. Technol. Trans. Inst. Min. Metall. Sect. A* **2001**, *110*, 163–171. [\[CrossRef\]](#)
47. Khekert, E.V.; Klyuev, R.V.; Antamoshkin, O.A.; Remezov, I.S. Battery Charging Simulation of a Passenger Electric Vehicle from a Traction Voltage Inverter with an Integrated Charger. *World Electr. Veh. J.* **2025**, *16*, 391. [\[CrossRef\]](#)
48. Abdollahpour, P.; Tabatabaee Moradi, S.S.; Leusheva, E.; Morenov, V. A Numerical Study on the Application of Stress Cage Technology. *Energies* **2022**, *15*, 5439. [\[CrossRef\]](#)
49. Coetzee, J.L. The role of NHPP models in the practical analysis of maintenance failure data. *Reliab. Eng. Syst. Saf.* **1997**, *56*, 161–168. [\[CrossRef\]](#)
50. Gabov, V.V.; Zadkov, D.A.; Pryaluhin, A.F.; Sadovsky, M.V.; Molchanov, V.V. Mining combine screw executive body design. *MIAB Min. Inf. Anal. Bull.* **2023**, *11*, 51–71.
51. Skamyin, A.N.; Dobush, I.V.; Gurevich, I.A. Influence of nonlinear load on the measurement of harmonic impedance of the power supply system. In Proceedings of the 2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering, Moscow, Russia, 16–18 March 2023.
52. Hall, R.A.; Daneshmend, L.K. Reliability Modelling of Surface Mining Equipment: Data Gathering and Analysis Methodologies. *Int. J. Surf. Min.* **2003**, *17*, 139–155. [\[CrossRef\]](#)

53. Abramovich, B.N.; Bogdanov, I.A. Improving the efficiency of autonomous electrical complexes of oil and gas enterprises. *J. Min. Inst.* **2021**, *249*, 408–416. [[CrossRef](#)]
54. Kondratiev, V.V.; Dorofeev, E.M.; Kononenko, R.V.; Vit'kina, G.Y. Optimization of Energy Balance and Powertrain for Electric Mining Dump Trucks in Coal Mine Reclamation Operations. *World Electr. Veh. J.* **2025**, *16*, 601. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.