NANYANG TECHNOLOGICAL UNIVERSITY

EE6509 – RENEWABLE ENERGY SYSTEMS IN SMART GRIDS

School of Electrical & Electronic Engineering

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ASSIGNMENT – 2

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Content

INTRODUCTION:

The rapid integration of electric vehicles (EVs) presents both opportunities and challenges for modern power grids, particularly in effectively balancing demand and ensuring grid stability. As EV adoption rises, so does the electricity demand, which necessitates smarter, data-driven solutions to manage energy loads effectively and avoid overwhelming the grid. Vehicle-to-grid (V2G) technology offers a promising approach by allowing EVs to function as energy storage units that can discharge energy back to the grid, supporting demand management and enhancing grid resilience. This work proposes a method that leverages predictive modeling and optimization algorithms to efficiently manage EV charging and discharging based on real-time and forecasted energy demands. First, an LSTM (Long Short-Term Memory) model is utilized to predict energy consumption in 5-minute intervals over 24 hours, excluding the impact of EV charging. This predictive step is essential for understanding baseline energy consumption and anticipating peaks V2G systems could alleviate.

The second stage concerns the data related to EVs registered at the charging stations connected to the Vehicle Model, Battery Capacity, Battery Condition, State of Charge, First Availability Time, and so on. By integrating user-defined time slots within availability periods, the charging station seamlessly coordinates the user's requirements with grid requirements and schedules the charging. A custom dataset is used here that emulates these dynamics by examining the distribution and assuming vehicles arrive in clusters in the day. An optimization algorithm is instructed based on the custom dataset and energy forecasts to monitor the charging and discharging cycles every 5 minutes. The algorithm focuses on those cars that have limited time. These cars are given priority for charging since these cars will leave sooner, and other cars are used over a longer period.

A custom dataset is utilized to simulate these dynamics, examining the distribution and assuming vehicles arrive in clusters throughout the day. An optimization algorithm, informed by the custom dataset and energy forecasts, monitors the charging and discharging cycles every five minutes. The algorithm prioritizes vehicles with limited availability, ensuring they are charged first, while vehicles with extended availability are optimized for later use. If a certain number of vehicles are connected to the grid and capable of returning energy, a custom algorithm accounts for battery conditions, user schedules, and grid demands to effectively manage the energy flow. The results highlight the potential for V2G systems to optimize energy flow within the grid, meet user requirements, and support a sustainable, resilient energy infrastructure.

LITERATURE REVIEW:

The increased insertion of renewable energy resources and coupled natural gas, electricity and multi-energy systems (MES) into supply grids, has shifted significant focus on developing methods to optimize the supply and demand balance [1]. Balancing supply-demand fluctuations through conventional optimization models that call for explicit system representations is often impractical due to the inherent complexity of such a model which hampers real-time disaster recovery management. At this conjecture, machine learning can overcome the negatives of this conventional approach by predicting the supply-demand fluctuations using patterns of generated data [1,2].

While reinforcement learning has been already shown to work well in dynamically adjusting the product price in a timely fashion, to allocate the right service to the right CU at the right time [3], it is also being explored for optimization of demand response (DR) for interruptible loads (IL) using a model-free deep reinforcement learning (DRL) technique based on Dueling Deep Q Network (DDQN) architecture. Using a Markov Decision Process to model the DR management problem, voltage control was preserved with low peak loads, and hence lower operating expenses, thus highlighting the optimality of DDQN for DR management problems [2].

AI-based DR management algorithms have also been explored in the context of integrated demand response (IDR) applications in coupled natural gas, electricity, and heat multi-energy systems (MES). While traditional DR management is concerned with information on how customers modify their energy usage in response to price signals, IDR prioritizes the requirement for flexibility in energy types and systems. For multi-energy source complex systems IDR optimization thus holds the potential to increase energy efficiency and system dependability [4].

However, so far demand response applications of reinforcement learning have been concentrated on single-agent energy systems like HVAC, electric cars, and storage devices with a particular focus on lowering costs and improving user comfort. In contrast, dynamic pricing with DR coordination, which prevents peak-shifting, calls for multi-agent reinforcement learning to facilitate the effective integration of renewable energy resources in dynamic urban environments. Further, the performance of AI-based DR management in non-stationary scenarios would be crucial for their real-world utility [5]. Another challenge is the considerably asymmetric progress in enabling the active participation of DR management in the power system procedures between different regions hampering a broader flexible accommodation of intermittent renewables and thus the development of a more robust AI-based DR management system [6].

METHODOLOGY:

Our solution for the problem is structured into the following components:

1. Nominal Energy Consumption Prediction: We use an LSTM model to predict nominal grid energy consumption (excluding EVs) every 5 minutes over the past 24 hours.
2. Optimization algorithm: This algorithm manages EV charging and discharging based on user availability, grid conditions, and battery health.

The code for this implementation can be found on GitHub here.

Application flowchart:

The flowchart below illustrates the proposed application, showcasing a smart EV charging station system focused on optimizing load management, charging, and pricing.

1. Grid Data: Information from the grid is fed into the charging station.
2. AI Charger Components:
    a. Load Prediction Model: Forecasts load requirements for the next 24 hours based on historical data.
    b. Charging Optimization: Optimizes the charging strategy to reduce peak load, minimize variance, and lower average load.
    c. Pricing Calculation: Determines charging costs based on peak/off-peak charging/discharging periods.
3. Vehicle Data: This includes state of charge (SOC), battery capacity, and user charging preferences for vehicles connected to the station.
4. Closed-loop Feedback: Vehicle data is fed back into the AI charger to refine predictions and optimize charging in real time.

This structure supports efficient charging for multiple EVs and adapts to fluctuating demand. The following sections delve into each process in detail.

