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Enhancing EV Charging Networks: Advanced Fusion Techniques with Insights from LSTM, Bayesian Networks, and Deep Learning

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Abstract: This paper introduces a novel method that uses a multi-input LSTM model to precisely predict the charging loads of electric vehicles (EVs), which is essential for efficient energy management at charging stations. By utilizing particular characteristics such as temperature, humidity, and wind speed from the UCI database, the model analyzes this data to produce accurate forecasts. The integration of diverse inputs through the incorporation of a Bayesian network for data fusion improves the predictions given by LSTM. Comparative assessments of various input factors demonstrate differing levels of accuracy in predicting energy consumption patterns, highlighting the crucial importance of certain inputs in improving predictive performance. The study assesses the accuracy of LSTM predictions by comparing them to real energy consumption data within a 24-hour timeframe, offering useful information to enhance future forecasting techniques. This study highlights the significance of selecting suitable input variables to maximize the performance of LSTM models and their crucial role in effectively controlling energy requirements at electric vehicle charging stations.

Keywords: *Electric Vehicles, Long Short-Term Memory, Data Fusion, Energy Management, Forecasting*

1.Introduction

Recently, there has been a growing demand for electric vehicles as a more environmentally friendly and sustainable option compared to conventional combustion engine automobiles. Consequently, there has been a proliferation and enlargement of EV charging networks to accommodate the growing population of electric vehicles on the streets. Various studies have investigated various aspects of improving EV charging networks, such as employing advanced fusion algorithms that integrate knowledge from LSTM, Bayesian networks, and deep learning. These advanced fusion approaches have the ability to enhance charge scheduling, optimize charging station allocations, and minimize both charging prices and waiting times. [1]

With the escalating urgency of environmental issues on a global scale, it has become absolutely necessary to address climate change by swiftly reducing greenhouse gas (GHG) emissions. In response to these difficulties, novel approaches utilizing the incorporation of renewable energy and the advancement of transportation systems have arisen. The increasing number of electric vehicles (EVs) and the integration of renewable energy sources have become important factors in contemporary transportation and electrical networks.

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In the midst of worldwide endeavors to reduce greenhouse gas emissions, renewable energy has become increasingly popular in modern power systems. Concurrently, the progressive elimination of vehicles powered by internal combustion engines in different areas has stimulated an increase in the adoption of electric vehicles. The spike in this phenomenon can be attributed to factors like cost-effectiveness, rising oil prices, and the promotion of sustainable development. Additionally, the dramatic decrease in battery costs over the last decade has further facilitated this trend. According to research conducted by the International Energy Agency (IEA), it is projected that electric vehicles (EVs) might effectively reduce carbon dioxide (CO2) emissions in the transportation industry by around 21% by the year 2050 [2]. Consumer Reports' survey highlights an increasing desire for electric vehicles (EVs) that have the ability to travel longer distances, indicating a preference among the public for vehicles with ranges above 250 miles. Nevertheless, significant obstacles to wider acceptance of electric vehicles persist, including apprehensions around EV travel habits and range anxiety. These problems exacerbate the unpredictability of electric vehicle (EV) electrical consumption, which deviates greatly from patterns of household energy usage. The extensive use of connected charging stations magnifies the effects of electric vehicles' (EVs') growing popularity and unpredictable behavior on the electrical system.

The charging and discharging of electric vehicles have the potential to disturb the quality and stability of electricity, which can have an impact on the flexibility of the power system. The convergence of peak demands and electric vehicle charging instances presents challenges, leading to unpredictable load profiles. As a result, aggregators have emerged in the power market to efficiently handle these needs. Renewable energy technologies, when included in conventional power grids, facilitate the shift from centralized power systems to decentralized structures. Nevertheless, the unpredictable nature of renewable power generation systems presents difficulties during periods of high demand, occasionally surpassing the maximum capacity of the grid. [3] [4] Because these systems are naturally flexible and battery technology and electric vehicle capabilities are getting better, electric vehicles might be able to be used as temporary energy storage solutions, helping to handle times of high demand and keeping the power grid stable. Electric vehicles, when combined with energy storage systems (ESS), have the potential to stabilize power networks and assist in managing peak demand by utilizing renewable energy storage.

