Optimization of Load Profiles and State-of-Charge of a Battery Energy Storage System in Energy Systems

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ABSTRACT

Battery Energy Storage Systems (BESSs) are increasingly used in buildings to smooth net load fluctuations, improve renewable self-consumption, and support demand-side management. This study formulates day-ahead load leveling as a convex quadratic programming problem that minimizes the variance of the net load subjected to charging/discharging power limits, State of Charge (SoC) bounds, and end-of-horizon energy constraints. In addition, this work evaluates the impact of the initial SoC on the performance of load leveling and introduces a method to determine the optimal SoC corresponding to the best performance. The method was tested on weekdays and weekend load profiles of a commercial office building using a 750 kWh/250 kW BESS. In all examined cases, the optimized schedule significantly flattened the load curve, regardless of the initial SoC level. Furthermore, the research results demonstrate that an appropriately selected initial SoC determines the amount of energy available for charging or discharging that best matches the load characteristics, thereby achieving a more effective improvement in the total load profile.

Keywords-BESS; optimal dispatch; load leveling; optimal initial SoC

I. INTRODUCTION

Modern energy systems are evolving toward smart and sustainable development, in which the integration of Renewable Energy Sources (RESs), such as solar and wind power, Energy Storage Systems (ESSs), and Electric Vehicles (EVs), is prevalent. This offers great potential for energy autonomy, environmental and techno-economic goals, and operational flexibility. However, it is also associated with significant challenges related to flexible dispatch strategies, which must pursue both economic and technical objectives while ensuring system reliability and stability.

In building energy systems with photovoltaic generation, the adoption of an ESS can mitigate the fluctuations in the net load profile caused by the intermittence of RESs and the mismatch between power consumption and power generation.

Demand Side Management (DSM) for building energy systems plays a crucial role in smart grids, especially since residential loads account for up to 30% of total electricity consumption [1]. From both the consumer and utility perspectives, implementing DSM in buildings' power grids can offer advantages, such as energy cost reduction, peak demand reduction, load profile improvement, and maximum utilization of RESs [2, 3].

In general, an ESS can be utilized as a buffer, storing energy during valley hours and discharging it during peak periods [4, 5]. This strategy not only helps improve the net load profile but may also help increase the self-consumption ratio in energy systems that utilize renewable sources. In such systems, a mismatch between renewable generation and load demand may cause valleys. In the case of no ESS integration, surplus power occurring at the valleys may be curtailed or injected into the distribution grid, thereby reducing the self-consumption ratio.

Owing to their modular capacity, high round-trip efficiency, fast response, and comparatively low maintenance requirements, Battery Energy Storage Systems (BESSs) are well-suited for load-shifting and peak-shaving applications [4, 5]. In systems with renewable generation, BESSs can further reduce the power imbalance caused by renewable intermittency and load-generation mismatch. Their use as flexible energy sources can reduce grid dependence and alleviate stress on the grid during high-demand periods [6].

Regarding load profile improvement, several solutions have been proposed and validated. Authors in [7] considered the consumer's energy bill and peak load demand as the primary objectives. An intelligent multi-objective household DSM approach incorporating BESSs was proposed to simultaneously minimize both objectives. The results showed that almost all residential consumers could recover their BESS investment within three years, while the utility company could benefit from reducing its peak demand.

In [8], a multi-objective Mixed Integer Linear Programming (MILP) technique was applied for residential DSM implementation, where electricity cost and electrical peak load were considered objectives. Meanwhile, authors in [9] proposed a model that enables residential consumers to significantly reduce their electricity bills by lowering the contracted capacity using a BESS. In this approach, peak demand was shaved without affecting customer comfort levels.

Several studies have considered the participation of EV batteries in the load profile improvement problem [10, 11]. In [10], the efficient utilization of EV batteries to their full potential was shown, where discarded EV batteries could be seen as cost-effective storage units for maximum demand shaving. Second-life EV batteries can be utilized for power peak shaving in commercial and industrial applications. Authors in [11] proposed an optimal real-time scheduling algorithm for photovoltaic-integrated electric two-wheeler charging stations, in which the objective function aims to minimize the load variance for load leveling.

Generally, research has shown that peak shaving and flexible energy dispatch in buildings are typically addressed through DSM, fixed BESS scheduling, and multi-energy management strategies [12, 13]. Experimental and simulation studies on solar-powered and hybrid renewable systems have also highlighted the importance of battery charging/discharging coordination in practical applications [14-16]. Representative optimization approaches include BESS capacity-and-control co-optimization for peak shaving [17], building-level integrated energy system optimization [18], peak shaving control in distribution grids [19], and MILP-based peak shaving in smart buildings [20]. These studies confirmed the important role of storage scheduling, but they generally prescribed the initial State of Charge (SoC) or treated it implicitly rather than explicitly optimizing it.

Accordingly, the research gap addressed in this study is the combined day-ahead problem of BESS dispatch scheduling and initial-SoC selection for net load variance minimization under battery power, SoC, energy-dynamic, and end-of-day SoC constraints. The novelty lies in explicitly optimizing the initial SoC as a scalar operational planning variable and quantifying the performance gain relative to conventional fixed initial-SoC assumptions.