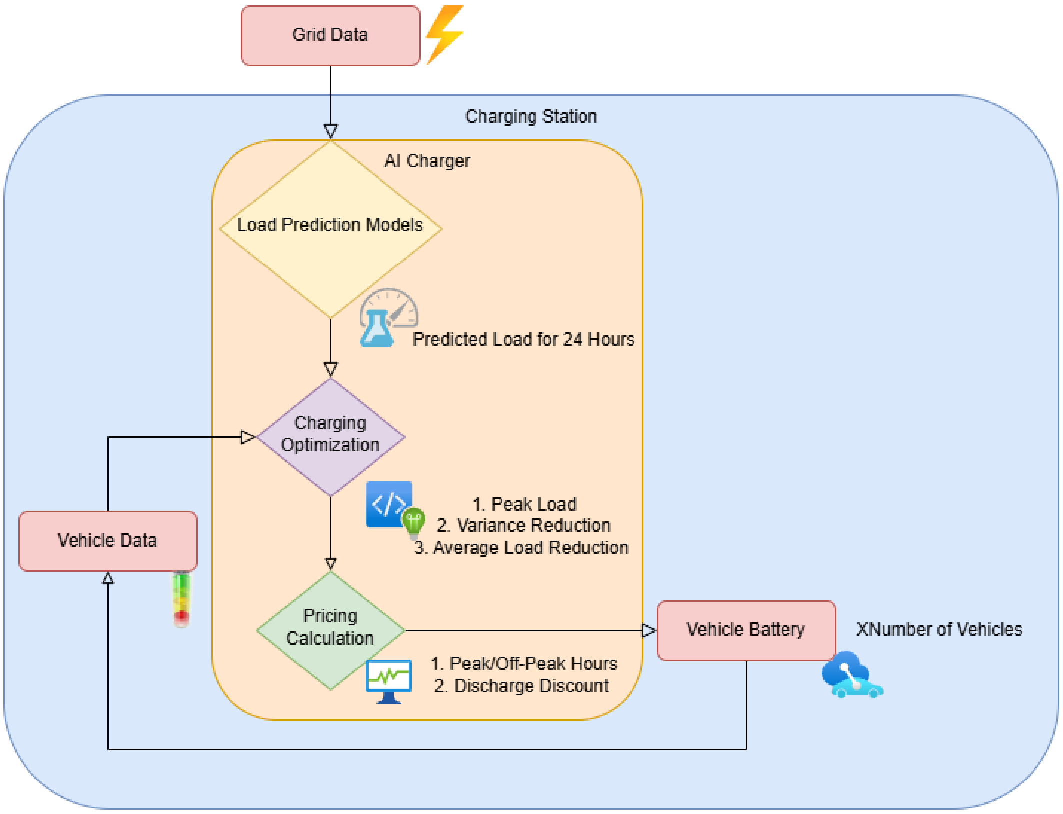
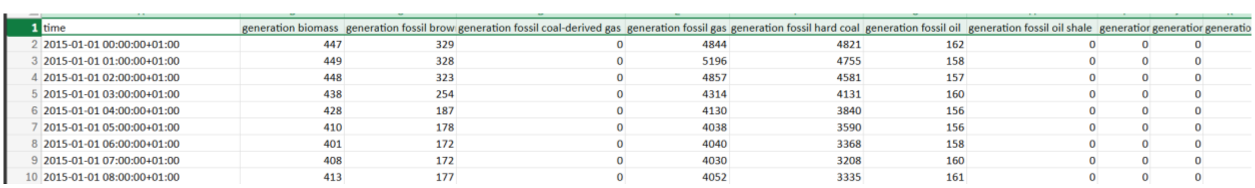


Figure 1 Schematic of our proposed solution.

The following sections provide a detailed and insightful explanation of the processes involved in optimization.

Grid energy consumption estimation using LSTM:



1	time	generation biomass	generation fossil brow	generation fossil coal-derived gas	generation fossil gas	generation fossil hard coal	generation fossil oil	generation fossil oil shale	generatior	generatior	generatio
2	2015-01-01 00:00:00+01:00	447	329	0	4844	4821	162	0	0	0	
3	2015-01-01 01:00:00+01:00	449	328	0	5196	4755	158	0	0	0	
4	2015-01-01 02:00:00+01:00	448	323	0	4857	4581	157	0	0	0	
5	2015-01-01 03:00:00+01:00	438	254	0	4314	4131	160	0	0	0	
6	2015-01-01 04:00:00+01:00	428	187	0	4130	3840	156	0	0	0	
7	2015-01-01 05:00:00+01:00	410	178	0	4038	3590	156	0	0	0	
8	2015-01-01 06:00:00+01:00	401	172	0	4040	3368	158	0	0	0	
9	2015-01-01 07:00:00+01:00	408	172	0	4030	3208	160	0	0	0	
10	2015-01-01 08:00:00+01:00	413	177	0	4052	3335	161	0	0	0	

Figure 2 Snippet of the dataset used for grid energy consumption estimation.

The dataset chosen for predicting grid energy consumption is an energy consumption metric chosen from Kaggle. The “energy_dataset.csv” dataset from Kaggle was used to train the model and predict energy consumption. This dataset contains the energy consumed over time, which is then input into the developed model to predict future energy consumption. The data is cleaned and preprocessed before being used in the LSTM model. The above figure is a sample content of the dataset used.

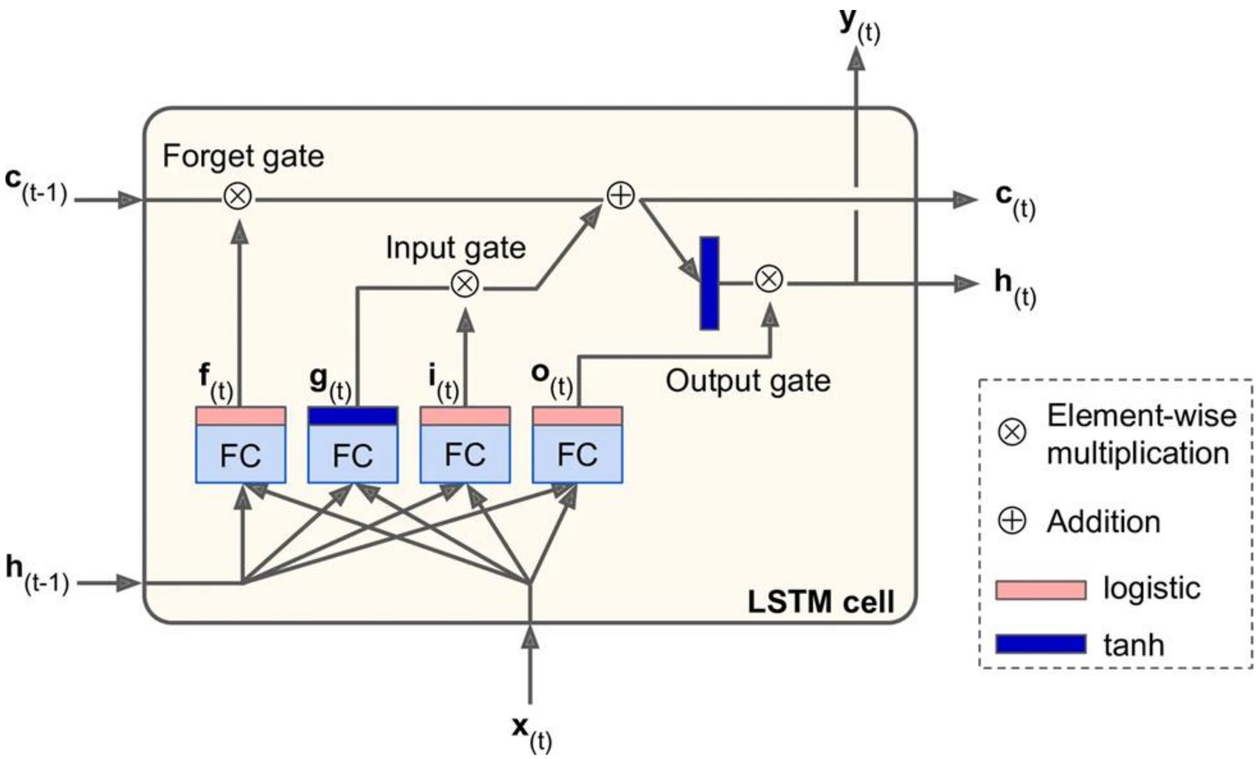


Figure 3 Basic LSTM block.

