CIBECS: Consumer Input Based Electric Vehicle Charge Scheduling for a Residential Home

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***Abstract*—Electrical utility companies offer dynamic electricity pricing to limit peak demand of residential homes to provide charging for the fast-growing Electric Vehicle (EV) fleet. Charging EV at off-peak hours is economical for a user; however, scheduling brings the possibility of an undercharged EV at the time of use. The user has the best knowledge about his driving schedule, so including his input about target charge level and available charging time is an effective way to avoid such discomfort. To this end, this work proposes a Consumer Input Based Electric Vehicle Charge Scheduling (CIBECS) for a residential home. CIBECS takes consumer input, electricity price, and load forecasts to propose an adaptive scheduling technique. Moreover, we utilize an artificial neural network, particularly an LSTM network, to predict highly volatile residential loads. Experiments show our model's superior performance in minimizing electricity cost compared to existing approaches.**

***Index Terms*—Electric Vehicle, charge scheduling, LSTM, electricity optimization, human-in-the-loop system.**

NOMENCLATURE

$\hat{L}_t$	Household load forecast in kW.
E_t	EV battery state in kWh at time t.
E_{cap}	EV battery capacity in kWh.
E_{comp}	Charge to be compensated in kWh.
E_{crit}	Threshold for critical state of charge in kWh.
E_{tgt}	Consumer input for target state of charge in kWh.
L_t	Household load in kW at time t.
L_{max}	Household maximum load capacity in kW.
L_{peak}	Household historical peak load in kW.
P_t	EV charge allocation in kW at time t.
P_{max}	Maximum EV charging capacity in kW.
$P_{a,t}$	Available power for EV charging in kW at time t.
R_t	Real time electricity price in \$/kWh at time t.
t	Index of time slot in hour.
T_{comp}	Charge compensation time in hour.
T_W	Consumer input for charging time window in hour.

I. INTRODUCTION

Electric Vehicles (EVs) do not have combustion engines to burn fuels; instead, they run on the power stored in their battery. It brings two significant benefits to the EV owner, higher fuel efficiency and low maintenance cost. The key challenges are affordable, adequate-sized batteries for long-distance travel and infrastructure support to accommodate EV battery charging. Contributions from the academic community and the automobile industry have brought EV battery price to an affordable range and expect to reach price parity with gasoline cars by the year 2027 [1], [2]. Subsequently, the number of EVs is growing faster than predictions, and the researchers are providing more aggressive EV adoption forecasts [1].

The vast number of EVs put a significant burden on the electrical power system. So, the power system requires expansion plans in energy generation, transmission, and distribution capacity at all levels. Many works provide guidelines for charging station planning and implementation techniques [3], [4]. However, EV charging is convenient and cheaper at home, especially in homes that have a garage [5]. Recent EV models need less time for charging but are more demanding than the other electrical loads in a residential home. The utility companies often limit maximum demand for a household to evade capacity expansion expenses [6]. They impose a demand charge proportional to the peak demand, and in some cases, set a controller-based load cut if demand goes above a threshold [7].

Utility companies employ Demand Response (DR) techniques like day or hour-ahead dynamic electricity pricing schemes for the customers, which is known as Time of Use (TOU) [8]. On the other hand, the consumers follow Demand Side Management (DSM) techniques that schedule electrical appliance usage to capitalize the TOU tariffs [9]. EV inclusion has further escalated the research scope, resulting in popular Home Energy Management (HEM) techniques [8], [10]. [11] demonstrates the impact of uncoordinated EV charging on residential demand. EV charge scheduling techniques need to satisfy two objectives from a user point of view, electricity cost minimization and a sufficiently charged battery before departure. Existing literature proposes rule-based or data-driven methods; however, human driving behavior is too stochastic to predict. So, even state-of-the-art Artificial Intelligence (AI) based techniques [12], [13] may suffer to manage their experimental success in real-life implementation.

