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Integrated Multi-Timescale Battery Dispatch and Overload Mitigation: An Agent-Based Optimization Framework for High EV Penetration in Danish Distribution Networks

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Abstract: The rapid integration of renewable energy and electric vehicles is challenging modern distribution networks with increased demand volatility and overload risks. To address these issues, we propose an integrated, multi-timescale battery dispatch framework that unifies long-term capacity planning, day-ahead/intra-day scheduling, and sub-minute real-time control. The framework combines HOMER Pro-based capacity sizing, a MISOCP model for economic scheduling, and an agent-based simulation for immediate overload mitigation. In a case study of a Danish distribution network projected to reach full EV penetration by 2034, our approach reduced moderate-to-severe overload incidents by 82.7%. Furthermore, a price-sensitive variant achieved a 27.4% reduction in operational costs, with only a 12.5% increase in minor overload events. These quantitative improvements, alongside qualitative enhancements in grid stability and battery longevity, provide actionable insights for distribution system operators.

Keywords: multi-timescale scheduling; battery energy storage systems; agent-based simulation; overload management; Mixed-Integer Second-Order Cone Programming (MISOCP); distribution networks

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1. Introduction

The accelerating integration of renewable energy sources and the widespread adoption of electric vehicles (EVs) are reshaping the operational landscape of modern distribution networks [1,2]. While these trends contribute to carbon reduction and energy sustainability, they also introduce significant challenges related to load volatility, infrastructure congestion, and real-time grid stability [3]. The increasing penetration of EVs amplifies peak demand, often surpassing local grid capacity, leading to frequent overloads and exacerbating network stress [4]. Simultaneously, the stochastic nature of renewable energy generation, particularly wind and solar, introduces uncertainties in both short-term operational balancing and long-term infrastructure planning [5]. These compounding issues demand innovative energy management strategies that can maintain grid stability, optimize economic performance, and mitigate excessive battery cycling under dynamic conditions [6].

The core challenge lies in effectively managing battery energy storage systems (BESS) within these evolving networks. Determining when and how to charge and discharge storage units remains a fundamental yet complex problem, as improper dispatch strategies can lead to inefficient economic outcomes, excessive degradation, and insufficient overload mitigation [2,7]. Conventional control methods fail to address the full temporal complexity of this problem. Day-ahead scheduling and hourly optimization approaches, while providing a structured framework for resource allocation, lack the responsiveness needed to manage second-level demand spikes and real-time fluctuations [8]. Conversely, purely real-time control methods prioritize short-term reliability but neglect economic optimization, leading to excessive operational costs and inefficient use of storage resources [9]. Existing approaches often treat these challenges in isolation, either focusing on long-term planning or reactive control, without providing a cohesive mechanism that integrates economic dispatch with real-time corrective actions [10].

Despite extensive research in this field, current methodologies suffer from notable shortcomings. In particular, existing studies do not adequately bridge the gap between long-term feasibility assessments and short-term dynamic control, resulting in fragmented solutions that either overlook economic optimization or lack real-time responsiveness. The limitations of current methodologies highlight the need for a holistic, multi-timescale dispatch framework that seamlessly integrates planning, economic optimization, and real-time event-driven control [11,12]. The absence of such an approach impairs the ability of system operators to effectively balance grid reliability, cost efficiency, and battery longevity [13,14]. Our work explicitly addresses these gaps by proposing a unified framework that not only links long-term capacity planning with immediate corrective actions but also quantifies the trade-offs among reliability, cost efficiency, and battery degradation. Addressing this gap requires a novel framework capable of aligning long-term feasibility assessments with immediate, high-resolution corrective measures, ensuring that battery storage is leveraged optimally across different timescales [2].

To bridge this gap, this study proposes an integrated, multi-timescale battery dispatch framework that combines capacity sizing and planning through HOMER Pro, day-ahead electricity pricing-based scheduling via a Python–Gurobi (10.x) Mixed-Integer Second-Order Cone Programming (MISOCP) model, and sub-minute real-time overload management through an agent-based simulation in AnyLogic (8.8.4). By integrating these three decision layers into a unified framework, this approach allows system operators to systematically compare and implement battery dispatch strategies that optimize both cost and grid resilience. Unlike prior studies, which typically focus on either high-level capacity planning or reactive real-time control, this work demonstrates how a single decision-support framework can simultaneously address long-term economic viability, short-term cost-efficient scheduling, and near-instantaneous overload mitigation [15,16].

The novelty of this research lies in its hierarchical coordination of battery storage across multiple timescales. While previous studies have explored agent-based methods for decentralized control and MISOCP formulations for battery scheduling, they have not systematically combined these approaches into a single decision-making pipeline [8,9]. This research demonstrates how a multi-timescale framework can enhance grid stability by harmonizing predictive economic scheduling with real-time intervention, allowing storage systems to react dynamically to unforeseen grid stress while minimizing unnecessary cycling. By quantifying the trade-offs between reliability, cost efficiency, and battery wear under different operational strategies, this work provides new insights into how distribution system operators can optimize storage utilization in high-renewable, high-EV penetration environments [11,14].

To evaluate the effectiveness of the proposed framework, a case study is conducted on a Danish distribution network projected to experience full EV adoption by 2034. The study systematically compares three dispatch strategies: a rule-based threshold approach derived from HOMER Pro, a multi-interval MISOCP optimization that minimizes overload severity and cycling, and a price-aware dispatch strategy that integrates dynamic electricity market signals. Through this comparative analysis, the study assesses the framework's ability to mitigate overloads, reduce operational costs, and balance economic efficiency with system reliability. The results provide empirical evidence on how integrating predictive scheduling with real-time control can yield superior operational outcomes compared to conventional dispatch methods.

The remainder of this paper is structured as follows. Section 2 presents a comprehensive review of the literature on hybrid energy system modeling, agent-based control, multi-timescale scheduling, and battery dispatch optimization, highlighting gaps addressed by this research. Section 3 details the methodology, outlining the integration of HOMER Pro, Python–Gurobi MISOCP, and agent-based simulation into a coherent framework. Section 4 describes the implementation framework, including preliminary load simulations, capacity sizing, and real-time control strategies. Section 5 introduces the case study setup for a Danish distribution network under high-EV adoption, while Section 6 presents the results comparing multiple dispatch strategies. Section 7 discusses the implications of these findings, emphasizing the trade-offs between economic efficiency and reliability, while Section 8 concludes by summarizing the key outcomes, identifying limitations, and proposing directions for future research.

2. Literature Review and Related Work

This section provides a comprehensive overview of the relevant literature on hybrid energy system simulation, agent-based methods, multi-timescale scheduling, battery dispatch optimization, dynamic pricing, and overload management. Drawing on numerous studies, the main gaps addressed by this research are highlighted, and the proposed multi-timescale dispatch framework is positioned within the broader body of knowledge.

2.1. Hybrid Energy System Simulation and Feasibility Assessment

Hybrid energy system simulation tools are widely used to examine the techno-economic viability of integrating renewable resources and storage devices under diverse operating conditions. Several studies employ platforms such as HOMER Pro, PVsyst, and others for capacity sizing and cost analysis in microgrids and larger distribution networks [17–19]. These tools typically optimize storage dimensions and energy mixes to reduce net-present costs or levelized costs of energy. For instance, Ref. [20] introduced an open-source simulation environment for microgrid optimization, emphasizing the need for transparent platforms that allow researchers to adapt simulation methods for site-specific constraints. Similarly, Ref. [21] explored how to transition from diesel generator reliance toward solar photovoltaic (PV) with battery energy storage under real-world constraints in Uganda, illustrating a measurable reduction in fuel consumption and greenhouse gas emissions.

A recurring limitation of these simulation tools is their reliance on aggregated demand profiles and simplified operational strategies for energy storage systems. For example, in [16], the authors showed that short-sighted or single-timescale methods may neglect high-frequency load and generation oscillations. Ref. [22] pointed out how diurnal changes and weather-driven fluctuations may create inaccuracies if simulations are performed with coarse time resolutions. These limitations demonstrate the need to integrate high-level feasibility assessments—such as those produced by HOMER Pro—with finer scheduling and real-time control modules that account for rapid demand variation and dynamic market conditions.

The present study addresses this gap by merging the long-term feasibility insights from HOMER Pro with a multi-interval optimization model and an agent-based simulation for real-time overload management. This multi-layer integration ensures that capacity sizing from hybrid system simulations directly influences operational strategies, improving consistency and adaptability.

2.2. Agent-Based Methods and Decentralized Control

Agent-based simulation (ABS) has emerged as a compelling paradigm for modeling decentralized control of heterogeneous grid elements, especially under high penetrations of renewable energy and electric vehicles. ABS frameworks treat each component, such as BESS, PV units, and flexible loads, as autonomous agents making local decisions based on system-level signals [5,10,23]. This decentralized approach is well suited to managing real-time events, such as overloads, demand surges, or local voltage instabilities.