Figure 3 Basic LSTM block.is a basic overall description of an LSTM block. The input gate determines the new information that will be added to the cell state. It has two layers, the sigmoid i(t) and tanh g(t) layer. The sigmoid layer is used to decide what values will be updated, and the tanh layer creates a new set of candidate values to be added to the state.

The forget gate f(t) decides what information to discard from the cell state c(t-1) using the sigmoid function. The forget gate takes current input x(t) and the hidden state h(t-1) and passes it through a fully connected layer to compute f(t). The cell state c(t) is updated by combining the previous cell state with information from the forget and input gates. Between f(t) and c(t-1), element-wise multiplication is performed to determine what information has to be retained, and simultaneously, element-wise multiplication between i(t) and g(t) is to determine what information to add.

The sum of these products updates the cell state c(t). The output o(t) gate controls what information will be output at that time step. The output from the tanh layer is multiplied by o(t) to produce the final output h(t).

The working of the LSTM cell is as follows: the input x(t) and the previous state h(t-1) enter the LSTM cell, inside the cell, it is passed through the forget gate to compute f(t). The x(t) and h(t-1) are used to calculate i(t) and g(t) to compute f(t). x(t) and h(t-1) and tanh layer are used to determine the outputs o(t) and h(t). This is how the LSTM cell works: remembering important information, forgetting unimportant details, and determining what to output in each step. The flowchart in Figure 4 Working of an LSTM cell. also demonstrates the same.

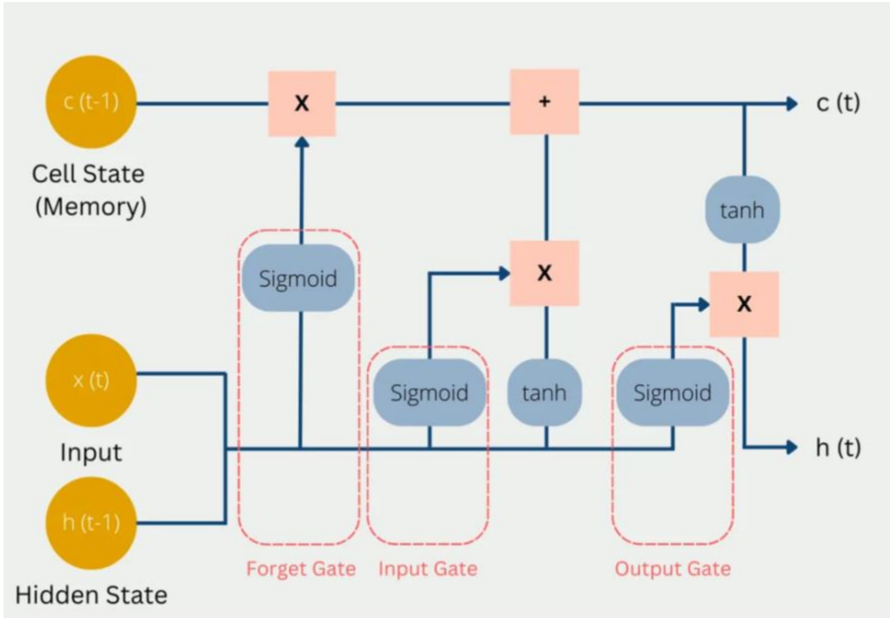


Figure 4 Working of an LSTM cell.

This LSTM (Long Short-Term Memory) model is being used to predict energy consumption over 24 hours. This model is designed to handle sequences of data and make them suitable for time-series forecasting. The LSTM cell's memory state retains information over time and forgets irrelevant data and is crucial for capturing the trends in energy consumption and improving the model's efficiency.

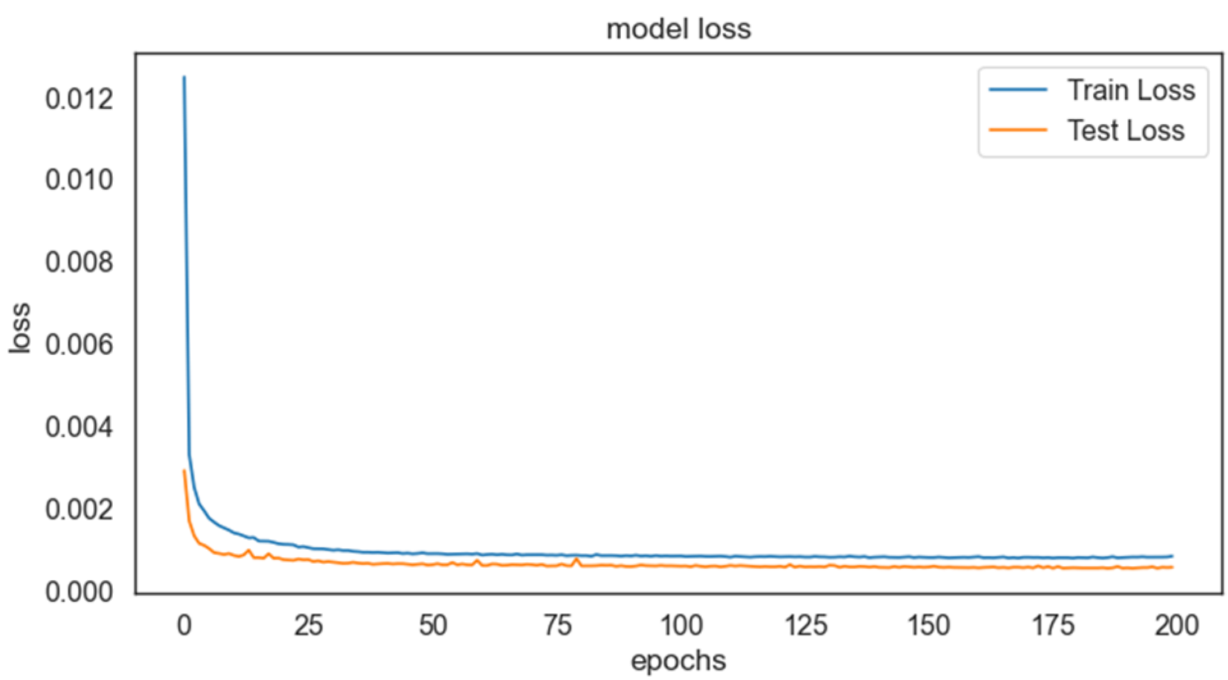


Figure 5 LSTM model loss over epochs.