The main contributions of this study are:

1. To formulate day-ahead BESS dispatch for load leveling as a convex quadratic programming problem with explicit power, SoC, and energy balance constraints.
2. To propose an outer-loop search procedure that identifies the initial SoC yielding the minimum achievable load variance.
3. To benchmark the optimized initial SoC against representative fixed initial SoC cases for different daily load profiles and quantify the technical gain in terms of load variance reduction.

II. METHODOLOGY

A. Load Leveling Optimization

Assuming that a scheduling horizon is divided into n time steps, the forecasted load profile over the time steps is given by:

$$\boldsymbol{l} = [l_1\ l_2\ \dots\ l_n]^T \tag{1}$$

The BESS charging/discharging power vector over the time-steps is $\boldsymbol{x} = [x_1\ x_2\ \dots\ x_n]^T$, in which $x_i > 0$ when the BESS discharges energy and $x_i < 0$ when the BESS absorbs energy from the grid.

The net load vector after the BESS participates in the dispatch operation is illustrated in:

$$\boldsymbol{y} = \boldsymbol{l} - \boldsymbol{x} = \begin{bmatrix} l_1 - x_1 \\ l_2 - x_2 \\ \vdots \\ l_n - x_n \end{bmatrix} \tag{2}$$

For load leveling, the objective function can be expressed as:

$$\min Var(\boldsymbol{y}) = \min \frac{1}{n} \sum_{k=1}^{n} (y_k - \bar{y})^2 \tag{3}$$

where $\bar{y}$ is the average value of $\boldsymbol{y}$ over the scheduling horizon:

$$\bar{y} = \frac{1}{n}(y_1 + y_2 + \dots + y_n) \tag{4}$$

The constraints are given below.

Charging/discharging power constraint:

$$-P_{chg} \le x_k \le P_{dis}, \forall k = \overline{1,n} \tag{5}$$

SoC constraint to ensure the lifetime of the BESS:

$$SoC_{min} \le SoC_k \le SoC_{max}, \forall k = \overline{1,n} \tag{7}$$

where, SoC_0 and SoC_n represent the SoC of the BESS at the beginning and the end of the scheduling horizon, respectively. η_k is the charging/discharging efficiency at time-step k.

If the BESS SoC at the end of the scheduling horizon is restored to its initial value to prepare for the next scheduling cycle, then constraint (7) becomes:

$$\sum_{k=1}^{n} x_k \eta_k . dt = 0 \Leftrightarrow \sum_{k=1}^{n} x_k \eta_k = 0 \tag{8}$$

Finding the vector $\boldsymbol{x}$ that satisfies the objective function (3) will result in a net load profile $\boldsymbol{y}$ that closely follows the target value $\bar{y}$. Consequently, this leads to a flatter load profile.

The optimization problem in (3) is a convex Quadratic Program (QP) [21, 22]. The objective is quadratic in the decision vector $\boldsymbol{x}$, whereas constraints (5)-(8) are linear equalities or inequalities. Therefore, for a given forecasted load and initial SoC, the dispatch problem admits a global optimum and can be solved using any standard convex QP solver.

For implementation, the workflow is: (i) obtain the forecasted load vector l and BESS parameters, (ii) assemble the QP matrices associated with the variance objective, power bounds, SoC limits, and energy balance constraint, (iii) solve the first-stage QP for a given initial SoC, and (iv) repeat the first-stage solution over candidate initial SoC values in the second-stage outer loop to identify the optimal initial SoC yielding the minimum achievable load variance.

B. Initial SoC Optimization

For a given load forecast, different feasible initial SoC values provide different charging and discharging margins. Consequently, the minimum variance obtained from the inner QP is itself a function of the initial SoC. The second stage evaluates this function over the admissible SoC interval and selects the value that yields the smallest objective.

The adopted outer loop is intentionally simple because the initial SoC is a single bounded scalar variable. Unlike the inner dispatch problem, which optimizes n hourly BESS power values, the outer loop only compares feasible initial-SoC candidates. This structure is transparent, reproducible, and appropriate for day-ahead building energy management.

The procedure is implemented as:

- Divide the interval $[SoC_{min}, SoC_{max}]$ into m equal sub-intervals separated by discrete values $SoC_1, SoC_2, \ldots, SoC_m$. Where $SoC_1 = SoC_{min}$ and $SoC_m = SoC_{max}$.
- At the k^{th} iteration, assign $SoC_0 = SoC_k$, where SoC_0 denotes the initial SoC of the BESS.
- With the assigned SoC_0, find the minimum value of the objective function (3). Denote the obtained value as V_k.
- Identify $V_{opt} = \min V_k, k = \overline{1, m}$. This value is obtained at $SoC_o = SoC_{opt}$.
- The obtained value V_{opt} corresponds to the optimal initial SoC that yields the best load leveling performance.