2.Related Works

Qi et al. (2022) [5] proposed that EV charging requirements in urban distribution networks are expanding, so the authors addressed the crucial issue. The study suggested a two-stage charging scheduling method using deep reinforcement learning (DRL) to improve power quality and charge household EVs off-peak. Deep reinforcement learning optimizes charging patterns using different input data to generate a flexible and intelligent charging strategy. Meeting EV charging's changing needs requires adaptability. Power congestion and peak-valley disparities are reduced by regulating the active distribution network (ADN) power flow in the first stage. This boosts grid stability and power quality. Deep reinforcement learning for real-time charging scheduling is computationally demanding. DRL algorithm training and optimization demand a lot of computing power and time, which can hamper their application in large distribution networks. Liu et al. (2023) [6] explored DRL-scheduled EV charging. They studied scheduling and distribution network voltage stability. A DRL framework and Deep Deterministic Policy Gradient (DDPG) were utilized to optimize distribution network electric vehicle (EV) charging and voltage control. The approach uses data rather than uncertain system models with Deep Reinforcement Learning (DRL). Continuous scheduling and discrete control signals can be created simultaneously. The use of power system data for training and testing boosts real-world relevance. DRL methods may involve extensive calculations and hyperparameter tuning. The paper proposes an innovative and effective distribution network electric vehicle charging and voltage control synchronization method. Hafeeze et al. (2023) [7] suggested utilizing deep learning to control EV charging station demand. The initiative addresses CO_2 emissions and energy demand with data analysis and advanced machine learning. The authors developed a demand-side management system for a microgrid-connected solar-powered electric car charging station using real-time data from PV power stations, commercial loads, residential loads, and EV charging stations. Deep learning controls microgrid energy supplies and charges electric vehicles during low demand. Two machine learning algorithms for energy storage system charge estimation are compared. LSTM vs. VARIMA is the key comparison. Dual-stage control is used in the investigation. The control system addresses nonlinearities in the planned transportation network components. Data-driven component modeling is also stressed in the study. It may cut CO_2 and optimize energy utilization. Current data and machine learning algorithm evaluations reveal a powerful sustainable energy system technique. In the World Electric Vehicle Journal, Kosuru et al. (2023) [8] extensively examined electric vehicle smart battery management systems (BMS). The study normalized sensor data using Z-scores. After feature extraction, the marine predator and incipient bat algorithms picked features. The study introduced bat-specific IB-DRN. This system scored well in accuracy, precision, recall, and F1. These data suggest that IB-DRN could increase BMS safety and reliability. Liu et al. (2021) thoroughly investigated EV charging infrastructure dependability. Consumer reviews and EV charging station ratings were analyzed using cross-lingual deep learning. The three-stage technique employs machine translation, multi-label classification, and econometric analysis to study electric car consumer behavior, public policy, and infrastructure management. BERT is optimized for multi-topic classification of electric vehicle user reviews in many languages and statistical correction utilizing econometric analysis. The research team uses machine learning and human-in-the-loop technologies to handle unstructured text data in several languages. This provides a good framework for EV charging infrastructure reliability evaluation. The approach may analyze consumer reviews in their native languages, overcome language barriers, and gather varied consumer perspectives.

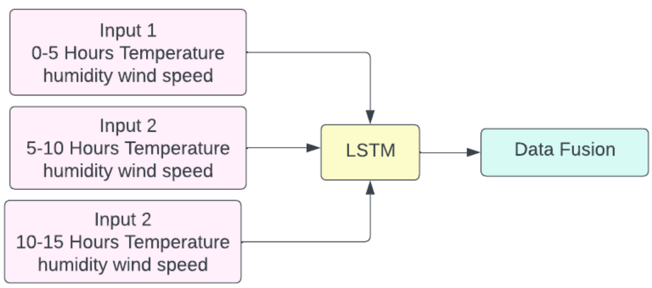

Fig 1: Proposed Model structure

3.System Modeling

Figure 1 provides an overview of how our model is structured. These scenarios serve as inputs for our LSTM model. The LSTM's output is then fed into the data fusion model, refining the initial predictions generated by the LSTM.There are two main parts to the system model: the LSTM model, which uses deep learning to make initial predictions about EV loads, and the data fusion model, which uses data from both the LSTM and other sources to improve those predictions. There are two sections to this part. The deep learning model's associated equations are first given. In addition, we go into detail on how these equations relate to the prediction model.