In [24], a scalable multi-agent system was proposed for black start restoration in microgrids, illustrating how local agents can coordinate to reconnect loads and resources without overwhelming a central controller. Similarly, Ref. [9] explored the feasibility of aggregating small- and medium-scale BESS to dynamically allocate power across multiple services, showing that coordinated agents can unlock multi-use benefits—such as frequency control, peak shaving, and ramp-rate mitigation. The advantage of these methods lies in their resilience to single points of failure and adaptability to uncertain operating conditions.

However, many agent-based solutions center on real-time or event-driven control without systematically integrating multi-timescale economic scheduling. This gap leads to purely reactive strategies that excel at immediate grid support but may neglect scheduling decisions driven by cost or market signals. By contrast, the proposed framework embeds an agent-based layer within a broader hierarchy that includes long-term capacity planning and day-ahead/intra-day scheduling. As a result, real-time ABS interventions align with higher-level economic objectives, overcoming a key shortcoming of decentralized control methods.

2.3. Multi-Timescale Scheduling and Hierarchical Coordination

Efficient battery operation in modern grids hinges on coordinating scheduling decisions over multiple timescales: from long-term planning (months to years) to day-ahead or hour-ahead horizons, down to real-time or sub-minute event management [8,12,25]. A day-ahead schedule, typically determined via deterministic or stochastic optimization, leverages forecasts of load, renewable generation, and prices. However, deviations from these forecasts often necessitate intra-day corrections and near-instantaneous control actions.

One common approach is to employ a hierarchical framework in which day-ahead optimization sets baseline commitments for generation units and energy storage devices, while shorter-interval scheduling refines these commitments as new information (e.g., updated load or price forecasts) becomes available [26]. Real-time dispatch then manages instantaneous imbalances, as shown in [15], where a multi-timescale co-optimization model achieved better overall performance by exploiting rapid-response capabilities from battery storage.

Despite their advantages, multi-layer scheduling systems pose computational challenges, particularly when the problem size grows with more network nodes and uncertainty dimensions. Reference [16] provided a thorough review of optimization methods for energy storage dispatch under uncertainty, noting that multi-timescale structures often require advanced mathematical programming or decomposition methods to remain tractable. Moreover, some existing frameworks underexploit agent-based local decision-making, which can simplify or distribute computational tasks.

By integrating HOMER Pro for capacity sizing, a MISOCP model for day-ahead and intra-day scheduling, and an agent-based environment for real-time overload responses, the proposed framework addresses both planning-level and operational-level complexities.

This design ensures that grid operators can adapt to forecast errors while harnessing sub-minute interventions to prevent overload incidents.

2.4. Battery Dispatch Optimization: Methods and Challenges

Battery dispatch optimization has attracted extensive research attention, focusing on the cost-effectiveness, reliability, and lifespan of battery systems [7,11]. Linear and quadratic programming models have been widely used, but they often simplify nonlinear battery aging dynamics or do not model real-time constraints. As recognized in [13], ignoring battery degradation can lead to operating schedules that maximize short-term gains but lead to premature aging and higher replacement costs. Ref. [27] demonstrated how carefully designed algorithms, integrating both technical (state-of-charge and temperature) and economic (market price) factors, can significantly boost the financial viability of PV-battery systems.

MISOCP has gained traction due to its ability to capture convex relaxations of nonlinear relationships, such as power-flow constraints, battery degradation, or AC/DC coupling [12,15]. Even so, large-scale MISOCP can be computationally expensive. Studies like [2,14] proposed advanced reformulations or approximation techniques to enhance scalability, while [16] surveyed diverse online and offline methods to manage the sequential decision-making nature of battery scheduling.

Key challenges persist regarding uncertainty in electricity prices, renewable outputs, and real-time load demands. Many existing methods assume near-perfect foresight, leading to suboptimal dispatch strategies when actual conditions deviate from forecasts. The framework presented in this work combines a price-sensitive day-ahead schedule with an event-driven agent-based mechanism, ensuring that batteries can respond adaptively to deviations from expected conditions while balancing long-term health and operational constraints.

2.5. Dynamic Pricing and Economic Signals

Dynamic pricing schemes, such as time-of-use (ToU), real-time pricing (RTP), and day-ahead markets, provide strong economic signals that can influence battery operation and consumer behavior [19]. In principle, storage owners can profit by charging during low-price intervals and discharging during high-price intervals, a strategy that many studies confirmed yields sizable energy cost savings [22,28]. Ref. [29] showed that while dynamic pricing can improve overall system efficiency, it may also give rise to congestion if many batteries or flexible loads respond similarly to the same price signal.

A growing body of research highlights the importance of coordinating dynamic tariffs with distribution network constraints to avoid such congestions. For instance, Ref. [6] adopted a multi-agent reinforcement learning approach for real-time pricing in a prosumer-dominated microgrid, showing that dynamic tariffs can be beneficial if they are carefully designed to account for local network limitations. This perspective aligns with [28], where intelligent algorithms were proposed to manage energy storage operation in a microgrid with dynamic price signals, achieving notable reductions in electricity costs and peak demands.

In this study, we consider a price-responsive variant of the MISOCP dispatch strategy that schedules battery operation in line with day-ahead electricity market prices. While this approach can reduce operational costs, we also note that it may sometimes defer or reduce the battery's real-time response to overloads, increasing the duration of minor events. The multi-agent corrective mechanism mitigates excessive congestion by overriding day-ahead schedules when severe overloads threaten network stability.

2.6. Overload Management and Grid Resilience

As distribution networks accommodate more electric vehicles, renewable generators, and flexible loads, overload incidents become more frequent and localized [4]. Conventional reinforcement-based solutions require significant capital investments and long lead times. Instead, grid operators can exploit BESS and flexible loads to provide peak shaving, congestion relief, and frequency or voltage support [3,30]. Although predictive scheduling mitigates many overloads, real-time corrective actions remain critical for addressing unexpected demand spikes and network contingencies.

Studies like [3] emphasized that multi-layer control can improve voltage profiles and mitigate overload by coordinating voltage regulators, inverters, and BESS in a hierarchical scheme. Ref. [1] proposed a resilience-informed capacity expansion framework that accounts for extreme weather events, underscoring how under-sizing the grid can lead to load shedding during events. Meanwhile, Ref. [31] explored energy management via a three-level hierarchical approach, showing that prompt local corrective actions can prevent cascading failures that more conservative scheduling might overlook.

However, these techniques often treat predictive scheduling and real-time control in disjointed manners. They may also overlook economic signals that shape how storage devices are utilized, especially when operators pursue peak shaving versus arbitrage. By coupling MISOCP-based scheduling with an agent-based platform for sub-minute, event-driven overload management, the proposed methodology bridges this gap, ensuring that reliability objectives and market-driven dispatch strategies coexist

2.7. Literature Summary and Contribution

Table 1 summarizes key literature contributions relevant to the proposed framework. These studies address various facets of hybrid energy system modeling, agent-based methods, multi-timescale scheduling, battery dispatch optimization, dynamic pricing, and overload management. The final column indicates the primary gap that each study leaves unaddressed, highlighting the novelty of this work in combining these methods into a single decision-support pipeline.

Table 1. Representative literature on battery dispatch and network management.

References	Focus	Key Approach/Result	Gap
[16–21]	Hybrid system feasibility	Simulation-based capacity sizing for PV, wind, and batteries	Limited real-time or multi-interval coordination
[5,9,23,24]	Agent-based methods	Decentralized real-time control of microgrids	Lacks integration with day-ahead or short-term scheduling
[8,12,15,16,25,26]	Multi-timescale scheduling	Hierarchical optimization to address uncertain forecasts	Often omits agent-based local interventions
[2,7,11,13,14,27]	Battery dispatch optimization	MILP/MISOCP with cost-minimization, some degrade modeling	Overlooks sub-minute overload or rule-based override
[6,19,22,28,29]	Dynamic pricing	Price-driven battery dispatch or consumer DR strategies	Potential local congestion and no explicit real-time correction
[1,3,4,30,31]	Overload management	Predictive and real-time control, some agent-based solutions	Typically separated from multi-timescale economic scheduling

The reviewed studies underscore the complexity of coordinating battery operations across different timescales and objectives, ranging from long-term capacity planning to sub-minute load relief [2,8,28]. Although recent works achieve partial integration (e.g., agent-based real-time control or price-sensitive scheduling), few combine all three key layers:

1. Capacity sizing via hybrid system simulation (long-term feasibility).
2. Multi-interval optimization with an economic objective (day-ahead/intra-day).
3. Real-time agent-based control for localized overload mitigation.