The pseudocode is:

Input: SoC_{min}, SoC_{max}, m
Output: SoC_{opt}, V_{opt}
Step 1: Divide interval $[SoC_{min}, SoC_{max}]$ into $m-1$ equal sub-intervals.
for $i = 1 \rightarrow m$:
    $SoC_i = SoC_{min} + (i-1)(SoC_{max} - SoC_{min})/(m-1)$
Step 2: initialize $V_{opt} = +\infty$, $SoC_{opt} = null$
Step 3: for $k = 1 \rightarrow m$:
        $SoC_0 = SoC_k$
        $V_k = Solve\ objective\ function\ (3)$
        if $V_k < V_{opt}$:
            $V_{opt} = V_k$
            $SoC_{opt} = SoC_k$
        end if
    end for
Step 4: return SoC_{opt}, V_{opt}

The inner dispatch problem is solved deterministically as a convex QP, whereas the outer initial SoC search is a one-dimensional discrete sweep over the admissible interval. This combination is selected to preserve transparency and reproducibility while keeping the implementation simple for day-ahead scheduling.

III. CASE STUDY AND SIMULATION RESULTS

A. Load Profile

To validate the effectiveness of the proposed solution, a simulation was implemented for a specific case study. Assuming that the forecasted load demand data are available and sufficiently accurate, the scheduling horizon is considered for one day, with a time step of 1 h.

The load under study is the electrical load of a commercial office building, which is characterized by typical daily profiles for the beginning, middle, and end of a week, as shown in Figure 1.

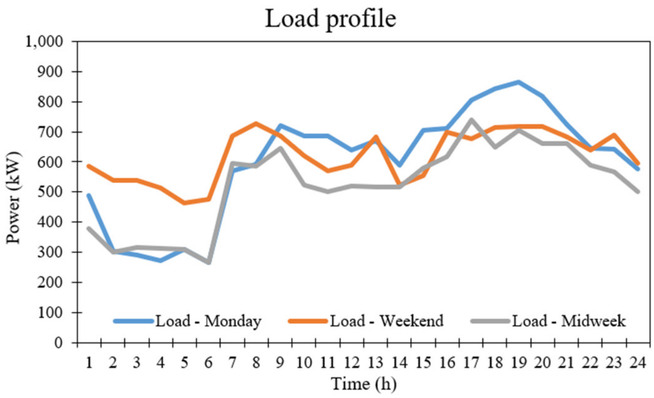

Fig. 1. Load profiles of the building.

It can be observed that the load profiles of the commercial and office buildings on weekdays (beginning and midweek) are quite similar. The average load from 8:00 to 24:00 was approximately 650 kW. The peak load occurred between 18:00 and 20:00, whereas the valley load appeared from midnight to approximately 7:00. Compared with weekdays, the weekend load profile is relatively flatter, with an average power of about 600 kW.

B. BESS Parameters

The investigated building adopts a BESS with a capacity of 750 kWh and a maximum allowable charging/discharging power of 250 kW, corresponding to an autonomy time of 3 h.

The charging/discharging efficiency of the BESS is 0.9, and the SoC should be controlled within the range of 0.2-0.9 to ensure the battery's longevity [23].

C. Load Leveling Optimization Results

To assess the influence of the initial SoC on load-leveling performance, the first-stage dispatch optimization is solved for three representative initial SoC values: 20%, 50%, and 80%. These values represent the low, medium, and high initial energy states of the BESS.

Because the dispatch cycle is considered in one day, at the end of the day, the BESS SoC should recover its initial value to prepare for the next scheduling cycle.

With the initial SoC values of 20%, 50%, and 80%, representing the low, medium, and high energy levels of the BESS at the beginning of the day, the simulation results of the load profile before and after BESS optimal scheduling, as well as the BESS power and energy level profiles for the beginning-of-week day, are presented in Figures 2-4, respectively.

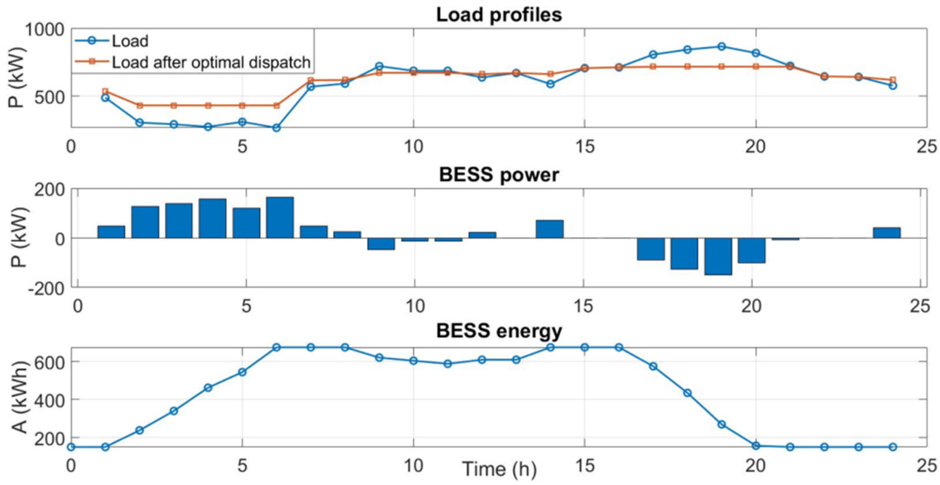

Fig. 2. Load profile and BESS's characteristics in the case of low initial *SoC* (Monday).