For the training model, the input is a sequence of past data points, and the output is the next hour's consumption. Backpropagation Through Time (BPTT) is used to train to learn the sequential dependencies by minimizing the error between predictions and actual values. To predict the energy for over 24 hours, the known data is input into the LSTM model, and prediction for the next hour is the output. From Figure 6 we can observe that there is no drastic difference between predicted energy consumption and actual energy consumption, which shows a high prediction accuracy (or low RMSE error) of our model. This comparison is used in energy management and forecasting to evaluate the accuracy of load prediction models, helping energy providers adjust their models and better manage grid demand. Accurate forecasting enables better load balancing, reducing the risk of overloading the grid or having excess unused capacity.

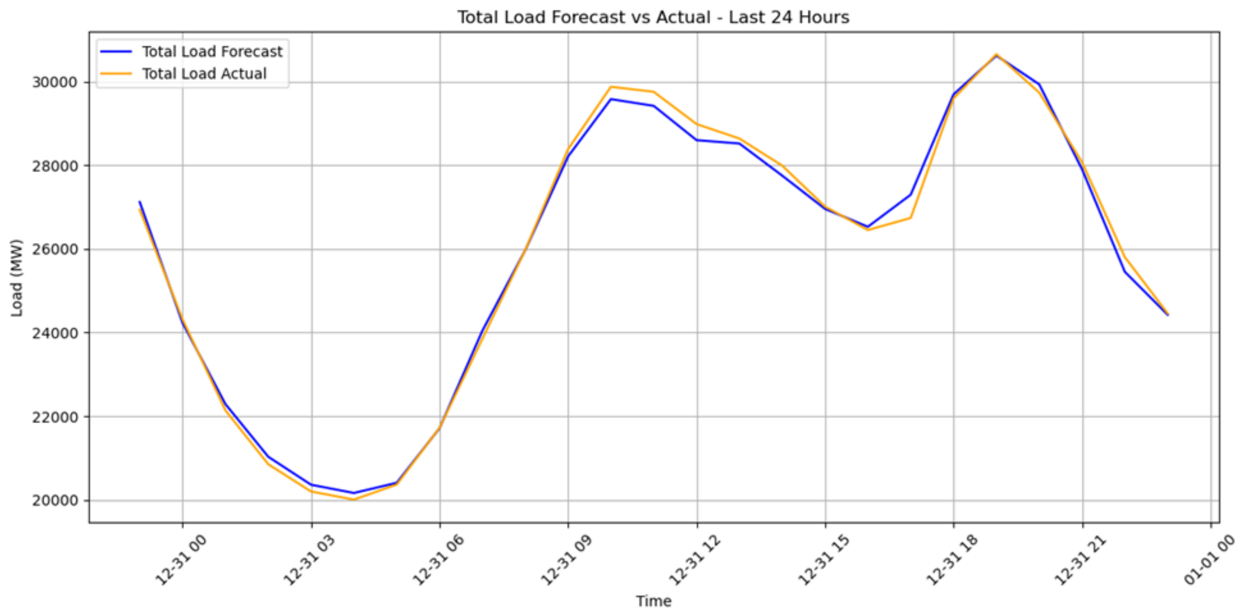


Figure 6 Comparison between total and actual daily energy forecast.

Figure 7 Comparison between total and actual monthly energy forecast. gives an insight into predicted energy consumption data over a month, along with the actual energy consumed. From the graph below, it can be observed that there is less energy consumed during the late night and early morning hours, the time when humans use fewer appliances. There is also a smaller dip during the evening that aligns with the end of the business day and reduced activity.

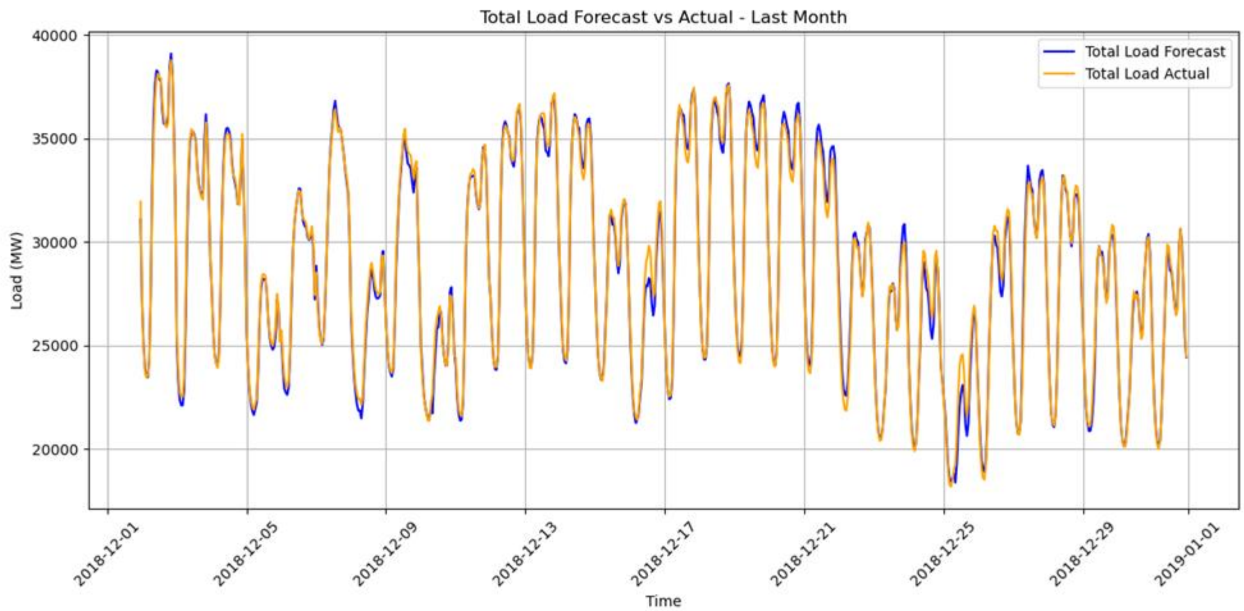


Figure 7 Comparison between total and actual monthly energy forecast.

This predicted grid energy load data, along with a custom dataset, is used for developing an optimization algorithm that creates an efficient charging and discharging system for electric vehicles.