In contrast to conventional approaches that treat these elements in isolation, this study bridges the gap by offering a cohesive decision pipeline. The HOMER Pro-based feasibility stage provides capacity parameters (e.g., battery power rating and SoC limits), feeding into a MISOCP scheduling model that optimizes cost and cycling. An agent-based simulation in AnyLogic then refines second-level or sub-minute control decisions, delivering event-driven corrections to handle unforeseen overloads. Through this holistic approach, the framework facilitates a more balanced trade-off among cost, reliability, and battery wear in high-renewable, high-EV distribution networks.

3. Methodology

As power systems rapidly evolve with the integration of renewables and advanced storage technologies, an effective methodological framework must reconcile complex operational constraints, diverse stakeholder objectives, and economic considerations. This study proposes a multi-pronged approach that combines agent-based modeling, optimization, and hierarchical scheduling. By capturing both large-scale coordination and real-time adaptability, the methodology ensures that battery dispatch strategies remain technically feasible, economically sound, and responsive to emergent grid conditions.

3.1. Agent-Based Simulation Framework

This study adopted an ABS paradigm to capture the complex dynamics of an energy system in which multiple heterogeneous entities interact. Instead of modeling the grid, loads, and storage components as a monolithic structure, each entity is represented as an agent with distinct behaviors and objectives [5,9,23]. The fundamental rationale for this approach is that decentralized interactions, such as real-time overload signaling and dynamic battery dispatch, are naturally captured by agent-level roles and capabilities. In contrast to top-down simulation strategies, ABS allows these individual decisions to aggregate into emergent phenomena, including overall grid load patterns and system stability metrics [10,24].

In the proposed framework, each agent's functionality derives from its designated roles, specifying how it can request or provide services within the system. For instance, a grid operator agent monitors potential overload conditions and communicates warnings to other agents. A battery agent dispatches charging and discharging actions in response to both immediate overload signals and economic signals (electricity prices). These agent-to-agent interactions are facilitated by interfaces defined in an object-oriented manner. Only through these interfaces can one agent query or affect another, reflecting realistic limitations in knowledge sharing among real-world stakeholders.

3.2. Hybrid Energy System Simulation and Optimization

After defining agent roles, a preliminary feasibility assessment was conducted using HOMER Pro (3.18.3). The objective was to determine economically and technically viable specifications for energy storage systems, including optimal battery size, rated power, state-of-charge operating limits, and round-trip efficiency [16,18,20,22]. HOMER Pro simulates a range of potential system configurations, evaluating each for net-present cost, levelized cost of energy, and technical feasibility.

The simulation results from HOMER Pro informed the core parameters used in the ABS. In particular, the battery agent was instantiated with capacities, power ratings, and SoC bounds that HOMER Pro identified as optimal [21]. While HOMER Pro itself can propose a high-level operational strategy, the agent-based framework subsequently refined real-time charging and discharging decisions once the battery was embedded in a multi-agent environment [23]. This seamless handoff ensured that the battery's specifications remained consistent across all dispatch strategies, even as the operational logic diverged.

3.3. Optimization Using Python and Gurobi

Following the HOMER-based specification of battery parameters, the simulation framework utilized a Python–Gurobi environment to optimize dispatch schedules. The mathematical formulation was structured as a MISOCP problem, accommodating both discrete decisions (e.g., on/off states) and continuous variables (e.g., charge/discharge levels and state-of-charge) [2,8,12,16]. Different objective functions were defined for different strategies:

- In scenarios focusing solely on overload prevention, the formulation ensured that battery charging and discharging actions minimized overload events and remained within technical limits [10]. This can be modeled as a rule-based or partially optimized schedule in the Gurobi environment.
- In scenarios explicitly incorporating electricity price signals, the optimization objective included cost-minimizing behavior while still respecting the technical constraints inherited from HOMER Pro. Hence, each strategy either integrated direct pricing data into the MISOCP model or applied simplified dispatch rules driven by overload thresholds.

Once an optimal or near-optimal dispatch schedule was generated for each time window, these results fed back into the ABS environment, where each agent implemented the schedule or performed local adjustments in real time. This integration of a centralized solver with agent-level roles preserved methodological consistency: the Python–Gurobi module provided a refined schedule, and the ABS ensured the schedule was applied according to each agent's role constraints and communication protocols [5,9].

3.4. Multi-Timescale Coordination

Efficient battery dispatch in a realistic environment requires accounting for varying data and control intervals. Electricity pricing is often available on an hourly or day-ahead basis, while consumption and grid load updates may be obtained every few minutes, and overloading can occur on second-level timeframes [6,25,26,32]. This study implemented a hierarchical scheduling scheme:

1. The day-ahead or hourly price signals were integrated into the optimization model to plan battery usage in a cost-efficient manner over a 24 h horizon.
2. A 10 min interval was used to refine or adjust the dispatch schedule, integrating updated load measurements and any changes in price or grid condition forecasts [8,15].
3. A real-time monitoring layer detected transient overloads. This rapid feedback loop ensured that when the grid operator agent signals showed approaching or actual overload, the battery agent could respond immediately, overriding or fine-tuning the 10 min schedule to alleviate grid stress [5,24].

In practice, this coordination unfolded in the agent-based framework, as follows. The grid operator agent continuously evaluated instantaneous load against grid capacity and issued an alert to the battery agent whenever overload thresholds were exceeded. The battery agent consulted both the 10 min dispatch plan (originating from the MISOCP optimization) and any real-time constraints (e.g., SoC limits) to choose the most appropriate action. The result was a dispatch strategy that balances long-term economic considerations with short-term reliability requirements [16,25].

Through this combined use of agent-based modeling, HOMER Pro feasibility checks, Python–Gurobi MISOCP, and multi-timescale coordination, the methodology ensured that each dispatch strategy was grounded in realistic technical constraints and that agent-level decisions reflected both high-level economic optimization and immediate overload prevention [9,23]. This methodological integration enabled a detailed exploration of the trade-offs among overload management, battery utilization, and cost within a complex energy ecosystem.

4. Implementation Framework

This section elaborates on the practical realization of the proposed methodology, beginning with preliminary simulations in AnyLogic and HOMER Pro and culminating in the development of a dedicated energy management system (EMS). The multi-pronged approach incorporated both agent-based modeling insights and optimization-based scheduling, ensuring that battery dispatch strategies were technically viable and economically justified.

4.1. Preliminary Simulation in AnyLogic and HOMER Pro

A preliminary simulation was conducted in AnyLogic to generate hourly electricity prices and load patterns. These outputs were subsequently input to HOMER Pro, where the platform's built-in dispatch algorithm was applied to determine an optimal battery capacity [18,20]. Within HOMER Pro, a generic 100 kWh lithium-ion battery with 95% round-trip efficiency and a maximum 0.5C charge rate was used. The operational SoC was constrained between 20% and 80%. HOMER Pro concluded that installing twenty-nine such batteries, equivalent to a total capacity of 2.9 MWh, would effectively mitigate overload in a future scenario with full EV adoption [21].

4.2. Refined Large-Scale Battery Simulation and EMS Development

To capture system behavior more accurately, the model was refined by specifying a single 2.9 MWh lithium-ion battery. Its charge and discharge efficiencies were set at 97.47%, producing a round-trip efficiency near 95%. The SoC constraints remained at 20% (minimum) and 80% (maximum), and the maximum charge/discharge rate was set to 0.5C, or 1450 kW. A subsequent AnyLogic simulation was conducted for a specific target year, assuming full EV adoption among all consumers in the study region. This phase adopted a real-time pricing mechanism for EV charging and maintained the same hourly electricity prices. The intent was to evaluate the battery's performance in reducing grid overload and to explore advanced dispatch control strategies [28,32]. These enhancements motivated the creation of an EMS to coordinate battery operation in real time, consistent with the multi-timescale framework developed in the methodology.

4.3. Dispatch Strategies

In parallel with the refined simulations, three dispatch strategies were implemented to test the EMS in high-fidelity scenarios. Each strategy built on the battery parameters established via HOMER Pro and further shaped by the multi-agent and optimization logic described in the methodology [5,8,16].

4.3.1. Strategy 1: HOMER Pro Logic

Strategy 1 reproduces the standard rule-based logic featured in HOMER Pro, in which the battery discharges upon detecting load levels above the 400 kW grid threshold and charges whenever the load remains below that threshold, provided the SoC is below its upper bound [21]. The EMS checks load signals at one-second intervals, calculating the battery's permissible charge or discharge rate based on how far the load deviates from the 400 kW capacity. As illustrated in Figure 1, this approach aims to keep the battery fully charged as often as possible, allowing prompt mitigation of overloads.

