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BALANCING AIRPORT GRID LOAD: THE ROLE OF SMART EV CHARGING, SOLAR, AND BATTERIES

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ABSTRACT

As the aviation industry works to reduce carbon emissions, airport energy optimization has also been brought into focus. This study explores strategies to reduce peak electricity demand at a major Swedish airport driven by increased electric vehicle charging (EV). EV charging increases grid load, but integrating solar power and battery storage helps stabilize fluctuations and reduce peaks. We present a framework and simulate the combined impact of these factors, demonstrating that smart scheduling with solar and battery systems effectively balances the load. This approach reduces high-load occurrences from 8.6% to 2.5%—where 100% would mean exceeding the threshold year-round—even with 500 additional charging points.

1 INTRODUCTION

Airports are large-scale energy consumers, requiring significant electricity to operate efficiently. As airports strive for greener operations, effective management of energy infrastructure becomes essential to support their sustainability goals. Swedavia, the Swedish state-owned company responsible for managing ten of the country's busiest airports, aims to achieve fossil-free domestic flights and Airport travel by 2030. One approach to achieving fossil-free travel is by enabling EV charging, which adds load to the electricity grid.

Over the past decade, vehicle charging scheduling has become a key research area driven by the increasing adoption of electric vehicles. Often paired with renewable energy sources, this approach helps minimize grid dependence. Swedavia, which is expanding electricity usage at its major airports, is also facing a growing strain on the grid during peak hours (Wedenberg 2024). They are exploring solutions to reduce peak demand introduced by additional load, such as EV charging, including solar production and battery storage systems to manage variability in solar energy. Since the airport requires an uninterrupted electricity supply, any additional energy load must be carefully managed. This paper presents a simulation framework to assess the impact of EV charging on grid load and evaluates how solar power and battery storage can optimize energy use, ensuring a more sustainable and resilient airport energy infrastructure.

We evaluate EV charging with different scheduling algorithms and their interaction with renewable energy and battery storage systems. We demonstrate that immediate charging significantly increases peak demand, whereas smarter Greedy scheduling shifts load to lower-demand periods, reducing grid stress. Additionally, solar production alone lowers high-load occurrences but remains sensitive to weather variability. The integration of battery storage further stabilizes the grid by compensating for solar fluctuations and peak demand. Our results indicate that combining Greedy scheduling, solar power, and five battery units can reduce the proportion of high-load occurrences from 8.6% to 2.5% for cases with 500 charging points.

The paper is structured as follows: Section 2 reviews related work on efficient vehicle charging, battery storage optimization, and simulations integrating renewable energy sources and batteries. Section 3 provides an in-depth overview of the simulation framework. Section 4 details the data and algorithms used to reduce grid load through intelligent car charging and battery management. Section 5 presents the simulation results. Finally, Section 6 concludes with a discussion on the benefits of optimized EV charging, combined with solar power and battery systems, to effectively balance grid load at a major airport.

2 RELATED WORK

Related research is grouped into three main areas. The first covers scheduling algorithms for electric vehicle charging, which is crucial to balance grid demand as the need for EV charging increases. The second focuses on control strategies for battery energy storage systems (BESS), which are vital to stabilizing grid fluctuations. The third examines studies that integrate EV charging scheduling, renewable energy sources, and BESS in a unified simulation model.

2.1 Vehicle Charging Scheduling Algorithms

Optimizing vehicle charging schedules is often classified as an NP-complete problem, prompting researchers to explore various algorithmic approaches for different objectives.

Genetic Algorithms (GA) are widely used for vehicle charging scheduling (Ghofrani et al. 2012; Hou et al. 2020; Su et al. 2020). GA are heuristic search algorithms inspired by evolutionary principles like natural selection. They optimize solutions by maintaining a population of candidates and refining them iteratively through operations like crossover and mutation. GA can produce high-quality solutions but do not guarantee optimality. They are effective at handling multiple objectives, though their convergence can be slow. To address this, Che et al. (2024) proposed a dual-population GA to enhance global optimization and reduce premature convergence.

Particle Swarm Optimization (PSO) is another bio-inspired method used in scheduling (Celli et al. 2012; Yang et al. 2014). Influenced by bird flock behavior, PSO iteratively adjusts particle positions based on past experiences and neighbors' best-known positions. PSO typically converges close to the global optimum but may get stuck in local optima in high-dimensional spaces.

Reinforcement Learning (RL) allows an agent to learn optimal actions through trial and error, maximizing rewards. RL is effective for complex tasks like EV charging scheduling but requires large datasets and significant computation. Wang et al. (2021) applied RL with an approximate Q-table to manage high-dimensionality. Deep reinforcement learning (DRL) further enhances this by using neural networks, overcoming high-dimensional state space limitations (Jin and Xu 2021; Wan et al. 2019). Multi-agent DRL (Aljafari et al. 2023; Park and Moon 2022) involves agents collaborating to improve efficiency.