Load balancing with dynamic rate optimization:

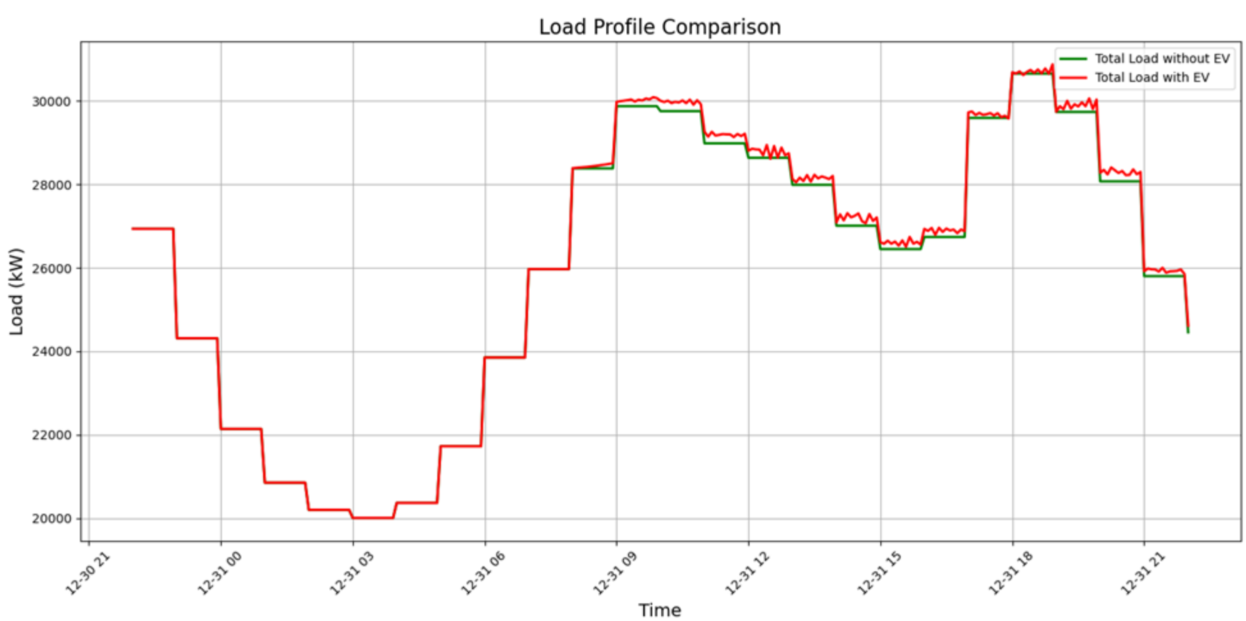


Figure 8 Load profile comparison with and without EV charging.

The load profile comparison graph Figure 8 illustrates the comparison between the total load on the grid with and without electric vehicles (EV) charging over a period. The red line represents the total load on the grid, including the additional demand from EV charging. The green line shows the baseline load without any EV charging, reflecting the normal load on the grid from non-EV sources. It is observed that additional demand is created by EV charging, and this additional load during certain periods makes the total load rise significantly above the baseline.

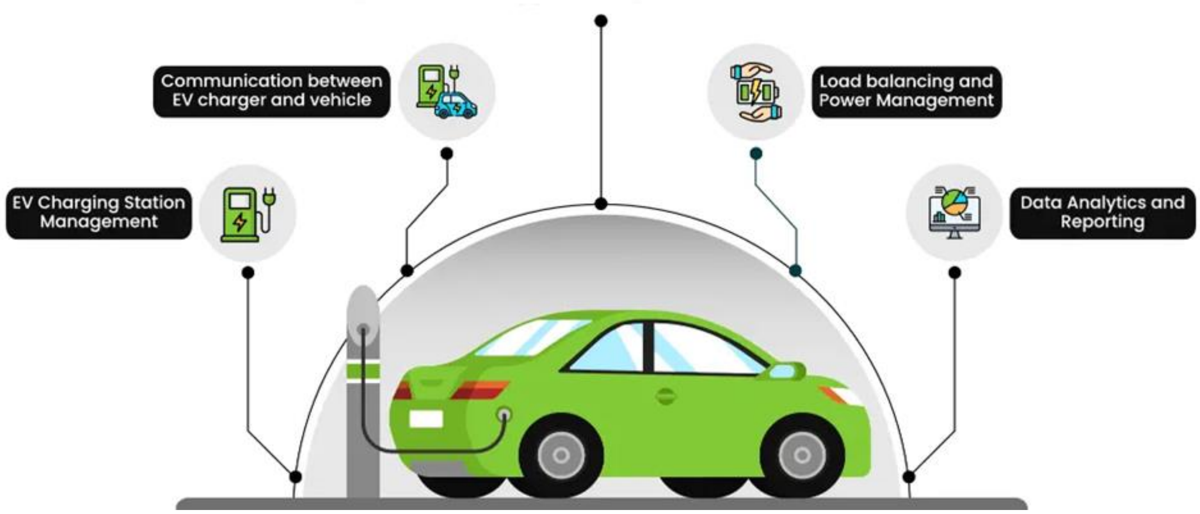


Figure 9 EV smart charging capabilities.

As the Electric vehicle (EV) adoption grows, there is a demand for effective management of EV charging and discharging stations for the users and the stability of the grid. Figure 9 shows what could be some typical capabilities offered by an EV smart charging station. For our application, we have focused on load balancing and charging/discharging optimization, which also aims at calculating costs for the consumer. A custom dataset was created for simulation such that every five minutes, a car arrives at the EV station for charging/discharging starting from 9 am with subsequent arrivals at 9:05, 9:10, and so on. It involves 25 EVs arriving at the station at different times (morning, noon, and evening). The communication between the EVs and the stations starts when the EVs share specific information like the car model, battery capacity and health, and the estimated time of availability (provided by the user). This duration of availability will vary from user to user and can differ from a small duration (1-2 hours) for urgent cases to a long duration (4-8 hours) for users with more flexibility. This duration of availability directly impacts the charging and discharging algorithm implemented.