The EMS first determines whether the consumption load exceeds the 400 kW capacity. If so, it checks whether the battery's SoC is above the minimum SoC threshold. If the battery has sufficient SoC, it discharges to alleviate the overload; otherwise, it remains idle. When the load is below the 400 kW limit, the EMS checks if the battery's SoC is below its maximum allowable SoC. If there is sufficient capacity to store energy, the battery charges; otherwise, no charging occurs. The SoC is monitored in real time to ensure that the battery neither over-discharges nor exceeds its maximum capacity. In this flowchart, "Consumption Load" refers to the instantaneous load measured by the EMS, "Grid Capacity" is set at 400 kW, and "SoC" indicates the state-of-charge of the battery (expressed as a percentage). The EMS updates the battery's charge or discharge setpoints every second, ensuring that overload conditions are quickly mitigated, and that the battery operates within safe SoC limits [10].

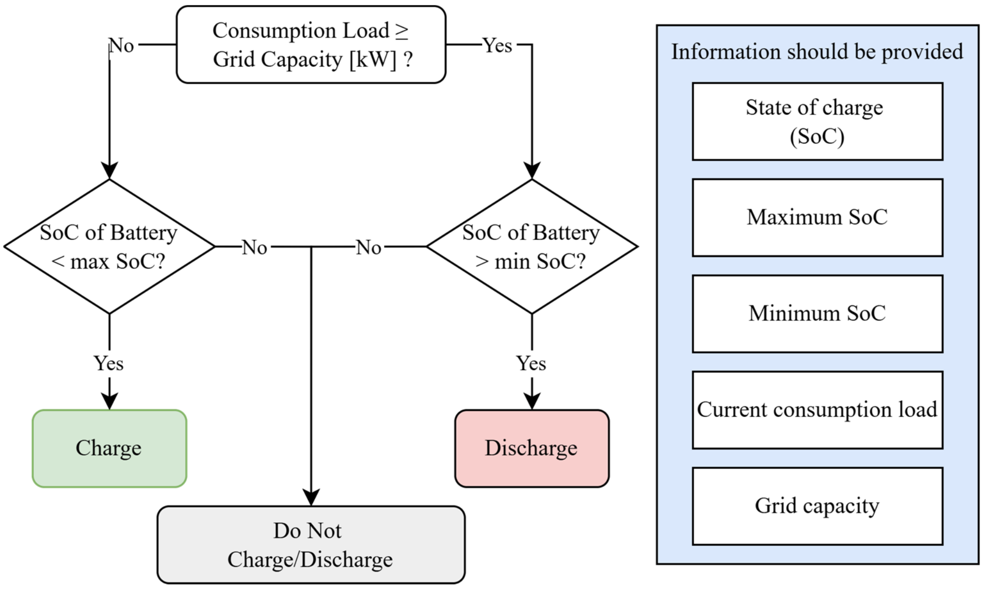

Figure 1. Flowchart of the dispatch strategy from HOMER Pro.

4.3.2. Strategy 2: Multi-Timescale Optimization

A convex optimization framework was introduced to minimize battery cycling and maintain the net load below the 400 kW capacity, in alignment with methods described in [1]. The simulation horizon was divided into ten-minute intervals ($\Delta t = 0.1667$ h). The 2.9 MWh battery had a 1450 kW power cap and SoC limits of 20% and 80%. The battery's charging efficiency was set to 97.47%. An additional smoothing term, parameterized by $\lambda_{smoothing} = 10$, penalized abrupt changes in the battery's power setpoint.

The optimization captured the BESS energy E_t, charging $P_{charging,t}$ (in kilowatt-hours, kWh), discharging $P_{discharging,t}$ (in kW), and net power $P_{BESS,t}$ (in kW).

The net battery power is defined as the difference between the charging and discharging powers:

$$P_{BESS,t} = P_{charging,\ t} - P_{discharging,t} \tag{1}$$

To ensure that the battery did not charge and discharge simultaneously, a binary variable was incorporated into the model to enforce mode exclusivity. The objective function consisted of two terms. The first term minimized the squared magnitude of the net battery power over all time intervals, thereby reducing high cycling that accelerated battery degradation. The second term penalized large differences between consecutive net battery power values—scaled by the smoothing parameter—which encouraged smoother transitions in battery dispatch. The complete optimization problem was formulated as follows:

$$\min\left\{\sum_{t=1}^{T} P_{BESS,t}^2 + \lambda_{smoothing} \sum_{t=2}^{T} \left(P_{BESS,t} - P_{BESS,t-1}\right)^2\right\} \quad (2)$$

Here, $P_{BESS,t}$ denotes the net battery power at time interval t (in s), T is the total number of ten-minute intervals within the simulation horizon, and $\lambda_{smoothing}$ is the dimensionless smoothing parameter that penalizes rapid changes in the power setpoint between consecutive intervals.

In addition to the objective function, the model was subject to SoC update equations, the binary constraint enforcing exclusivity, the upper and lower SoC bounds, and a constraint ensuring that the net grid load did not exceed 400 kW [16,26]. If the grid load falls below the threshold, the battery is programmed to refrain from discharging.

Once the optimal schedule was computed, it was uploaded to the AnyLogic platform, where the EMS executed the schedule in real time. The EMS updated the setpoints every ten min, while a one-second loop continuously monitored for unexpected overload events. In the event of a sudden overload, the battery immediately deviated from the scheduled setpoint to alleviate the stress and then resumed normal operation [5,25].

Figure 2 illustrates these key steps. The process began by defining the battery parameters and constraints, then running the MISOCP optimization to determine charge and discharge setpoints. The EMS applied these setpoints every ten min but continuously monitored the load at one-second intervals, ensuring that any overload was addressed immediately without waiting for the next optimization update.

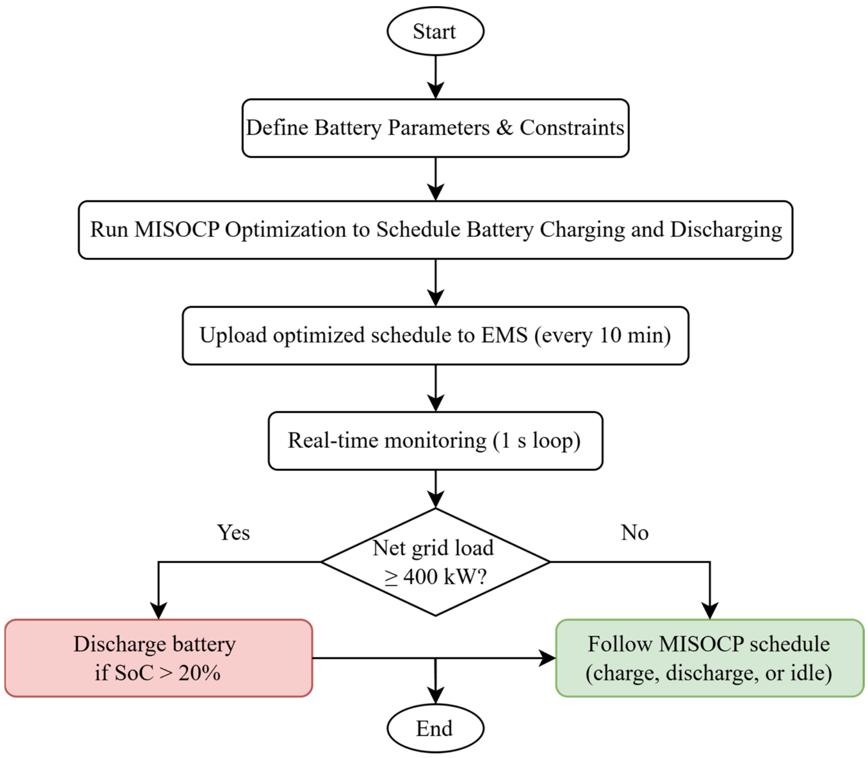

Figure 2. Flowchart of the dispatch strategy from MISOCP optimization.

4.3.3. Strategy 3: Electricity Price Sensitivity

The final strategy extends the multi-timescale optimization by factoring in day-ahead electricity prices. The physical constraints remain identical, but the objective function explicitly targets cheaper charging periods, and the battery discharges preferentially during higher-priced intervals [22,28]. Compared to Strategy 2, the real-time overload check occurs every 30 s, aligning more closely with practical market procedures. This approach still prevents severe overloads but relaxes the response to minor or transient excursions.