Scheduling can also be formulated as a mathematical optimization problem, where decision variables are optimized under constraints using solvers. Korolko and Sahinoglu (2017) and Koufakis et al. (2020) tackled this with mixed-integer programming, using cutting-plane optimization and commercial CPLEX solvers, respectively. Similarly, Ioakimidis et al. (2018) used linear programming with an interior-point scheduling algorithm. Due to its complexity, dynamic programming is challenging for EV scheduling. Zhang and Li (2017) introduced approximate dynamic programming as a computationally simpler alternative.

Most studies (Aljafari et al. 2023; Che et al. 2024; Hou et al. 2020; Ioakimidis et al. 2018; Jin and Xu 2021; Koufakis et al. 2020; Park and Moon 2022; Su et al. 2020; Wang et al. 2021; Yang et al. 2014; Zhang and Li 2017) focus on optimizing charging at public stations with short parking durations, typically during daytime hours. In contrast, airport EV charging follows a different pattern, where vehicles are parked for extended periods, allowing for overnight charging during off-peak hours.

Our goal is to reduce peak grid loads by shifting charging to off-peak times. We focus on a computationally efficient approach instead of aiming for the absolute optimal solution. We implemented a simple yet effective greedy algorithm integrated into broader electricity usage simulations, offering greater transparency than black-box machine learning models.

2.2 Control Algorithms for Battery Energy Storage Systems

The performance of a battery energy storage system (BESS) is heavily influenced by the control algorithm governing its operation. A well-designed control strategy ensures optimal charging and discharging, aligning with grid demands and energy requirements.

Real-time control algorithms adjust dynamically to load variations using real-time data, managing BESS operations without predictive models. Danish et al. (2020) and Lange et al. (2020) use charge and discharge thresholds. The BESS supplies energy when the demand exceeds the discharge threshold and charges when the load falls below the charge threshold. Chua et al. (2016) further refine this by adjusting the discharge threshold based on the current load, increasing it when demand exceeds supply, and decreasing it when excess energy is available. Real-time algorithms are simple, computationally efficient, and avoid forecast errors. However, with limited battery capacity, they can prematurely deplete the battery, failing to address peak demand effectively.

Predictive algorithms use load forecasts, often powered by neural networks, to anticipate peak loads and optimize BESS operation. Chapaloglou et al. (2019) use day-ahead load forecasts from neural networks to set charge and discharge thresholds for effective peak shaving. Efkarpidis et al. (2023) propose a rule-based method, setting the discharge threshold based on predicted loads and the peak from the previous month, with immediate charging occurring when the load falls below this threshold.

Optimization-based algorithms use mathematical models to minimize load variance or reduce peak-to-valley differences, relying on load predictions for complex, multi-peak scenarios. Lu et al. (2014) employ mixed-integer programming for peak shaving based on predicted load profiles. Barzkar and Hosseini (2018) use Lagrangian multiplier optimization with GAMS to solve peak shaving, while Rostamnezhad et al. (2023) apply Particle Swarm Optimization with historical data. Mary et al. (2023) use linear programming with day-ahead load forecasts by a neural network to optimize BESS operation.

Our goal is to design a system optimized for scenarios with a single daily peak and night valley. To achieve this, we prioritize simpler, faster algorithms that set thresholds based on predicted load, avoiding more computationally intensive optimization methods.

2.3 Simulation of EV Charging with Renewable Energy and Battery Storage

Simulations of EV charging that integrate renewable energy and battery storage focus on optimizing energy efficiency, economic viability, and testing system feasibility.

Several studies have incorporated renewable energy into charging strategies. Jin and Xu (2021) use reinforcement learning to optimize EV charging scheduling combined with solar power. Koufakis et al. (2020) simulate solar-integrated EV charging to reduce energy costs and maximize solar use. Ghofrani et al. (2012) explore wind-powered vehicle-to-grid scenarios to minimize reliance on conventional energy. Some studies integrate battery energy storage systems (BESS) to address renewable intermittency. Badea et al. (2019) simulate a solar-powered charging station with BESS, using a genetic algorithm for system optimization evaluating solution feasibility and islanded operation. Gogoi et al. (2024) examine power balance at a solar-powered charging station with BESS in various scenarios. Yadav et al. (2023) validate a charging station design and management strategies with solar and BESS through simulations. Sing et al. (2022) use real-world data to assess self-sufficiency at different charging station locations, finding that moderate solar power plant sizes yield high self-sufficiency. Gopal et al. (2023) simulate strategies to reduce peak demand at fast charging stations with solar and BESS. Kucevic et al. (2021) simulate the impact of BESS (without renewable energy) on peak load reduction at charging stations, exploring different battery capacities and charging units.

Similar to Gopal et al. (2023) and Kucevic et al. (2021), we simulate the impact of various charging station configurations, solar power plant sizes, and battery capacities on grid load, focusing on mitigating peak demand to avoid grid overloading at the airport.