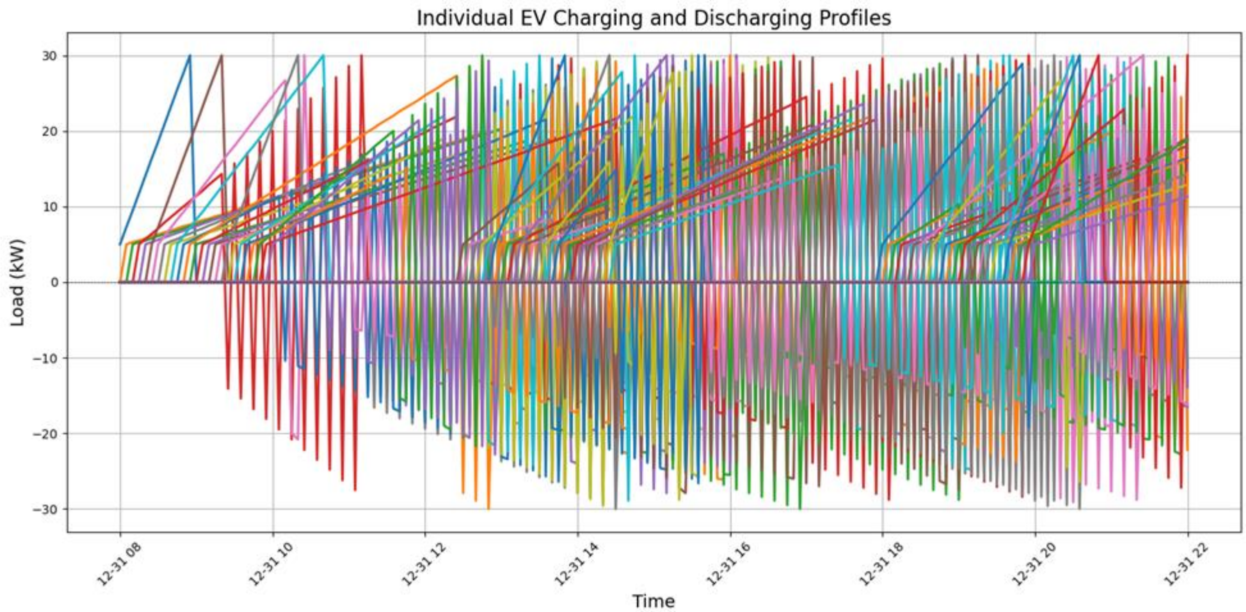


Figure 10 EV charging and discharging profiles.

In Figure 10, each colored line represents an individual EV's charging and discharging profile over the day. The load values for every EV vary widely in frequency and magnitude, as shown by the numerous vertical lines in the graph. This visualizes the dynamic charging and discharging behaviors of multiple EVs.

Eligibility criteria for Discharging:

Once the Electric Vehicle shares information with the station, to ensure effective and safe energy management, a set of criteria is established to determine whether the EV is eligible for discharge. The criteria:

a) Battery Health: EV battery health should be at least 80%.

$$Battery\ health \geq 0.80$$

b) SOC Start: The SOC of the battery should be 70% of the total battery capacity:

$$SOCstart \geq 0.70 \times Battery\ Capacity$$

c) User Time Availability: the minimum time of availability for both the charging/discharging processes.

$$User\ Time\ Availability\ (minutes) \geq 60$$

All these conditions must be met for the electric vehicle to be eligible for discharge, or else discharge does not happen.

Rate of Charging:

The charging rates for the EVs are dynamically adjusted based on the user duration of availability and SOC. The charging rate is between the range of 5kW and 30kW; this is the range of power rating used for charging/discharging the EV. If the SOC is below 80% of capacity, the rate increases linearly up to 30kW, and if the SOC is above 80% of the capacity, the charging is reduced to stop overcharging.

$5 \leq Charge\ Rate \leq 30$

Charge Rate:

$30KW = if\ SOC < 0.8 \times Battery\ Capacity\ \&\ User\ Time\ Availability \geq Time\ Available$

$15KW = if\ SOC \geq 0.8 \times Battery\ Capacity$

$5KW = if\ SOC \geq Battery\ Capacity$

Updating SOC:

The state of charge of the battery is dynamic for an efficient charging/discharging process. The update equations are different for the charging and discharging process.

Updating SOC (charging):

$$SOCnew = SOCcurrent + \frac{charge\ rate \times tdiff}{battery\ capacity}$$

Updating SOC (discharging):

$$SOCnew = SOCcurrent - \frac{charge\ rate \times tdiff}{battery\ capacity}$$

Here, the “tdiff” is the time interval in hours

Load Contribution:

Every EV that uses power from the grid is considered a load; to calculate the total load contributions from all the EVs over time, we calculate the summation.

$$Peak\ Load\ Reduction = \frac{Peak\ Loadbefore - Peak\ Loadafter}{Peak\ Loadbefore} \times 100$$

$$\text{Variance reduction} = \frac{\text{Variancebefore} - \text{Varianceafter}}{\text{Variancebefore}} \times 100$$

Peak EV load before optimization: Peak load before

Peak EV load after optimization: Peak Load after

Variance of total EV load before optimization: Variance before

Variance of total EV load after optimization: Variance after

Average load before Optimization = mean (total EV load before optimization)

Average load after Optimization = mean (total EV load after optimization)

Pricing Equations:

To calculate the final cost for each EV user, the system employs a dynamic pricing mechanism that considers both the user's charging/discharging behavior and the overall grid conditions. This mechanism incorporates two key aspects: price calculation and price prediction. Price prediction, which occurs when the EV first connects to the grid, provides the user with an estimated cost based on factors such as the vehicle's battery capacity, current battery level, anticipated charging time, and predicted grid conditions. This allows users to make informed decisions about their charging strategy. Once the EV disconnects from the grid, price calculation determines the final cost by considering the actual charging/discharging behavior, time of day, and applicable discounts. This ensures fair and transparent billing while incentivizing users to support grid stability by discharging during peak hours. The equation below gives the total cost the user must pay.

$$Final\ Cost = (Peak\ Charging + OffPeak\ Charging) - Discharge\ Discount$$

This total cost can be broken down into sub-parts like Peak Charging, Off-Peak Charging, and Discharge Discount. Here, the vehicle arrives at the interval of five minutes into the grid.

$$Peak\ Charging\ = \sum \left(charge\ rate * Peak\ multiplier * Base\ rate\ per\ KWh * \frac{5}{60}\right)$$

During peak charging, “peak multiplier is applied to account for the higher cost during peak hours.

$$OffPeak\ Charging\ = \sum \left(charge\ rate * Base\ rate\ per\ KWh * \frac{5}{60}\right)$$

As the electricity is relatively cheaper during off-peak hours, the peak multiplier is not in the equation, and the cost is lower.

$$Discharge\ Discount\ = \ Total\ discharge\ during\ peak \times Discharge\ Discount\ per\ kWh$$

This applies only if the user discharges energy during peak times.

This kind of pricing structure incentivizes users to charge during off-peak hours (when electricity is cheaper) and provides a discount for discharging during peak hours (when the grid benefits most from additional power). The result is a cost-effective charging plan that promotes grid stability by aligning user costs with grid demands.

Optimization Algorithm:

The dynamic load optimization algorithm is used for the efficient charging and discharging of electric vehicles in the grid for reasonable prices. If the user is available for only a short period in the grid, then the electric vehicles are charged to the maximum constant rate of 30 kW/h. When the vehicle is available for a longer period on the grid, it is also used as an energy storage entity to shift the load and maximize its final state of charge, and accordingly, incentives or discounts in rates are given to the users.

This algorithm operates every five minutes when a vehicle enters the grid for charging and discharging and performs a set of functions. When an EV with shorter availability is charged at a constant 30 W/h to ensure quick and energy replenishment. When the EVs are available for a longer time, they contribute to energy storage; this is to keep the balance of the grid's load by shifting energy demands to off-peak hours and thus maximizing the final SOC. Considering the battery health, vehicle availability, and grid availability, the EV's discharge rate can be computed.

