Study on the Operation Mode of Electric Vehicle-Based Virtual Power Plants Using TGCN-MPC

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***Abstract*—The surge in electric vehicles (EVs) necessitates effective load management and scheduling for charging stations. This study introduces an optimized scheduling method for an EV Virtual Power Plant (EVPP) using Temporal Graph Convolution Network (TGCN) and Model Predictive Control (MPC). TGCN predicts charging station load by capturing spatial and temporal dependencies, utilizing historical load data and influencing factors. Combined with MPC, it enables real-time, optimized resource allocation based on forecasted loads. Experimental results indicate substantial improvements in load prediction accuracy and scheduling efficiency, enhancing EVPP operational stability and reducing grid fluctuations compared to traditional methods.**

Keywords*—electric vehicle, virtual power plant, temporal graph convolution network, model predictive control

I. Introduction

With the growing scale of EVs, their dynamic driving and charging (discharging) behaviors are increasingly coupled with urban road networks and power grids. This coupling presents new challenges and opportunities for urban infrastructure planning and energy management. Currently, EVCS operation is regarded as an emerging variable load, directly impacting grid stability and operational efficiency. In the field of virtual power plant research, EVCSs are typically viewed as adjustable load resources. The volatility and randomness of EV charging loads impose substantial pressure on traditional power system scheduling. Therefore, accurately forecasting EVCS loads and optimizing scheduling are crucial for the stable operation of the power grid [1].

Reference [2] provides a comprehensive overview of current research on GCN in energy systems, highlighting their diverse applications in forecasting and optimization. The authors in [3] introduce the concept and model of Temporal Graph Convolutional Networks, applying it to traffic flow prediction within transportation networks. A multi-time scale assessment model for evaluating EVPP response capability, including day-ahead and intraday scheduling strategies, is proposed in [4]. For EV charging management, [5] employs deep reinforcement learning to reduce EV owners' charging costs via a time-variable pricing mechanism. This method optimizes charging strategies by combining a deep deterministic policy gradient algorithm with a long short-term memory network, addressing price fluctuations and the variability in owner commuting behavior.

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A short-term EV charging load forecasting model is proposed in [6], based on a multi-channel convolutional neural network and temporal convolutional network, which improves forecast accuracy and stability through multi-scale feature extraction and temporal dependency modeling. In [7], an overview of MPC's theoretical and application aspects in HVAC system control is provided, emphasizing MPC's benefits in managing dynamic changes and uncertainties. Additionally, [8] explores an energy-based MPC algorithm for the optimal operation of a power-hydrogen integrated virtual power plant in real-time markets, enhancing operational flexibility and economic efficiency by reducing computational burdens and incorporating probabilistic forecasting.

The above references provide valuable research on EV charging and discharging patterns, the application of GCN in EV charging and discharging studies, the coordinated operation of EVPP, and the use of MPC in virtual power plants. However, they lack research on optimizing EVPP scheduling strategies based on accurate forecasting of EV charging station loads. To address this, this paper develops a prediction-declaration-scheduling optimization model for EVPP operations using the TGCN-MPC method. By leveraging the predictive capabilities of TGCN and the rolling optimization abilities of MPC, a feedback mechanism is proposed: prediction results inform the rolling optimization, while optimization outcomes act as historical data influencing future predictions. This model enables real-time, refined load forecasting, declaration, and optimized scheduling for EVPPs. The overall structure of this paper is shown in Figure 1.

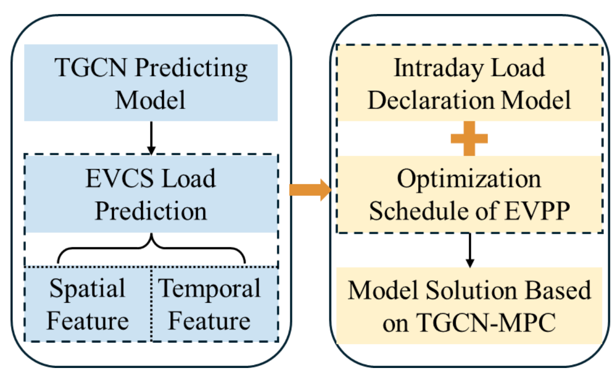

Fig. 1. Overall structure

II. TGCN PREDICTION MODEL

A. TGCN Prediction Model

In this chapter we will introduce the TGCN model used in our work. The method's overall structure is illustrated in Figure 2.