3 SIMULATION FRAMEWORK

We present a simulation framework, illustrated in Figure 1, and conduct simulations using the proposed framework. The framework initializes all modules before executing simulations at predefined intervals (every 2 hours in this study). Each simulation step comprises six phases, with two phases per module.

First, future consumption is planned in the following order: solar generation, EV charging, and battery usage. EV charging is scheduled based on predicted solar production, while the battery plans peak shaving after accounting for solar generation and EV charging. Execution follows the same sequence.

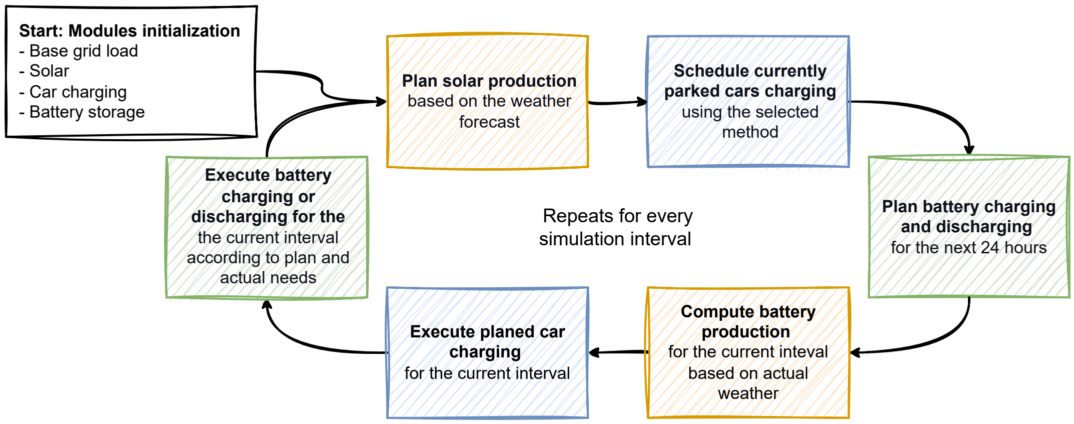

Figure 1: Schema of the simulation framework, which initializes modules before iterating through three planning steps per time interval—solar estimation, EV scheduling, and battery consumption planning—followed by three execution steps: computing solar production, EV charging, and battery operation.

3.1 Solar Module

We use pvlib's ModelChain module (Anderson et al. 2023) for solar production simulation. We simulate "REC Group REC740AA Pro XL" monocrystalline modules (power 739.4 W under standard test conditions) with properties similar to modern modules, using parameters from the California Energy Commission (CEC) library (National Renewable Energy Laboratory 2024). Inverters are dynamically selected from the CEC library (National Renewable Energy Laboratory 2024), ensuring the PV array's rated power closely matches the inverter's rated power while adhering to array-to-inverter sizing ratios (Zidane et al. 2021). Arrays are configured in parallel strings to keep the voltage within the inverter's operating range under all temperatures (Omar et al. 2020).

The solar module estimates production in both the planning and execution phases. The key difference between phases is the weather data used: execution relies on past observations, while planning uses simulated forecasts, introducing uncertainty. This uncertainty is modeled using an autoregressive approach (Zheng et al. 2025). Distributions and autoregressive model parameters are obtained by analyzing past weather forecasts against actual observations (see Section 4.1) for each weather variable. During simulation, these distributions and models are used to model uncertainties.

As shown in Figure 2-A, solar production (orange) reduces the base load of the grid (blue), with daily variations due to weather conditions, as shown in Figure 2-B.

3.2 EV Charging Module

During the planning phase, a charging schedule for the cars currently parked is generated using the algorithms in Section 4.2. Charging is simulated based on real airport station data, scaled as needed, as detailed in Section 4.1. In each simulation step, vehicles not yet fully charged are rescheduled to optimize resource allocation. Although this may shift a charging vehicle to a different time slot, interruptions remain limited.

Our simulation assumes unknown car arrival times, so charging is scheduled only after arrival. However, the last available charging slot is known, as owners will report departure times. Departure times were inferred from actual data for simulation purposes. Scheduled car charging is performed for the current simulation interval (the next two hours in this study) in the execution phase according to the schedule from the planning phase. Since rescheduling occurs at fixed intervals, some vehicles may not receive enough charge if they arrive and depart between two events or if there is not enough time for a full charge after the next rescheduling. To address this, we initiate charging immediately upon arrival.