As illustrated in Figure 3, the EMS uploads the price-sensitive schedule every ten min while continuously monitoring the net grid load. If the net load approaches or exceeds 400 kW, the EMS confirms whether the battery's SoC is above 20%; if so, it overrides the economic schedule and discharges to mitigate the overload. Once normal conditions resume, the system reverts to the price-driven plan. This approach balances operational reliability with economic efficiency, demonstrating how rapid corrective actions can coexist with market-based dispatch strategies [6,32].

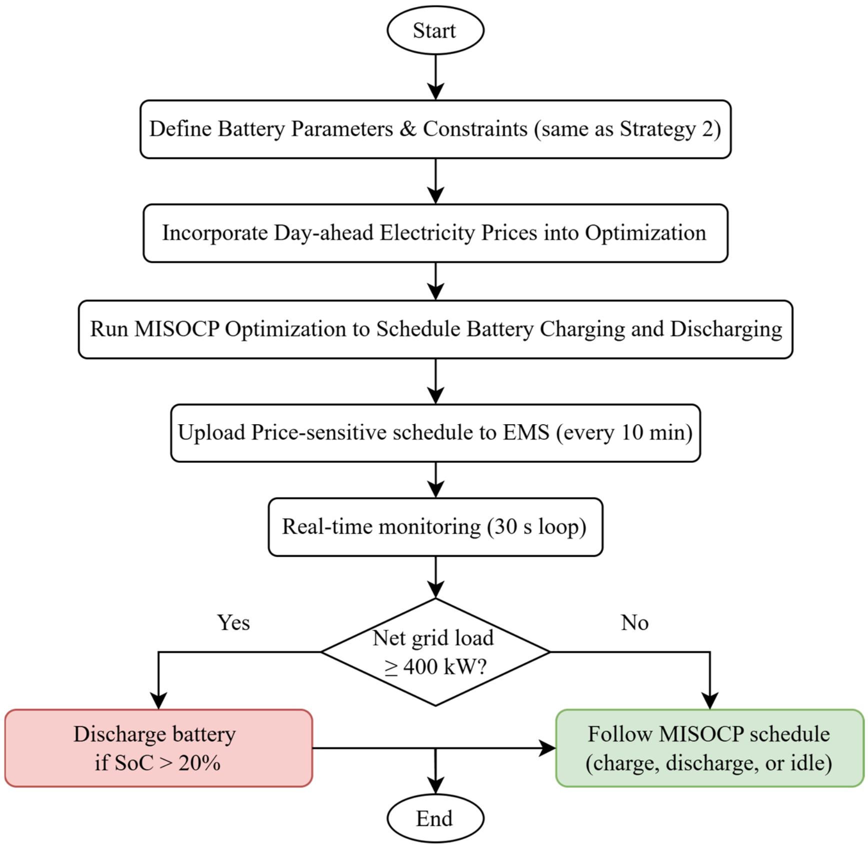

Figure 3. Flowchart of the dispatch strategy with electricity price sensitivity.

5. Case Study

The case study focused on the urban area of Nørre Bjert, Denmark—a mid-sized community comprising approximately 160 households, each assumed to eventually own one electric vehicle (EV) under a full EV adoption scenario. This setting was chosen because it exhibited a high concentration of EVs, which created significant peak demand stress for distribution network operators. The study examined the effectiveness of the framework in mitigating overloads, optimizing energy costs, and managing battery utilization under projected EV adoption scenarios. The results offer insights into scalability, assumption validity, and policy implications for broader implementation in more extensive distribution networks.

5.1. EV Penetration Modeling and Load Assumptions

A logistic growth function was used to model the anticipated increase in EV adoption within Nørre Bjert. This function, widely applied in technology diffusion models, represents saturation effects, ensuring that growth rates slow down as the EV penetration approaches the upper limit defined by household capacity. The model is formulated as:

$$P(t) = \frac{K}{1 + \frac{K - P_0}{P_0} * e^{-r*t}}, \tag{3}$$

where $P(t)$ represents the number of EVs at time t (measured in years), $P_0 = 17$ is the initial number of EVs in 2024, $r = 0.7712$ is the growth rate, and $K = 160$ denotes the maximum number of EVs, assuming that each of the 160 households in the area owns one EV by 2033. This model is consistent with empirical trends observed in other Nordic regions, where policy incentives, charging infrastructure expansion, and declining vehicle costs drive widespread adoption [10,25].

The study incorporated realistic driving and charging behavior patterns, sourced from regional mobility data. These data ensure that EV charging demand profiles reflect actual consumer behavior, with peak charging typically occurring during the evening hours when households return home [1,16].

5.2. Electricity Market and Pricing Model

To ensure the realism of the dispatch strategy, the case study aligns with the Nordic day-ahead electricity market, where spot prices are determined 24 h in advance based on market coupling protocols [8,28]. Consumers are subject to a tariff structure combining real-time electricity prices with capacity-based distribution elements, which significantly influences battery dispatch decisions by penalizing peak-time consumption and incentivizing load shifting. Such an approach has been highlighted in other studies examining flexible tariffs and their impact on storage scheduling [6,22].

The battery dispatch model accounts for dynamic price signals, ensuring that cost savings from arbitrage are optimized while maintaining grid stability. The spot price data for year 2023 were downloaded directly from ENERGINET's webpage, ensuring that the pricing inputs reflected current market conditions [33]. These historical data serve as the basis for forecasting future electricity prices. AnyLogic employs a forecasting model—detailed in our published work [34]—to predict electricity prices for subsequent years up to 2034. By integrating these market dynamics into the MISOCP optimization stage, the study evaluated how price-sensitive battery control affects both economic performance and system reliability [28].

5.3. Simulation Setup and Model Parameters

The case study simulation for the year 2034 incorporated baseline household consumption, supplemented by incremental demand from full EV penetration. The method used to predict future load was fully described in our published work [34,35]. Battery parameters were derived directly from the "Generic 100 kWh Li-Ion" battery model defined in HOMER Pro, ensuring that storage capacity and operational constraints reflected technically and economically feasible configurations [18,21].

Table 2 summarizes the key battery system attributes used across all three dispatch strategies, ensuring a consistent basis for comparative analysis.

Table 2. Key battery system attributes for comparative analysis.

Parameter	Value	Remarks
Battery Capacity	2.9 MWh	29 modules (100 kWh each); refined from HOMER Pro
Rated Power	1.45 MW	Corresponds to a 0.5C discharge rate
SoC Range	20–80%	Derived from HOMER Pro analyses to prevent deep discharge degradation
Charging Efficiency	97.47%	Approximately 95% round-trip efficiency
Optimization Interval	10 min	Applied in Strategies 2 and 3

The optimization framework executed battery scheduling every 10 min, balancing computational efficiency and system responsiveness while allowing for real-time adjustments in response to overload conditions [16,25].

6. Results

This section provides a comparative evaluation of the three dispatch strategies, which all coordinated within an integrated simulation framework that synchronized their scheduling outputs for real-time battery operation, focusing on grid overload mitigation, battery usage patterns, and operational costs. Figures 4–9 illustrate annual and short-term behaviors of total grid load, battery load, and electricity prices. Table 3 summarizes key performance metrics, highlighting the differences in overload occurrences, battery cycling, and total charging costs.

6.1. Strategy 1: HOMER Pro Scenario Results

Strategy 1 used the rule-based logic from HOMER Pro, discharging whenever the grid load exceeded 400 kW and charging below this threshold, subject to the battery's SoC limits. Within the integrated simulation framework, the scheduling output from Strategy 1 was implemented to update battery states every second. Figure 4 presents the annual profile of total grid load (kW), battery load (kW), and electricity price (DKK/kWh). The left axis denotes load in kW, the right axis the electricity price in DKK/kWh, and the time axis follows the YYYY–MM–DD format. A one-second resolution in AnyLogic captures numerous short-lived overload spikes, each triggered the instant the 400 kW limit is breached.

Figure 5 offers a one-week close-up, with the 400 kW threshold shown as a red line. Because Strategy 1 ignores electricity prices, the battery maintained a high SoC to rapidly address overload incidents. Although this ensured timely overload mitigation, it also led to frequent recharge cycles whenever demand dropped, contributing to moderate operational costs. As indicated in Table 3 in Section 6.4, Strategy 1 achieved adequate overload management but did not minimize overall costs or battery cycling when compared with more advanced approaches.