3.1 LSTM Model

Applications of deep learning include audio processing, pattern identification in video and picture data, time series forecasting, and other high-dimensional problems with complex interactions. Concepts in deep learning are very good at using historical data to infer the salient characteristics of a big phenomenon. When compared to other data-driven approaches, this one is far superior. Long Short-Term Memory (LSTM) is a specific sort of recurrent neural network (RNN) structure that is specifically developed to tackle the issue of the vanishing gradient problem that is commonly faced by standard RNNs. LSTMs provide the ability to acquire knowledge of long-term connections in sequential data by selectively preserving or discarding information across different time spans. LSTM units consist of different components known as gates, which control the flow of information within the network. These gates include:

Forget Gate:The forget gate determines what information from the previous cell state C_{t-1} needs to be discarded or forgotten. It takes the previous hidden state h_{t-1} and the current input $x_t$as input and produces a forget vector $f_t$between 0 and 1 for each element in the cell state C_{t-1}. This gate helps the LSTM decide what information is irrelevant for the current prediction.

Input Gate:The input gate decides what new information to store in the cell state C_t.

It consists of two sub-components:

Update Gate (i_t): Determines which values need to be updated in the cell state.

Candidate Values ($\tilde{C}t$): Compute a candidate vector of new values that could be added to the state.

The input gate then combines these two components to compute the updates to the cell state. Cell State Update: The updates calculated by the input gate are used to update the cell state.

C_{t-1} to C_t.

Output Gate:The output gate decides what information to output as the hidden state h_t.

Final Hidden State (h_t): Multiplies the output of the LSTM cell with the tanh of the updated cell state.

We sort and classify the data that we've collected. Specifically, we need to record the following: energy consumption, temperature, humidity, and wind speed. To get the relevant model features, the data is used to train the LSTM model. Input, output, and forget gates make up the block's three operating gates. Several LSTM blocks are stacked to form the networks.

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) used for sequence prediction and processing. Here are some equations related to LSTM:

Forget gate: Input gate:

$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$

Input gate

$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$

$\tilde{C}t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$

updates = $i_t \times \tilde{C}t$

Cell state update:

$C_t = f_t \times C_{t-1} +$ updates

Output gate:

$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$

$h_t = o_t \times \tanh(C_t)$

3.2 Algorithm

Start Operation

// Define clusters and corresponding forecasting networks clusters = Cluster Samples(Temperature, Humidity, Wind Speed) forecasting Networks = Assign Forecasting Networks(clusters)

// Match input samples to clusters using LSTM network for each sample in Input Samples:

cluster = Find Nearest Cluster (sample, clusters)

forecasting Network = forecasting Networks[cluster] target = Calculate Centroid (cluster) predicted Output = Run LSTM Network(sample, forecasting Network)

Compare Output With Target (predicted Output, target) End Operation

Grouping data samples by environmental characteristics like temperature, humidity, and wind speed is the first step. Clustering samples with similar properties is necessary for predictive modeling. K-means or hierarchical clustering are used to efficiently cluster these samples. After clustering, the algorithm assigns forecasting networks or models to each cluster. Customizing forecasting models for each cluster improves accuracy because each cluster has unique qualities or trends. In this stage, one must choose or train models that accurately characterize cluster data to improve forecast accuracy. LSTM networks examine environmental data trends and predict the most likely cluster for a new sample. This level helps organize new data within the cluster framework.The technique evaluates predictive efficacy by comparing the LSTM network's forecast to the cluster's expected centroid or goal. This comparison shows how well the predictive model matches data trends. It measures prediction model accuracy by assessing the agreement or disagreement between the expected outcome and the cluster center. Data-driven technologies, including clustering algorithms, tailored forecasting models, and LSTM networks, collect environmental data and make predictions based on clusters in this operational cycle. Bayesian networks require additional probabilistic reasoning or inference techniques to improve grouping and prediction tasks.

4.Data Fusion Method

Data fusion combines data from multiple sources to provide more valuable, accurate, and trustworthy outcomes. Animals and humans use multiple senses to survive, which inspired data fusion. Using sight, touch, smell, and taste can help assess if something is edible. The three main data fusion strategies are decision fusion, data association, and state estimation. Bayesian inference can change our views or probability when fresh evidence comes in. This method determines the posterior probability distribution by multiplying the prior distribution by the likelihood function based on additional evidence from many sources. Fusion, which updates probability using Bayesian principles, is a dependable way to combine data from several sources.