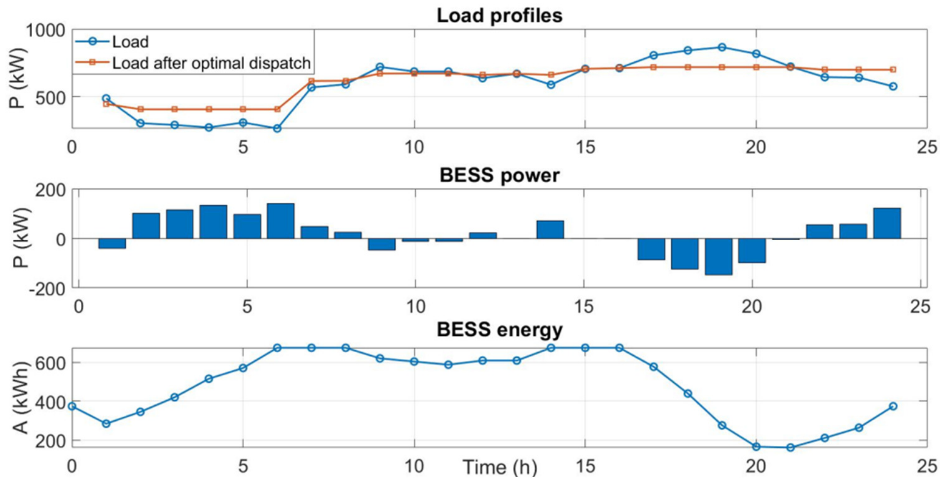

Fig. 3. Load profile and BESS's characteristics in the case of medium initial SoC (Monday).

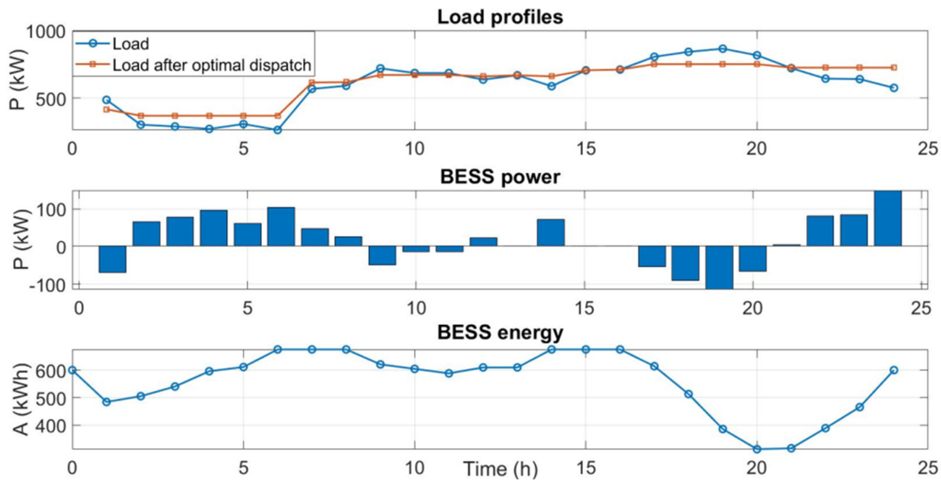

Fig. 4. Load profile and BESS's characteristics in the case of high initial SoC (Monday).

In all three cases, the load profile after BESS dispatch following the first optimization step shows a significant improvement. However, the level of improvement varies with different initial SoC levels. The best improvement is achieved when the initial SoC of the BESS is 20%. As the initial SoC increases, the level of load profile improvement decreases.

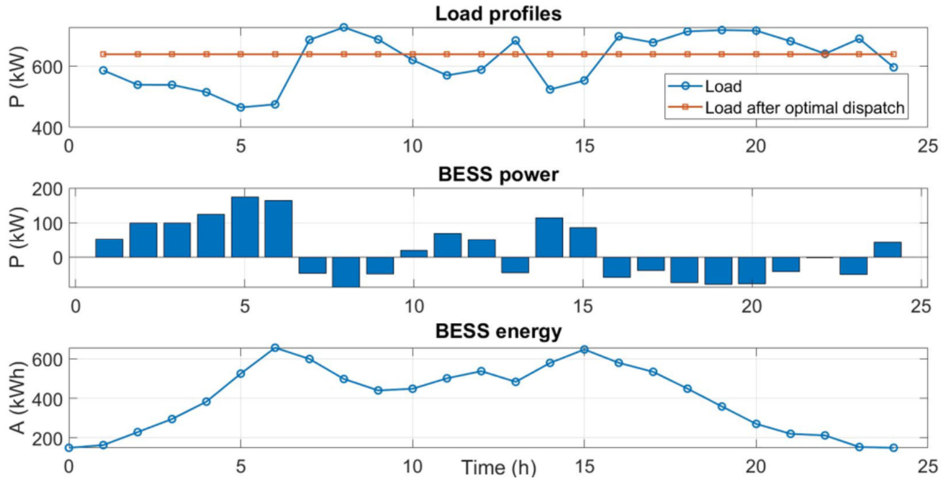

Fig. 5. Load profile and BESS's characteristics in the case of low initial SoC (weekend).