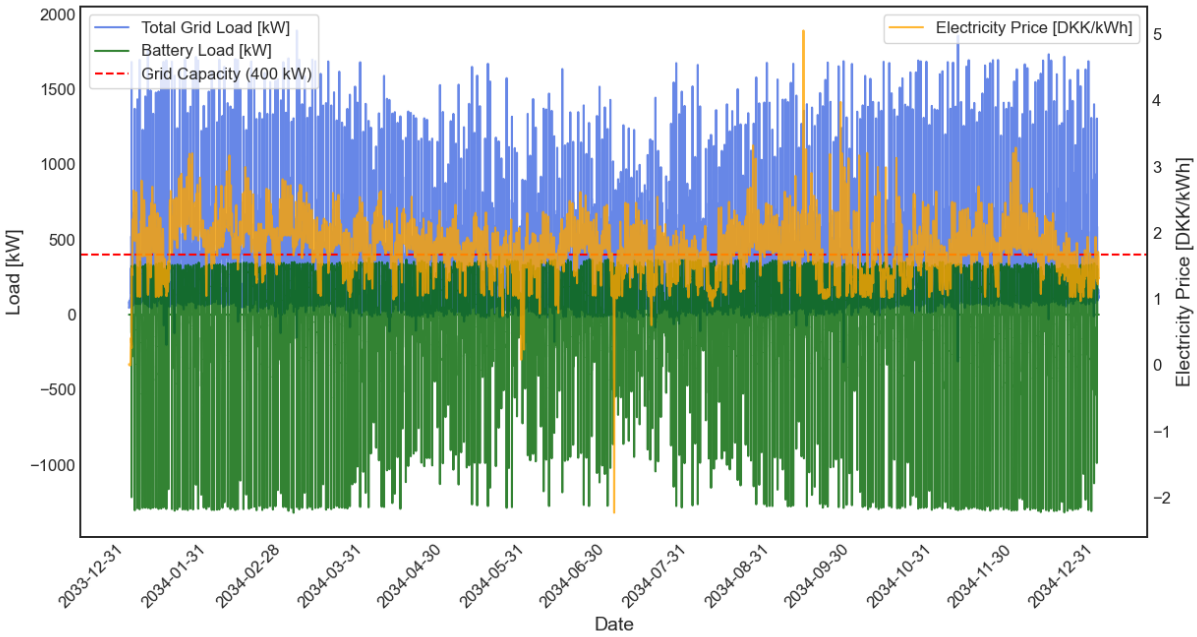

Figure 4. Annual grid load and electricity price profile under Strategy 1 (HOMER Pro scenario).

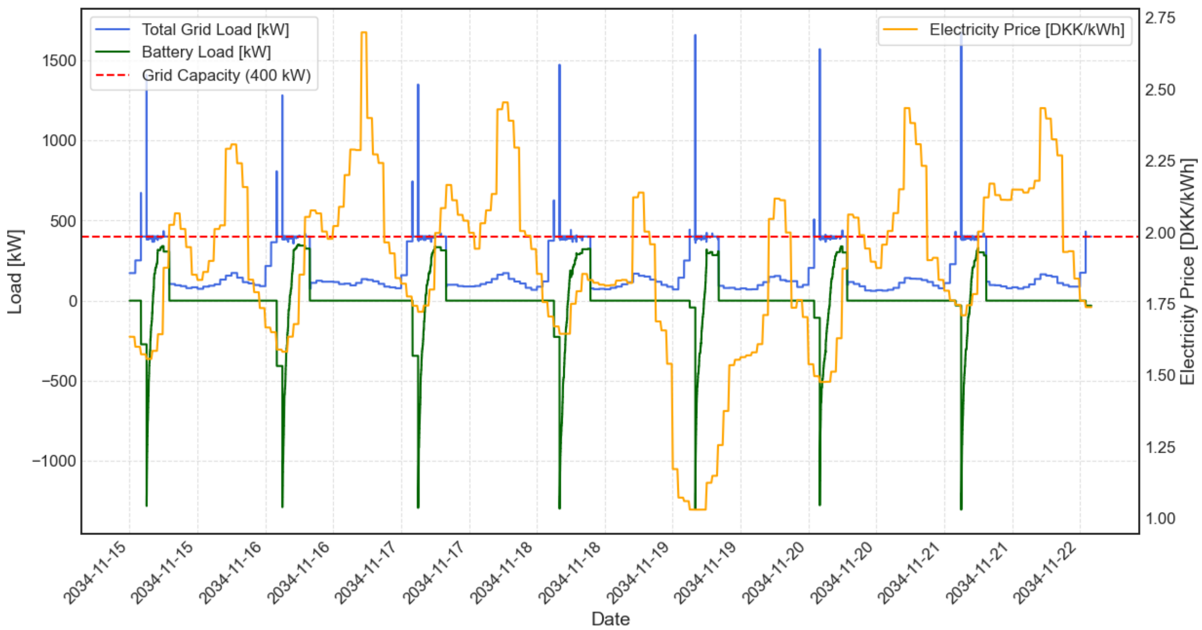

Figure 5. Detailed view of grid load, battery operation, and electricity price profile (Strategy 1)—one-week period.

6.2. Strategy 2: Multi-Timescale Scenario Results

Strategy 2 relied on a convex optimization framework in Python–Gurobi, generating dispatch setpoints every ten min. These setpoints were enforced in AnyLogic unless a sudden overload arose mid-interval, prompting an immediate deviation to reduce the overload. Figure 6 depicts the annual time series of load, battery output, and electricity price, with the 400 kW threshold shown as a red dashed line. Although the optimization smoothed transitions in battery power by penalizing abrupt changes, it resulted in an overall increase in battery cycling compared to Strategy 1.

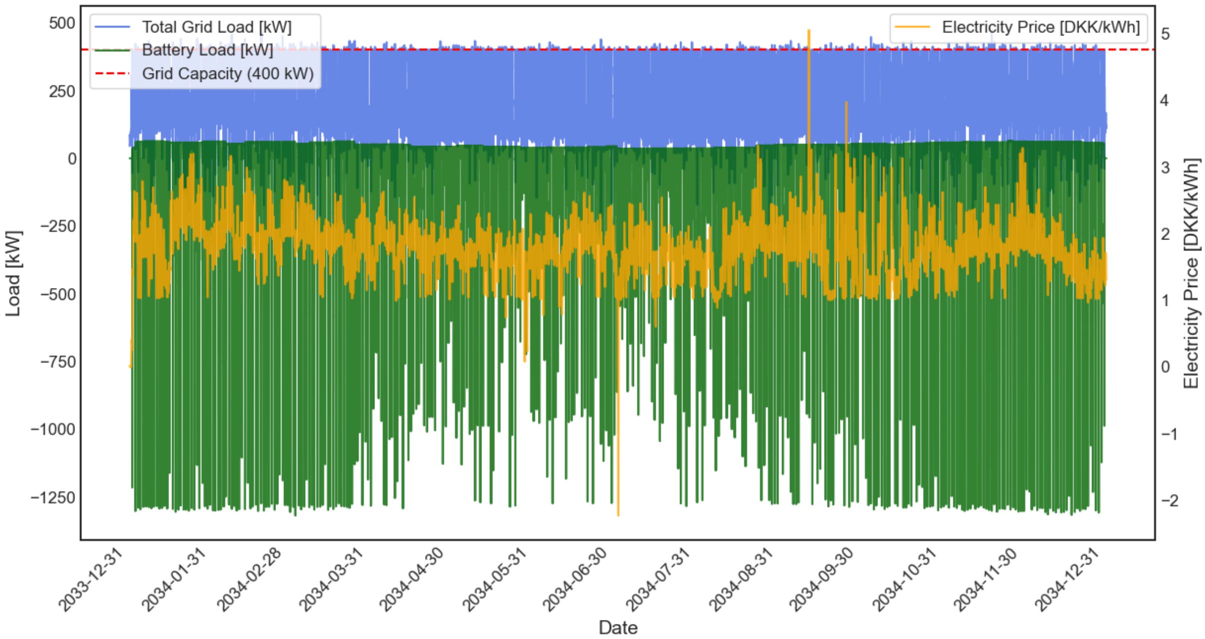

Figure 6. Annual grid load, battery load, and electricity price profile under Strategy 2 (multi-timescale scenario).

A weekly snapshot in Figure 7 reveals that multi-timescale optimization kept most overload events within minor or moderate thresholds. However, Table 3 in Section 6.4 shows an overall increase in total battery usage and associated costs, as the battery cycled more frequently to maintain the net load below 400 kW. Despite these higher costs, Strategy 2 significantly reduced the intensity and duration of overloads, illustrating that improved grid stability can come at the expense of increased battery cycling and higher operational costs.