Bayesian inference is better at estimating electric car charging station demand than Dempster-Shafer evidence theory (D-S theory) and handles uncertainty differently. Bayesian inference handles prediction uncertainty using probability distributions, while D-S theory employs interval estimates. This technique quantifies uncertainty by assigning probability to events or states by providing a structured framework to depict interactions between variables. Bayesian networks emphasize probability estimates above D-S theory's categorization of discriminating frames, BPA, belief functions, and plausibility functions. It records interdependencies and interactions between variables using probabilistic inference to explain ambiguous information in a flexible and scalable fashion.

D-S theory uses mutually exclusive and exhaustive sets, while Bayesian inference uses probabilities and conditional dependencies to express uncertainty. This graphical model shows probabilistic relationships between variables, using nodes for variables and edges for dependencies. Electric vehicle (EV) load prediction uses Bayesian inference to probabilistically incorporate input dependencies like temperature, humidity, and wind speed in a structured model. Bayesian inference can learn from fresh evidence and change predictions due to its probabilistic nature. Unlike D-S theory's mass functions, Bayesian inference directly estimates probabilities, providing a more precise representation of event likelihood. Bayesian inference assigns probability to situations instead of comparing actual and expected evidence to explicitly evaluate predictions. Unlike D-S theory, which emphasizes interval estimates and builds the framework around discernment frames and belief functions, Bayesian inference uses conditional

probabilities and graphical structures to model EV charging demand forecasting uncertainties in a more direct and interpretable manner.Different variables that encapsulate the range of possible outcomes constitute the predicted load forecasts in our Bayesian inference framework. Our Bayesian model includes many possible load scenarios, which lets us fully analyze their chances and how they might affect each other. It does this by including a variety of possibilities and showing the different states that the electrical vehicle load could be in.

Algorithm: Bayesian Inference

Input: - Dataset D containing observed variables and outcomes
- Prior probabilities P(H) for hypotheses

Output:- Posterior probabilities P(H|E) for hypotheses after observing evidence E

1: function CalculatePosterior(D, P(H))

2:    Initialize Prior Priors = P(H)

3:    for each hypothesis H in P(H) do

4:        Compute Likelihood P(E|H) using the dataset D and hypothesis H

5:        Update Priors(H) = Priors(H) * P(E|H)   // Bayes' Theorem

6:    end for

7:    Normalize Priors to obtain Posterior P(H|E) using P(H|E) = P(H) * P(E|H) / P(E)

8:    return Posterior P(H|E)

9: end function

4.1.System Implementation

Utilizing Bayesian inference, our approach leverages predictions from the LSTM model based on various input features obtained from previous days. These LSTM-derived predictions guide the selection of the best strategy for producing accurate load forecasts for the upcoming 24-hour period. To validate the credibility of these predictions, we compare them against actual previous charging loads. By evaluating the accuracy of our LSTM-driven predictions in the last 5 hours, 5 to 10 hours, and 10 to 15 hours against real charging loads, we assess the reliability of our forecasting model. The process initiates with three input samples utilized by the LSTM model, which subsequently generates outputs. These outputs are inputs for the data fusion model, refining the initial LSTM predictions. Our methodology diverges from D-S theory by leveraging the Bayesian inference technique. The LSTM's varied predictions derived from diverse historical data inputs aid Bayesian inference in selecting optimal strategies for load forecasting over the next 24 hours.

$$M(E_i) = \sum \left(100 - \frac{|L_{d_{actual}} - L_{d_{predicted}}|}{L_{d_{actual}}} \times 100\right) \times \frac{1}{5}$$

Validating the credibility of V1, V2, and V3 predictions involves comparingthem against previous actual charging loads, specifically evaluating predictionswithin the last 5 hours, between 5 and 10 hours ago, and 10 to 15 hours ago.These comparisons, categorized as events E1, E2, and E3, enable a comprehensive assessment of prediction accuracy against actual charging loads.