Figure 2-A shows the impact of the station with 500 charging points using a Greedy scheduler on grid load (green line). The graph shows that the Greedy scheduler (described in Section 4.2) primarily shifts charging to grid load valleys, minimizing additional demand during peak hours. Figure 2-C illustrates charging behavior for 15 charging points, where black lines denote charging sessions and blue bars indicate active charging. The Greedy algorithm schedules charging during lower grid load or high predicted solar production periods. Charging schedules account for planned maintenance (gray bar), and charging in the execution stage is interrupted by unexpected failures (red bar). In Figure 2-C, maintenance at charger 100 shifts the third session, while a failure at charger 109 disrupts session two, forcing a rescheduled rescheduling to a less favorable time. Swedavia reports a 1% failure rate, so our simulations assume a 1% probability for both events, with durations randomly varying from 30 seconds to 12 hours.

3.3 Battery Storage Module

Since solar alone cannot reliably mitigate peak loads due to weather variability, we integrate a battery energy storage system (BESS) into our framework. Our BESS follows the specifications of the popular Tesla Megapack 2 XL, with each unit providing 3.916 MWh capacity and 1.927 MW peak power. We incorporate a round-trip efficiency of 93.7% into the BESS module.

Battery charging and discharging are scheduled based on initial grid load, predicted solar production and EV charging demand using the algorithm in Section 4.3. Model updates charging and discharging thresholds at every simulation step to account for dynamic changes in grid load forecasts, solar predictions, vehicle charging schedules, and battery state of charge.

Execution follows the planned thresholds, ensuring battery operations align with actual demand. Figure 2-A (red) illustrates the battery's impact on peak shaving. For example, on 2025-03-21, when solar production is insufficient, BESS helps to shave the peak. Figure 2-D shows the battery's state of charge.

4 DATA AND METHODOLOGY

We simulate using real data from an airport and a national weather agency. This section first details the dataset, followed by EV charging scheduling methods and battery control. Finally, we define the performance metric for evaluating the strategies.

4.1 Data

We use three datasets: airport grid load, airport's public charging station data, and past weather observations from the Swedish Meteorological and Hydrological Institute. Simulations are based on data from January 1 to December 31, 2023, ensuring alignment across all datasets.

The grid load data comprises hourly electricity consumption (kWh) with corresponding timestamps. Since future grid load is expected to resemble past trends, we use historical data for simulations. Unlike averaged values, actual past data retains peaks and valleys, making it a more accurate representation.

EV charging is modeled using real data from the airport's station with 10 charging points, totaling 937 sessions in 2023. Each session records the charger ID, the car's arrival and departure times, and charged energy (kWh), which we consider to be the charging need for the EV. Since most cars stay longer than required for charging, we assume each session represents a full charge. To simulate different charging station capacities, we upsample sessions by shifting start and end times by ±4 hours and adjusting energy needs by ±2 kWh while maintaining realistic distributions.

Weather observations are retrieved from the Swedish Meteorological and Hydrological Institute's API (SMHI 2025), where we export temperature and wind data from observations at the meteorological

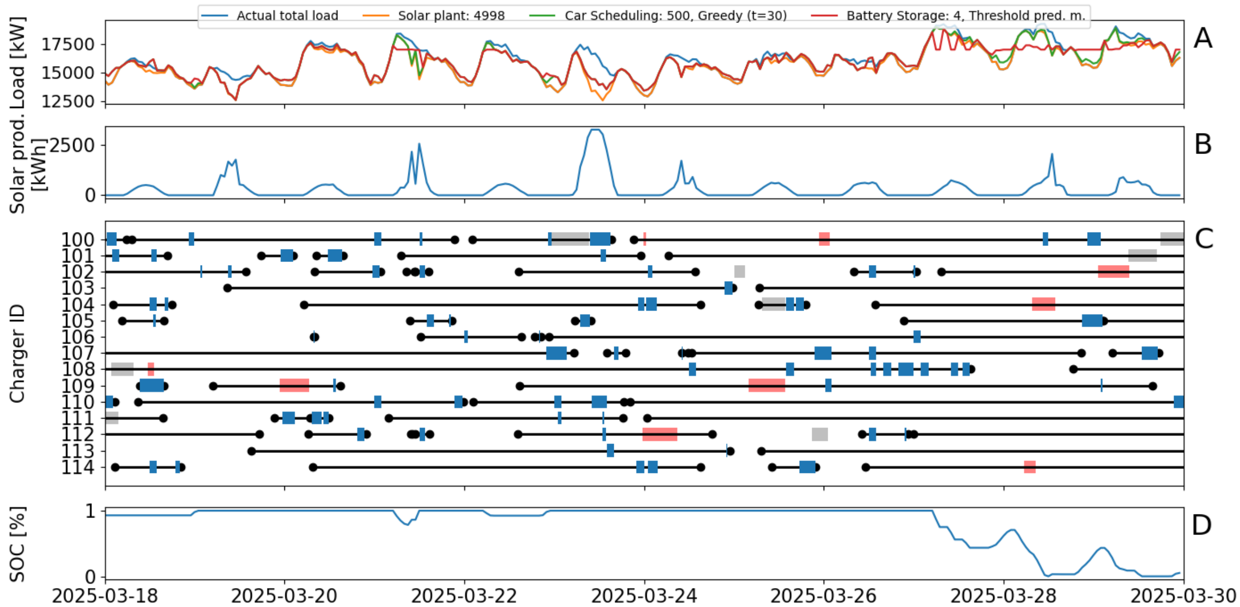

Figure 2: The figure shows a 12-day excerpt from a year-long simulation of solar production, EV charging with a Greedy scheduler, and battery storage. A) Grid load with no modifications (blue), after solar production (orange), with EV charging (green), and with battery support (red). B) Hourly solar production (kWh). C) Charging behavior for 15 charging points: black lines show parked cars, blue bars active charging, gray bars maintenance, red bars failures. D) The battery's state of charge (%).