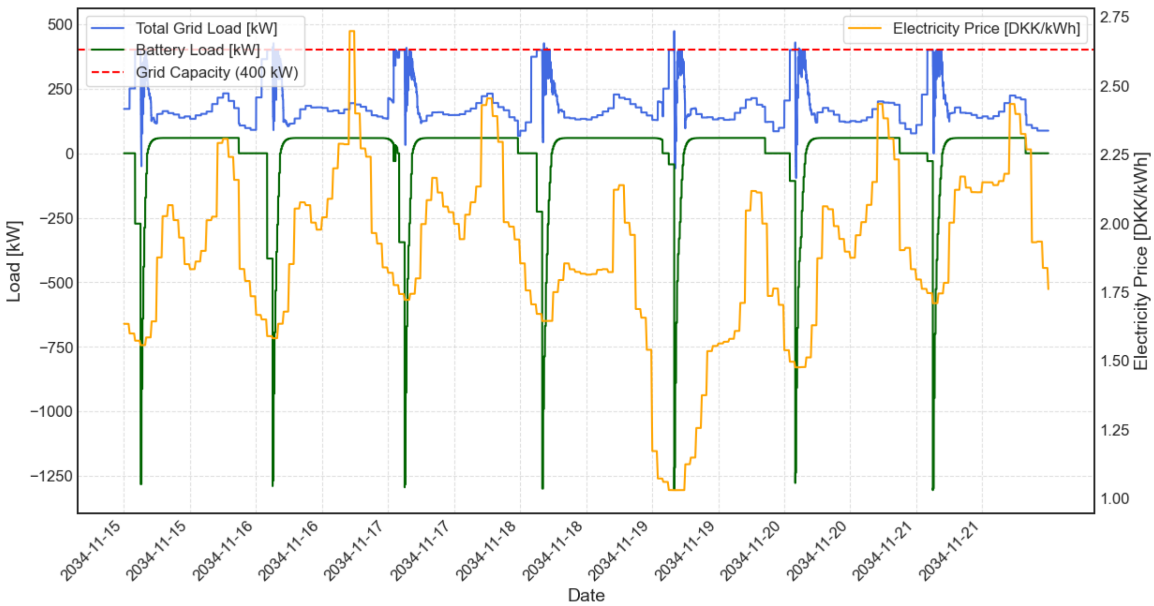

Figure 7. Detailed view of grid load, battery operation, and electricity price profile (Strategy 2)—one-week period.

6.3. Strategy 3: Electricity Price Signal Consideration Scenario Results

Strategy 3 extended the optimization framework by incorporating day-ahead electricity price signals. The scheduling outputs from this strategy were synchronized with the simulation framework, which updated setpoints every ten min and monitored grid conditions every 30 s. Figures 8 and 9 show how the battery shifted charging to lower-price hours and discharged preferentially during higher-price intervals, potentially allowing brief periods of minor or moderate overload if the anticipated savings outweighed the immediate need to reduce load.

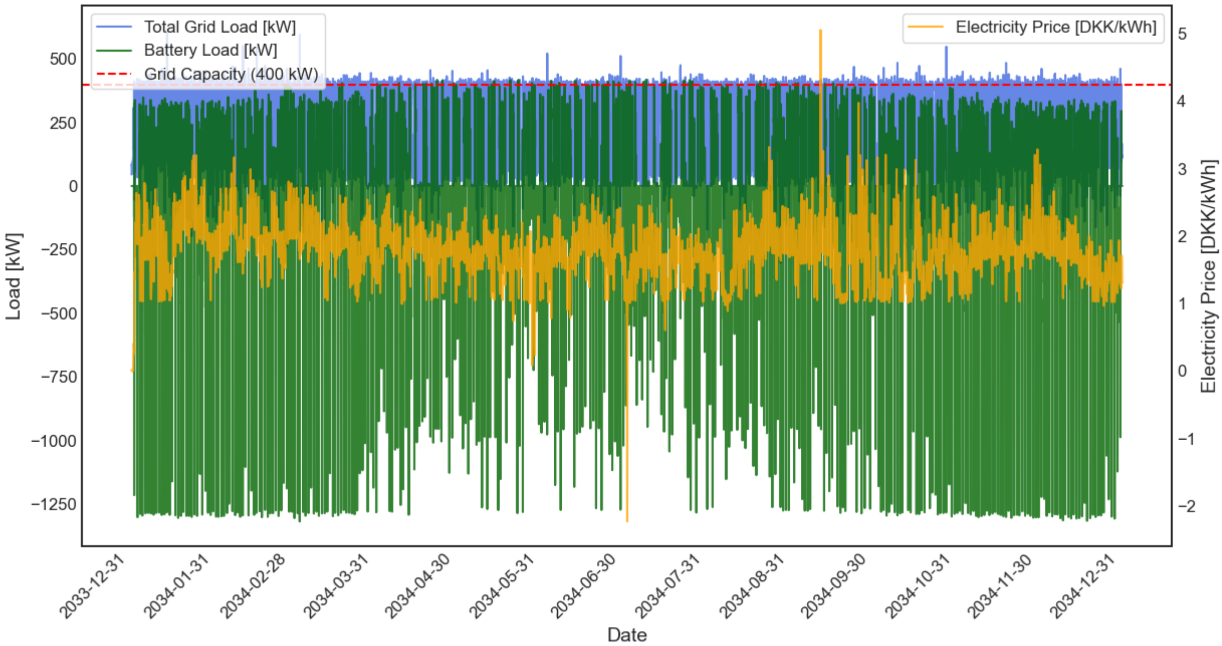

Figure 8. Annual grid load, battery load, and electricity price profile under Strategy 3 (electricity price signal scenario).

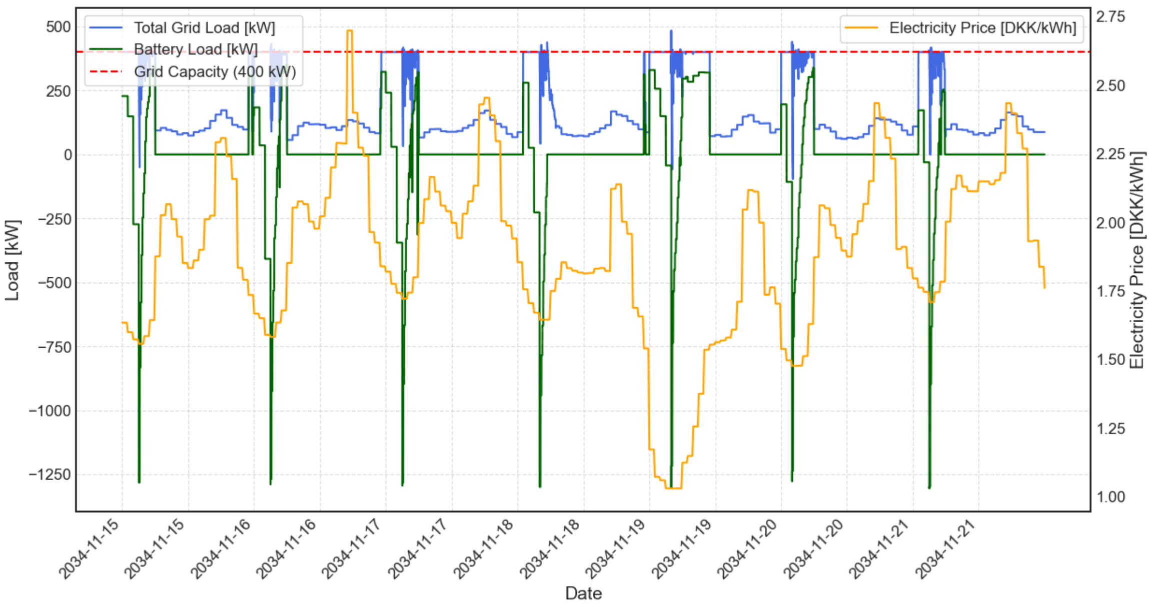

Figure 9. Detailed view of grid load, battery operation, and electricity price profile (Strategy 3)—one-week period.

Figure 8 provides annual profiles for load, battery output, and electricity prices, where the strategy retained the 400 kW overload threshold to prevent severe events. Figure 9 zooms in on a one-week period and illustrates how cost-driven dispatch lowered total charging costs (Table 3 in Section 6.4). Nonetheless, sporadic prolonged overloads may occur if the battery delays discharge to capitalize on cheaper future charging or costlier future discharging. This underscores the trade-off between cost minimization and maintaining strict overload control.

6.4. Comparison of Simulation Results Across Three Battery Dispatch Strategies

Table 3 below contrasts the performances of the three strategies in terms of overload management, battery cycling, and economic outcomes. Overload thresholds were designated as minor (0–5% above 400 kW), moderate (5–50% above 400 kW), and major (>50% above 400 kW). Battery cycling was measured by total charging and discharging over the year, while the charging cost captured financial outlays for grid power.

Table 3. Comparative analysis of different criteria for three battery dispatch strategies.