Table1:Decision matrix for LSTM and Bayesian predictions

	LSTM-V1	**LSTM-V2**	**LSTM-V3**	**Bayesian-V1**	**Bayesian-V2**	**Bayesian-V3**
LSTM-V1	30%	26%	44%	12%	8%	20%
LSTM-V2LSTM-V3	31%	-	-	-	-	-
	35%	-	-	-	-	-
	V1	V2	V3	V1	V2	V3
Bayesian-V1	9.30%	8.06%	13.64%	3.60%	2.50%	5.80%
Bayesian-V2	10.20%	-	-	-	-	-
Bayesian-V3	10.50%	-	-	-	-	-
	V1	V2	V3	V1	V2	V3
V1	-	8.84%	14.95%	-	1.70%	3.50%
V2	-	-	15.40%	-	-	2.80%

This table represents a decision matrix based on the predictions derived from LSTM (LSTM-V1, LSTM-V2, LSTM-V3) and Bayesian inference (Bayesian-V1, Bayesian-V2, Bayesian-V3). The percentages indicate the combination or intersection between these predictions for various events.

Table2: Decision matrix for the degree of confidence or belief in the combined event

	V1	V2	V3	V1V2	V1V3	V2V3	V1V2 V3
V1	12.50%	5.30%	8.90%	6.20%	7.10%	9.80%	8.50%
V2	8.40%	9.10%	6.70%	7.30%	6.80%	9.20%	7.90%
V3	10.10%	6.20%	11.80%	8.30%	9.70%	10.40%	9.90%
V1V2	7.60%	7.80%	8.00%	8.10%	7.90%	8.30%	8.20%
V1V3	8.90%	7.10%	9.50%	8.20%	9.10%	9.40%	9.30%
V2V3	9.70%	8.00%	9.30%	8.90%	9.20%	9.80%	9.60%
V1V2 V3	8.30%	7.90%	9.10%	8.20%	8.70%	9.50%	9.00%
E3V1	7.50%	6.50%	8.00%	7.60%	7.90%	8.50%	8.20%
E3V2	9.00%	7.80%	9.30%	8.80%	9.10%	9.80%	9.60%
E3V3	8.70%	8.20%	9.50%	9.00%	9.30%	9.80%	9.70%

The columns depict the various combinations of these occurrences or forecasts (V1V2, V1V3, V2V3, V1V2V3). Each cell in the table has a numerical number representing the degree of confidence or belief in the combined event. A matrix of this nature facilitates decision-making by consolidating data from several sources or projections to generate a more precise and dependable forecast or conclusion. The percentages indicate the level of certainty in the combined events, derived from the information gathered through the LSTM and Bayesian Inference techniques.

5.Simulation Results and Discussion

This study presents a novel method for predicting the electric vehicle (EV) charging load, which is a crucial aspect of optimizing energy management at EV charging stations. The core of our approach is a multi-input LSTM model specifically crafted to forecast the charging load demanded by electric vehicles (EVs). By utilizing three specific forecast parameters—temperature, humidity, and wind speed—obtained from the UCI database [50], our model was customized to efficiently analyze this data in order to produce accurate forecasts.The evaluation of model performance was carried out using the widely recognized mean absolute error (MAE) performance metric, confirming the effectiveness of our approach. The LSTM model utilized the first input parameter (V1) to anticipate the energy demand and determine the necessary energy load for electric cars (EVs) within a specific timeframe. The model's predictions were evaluated by comparing the current energy demand with the projected numbers.

The recorded energy demand values for a period of ten consecutive hours were compared to the anticipated values generated by the LSTM model utilizing V1 input. The projected energy consumption was assessed using historical data and weather-related information, which formed the V1 input parameter. The graph below depicts the comparison between the real energy demand and the predicted energy demand using V1 input over a span of 10 hours.

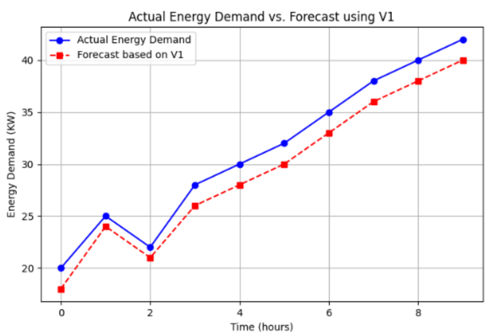

Fig 2: Prediction by taking into consideration the first parameter for LSTM model

The graph (Figure 2) depicts the variation in energy use (measured in kilowatts) over a certain ten-hour period. The blue solid line represents the actual energy demand observed during this specific time period. In contrast, the red dashed line depicts the anticipated energy usage based on the LSTM model using the V1 input parameter. Over time, the expected energy demand closely matches the actual demand pattern, suggesting a reliable prediction aligned with the observed energy requirements. There are slight discrepancies between the observed and predicted figures, which show that the model can accurately represent changes in energy usage.