station located at the airport and irradiance (direct normal irradiance, global horizontal irradiance, and diffuse horizontal irradiance) parameters from the STRÅNG module.

To model uncertainty in the weather forecast described in Section 3.1, we retrieve historic forecasts for every three hours in the year 2024 from the Norwegian Meteorological Institute's Thredds service (MET 2025). The forecast includes temperature, wind speed, direct normal irradiance, and global horizontal irradiance. The diffuse horizontal irradiance is computed from the other two parameters after uncertainty is modeled. We compared the forecast to the SMHI observations from the same period to build the model.

4.2 EV Charging Scheduling Algorithms

We implemented four distinct EV charging scheduling algorithms.

The Immediate Scheduler mimics real-time charging, starting immediately upon arrival and continuing until the EV is fully charged or departs, without considering grid load.

The Greedy Scheduler schedules charging based on departure time and electricity demand. Vehicles departing soonest are scheduled first, using time slots with the lowest predicted grid load. Scheduling is limited to available time slots between the moment of scheduling and departure. Once an EV is scheduled, its expected charging load is incorporated into the overall grid load, and the next vehicle is scheduled accordingly. We use 30-minute slots to balance computational speed and scheduling accuracy. Shorter durations offer minimal improvement (Godec and McKeever 2024).

Since EVs often remain parked at the airport for days or weeks, delaying charging improves battery health. Neither the Immediate nor Greedy Scheduler accounts for this, so we introduce two additional approaches: **The Before-departure Scheduler** takes the opposite approach of the Immediate Scheduler. It delays charging until just before departure, ignoring grid load. **The Greedy Last-day Scheduler** is a modified version of the Greedy Scheduler, which restricts scheduling to 36 hours before departure, ensuring at least one full night—when demand is lower—is available for charging.

Figure 2-C presents a ten-day schedule using the Greedy Scheduler. The grid load graphs reveal its preference for nighttime or high-solar daytime charging (orange line in the top graph). In contrast, the Immediate Scheduler increases demand during peak hours, as most vehicles arrive during the day.

4.3 Battery Energy Storage System Control Algorithm

A Battery Energy Storage System (BESS) requires effective control algorithms to optimize its performance. We chose a simple yet effective algorithm (Godec and McKeever. 2025) ensuring transparency and efficiency.

Predictive Threshold Algorithm schedules charging and discharging 24 hours ahead based on predicted grid load (including solar prediction forecast and scheduled EV charging). It identifies charging periods when the grid load is below the threshold and discharging periods when it exceeds the threshold (in this experiment, the threshold is set to 17 MW). The method dynamically adjusts the discharge threshold within discharge periods to ensure that energy is reserved for grid load peaks rather than being depleted prematurely. Similarly, it predicts a charging threshold for charging cycles, ensuring that charging occurs when the grid load is at its lowest (i.e., the deepest valley).

During execution, the battery discharges when the actual grid load exceeds the predicted threshold, supplying power to bridge the gap. It charges when the grid load is below the predicted threshold, limiting the charging and discharging by the battery's maximum power rate and available energy in the battery.

4.4 Metrics

We assess grid load impact using *deviation from mean load*, *daily maximum mean*, and *peak ratio*.

Deviation from mean load is computed as the root mean square deviation from the mean grid load. Grid load is computed as the rolling 10-day grid load average, mitigating seasonal shifts. It measures how effectively the charging schedule, solar production, and battery storage stabilize grid fluctuations by reducing peaks and filling valleys. A lower value signifies better load balancing.

Daily maximum mean measures the average of daily maximum values over the simulation period, measuring the effectiveness of peak shaving. A lower value indicates a greater average peak reduction.

The daily maximum mean does not fully capture how many peaks were successfully reduced, as it only reflects average peak shaving. We address this with the **Peak Ratio**, which measures the proportion of grid load values exceeding a set threshold, indicating the number of peaks eliminated. We set this threshold at 18 MW, close to the airport's maximum allowable load while retaining flexibility for unforeseen demand.

5 RESULTS

Adding more EV chargers increases grid demand, potentially exceeding the airport's energy capacity. In Section 5.1, we assess the impact of different charging algorithms on grid load. Section 5.2 examines how solar power mitigates this additional load, while Section 5.3 evaluates battery storage's role in compensating for solar variability due to weather and daylight fluctuations. All simulations are run in 2-hour planning-execution cycles over 2025, with 10 buffer days before and after for warm-up and cool-down.