Criteria		Strategy 1	Strategy 2	Strategy 3
Overload Management	Minor Overload (0–5% above 400 kW) (min)	10.1	11.1	226.4
	Moderate Overload (5–50% above 400 kW) (min)	9.4	1.8	129.2
	Major Overload (>50% above 400 kW) (min)	10.8	0	1.6
Battery Cycling	Charging Energy (MWh)	268.3	330.3	304.7
	Discharging Energy (MWh)	254.9	315.0	291.0
	Minimum SoC	28.9%	24.7%	20%
	Maximum SoC	80%	80%	80%
Battery Charging Cost	In DKK	445,897.8	594,691.4	428,949.3
	In USD (approximate)	59,750	79,694	57,479

Strategy 1 produced a simple operational logic and moderate charging costs but allowed short overload spikes above the 400 kW threshold. Strategy 2 significantly reduced overload intensity yet led to higher cycling and charging costs. Strategy 3 achieved the lowest charging cost by responding to dynamic price signals but slightly increased minor and moderate overload durations. The integrated simulation framework's coordination of these scheduling outputs highlights the trade-offs between cost efficiency, grid stability, and battery degradation, demonstrating the benefits of a coordinated, multi-timescale approach.

7. Discussion

The results demonstrated that the proposed multi-timescale battery dispatch framework effectively balanced grid reliability, economic efficiency, and operational sustainability in high-renewable, high-EV penetration networks. The integration of capacity planning, multi-interval economic scheduling, and real-time agent-based control has proven to be a robust approach to managing system constraints while optimizing storage utilization. The comparative evaluation of three dispatch strategies—HOMER Pro rule-based logic, MISOCP multi-timescale optimization, and price-responsive scheduling—highlighted the strengths and weaknesses of different scheduling approaches, emphasizing the importance of adaptive control mechanisms in modern distribution networks.

The rule-based strategy (Strategy 1), derived from HOMER Pro's static threshold-based logic, provided a straightforward and reliable approach to overload mitigation. However, it lacked economic optimization, leading to higher operational costs and inefficient battery cycling. This finding is consistent with prior research, indicating that static dispatch methods, while effective in preventing grid stress, fail to optimize long-term battery health and economic performance [21,27].

The MISOCP-based multi-timescale optimization (Strategy 2) significantly improved battery scheduling by generating smoother transitions in charge/discharge setpoints, thereby mitigating the intensity and duration of severe overload events while ensuring that battery dispatch aligned with grid constraints. However, while the optimization penalized abrupt power changes to smooth operations, it resulted in increased overall battery cycling compared to the rule-based approach, leading to higher operational costs and potentially accelerated battery degradation. The findings align with studies on hierarchical coordination of scheduling decisions, which have shown that multi-interval scheduling reduces reliance on real-time corrective actions and minimizes operational inefficiencies [16,26].

The price-responsive dispatch strategy (Strategy 3) confirmed that integrating day-ahead electricity pricing signals into battery scheduling reduced total energy costs. This aligns with previous research highlighting the benefits of dynamic pricing strategies, which leverage arbitrage opportunities to enhance cost savings [22,28]. However, the model tolerated slightly longer durations of minor and moderate overloads, as economic incentives sometimes override real-time corrective actions. The trade-off between cost efficiency and grid stability has been well documented in price-based scheduling studies, where over-reliance on market signals can result in localized congestion issues if not carefully managed [6,32].

The case study in Nørre Bjert, Denmark, representing a high-EV penetration distribution network, provided empirical validation of the proposed methodology. The results confirmed that the coordinated multi-timescale dispatch approach significantly reduced major overload incidents while ensuring cost efficiency. The differences in performance across the three strategies emphasized the importance of flexible objective functions that can be adjusted based on regional grid constraints and regulatory policies.

Although the case study was based on a local, medium-sized urban network, the framework's modular design ensures scalability and adaptability to larger, more complex distribution systems. The HOMER Pro capacity sizing stage can be recalibrated to account for regional variations in load profiles and storage constraints. The MISOCP optimization model is applicable to different market structures, making it suitable for both regulated and deregulated electricity markets. The agent-based control layer in AnyLogic can be extended to manage multi-agent DER coordination, demand response, and multi-storage unit operations, further enhancing system resilience and operational flexibility [5,10,23].

Despite its effectiveness, the framework presents several limitations. One of the primary challenges is computational complexity, as the integration of MISOCP-based scheduling with real-time agent-based controls increases solver execution times. Future large-scale implementations may require parallel computing, distributed optimization, or reduced-order modeling techniques to ensure computational feasibility in real-time applications [16]. Another limitation is the sensitivity of scheduling decisions to forecast accuracy, as the model relies on historical and predictive data for load demand, renewable generation, and market pricing. The integration of machine-learning-based forecasting models could improve the accuracy of adaptive scheduling, mitigating uncertainty-related inefficiencies [2,14].

Battery degradation modeling is another area requiring improvement. The current approach discourages excessive cycling, but it does not fully capture temperature-dependent degradation, depth-of-discharge effects, or nonlinear aging dynamics. Future research could incorporate physics-based degradation models or data-driven predictive aging functions to optimize dispatch schedules in a way that explicitly considers battery health over the long term [13,27].

Market-driven dispatch strategies, while beneficial for cost optimization, require careful coordination to prevent congestion risks and unwanted grid stress. The integration of coordinated storage dispatch strategies, such as aggregator-led demand-side flexibility programs, could improve network-wide stability while maximizing economic benefits [6,32]. Future work should also investigate hybrid optimization techniques, combining MISOCP with alternative methodologies, such as reinforcement learning and stochastic optimization, to better handle uncertainty in real-time market conditions and load fluctuations [8,14].

8. Conclusions

This study proposed an integrated multi-timescale battery dispatch framework that effectively balances grid reliability, cost efficiency, and operational sustainability in high-renewable, high-EV penetration scenarios. The framework couples long-term capacity planning (via HOMER Pro), economic scheduling (via Python–Gurobi MISOCP), and real-time overload mitigation (via AnyLogic agent-based simulation) into a unified decision-support tool for distribution system operators.

A case study on a Danish distribution network projected to reach full EV adoption by 2034 demonstrated the framework's practical effectiveness. Compared to the baseline rule-based dispatch, the multi-timescale optimization approach reduced moderate-to-severe overload durations by 82.7%, and the price-sensitive variant lowered battery charging costs by 27.4%, albeit with a 12.5% increase in minor overload occurrences. These quantitative findings illustrate the framework's capacity to reduce grid stress and operational expenses while navigating trade-offs among overload frequency, battery wear, and cost performance.

Qualitatively, the study highlighted that rule-based dispatch strategies offer simplicity and reliability but lack economic responsiveness. The multi-timescale MISOCP approach enabled smoother battery cycling and enhanced grid stability, while the price-aware variant introduced flexibility to exploit market dynamics. These strategies reflect varying degrees of responsiveness and complexity, emphasizing the importance of adaptive dispatch mechanisms.

Despite its demonstrated benefits, the framework faces several limitations. Computational scalability remains a concern, particularly for larger networks with high optimization granularity; thus, the development of advanced solvers, distributed computing architectures, or model simplification techniques is necessary for real-time applicability. The framework's reliance on historical and forecasted data for load, generation, and market signals also poses challenges, underscoring the need for improved forecasting accuracy—potentially through machine-learning-based models. Furthermore, the current model does not fully capture battery aging dynamics, such as temperature effects and variable depth-of-discharge impacts, which could be addressed by integrating more detailed degradation models. Finally, incorporating reinforcement learning may further enhance the system's ability to adapt dynamically under uncertainty.

Additionally, future work should extend the framework to encompass multi-energy systems—including thermal storage, hydrogen, and vehicle-to-grid (V2G) interactions—to support a broader energy transition. It is also important to explore the framework's resilience under extreme weather, cyberattacks, and market disruptions.

In summary, this work established a scalable, modular, and adaptive foundation for intelligent battery dispatch in evolving energy systems. By quantifying performance trade-offs and integrating multi-layered control mechanisms, the proposed framework supports the dual objectives of operational resilience and economic viability in modern power distribution networks.

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Data Availability Statement: The electricity consumption data utilized in this study are proprietary and cannot be shared. In contrast, the electricity price data used for the analysis are publicly available and can be accessed through the relevant market data sources.

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

Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric vehicle
BESS	Battery energy storage system(s)
HOMER Pro	Hybrid Optimization Model for Electric Renewables (Pro)
MISOCP	Mixed-Integer Second-Order Cone Programming
ABS	Agent-based simulation
EMS	Energy management system
SoC	State-of-charge
MILP	Mixed-integer linear programming
ToU	Time-of-use
RTP	Real-time pricing
PV	Photovoltaic
DER	Distributed energy resources
RL	Reinforcement learning
DKK	Danish Krone
AC/DC	Alternating current/direct current

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