EV charging event is determined by the battery's state of charge and available charging time. However, these features depend on daily life needs that are too complex to predict. We hypothesize that human input is the most viable and straightforward way to optimize an EV charging event. Therefore, we propose a direct approach of integrating human preference and control over the scheduling method (i.e., a human-in-the-loop system). The proposed algorithm prompts the user to set the required charging amount and available time at the start of every charging event. This Consumer Input Based Electric Vehicle Charge Scheduling (CIBECS) technique schedules the required charging within the time window based on the electricity price R_t (provided by the utility company) and

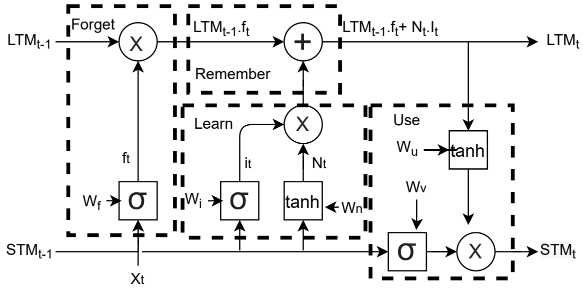

Fig. 1. LSTM block architecture. σ and $\tanh$ denote the logistic sigmoid and hyperbolic tangent functions

the forecasted household load L_t. Recursive Neural Network (RNN) based Long Short-Term Memory (LSTM) network is widely popular for time series prediction tasks [14], [15]. Our scheduling technique proposes a customized LSTM network to predict the highly volatile residential load L_t. Furthermore, we include an adaptive strategy in our model to compensate for any prediction error of L_t. This method is the first such work to the best of our knowledge. Our main contributions are:

- an adaptive scheduling technique formulation that includes human input for EV charge scheduling,
- formulation of an LSTM based household load forecast method,
- adaptability analysis of the proposed technique,
- performance comparisons with an uncoordinated case and an RL-based approach [12] in terms of electricity cost minimization.

The remainder of the paper is organized as follows. We provide background information in Section II. Then, the adaptive EV charge scheduling technique and its adaptability analysis are given in Section III and Section IV, respectively. The experimental setup and results are discussed in Section V. We discuss the insights of the paper in Section VI. Finally, the paper is concluded in Section VII.

II. Background

A. Recurrent Neural Network (RNN)

RNN is a particular type of Artificial Neural Network (ANN) suitable for sequential prediction tasks like speech synthesis and recognition, handwriting recognition, and machine translation [14]. RNN captures the temporal behavior of the data by connecting the output neurons to the input neurons, thus building a memory of previous events within the neural network architecture. RNN-based algorithms have recently outperformed the state-of-the-art methods for most of the time series tasks.

B. Long Short-Term Memory (LSTM) Network

LSTM network is a popular adaptation of the RNN idea [15]. The LSTM network maintains a long-term memory and short-term memory that gives it the leverage to remember the critical information for a long term without using enormous memory resources. LSTM is especially suitable for cases where significant events appear periodically and intermittently within a long time window, making residential load prediction a good application for LSTM. Forgetting and saving