5.1 Impact of EV Charging on the Grid Load

We compare how different EV charging algorithms from Section 4.2 impact grid load. Figure 3-A shows that Immediate and Before Departure scheduling increases load deviation by adding demand during peak hours, while the Greedy algorithm reduces deviation by shifting charging to valleys.

Since our goal is to minimize peak load, Figure 3-B analyzes how each scheduler affects daily peak power. Immediate scheduling adds the most load to peaks, followed by Before-departure. The difference arises because cars typically arrive when the grid load is already high (Immediate charges upon arrival), whereas departures often occur when the load is slightly lower. Additionally, Before Departure may fail to fully charge if a failure occurs, reducing overall load. Greedy algorithms keep peak loads low, even in the case of 500 chargers.

Figure 3-C shows the proportion of hours with high load (exceeding 18 MW). The Immediate and Before-departure algorithms increase high-load hours more than Greedy; the difference between Immediate and Before-departure arises due to the same reasons as in Figure 3-B. Both greedy algorithms introduce significantly fewer new high-load hours through smarter scheduling.

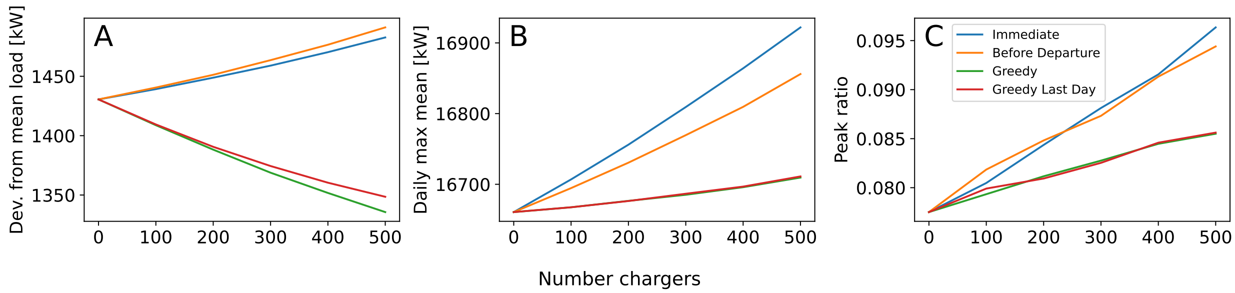

Figure 3: Comparison of EV charging impact on airport grid load across different scheduling algorithms and charger counts. A) Deviation from the mean grid load quantifies algorithms' impact on the grid load balance by filling valleys and avoiding peak overload. B) Daily maximum mean measures additional demand during daily load peaks. C) The proportion of hours exceeding 18 MW evaluates each algorithm's effectiveness in limiting high-load occurrences.

5.2 Impact of EV Charging with Solar Power on the Grid Load

Solar power helps mitigate the impact of load added by EV charging on the grid. Figure 4 examines the effect of solar production on load balancing and peak reduction.

Figure 4-A presents the charging and solar effect on grid load balancing. It shows that adding up to 3000–4000 solar modules improves grid balancing for both Greedy and Immediate charging, but worsens it beyond this point. This occurs because excess solar generation creates additional valleys. Greedy algorithms complement solar better, filling valleys while solar reduces daytime peaks.

Figure 4-B examines the effect of charging and solar scenarios on daily grid load peaks. It illustrates that all charging algorithms increase the mean daily peak load compared to the baseline (16660.7 kW), with Immediate more significantly reaching 16921.9 kW and Greedy 16709.5 kW for 500 chargers. However, solar production reduces mean daily peak loads, with 1000 modules already negating the impact of 500 Greedy chargers, while Immediate requires at least 3000 modules. Solar production with 4998 modules reduces the mean daily peak load of Immediate charging with 500 chargers to 16476.4 kW, just below the initial level, while Greedy achieves a more significant drop to 16272.0 kW.

Figure 4-C highlights that solar reduces the number of high-load hours (above 18 MW). For the Immediate algorithm, at least 4998 modules offset the impact of 500 chargers, while Greedy achieves this with only 1992. Solar also removes pre-existing peaks (values below the black line). For example, the proportion of hours above 18 MW is reduced from 7.8% to 6.1% without extra chargers and from 8.6% to 6.9% with 500 Greedy chargers.