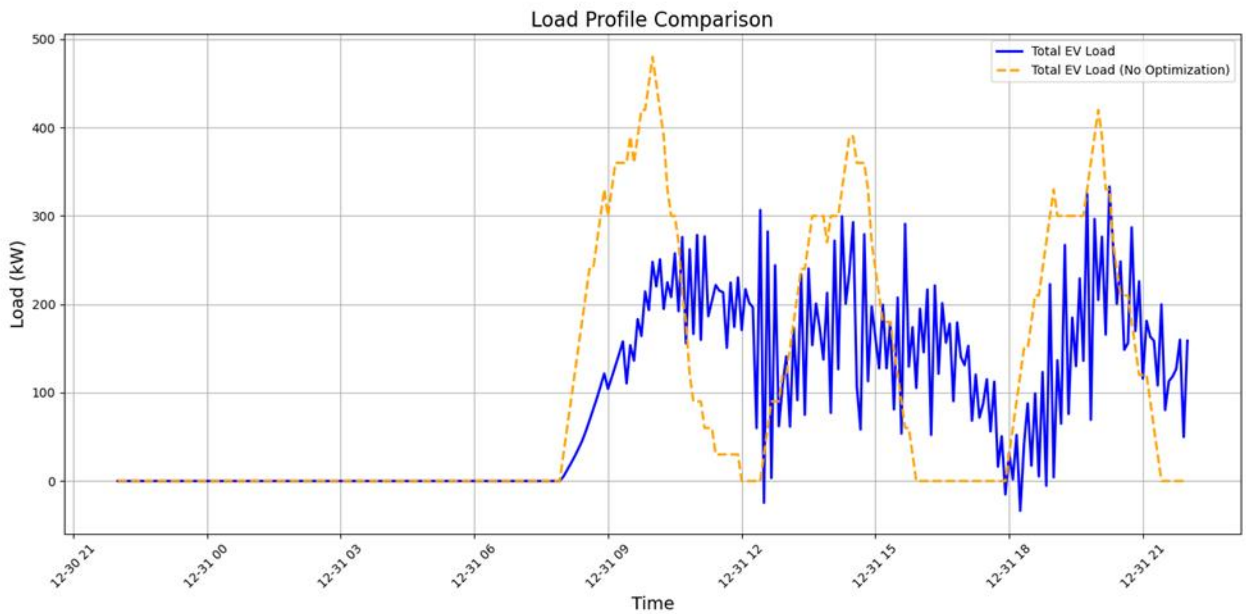


Figure 11 EV load profile comparison

From Figure 11, we can observe load comparison before and after optimization is applied. The orange dashed line represents the EV load without any optimization, here, the load pattern is more predictable and forms distinct peaks without any load adjustments. The blue line represents the EV load after the optimization algorithm is applied, and the irregular lines indicate that the optimization algorithm is actively adjusting the load to balance energy requirements.

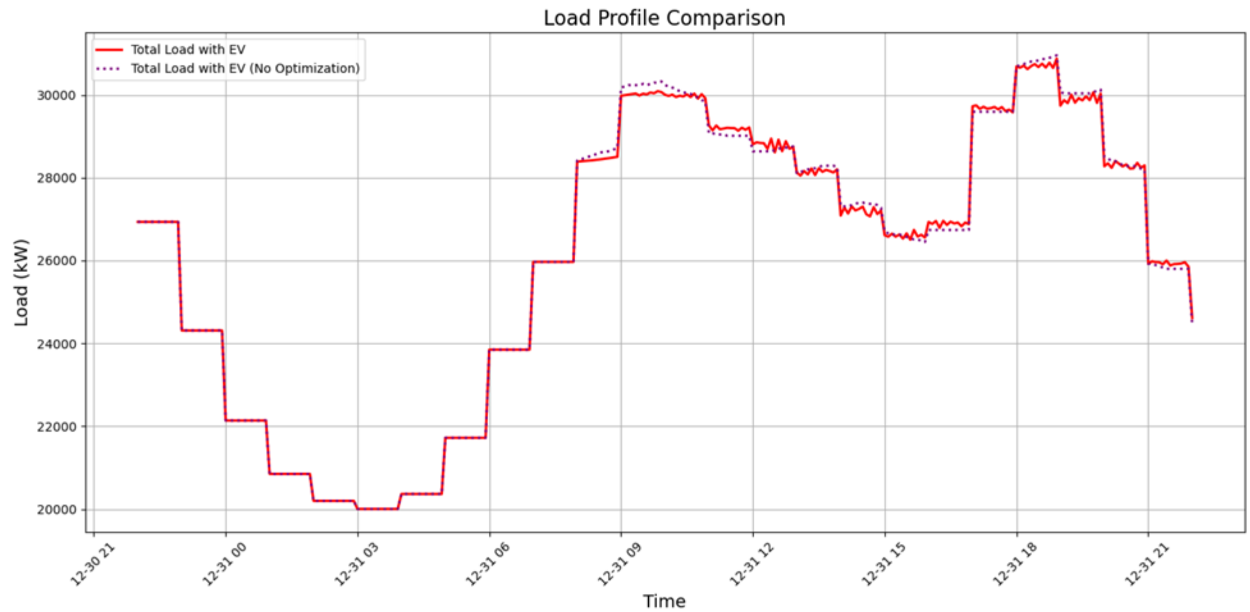


Figure 12 Total load profile comparison

Figure 12 shows the comparison between load with EV with and without optimization. The red solid line shows the increase in load every five minutes in a stepwise pattern representing the varying load levels, indicating the load is actively managed. The purple dotted line represents the data without optimization. It has a similar pattern with noticeable peaks and higher values at certain times that indicate periods of high demand without any control measures.

Results and Discussion:

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Metrics:
Peak Load Reduction: 44.51%
Variance Reduction: 59.78%
Average Load Before Optimization: 100.48 kW
Average Load After Optimization: 87.25 kW
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Figure 13 Results after optimization.

This the performance metrics related to the optimization algorithm implemented for managing EV charging and discharging, these metrics assess the impact of optimization on load levels.

The peak load reduction denotes that the optimization process reduced the peak load by 44.51%. Variance Reduction represents the reduction in the variability of the load.

Lower variance means a more stable and balanced load profile. This helps in maintaining grid efficiency and reducing the likelihood of sudden spikes in demand. The reduction in variance is 59.78%.

With the average load before (100.48 kW) and after optimization (87.25 kW) values, we can see there is a decrease in average load optimization. This suggests that the optimization algorithm not only reduced peaks but also spread the demand more evenly, lowering the overall load level.

Through the obtained results, we can demonstrate the effectiveness of the optimization approach. The significant reductions in peak load and variance indicate that the system is more stable and efficient post-optimization. Additionally, the lower average load after optimization suggests a more balanced and sustainable load on the power grid, contributing to potential energy savings and better load management over time.