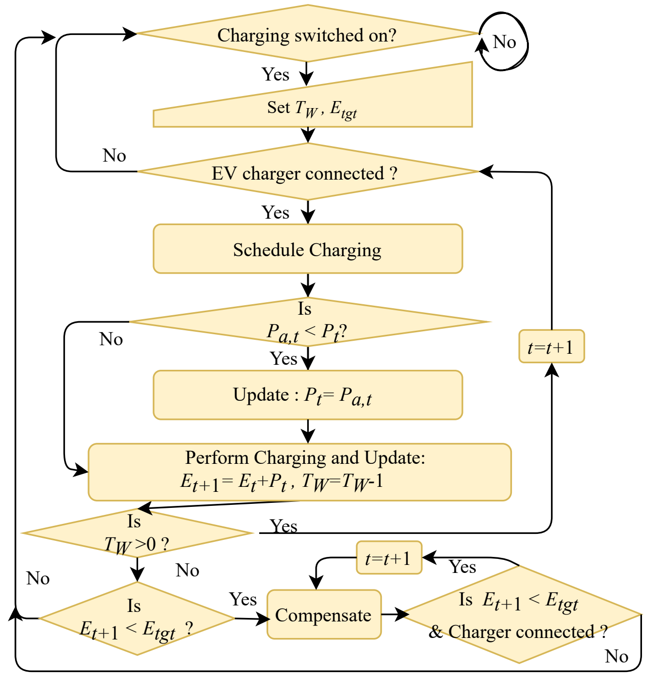

Fig. 2. EV Charging Flow Chart.

mechanisms are critical for LSTM, which balances forgetting irrelevant information and saving essential information. Fig. 1 shows the LSTM architecture that operates with the help of 4 concept gates:

(1) The Learn Gate captures the relevant information from the current event X_t and Short Term Memory STM$_{t-1}$ for the LSTM network.

(2) The Forget Gate passes some information from the previous Long Term Memory LTM$_{t-1}$ to the next one LTM$_t$ and forgets some information.

(3) The Remember Gate combines the outputs of Forget Gate and Learn Gate, which directly forms the LTM$_t$.

(4) The Use Gate combines information from LTM$_t$, STM$_{t-1}$, and X_t to create STM$_t$ and output for the current event.

LSTM achieves its objective by passing the event data, previous long and short-term memories through several ANNs. These ANNs hold the correlation between their inputs and outputs through weight matrices $W_i, W_n, W_f, W_u, and\ W_v$ and activation functions like the logistic sigmoid and tanh functions shown in Fig. 1.

III. Proposed Technique

We propose an adaptive EV charge scheduling technique that aims to satisfy two objectives: attain target charge level within the allowed time and minimize electricity cost by charging in the low tariff periods. The proposed CIBECS technique makes scheduling decisions based on the user input, the electricity price, and forecasted household load. The flow chart in Fig. 2 summarizes the proposed scheduling technique. We divide the technique into the following tasks.

A. Consumer Input

In the beginning, CIBECS waits for an EV charging event to switch on. Whenever the EV gets connected to the charger,

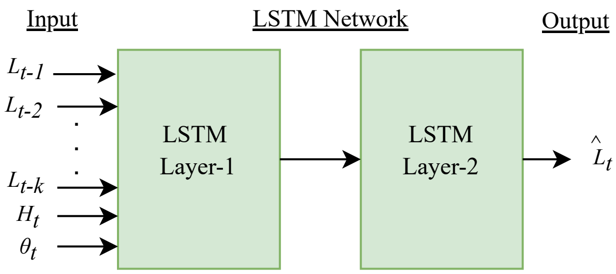

Fig. 3. LSTM network for load forecasting.

Algorithm 1 EV Charge Scheduling Technique

Input: $E_L = E_t$, T_W, E_{tgt}, $R = \{R_t, \ldots, R_{t+T_W-1}\}$, $\hat{L} = \{\hat{L}_t, \ldots, \hat{L}_{t+T_W-1}\}$.
Sort electricity prices R in ascending order and store the indices in vector I.
for $\tau = 1, 2, ..., T_W$ **do**
  Forecast available power: $\hat{P}_{a,I(\tau)} = L_{max} - \hat{L}_{I(\tau)}$.
  Remaining charge $E_R = E_{\text{tgt}} - E_L$.
  EV charge allocation $P_{I(\tau)} = \min(P_{\max}, E_R, \hat{P}_{a,I(\tau)})$
  Update $E_L = E_L + P_{I(\tau)}$
  Update $P_{t+I(\tau)-1} = P_{I(\tau)}$
end for
Output: EV charge schedule $\{P_t, P_{t+1}, \ldots, P_{t+T_W-1}\}$.