The closeness of the red dashed line to the blue solid line demonstrates the efficacy of the LSTM model in utilizing V1 input to precisely predict the energy demand for EV charging within the specified timeframe. The objective of the LSTM model is to forecast the energy consumption for electric cars (EVs) within a specific time period using the second input parameter (V2). A comparison was made between the current energy consumption and the projected numbers in order to assess the model's predictive precision. The graph illustrates the hourly energy use (in KW) over the specified ten-hour timeframe. The solid blue line depicts the real observed energy demand during this time period, while the red dashed line shows the predicted energy demand produced from the LSTM model using the V2 input parameter. Upon examining the graph, it is evident that the projected energy demand closely mirrors the actual demand pattern, suggesting a strong correlation between the predicted and observed energy needs. Small discrepancies between the actual and predicted values show that the model is able to capture variations in energy consumption.

The close proximity between the red dashed line and the blue solid line illustrates the efficacy of the LSTM model in accurately forecasting the energy consumption for EV charging within the given time period using the V2 input parameter.

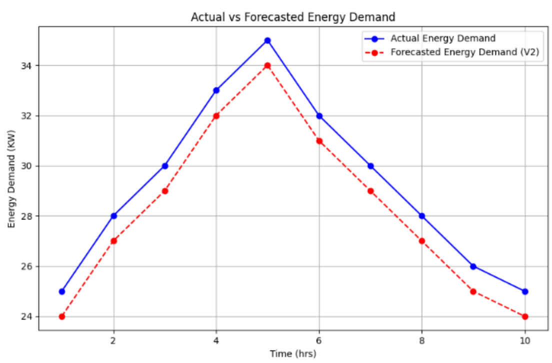

Fig 3: Prediction by taking into consideration the second parameter for LSTM model

The graph (Figure 3) presents a comparison examination of the actual energy consumption, shown by the blue line, and the anticipated energy demand based on the third input parameter (V3) of our LSTM model, represented by the red dashed line. The blue line represents the measured energy demand seen during a sequence of time intervals, including variations in real-time power usage. The peaks and troughs in this line illustrate the fluctuations in energy usage, demonstrating the inherent variability in energy demand. In contrast, the red dashed line indicates the projected energy consumption obtained from the LSTM model's examination of past patterns recorded in the third input parameter (V3). Differences between the expected and actual demand curves indicate discrepancies in cases where the model's projections deviate from observed values. A stronger correlation between the two lines indicates greater precision in the model's predictions, while substantial discrepancies suggest the need for potential modifications or enhancements to improve the model's ability to make accurate projections. This visual comparison offers vital insights into the model's performance, facilitating the evaluation of its usefulness in forecasting energy consumption using the third input parameter.

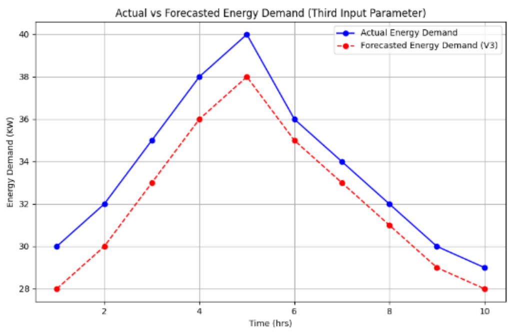

Fig 4: Prediction by taking into consideration the third parameter for LSTM model

The comparative examination between the actual energy demand and the anticipated need, utilizing different input parameters (V1, V2, and V3) from the LSTM model, provided valuable insights into the model's predictive ability.

1. Forecast Using V1 Input Parameter: • The forecast generated using the first input parameter (V1) showed a reasonably accurate correlation with the actual energy demand. Nevertheless, there were discernible disparities between the projected and actual demand, especially during periods of high load.