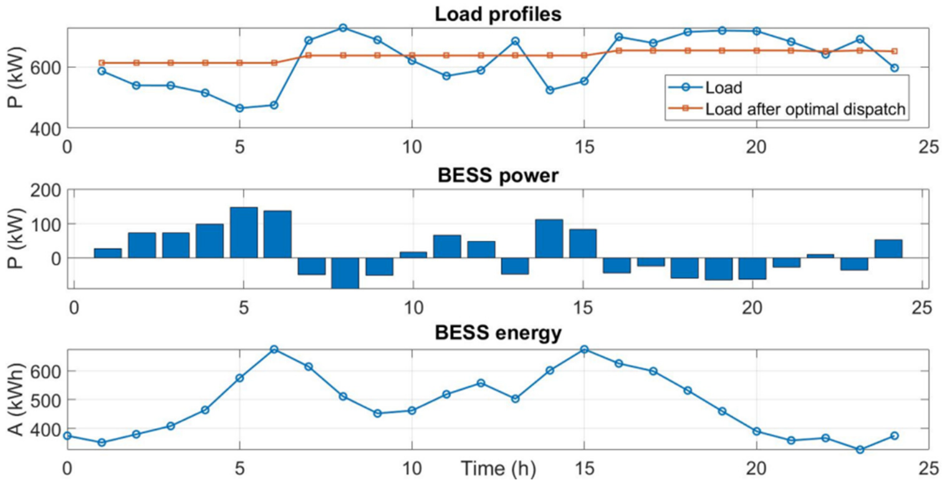

Fig. 6. Load profile and BESS's characteristics in the case of medium initial SoC (weekend).

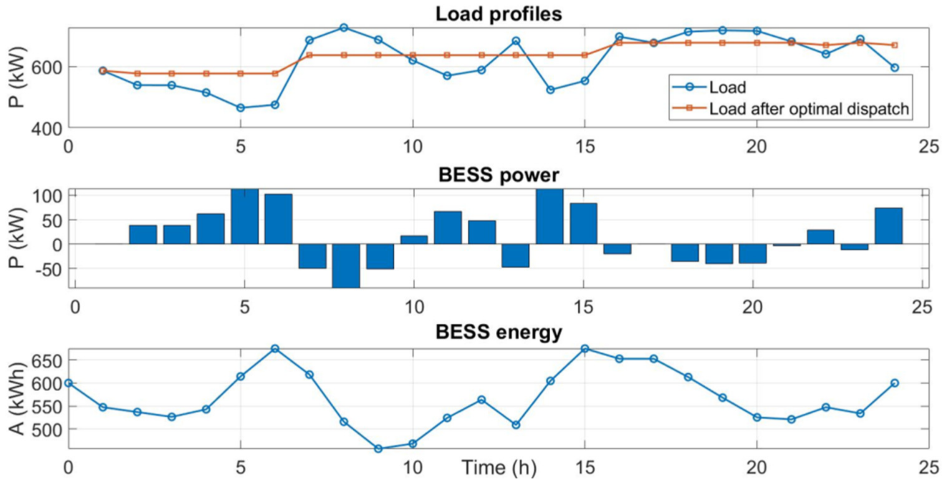

Fig. 7. Load profile and BESS's characteristics in the case of high initial SoC (weekend).

At the end of the day, the SoC of the BESS returns to its initial value, preparing for the next scheduling cycle. In addition, the simulated profiles also show that the SoC bounds and charge/discharge power limits are respected throughout the scheduling horizon.

For the weekend scheduling case, where the load curve differs significantly from those on weekdays, Figures 5-7 present the simulation results corresponding to the initial SoC levels of 20%, 50%, and 80%, respectively.

It is observed that in this case, the load profile also achieves a better load leveling performance when the initial SoC is low. As the initial SoC increases, the reserve of the BESS to absorb power during early hours (i.e., periods of low load from 00:00 to 06:00) becomes more limited. This may be a key factor affecting the effectiveness of load profile improvement.

To quantitatively compare the load-profile improvement, the daily net load variance is used as the main performance indicator. Table I benchmarks the original no-BESS case against three fixed initial SoC cases. The same BESS energy capacity, power rating, efficiency, and SoC limits are used in all cases.