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the user is asked to set a charging time range T_W in hours and target battery state of charge E_{tgt} in kWh. Users may select default values for these parameters in case they skip the manual input. CIBECS collects T_W, E_{tgt}, and the battery's current state of charge E_t from the EV device memory.

B. Electricity Price and Household Load Forecast

Electricity price and household electrical load for the following T_W hours are the other two inputs for the scheduling technique. CIBECS collects day-ahead hourly prices R_t from the electrical utility company. However, the future household load is unknown, and an accurate forecast $\hat{L}_t$ is essential for the success of CIBECS. Household load is sequential data that depends on previous values apart from some other features. So, the LSTM network discussed in Section II provides a suitable framework for making the forecasts. We customize and shape the LSTM network to fit our problem, as shown in Fig. 3. Household load typically follows periodical patterns, such as daily, weekly, and yearly. For the experiments, we choose the following inputs for the LSTM network: the load data of the last k time steps $\{L_{t-k}, L_{t-k-1}, ..., L_{t-2}, L_{t-1}\}$, the temperature forecast θ_t, and the holiday flag $H_t \in \{0, 1\}$.

C. Scheduling

EV charging scheduling within a user-defined time range is a critical part of our proposed technique in Fig. 2. The pseudo-code is given in Algorithm 1. Firstly, the agent takes user inputs T_W and E_{tgt}, the current battery state E_t, the electricity price data R, and the LSTM-based load forecast data $\hat{L}$ for the next T_W time steps. The algorithm sorts the electricity prices in ascending order and stores their index

Condition	Power compensation
$E_t > E_{\text{tgt}}$	No
$E_{\text{crit}} < E_t < E_{\text{tgt}}$	$\min\{0.5 \times P_{\max}, E_{\text{comp}}, P_{a,t}\}$
$E_t < E_{\text{crit}}$	$\min\{P_{\max}, E_{\text{comp}}, P_{a,t}\}$

Table I: Charge Compensation Logic.

in the vector I. Then, the algorithm schedules EV charging starting from the cheapest hour. Next, it predicts the available power $\hat{P}_{a,I(\tau)}$ for EV charging by subtracting the predicted load for the hour $\hat{L}_{I(\tau)}$ from the electrical power capacity of the household L_{max}.

Then, it calculates the remaining EV charging E_R by subtracting the battery state of charge E_L from the target EV charging E_{tgt}. The allocated EV charge is the minimum among the maximum EV charging capacity $P_{\max}$, remaining charge E_R, and power available $\hat{P}_{a,I(\tau)}$. Note that the unit time step is one hour; hence the power and energy amounts coincide in unit time. The loop continues for T_W time steps and the algorithm outputs the scheduled charge $\{P_t\}$ for the T_W time steps.

D. Adaptation & Implementation

The scheduling technique shown in Algorithm 1 is based on load forecast, so the actual available power $P_{a,t} = L_{max} - L_t$ may be less than the scheduled charge P_t. In that case, the charge allocation will be updated as $P_t = P_{a,t}$. The battery state of charge for the next time step will be $E_{t+1} = E_t + P_t$. If the charging time range is not over, i.e., $T_W > 0$, then the process will move back to check if the EV charge reached the target amount, i.e., $E_{t+1} = E_{\text{tgt}}$. If no, repeat Algorithm 1 for scheduling at time $t + 1$; otherwise, the system restarts and waits for a new charging session. If the charging time is over, but the charging target is not achieved, i.e., $T_W = 0, E_{t+1} < E_{\text{tgt}}$, then we propose charging compensation (discussed next). In case of completed charging $E_{t+1} = E_{\text{tgt}}$, the process moves back to wait for a new EV charging initiation.

E. Charge Compensation

The forecasted and actual load difference yields lower than estimated charging in the EV, which we aim to compensate. The compensation charge amount is

$$E_{\text{comp}} = E_{\text{tgt}} - E_t.$$

The compensation takes place during the gap (if any) between the end of requested charging duration T_W and EV disconnection. The proposed compensation EV charge depends on two user-defined variables, E_{tgt} and critical charge level E_{crit} as shown in Table I. If the battery level is greater than E_{tgt}, then no compensation takes place. If the battery level is less than E_{crit}, then compensation takes place at the maximum possible level.