5.3 Impact of EV Charging, Solar Power, and Battery Storage on Grid Load

In the previous section, we showed that solar power reduces both existing peaks and those introduced by EV charging. However, a significant number of peaks remain due to weather-dependent solar production. In Figure 5, we further examine how Battery Energy Storage Systems (BESS) help redistribute energy load on days with lower solar output, using a fixed set of 4,998 solar modules. Figure 5-A shows that

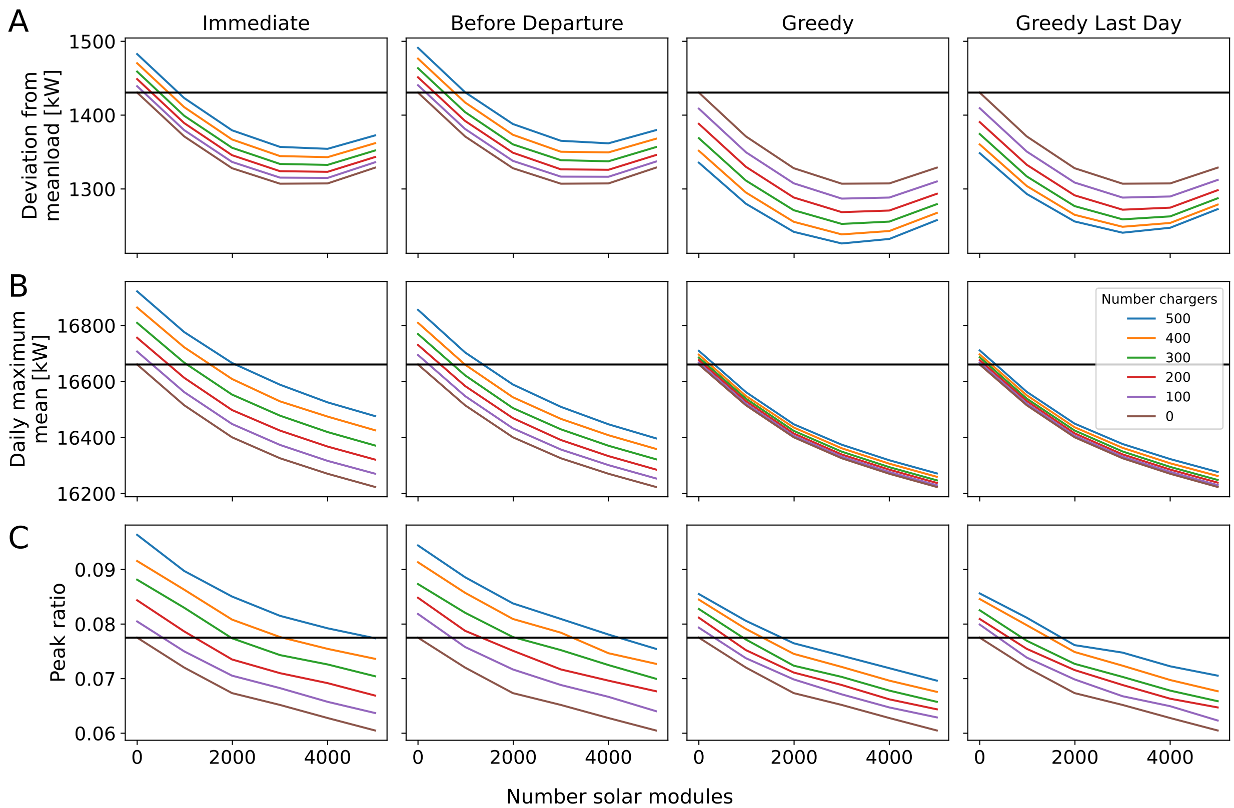

Figure 4: The graphs show how solar plant size mitigates the load added by charging. The x-axis represents the number of solar modules, the y-axis shows scores, and the lines' colors indicate charger counts. The black line marks score without EV charging or solar. A) Deviation from mean load quantifies grid balance. B) Daily max mean shows added peak demand. C) The proportion of occurrences exceeding 18 MW is evaluated for the reduction of high-load occurrences.

BESS consistently balances grid load by mitigating peaks and filling valleys, with even better results when combined with the Greedy charging algorithm, which also aims for load balancing.

As shown in Figure 5-B, BESS also significantly lowers the daily peak load mean. The improvement is more pronounced when combined with the Greedy scheduler. For example, with 500 chargers and 4,998 solar panels, the daily maximum load drops from 16,273.7 kW (without BESS) to 16,028.6 kW when adding five battery units.

A similar trend is seen in Figure 5-C, where the proportion of grid load hours exceeding the threshold of 18 MW is drastically reduced compared to solar-only cases. While BESS improves cases with all algorithms, it performs slightly better with Greedy scheduling when fewer battery units are used. For instance, with 500 chargers using Greedy scheduling, solar production lowers the proportion of high-load occurrences to 6.9% (Section 5.2). The proportion of high-load occurrences further improves to 2.5% with the addition of five battery units. The remaining peaks result from inaccurate load forecasts affecting battery control performance or insufficient stored energy during prolonged high-demand periods, such as winter.