TABLE I. LOAD VARIANCE BENCHMARKING FOR NO-BESS AND DIFFERENT INITIAL SOC CASES

Weekday	Load variance			
	Before dispatch	**Optimal dispatch with low initial SoC**	**Optimal dispatch with medium initial SoC**	**Optimal dispatch with high initial SoC**
Monday	34536.2	11374.75	15362.32	21446
Midweek	19343.93	3594.53	6425.74	10526.59
Weekends	6889.55	2.42.10-19	252.17	1484.88

The results confirm that BESS participation reduces load variance for all tested profiles. For Monday, the variance reductions relative to the no-BESS case are 67.1%, 55.5%, and 37.9% for initial SoC values of 20%, 50%, and 80%, respectively. For the midweek profile, the corresponding reductions are 81.4%, 66.8%, and 45.6%. For the weekend profile, the reductions are approximately 100.0%, 96.3%, and 78.5%, respectively.

The greatest improvement is obtained for the weekend profile at 20% initial SoC, where the optimized net load becomes nearly flat. This result should not be interpreted as a universal preference for the lowest possible SoC. Instead, it follows from the tested load profiles, in which the main valley occurs near the beginning of the scheduling horizon. If a daily profile started with high demand, a higher initial SoC would be preferable because more stored energy would be available for immediate discharge.

Figures 8 and 9 compare the original and optimized load profiles for the Monday and weekend cases, respectively, under the three representative initial SoC levels.

The valley-filling and peak-shaving effects are observed. During off-peak early-morning hours, the BESS charges to fill the demand valley. The stored energy is then discharged during periods of high demand, producing a flatter total load profile.

To benchmark the practical value of second-stage SoC optimization, the best initial SoC identified for the tested profiles is compared with conventional fixed initial-SoC assumptions. Relative to the 50% initial-SoC baseline, the optimized low-SoC case further reduces variance by 26.0% on Monday, 44.1% on the midweek profile, and almost 100% on the weekend profile. Relative to the 80% initial-SoC baseline, the additional reductions are 47.0%, 65.9%, and almost 100%, respectively.

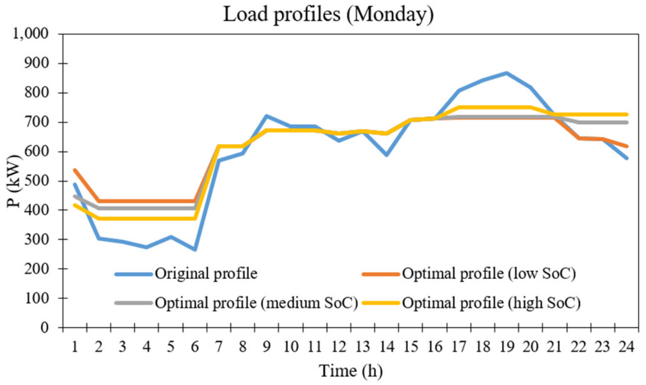

Fig. 8. Original and optimal load profiles at different initial SoCs (Monday).

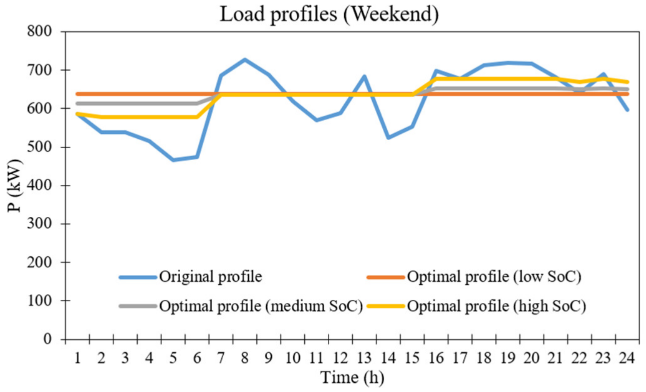

Fig. 9. Original and optimal load profiles at different initial SoCs (weekend).

These results are consistent with previous studies showing that BESS scheduling can reduce peak demand and flatten building or distribution grid load curves [12-15]. The distinguishing feature of the present study is that the initial SoC was evaluated as an explicit planning variable. The benchmark demonstrates that even with unchanged battery capacity, power rating, efficiency, constraints, and load forecast, the selected initial SoC can materially change the minimum achievable load variance.

D. Initial Soc Optimization Results

To determine the best initial SoC over the full allowable SoC range, a second-stage search was applied. The resulting minimum achievable variance as a function of the initial SoC is shown in Figure 10.

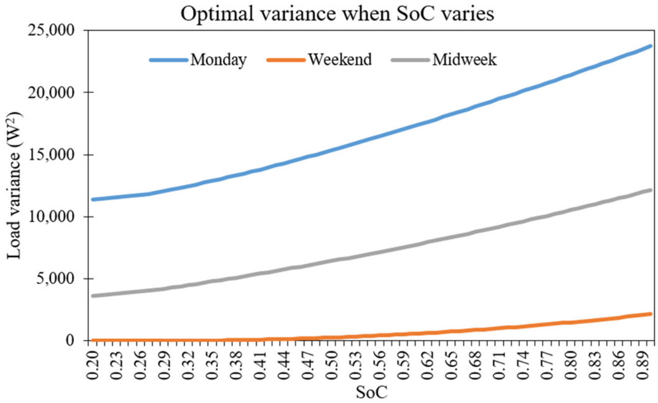

Fig. 10. Optimal variance when the initial SoC varies.