IV. Adaptability Analysis

This section demonstrates the benefit of our adaptive approach. The presented analysis assumes the consumer assigns enough time to reach the target charge level. In other words, the remaining charge is attainable by charging at full capacity P_{max} or using all the available power $P_{a,t}$ (whichever is smaller).

A. Toy exmaple

Fig. 4 shows a toy example of charge scheduling with the x-axis representing time steps, $T_W = 4$. The right y-axis represents the electricity price for the corresponding hours, indicating that $R_1 = R_4 < R_3 < R_2$. The left y-axis represents the household load, where solid lines are for the actual load and dashed lines are for the load forecast. The horizontal line at the top represents the maximum load capacity of the household L_{max}. CIBECS schedules charging from low to high electricity prices according to the electricity price, as shown in the algorithm. The area in the shaded regions represents energy transfer in kWh to the battery. So, the initially scheduled energy is given by

$$\Delta E = E_{\text{tgt}} - E_t = A_1 + A_2 + A_3 + A_4 + A_5.$$

In a non-adaptive approach, area $(A_1 + A_3)$ remains uncharged due to higher actual load in time steps 1 and 3. However, in our adaptive technique, after the first time step, CIBECS will reschedule the uncharged portion A_1 in time step 1 through areas A_6 and A_7, where $A_1 = A_6 + A_7$. The process will go on till the charging time range T_W ends. No rescheduling is required after the second time step as the actual load is lower than the forecast. However, CIBECS can not adjust for all the uncharged energy in time step 3 as represented by A_3. The adaptive approach utilizes the lower actual load of the final time step to accommodate additional A_8 energy. In summary, CIBECS misses the target by $(A_3 - A_8)$ energy compared to $(A_1 + A_3)$ in a non-adaptive approach, where clearly $(A_3 - A_8) < (A_1 + A_3)$.

B. Worst case scenario

Further, we analyze the adaptability of our model in a worst-case scenario which will occur if all of the charging is scheduled for the last n hours and the actual load is higher than the forecasts for each of those hours. We can limit n as,

$$n \leq \frac{E_{\text{cap}}}{P_{max}}.$$

The uncharged amount E_{comp} after the charging window ends gets compensation charging, as discussed in the previous section. The algorithm aims to minimize the compensation charging amount E_{comp} and time T_{comp}. The compensation charge and charging time depends on the load prediction error Err. By plotting Err (forecast-actual) values of an adequate size load forecasting sample, we get a normal distribution with the mean $\mu = 0$ (Fig. 5). Denoting the standard deviation of this distribution with σ, the error range $[-2\sigma, \infty]$, covers 97.8% of predictions. Thus, we define the worst case as n consecutive hours of $-\infty < Err < -2\sigma$ to draw the following conclusions,

(1) Probability of the worst-case scenario is $P_{\text{worst}} = 0.022^n$.
(2) Compensation charge is $E_{\text{comp}} < 2n\sigma$.
(3) Compensation charging time is $T_{\text{comp}} < \frac{2n\sigma}{L_{\text{max}} - L_{\text{peak}}}$, where L_{max} is the household maximum load capacity and L_{peak} is the household historical peak load.