Effects of Optimization:

Peak load reduction: The optimization algorithm successfully reduces peak loads. This reduction helps prevent grid overload and spreads the demand more evenly over time. This suggests that the optimization effectively reduces the total load at high-demand periods, helping to prevent sudden surges in power consumption.

Load Shifting and Balancing: The optimized load shows fluctuations and adjustments that seem to smooth out the load profile compared to the non-optimized load, which has a sharp increase and decrease. This pattern shows that the algorithm is likely implementing load shifting, distributing the charging times more evenly throughout the day.

Peak Load Smoothening: in the absence of optimization, distinct peaks can be observed denoting the EV load, especially in the morning and in the late afternoon. These peaks correspond to the common charging hours that result in a high-demand period that could strain the grid. The optimized load line avoids sharp peaks, which are evident in the non-optimized profile. This smoothing effect helps reduce strain on the power grid during peak demand hours, making it easier for the grid to handle the EV load alongside other demands. The figure below shows the effect of smoothening.

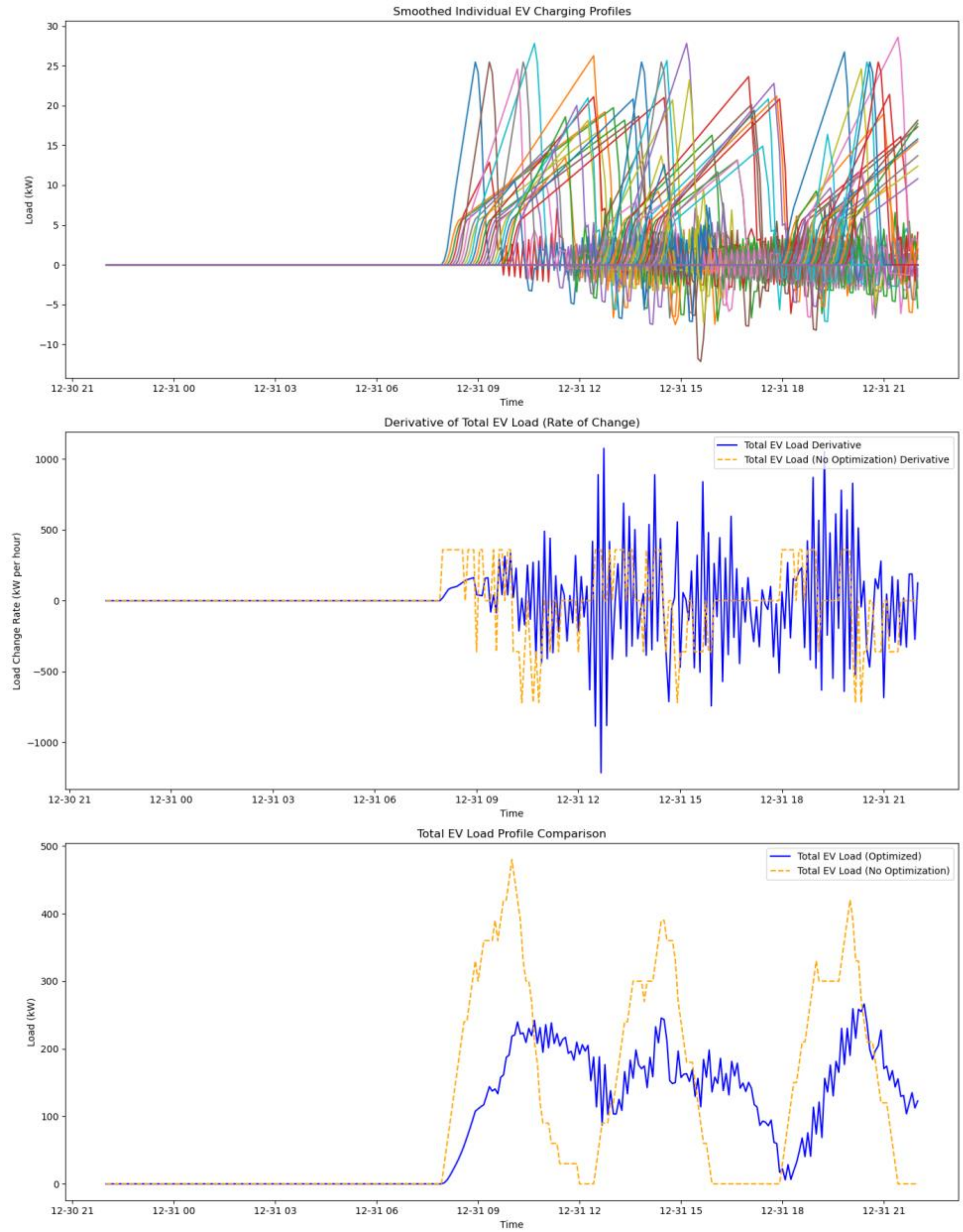

Figure 14 Smoothened charging profiles. Rate of change of EV load. Load profile comparison.

Load Reduction During Evening Hours: Around the evening hours, the optimized load profile decreases more quickly than the non-optimized load. This adjustment might indicate a response to decreased grid demand or optimized discharging of EVs, contributing stored energy back to the grid.

CONCLUSION:

The results reported in this work emphasize the impact of V2G technology on balancing the electrical needs anticipated by an increasing number of electric vehicles (EVs). This research employs predictive models using LSTM and optimization techniques to strike an efficient balance between the need for grid and electric vehicle (EV) charging. The outcomes portray a peak load reduction of 44.51%, which shows the enhancement of load smoothing, which reduces stress on the grid during peak times of energy use, thereby creating a sustainable power distribution system. In addition, the optimization algorithm attempts to reduce load variance by 59.78% as a way of improving a grid's supply and demand characteristics but also enhances the ability of the grid to withstand shocks posed by extreme climbs in demand that increase the risk of blackouts. Such an approach improves the reliability of the distribution system by promoting a fast drop in the frequency of extreme peaks, allowing for the EVs, however, to variable their energy profiles to maintain an uncompromised power grid.

The perspective in the study also stresses V2G systems as an important step in developing smart grid systems. V2G technology, by utilizing the energy storage of EVs and their connection to the grid effectively, facilitates not only peak load control but also enables environmental sustainability. The number of EV users is continuously growing, providing a premise for the use of algorithms developed in the study for scalable, cost-effective, and user-centric optimization of complex systems such as power grids. A potential drawback could be the limited dataset we have used and the lack of varied vehicle data in that dataset specifically. We believe that over the years with more adoption of such technologies the dataset will be more robust.

To summarize, this work offers a comprehensive guide for the effective optimization of EV loads and enhances the understanding of how smart grids integrate V2G systems to optimize EV power consumption. The positive findings obtained in this case suggest that in the future, vis-optimized EV charging solutions will be exploited widely to deliver a more efficient and greener energy grid. Further improvement of prediction and optimization methods will be necessary to meet new challenges arising from the increasing penetration of renewable technologies and the growing pressure on the energy system.

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