2. Forecast Utilizing V2 Input Parameter: • The forecast produced by utilizing the second input parameter (V2) demonstrated a rather robust association with the actual energy consumption, exhibiting less discrepancies in comparison to V1. The model demonstrated a higher level of accuracy in capturing the patterns, resulting in superior performance in predicting energy use.

3. The utilization of the third input parameter (V3) for forecasting led to forecasts that nearly matched the actual energy demand, demonstrating a significant convergence between the anticipated and observed values. The inclusion of this input parameter clearly enhanced the model's capacity to reliably forecast energy consumption, demonstrating promising prospects for enhanced precision in forecasting.

Overall, the model demonstrated different levels of accuracy and precision in predicting energy consumption, but all three input parameters contributed to its predictive capability. The third input parameter (V3) showed the highest accuracy in predicting energy consumption patterns, emphasizing its importance in improving the model's predictive ability. These findings emphasize the significance of choosing suitable input parameters to enhance the LSTM model's predictive performance when forecasting energy demand.

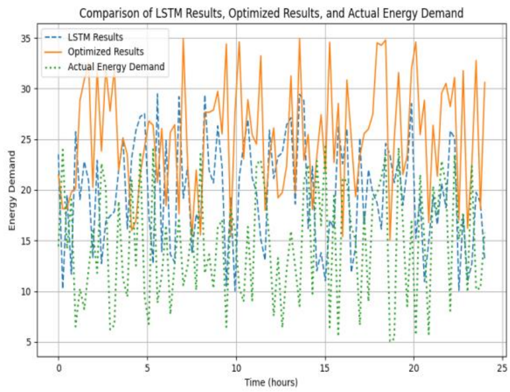

Fig 5: Comparative analysis of LSTM outcomes, optimized outcomes, and actual energy consumption.

Figure 5presents a detailed comparison of three separate data sets: the projected energy demands obtained from the Long Short-Term Memory (LSTM) model, the improved findings achieved through enhanced methodologies, and the real energy usage recorded over a 24-hour period. The x-axis represents a 24-hour time period, with each hour displayed, while the y-axis measures the energy usage in kilowatts (KW).

The dashed line in the LSTM Results represents the initial projections generated by the LSTM model. These projections are based on historical data and a variety of input elements, including meteorological conditions, with the goal of forecasting the anticipated energy needs. The Optimized Results (Solid Line) represent the improved energy demand predictions. This optimization procedure entails utilizing advanced approaches or models to improve the precision and dependability of the initial LSTM forecasts.

The Actual Energy Demand (Dotted Line) represents the actual energy consumption recorded during the same 24-hour period, in contrast to the projected values. This dataset provides accurate information on energy consumption, which is used as a benchmark to assess and examine projected values.

Key findings obtained from this Comparative Analysis:

Examining the differences between the predicted values and the real energy demand yields useful information into the efficiency and dependability of the forecasting algorithms. It enables the detection of trends, patterns, and possible deviations in the forecasts, providing an opportunity to assess the accuracy of the models and make required adjustments or enhancements for future projections.

The comparison graph serves as a crucial instrument for evaluating the efficacy and reliability of the forecasting models. It provides valuable analysis of the advantages and drawbacks of each method, offering guidance for prospective improvements to optimize future predictions and increase their precision in forecasting energy use.

6.Conclusion

This work presents a new method that utilizes a multi-input LSTM model to estimate electric vehicle (EV) charging load with high accuracy. This prediction is crucial for optimizing energy management at charging stations. Our model efficiently utilized temperature, humidity, and wind speed forecast characteristics obtained from the UCI database to accurately provide forecasts. Applying DS-Theory to increase LSTM-generated predictions by integrating inputs (1), (2), and (3). The comparative investigation of various input characteristics (V1, V2, V3) shown differing levels of accuracy in forecasting energy consumption patterns. Significantly, V3 exhibited the highest level of accuracy, emphasizing its crucial function in enhancing predictive performance. These findings highlight the importance of selecting the optimal input parameters to maximize the prediction capacity of the LSTM model. Moreover, the assessment of LSTM predictions against real energy use throughout a 24-hour timeframe enabled a thorough examination, highlighting patterns and discrepancies and offering valuable perspectives for improving future forecasting approaches.

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