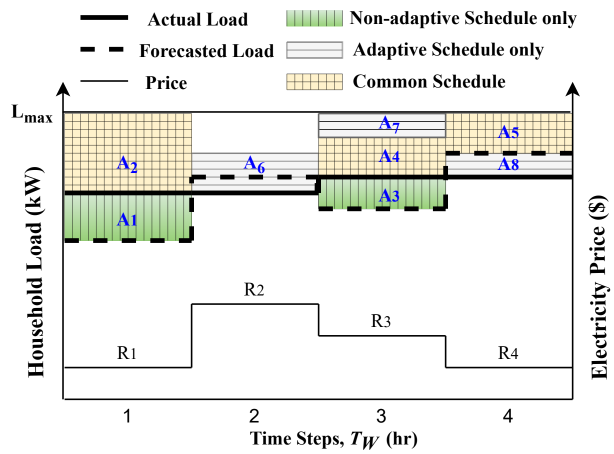

Fig. 4. CIBECS toy example.

Energy (kWh)	E_{cap}= 40	E_{crit}= 15	E_{tgt}= 36
Power (kW)	L_{max}= 10	L_{peak}= 6	P_{max}= 6.6

Table II: Experiment parameters.

V. Results

A. Experimental Setup

[11] provides meter-validated load data for 200 households in the Midwestern USA for 2010 with 10-minute granularity. We use these household data for our LSTM network training and implementation. This dataset also provides EV charging data associated with those households based on the model in [16]. We choose 'household 2' for our experiments whose residents drive two vehicles. As the dataset does not give the EV at-home period, we generate the consumer input of time window T_W and the EV at-home time T_{home} (assuming the EV is always connected to the charger while at home) as follows:

$$\begin{aligned} T_W &= T_C + \text{Poisson } (\lambda = 3), \\ T_{\text{home}} &= T_W + \text{Poisson } (\lambda = 1). \end{aligned} \tag{1}$$

Here, T_C is the charging time observed from the dataset in [11]. The dataset models uncoordinated EV charging, meaning the EVs immediately charge at P_{max} rate till the battery is fully charged. Ideally, $T_C < T_W \leq T_{\text{home}}$ and the consumer might set T_W close enough to T_{home} to maximize his benefit. We establish the relation with Poisson distribution, which is suitable for generating integer-valued extra time. Poisson means $\lambda = 3$ and $\lambda = 1$ work well for our purpose in Eq. 1. We use one-year hourly electricity price data between July 1, 2020, to June 30, 2021, from the real-time Locational Based Marginal Pricing (LBMP) of NYISO [17]. 2021 Nissan Leaf is a popular EV model with a 147 hp (110 kW) engine and 40 kWh battery that gives 149 miles of range. The Level–2 charging of 6.6 kW (240 V, 32 A) would require $n = 6$ hours to charge a completely depleted EV battery. Table II shows the parameters used for the experiments.

B. Forecasting accuracy

Household electrical load for the last 24 time steps, current temperature ($°C$), and holiday flag are the inputs to the

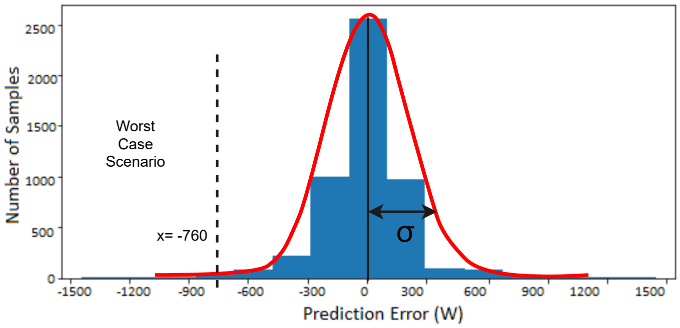

Fig. 5. Histogram of load prediction error in Watts.

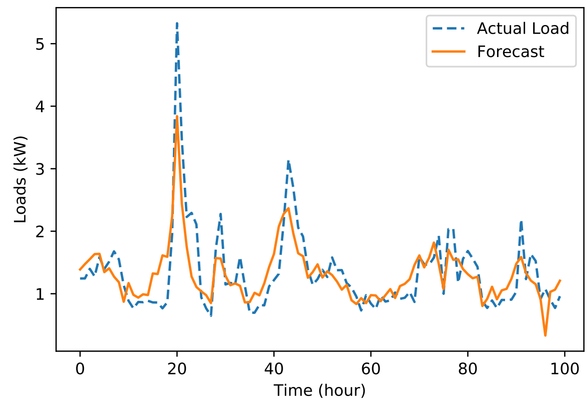

Fig. 6. Actual load and LSTM network forecast for household 2 of the dataset in [11].