6 DISCUSSION

This paper presents a simulation framework for assessing airport grid load impacts from additional EV chargers and evaluates how solar and battery storage can mitigate these effects. Results show that immediate

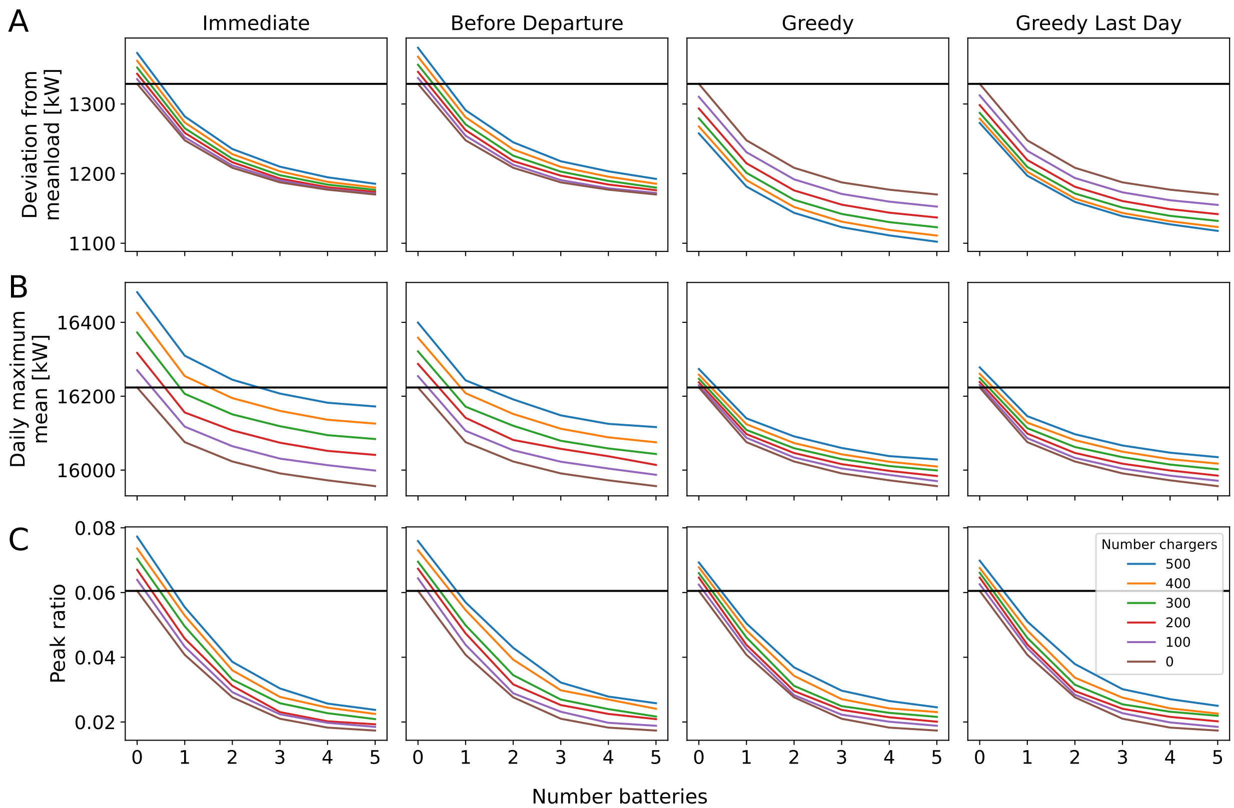

Figure 5: The graphs illustrate how battery units further improve grid load with EV charging and 4,998 solar panels. The horizontal axis represents the number of battery units, while the vertical axes present the corresponding measure, as in Figure 5. Lines indicate the number of chargers. Black lines denote scores for the scenario with 4,998 solar panels but without additional charging or BESS.

charging increases peak demand, while smarter scheduling mitigates this by shifting the charging to lower-demand periods. Solar production further offsets peaks, while battery storage compensates for solar variability. Our simulations reveal that combining these strategies not only neutralizes the added EV charging load but also additionally reduces the proportion of high-load occurrences from 8.6% to 2.5%, even with 500 additional chargers using Greedy scheduling. A key contribution is our analysis of the combined impact of EV scheduling, solar power, and battery storage on grid load.

Despite reducing the proportion of high-load occurrences to 2.5%, complete minimization remains challenging due to forecast inaccuracies affecting battery control and insufficient stored energy during prolonged high-demand periods, such as winter. While the latter requires additional battery capacity, the former can be mitigated with a more robust, prediction-error-resistant control algorithm. In the future, vehicle-to-grid (V2G) technology could provide additional battery capacity. Before deploying V2G systems, it is important to examine both EV owners' willingness to participate and the incentive structures required, given the impact of V2G on battery wear and longevity. The framework currently operates via a script, limiting accessibility for non-developer Swedavia users in energy planning. The next phase will focus on developing a user-friendly interface to address this. Although the implementation is currently proprietary, we are committed to making the key algorithms publicly accessible in a structured, ontology-driven format as future digital-twin development progresses.

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