It can be observed that in all three cases (beginning, middle, and end of the week), the load variance increases as the initial SoC rises within the range of 0.2-0.9. For the tested load profiles, the best performance is achieved at the lower bound of the admissible SoC range. This result may be attributed to the low load duration occurring at the beginning of the day, which tends to favor BESS charging to fill the demand valley. A low initial SoC is therefore advantageous for this type of load profile. However, if the load pattern changes, for example, with a higher demand at the beginning of the scheduling horizon, a low initial SoC may no longer be optimal. Thus, the best initial SoC is profile-dependent and should be re-evaluated whenever the load pattern changes.

If the optimal initial SoCs obtained for two consecutive days differ, the algorithm should adjust the SoC at the end of the first day to match the optimal SoC of the next day. In this case, the solution of the objective function (3) should satisfy constraint (7).

IV. CONCLUSIONS

This study presented a two-stage method for Battery Energy Storage System (BESS)-based load leveling in building energy systems. The first stage formulates the day-ahead BESS dispatch as a convex Quadratic Program (QP) that minimizes the net load variance under power limits, State of Charge (SoC) bounds, and energy balance constraints. The second stage searches the admissible initial SoC range to determine the value that yields the minimum achievable variance.

For the case study with a 750 kWh/250 kW BESS, substantial load-profile improvement was demonstrated for Monday, midweek, and weekend conditions. With the best initial SoC identified for the tested profiles, the load variance decreased from 34536.2 to 11374.75 for Monday, from 19343.93 to 3594.53 for the midweek profile, and from 6889.55 to a negligible value for the weekend. Compared with the conventional 50% initial SoC assumption, the optimized initial SoC reduced the variance by 26.0%, 44.1%, and nearly 100%. The difference in the level of load profile improvement can be attributed to the variation in the load curves on different days and the differences in the initial SoC of the BESS at the beginning of the scheduling process.

The results indicate that the initial SoC should not be treated as an arbitrary initialization parameter. It directly determines the amount of energy available for charging or discharging that best matches the load characteristics, thereby achieving the most effective load profile improvement. It affects how effectively the BESS can perform valley filling and peak shaving over the daily cycle.

The practical contribution of this study is a reproducible and computationally transparent procedure for selecting the initial SoC in day-ahead building energy management when the primary objective is technical load leveling rather than tariff-based economic optimization.

The present work is intentionally focused on deterministic technical load leveling under accurate day-ahead load forecasts. Battery degradation cost, electricity tariffs, inverter efficiency curves, network constraints, forecast uncertainty, and solver-to-solver or method-to-method benchmarking are outside the present scope. These aspects, as well as further validation using a larger dataset and experimental or field implementation, will be investigated in future work.

DECLARATION OF COMPETING INTERESTS

The author declares no conflict of interest.

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DATA AVAILABILITY

The load-profile data used in this study are available from the author upon reasonable request.

REFERENCES

[1] T. Wang, Q. Zhao, W. Gao, and X. He, "Research on energy consumption in household sector: a comprehensive review based on bibliometric analysis," *Frontiers in Energy Research*, vol. 11, Jan. 2024, Art. no. 1209290, https://doi.org/10.3389/fenrg.2023.1209290.

[2] E. Sarker *et al.*, "Progress on the demand side management in smart grid and optimization approaches," *International Journal of Energy Research*, vol. 45, no. 1, pp. 36–64, 2021, https://doi.org/10.1002/er.5631.

[3] T. V. Krishna, M. K. Maharana, and C. K. Panigrahi, "Integrated Design and Control of Renewable Energy Sources for Energy Management," *Engineering, Technology & Applied Science Research*, vol. 10, no. 3, pp. 5857–5863, June 2020, https://doi.org/10.48084/etasr.3613.

[4] N. G. Chatzigeorgiou, S. Theocharides, G. Makrides, and G. E. Georghiou, "A review on battery energy storage systems: Applications, developments, and research trends of hybrid installations in the end-user sector," *Journal of Energy Storage*, vol. 86, May 2024, Art. no. 111192, https://doi.org/10.1016/j.est.2024.111192.

[5] C. Rahmann, B. Mac-Clure, V. Vittal, and F. Valencia, "Break-Even Points of Battery Energy Storage Systems for Peak Shaving Applications," *Energies*, vol. 10, no. 7, June 2017, Art. no. 833, https://doi.org/10.3390/en10070833.

[6] T. Dias de Lima, P. Faria, and Z. Vale, "Optimizing home energy management systems: A mixed integer linear programming model considering battery cycle degradation," *Energy and Buildings*, vol. 329, Feb. 2025, Art. no. 115251, https://doi.org/10.1016/j.enbuild.2024.115251.

[7] B. Lokeshgupta and S. Sivasubramani, "Multi-objective home energy management with battery energy storage systems," *Sustainable Cities and Society*, vol. 47, May 2019, Art. no. 101458, https://doi.org/10.1016/j.scs.2019.101458.