Hardware	Software	Task	Computation time
Intel(R) Core i7,3.60 GHz, 16 GB RAM	Python 3.7	LSTM Training	12 min
	Pytorch 1.8.1	Online Scheduling	1.6 sec

Table III: Compute time for the experiments.

LSTM network in Fig. 3. The LSTM network consists of 2 LSTM layers in series, each of which has 100 neurons and Rectified Linear Unit (ReLU) activation function. The second LSTM layer outputs the load forecast for the current time step. We train our LSTM network for each of the 200 households in the dataset. The trained LSTM network achieves 95% accuracy in predicting the selected household, as shown in Fig. 6. Importantly, the forecast picks up fast to follow the current trend, negating the probability of consecutive hours of forecast lower than actual load, i.e., the worst-case scenario in Section IV-B. The load forecasting accuracy is critical for our adaptive CIBECS technique as discussed in Section IV. The error histogram in Fig. 5 shows the resemblence of normal distribution in Err values. We fit a Gaussian curve and compute the mean $\mu = 14$ W and standard deviation $\sigma = 380$ W. The left side of the dashed line in Fig. 5 represents the worst case scenario as defined in Section IV, that occurs when errors for all n consecutive hours are $Err < -760$. We get the following quantities for our experimental setup with the 2021 Nissan Leaf:

(1) $n = \frac{40\ kWh}{6.6\ kW} \approx 6h$
(2) $P_{\text{worst}} = 0.022^6 = 1.13 \times 10^{-10}$
(3) $E_{\text{comp}} < 2 \times 6 \times 380 = 4560\ Wh$
(4) $T_{\text{comp}} < \frac{4560\ Wh}{10000\ W - 6000\ W} = 1.14\ h$

Hence, in such an improbable worst-case event, the EV will remain less than 12.7% undercharged than the consumer's target charge. This amount of charge requires less than 1.14 hours (1hr 8min) to compensate completely. The viable upper limit of compensation charging amount and time indicates that CIBECS does well to minimize consumer discomfort due to undercharged EV.

C. Benchmark Policies

We compare our proposed technique with the following policies in terms of electricity cost minimization.

1) Uncoordinated Charging: [11] demonstrates the impact of uncoordinated EV charging in residential power demand. In this policy, the EV gets immediate charging at P_{max} or $P_{a,t}$ (whichever is lower). This policy emphasizes immediate charging and does not consider cost optimization, hence called uncoordinated charging. We take this as the baseline policy.

2) RL-based approach: [12] proposes a Deep Reinforcement Learning (RL) based appliance scheduling method for electricity cost optimization of a home. They use the last 24 hour data to predict the next 24-hour electricity price. These forecasts work as the deciding factors (states) for the RL agent. For a fair comparison, we use the same LSTM forecast for this policy. In addition, we make the following adaptations to perform this comparative analysis.

(i) We do not consider photovoltaic (PV) generation in this analysis.

(ii) The RL method makes decision whenever the EV is connected to the charger. The state for RL is given by

$$S_t = (\Delta E, T_w, L_t, R_t)$$

where $\Delta E = E_t - E_{\text{tgt}}$.

(iii) The RL agent tries to minimize the electricity cost.

D. Electricity Cost Minimization

Table III shows that LSTM training takes 12 minutes and online scheduling requires 1.6 seconds, exhibiting the real-life applicability. Note that the LSTM network is trained only once in a while (e.g., a year).

We consider two scenarios. In scenario 1, only one of the two vehicles is EV; and in scenario 2, both vehicles are EVs. Fig. 7 shows the cumulative electricity cost comparison among the three policies for both scenarios for one year.

In scenario 1 (left figure), the single EV consumes 2905.1 kWh of energy for the one-year period. The uncoordinated charging costs 509.2$ for providing the energy, whereas the deep RL-based policy costs 444.1$ and achieves 12.78% cost reduction. Our CIBECS technique costs only 400.1$ and reduces the uncoordinated method's cost by 21.43%.

In scenario 2 (right figure), the second EV consumes 3514.5 kWh of energy, making the total energy consumption by both EVs 6419.6 kWh for one year. The uncoordinated charging costs 1142.5$ for providing the energy, whereas the deep RL-based policy costs 976.2$ and achieves 14.55% cost reduction. Again, CIBECS outperforms the other two policies and costs 879.6$ with a 23.01% reduction with respect to the uncoordinated charging method. Both CIBECS and the

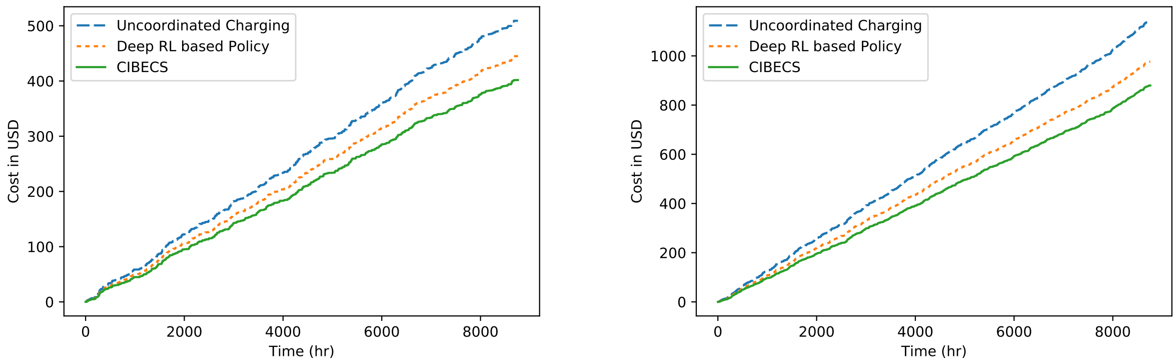

Fig. 7. Hourly cumulative cost comparison among CIBECS and the benchmark policies for scenario 1 (left) and scenario 2 (right).

deep RL-based method are more cost efficient for the 2 EV case, indicating the necessity of smart scheduling for high EV penetration.

VI. Discussion

Experimental results show that our prediction and rule-based technique (CIBECS) outperforms the state-of-the-art deep RL-based charge scheduling. Although important features are included in the RL state definition, it lacks the advantage of looking at the electricity price and the load forecasts of future time steps. This result shows that a one-step look-ahead is not sufficient in cost minimization; the RL needs to look at T_W future time steps like CIBECS. However, T_W may vary for each user and each charging event; thus, the deep neural network in RL has to deal with variable-length inputs, which complicates the design, implementation, and learning process for the RL technique. This limitation paves the way for further research to include RL in our CIBECS technique. Moreover, research may include other features and prediction techniques for more accurate load forecasting to make CIBECS more efficient.

VII. conclusion

The residential homes need immediate and feasible scheduling techniques to accommodate the fast-growing Electric Vehicle (EV) charging load. We proposed an adaptive process that schedules each EV charging event within a consumer assigned time window, based on electricity price and household load forecast. We designed a suitable LSTM neural network to accurately predict household load during the charging time window for load forecasting. Furthermore, since a single household load bears much uncertainty for precise prediction, we provided compensation charging measures for situations when the actual load differs from the prediction. We presented an adaptability analysis, worst-case scenario analysis, and a comparative experimental analysis with respect to the uncoordinated charging method [11] and the Deep Reinforcement Learning (RL) based approach [12]. Our experiments showed the superiority of our technique in electricity cost minimization.

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