[8] H. Shakouri G. and A. Kazemi, "Multi-objective cost-load optimization for demand side management of a residential area in smart grids," *Sustainable Cities and Society*, vol. 32, pp. 171–180, July 2017, https://doi.org/10.1016/j.scs.2017.03.018.

[9] A. Arcos-Vargas, D. Lugo, and F. Núñez, "Residential peak electricity management. A storage and control systems application taking advantages of smart meters," *International Journal of Electrical Power & Energy Systems*, vol. 102, pp. 110–121, Nov. 2018, https://doi.org/10.1016/j.ijepes.2018.04.016.

[10] J. W. Lee, M. H. S. M. Haram, G. Ramasamy, S. P. Thiagarajah, E. E. Ngu, and Y. H. Lee, "Technical feasibility and economics of repurposed electric vehicles batteries for power peak shaving," *Journal of Energy Storage*, vol. 40, Aug. 2021, Art. no. 102752, https://doi.org/10.1016/j.est.2021.102752.

[11] V. N. Ngoc and D. N. Huu, "Optimal Charging Algorithm Based on Receding Horizon Framework for Electric Two-Wheeler Charging Stations," *IEEE Access*, vol. 13, pp. 130125–130137, 2025, https://doi.org/10.1109/ACCESS.2025.3591193.

[12] X. Xu, Y. Fu, and Y. Luo, "Building energy flexibility with battery energy storage system: a comprehensive review," *Discover Mechanical Engineering*, vol. 1, no. 1, Sept. 2022, Art. no. 4, https://doi.org/10.1007/s44245-022-00004-1.

[13] M. Uddin, M. F. Romlie, M. F. Abdullah, S. Abd Halim, A. H. Abu Bakar, and T. Chia Kwang, "A review on peak load shaving strategies," *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 3323–3332, Feb. 2018, https://doi.org/10.1016/j.rser.2017.10.056.

[14] G. V. N. Harshitha and K. N. Sujatha, "Standalone PV Fed Electric Vehicle Battery Charging System," *International Transactions on Electrical Engineering and Computer Science*, vol. 4, no. 1, pp. 13–24, Apr. 2025, https://doi.org/10.62760/iteecs.4.1.2025.128.

[15] N. L. Chowdary and M. S. Kalavathi, "Enhancing the Performance of Integrated Solar Wind and Battery System with Grid using Fuzzy Based MPPT," *International Transactions on Electrical Engineering and Computer Science*, vol. 3, no. 4, pp. 163–172, 2024, https://doi.org/10.62760/iteecs.3.4.2024.110.

[16] A. Muthyala, "Solar Powered Battery Charging System by Using Arduino: Experimental design," *International Transactions on Electrical Engineering and Computer Science*, vol. 2, no. 2, pp. 52–59, June 2023, https://doi.org/10.62760/iteecs.2.2.2023.49.

[17] C. Lu, H. Xu, X. Pan, and J. Song, "Optimal Sizing and Control of Battery Energy Storage System for Peak Load Shaving," *Energies*, vol. 7, no. 12, pp. 8396–8410, Dec. 2014, https://doi.org/10.3390/en7128396.

[18] S. Liu *et al.*, "Operational optimization of a building-level integrated energy system considering additional potential benefits of energy storage," *Protection and Control of Modern Power Systems*, vol. 6, no. 1, Feb. 2021, Art. no. 4, https://doi.org/10.1186/s41601-021-00184-0.

[19] D. Kucevic, L. Semmelmann, N. Collath, A. Jossen, and H. Hesse, "Peak Shaving with Battery Energy Storage Systems in Distribution Grids: A Novel Approach to Reduce Local and Global Peak Loads," *Electricity*, vol. 2, no. 4, pp. 573–589, Nov. 2021, https://doi.org/10.3390/electricity2040033.

[20] L. Chen, Q. Xu, Y. Yang, and J. Song, "Optimal energy management of smart building for peak shaving considering multi-energy flexibility measures," *Energy and Buildings*, vol. 241, June 2021, Art. no. 110932, https://doi.org/10.1016/j.enbuild.2021.110932.

[21] E. Sortomme, M. M. Hindi, S. D. J. MacPherson, and S. S. Venkata, "Coordinated Charging of Plug-In Hybrid Electric Vehicles to Minimize Distribution System Losses," *IEEE Transactions on Smart Grid*, vol. 2, no. 1, pp. 198–205, Mar. 2011, https://doi.org/10.1109/TSG.2010.2090913.

[22] J. A. Taylor, *Convex optimization of power systems*. Cambridge, United Kingdom: Cambridge university press, 2015.

[23] S. H. Kim and Y.-J. Shin, "Optimize the operating range for improving the cycle life of battery energy storage systems under uncertainty by managing the depth of discharge," *Journal of Energy Storage*, vol. 73, Dec. 2023, Art. no. 109144, https://doi.org/10.1016/j.est.2023.109144.