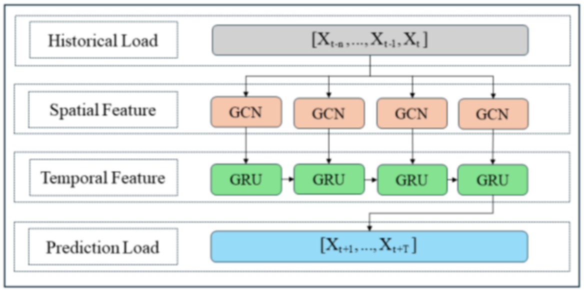

Fig. 2. Overall structure

Construct and define network $G=(R,E)$, in which $R=\{r_1,r_2,\ldots,r_N\}$ is the set of nodes representing EVCSs, N is the number of the nodes, and the edges connecting the nodes are represented by E. In the charging station problem, the weights of the edges are determined by the results of the correlation analysis discussed in chapter II. The feature matrix $X^{N\times P}$ is defined, with P representing the number of features of a node. This matrix is used to represent the load of each node.

Therefore, the problem of forecasting EVCSs' load can be seen as learning the mapping function f, given the network topology G and the feature matrix X, and then calculating the load information for the next T time intervals, as stated below:

$$[X_{t+1},\ldots,X_{t+T}]=f(G,(X_{t-n},\ldots,X_t)) \tag{1}$$

where n is the length of the historical time series and T is the length of the time series to be predicted. In our work, X_t is expressed as follow:

$$X_t=[P_{EVCS_{1,t}},P_{EVCS_{2,t}},\ldots,P_{EVCS_{i,t}}]^{\mathrm{T}} \tag{2}$$

where $P_{EVCS_{i,t}}$ is the load power of EVCS$_i$ at time t.

To construct a GCN model, multiple convolutional layers can be stacked. In this paper, we utilize GCN models to acquire spatial features from data. A multi-layer GCN with the following layer-wise propagation rule is considered:

$$H^{(l+1)}=\sigma(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}H^{(l)}W^{(l)}) \tag{3}$$

in which adjacency matrix with self-loop is:

$$\tilde{A}=A+I_N \tag{4}$$

A is the adjacency matrix representing connection between nodes, degree matrix is:

$$\tilde{D}=\sum_j \tilde{A}_{ij} \tag{5}$$

and $H^{(l)}\in\mathbb{R}^{N\times D}$ is the matrix of activations in the l^{th} layer, $H^{(0)}=X$. I_N is the identity matrix and $W^{(l)}$ is a layer-specific trainable weight matrix.

The representation of a two-layer GCN model is as follows:

$$f(A,X)=\sigma(\hat{A}\,\mathrm{ReLU}(\hat{A}XW_0)W_1) \tag{6}$$

$$\hat{A}=\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2} \tag{7}$$

where W_0 and W_1 denote the weight matrices of the first and second layers, respectively, and $\sigma(\cdot)$ and ReLU$(\cdot)$ denote the activation function.

In order to capture both spatial and temporal dependencies in the data, this paper considers the TGCN model based on graph convolutional networks and gated cyclic cells. It is shown in the following equation:

$$u_t=\sigma(W_u\left[f(A,X_t),h_{t-1}\right]+b_u) \tag{8}$$

$$r_t=\sigma(W_r\left[f(A,X_t),h_{t-1}\right]+b_r) \tag{9}$$

$$\tilde{h}_t=\tanh(W_c[f(A,X_t),r_t*h_{t-1}]+b_c) \tag{10}$$

$$h_t=u_t*h_{t-1}+(1-u_t)*\tilde{h}_t \tag{11}$$

where: $f(A, X_t)$ represents Graph convolution function applied to the adjacency matrix A and the input features X_t at time t; u_t and r_t represent the update and reset gates at time t, which control how much of the previous hidden state h_{t-1} is retained in computing the current state. The variable $\tilde{h}_t$ is the candidate hidden state, determined by the reset gate r_t and the previous hidden state h_{t-1}, representing the potential new state without considering the update gate. The final hidden state h_t is then computed as a combination of h_{t-1} and $\tilde{h}_t$ based on u_t. In these computations, W_u, W_r, and W_c are weight matrices for the update gate, reset gate, and candidate hidden state, respectively, which learn the influence of the input features and previous hidden state. The terms b_u, b_r, and b_c are biases associated with each gate and hidden state. The sigmoid function σ is used to constrain the gate values between 0 and 1, while tanh is used to compute the candidate hidden state. Element-wise multiplication (∗) is applied to incorporate the effects of the gates into the hidden states. This gated mechanism, similar to a GRU [10], integrates both temporal dynamics and spatial information from the graph structure.

The loss function is represented as follows:

$$loss=\|L_t-L_t\|+\lambda L_{reg} \tag{12}$$

L_{reg} is the regularization term used to avoid overfitting problems [9]. λ is a hyperparameter to adjust the strength of the regularization. L_t and $\widehat{L}_t$ are used to denote the real load and the predicted load.

B. Evaluation Metrics

The calculation of the prediction accuracy is given by the following equation:

(1) Accuracy:

$$Accuracy = 1 - \frac{\| L - \hat{L} \|_F}{\| L \|_F} \tag{13}$$

(2) Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{mn}\sum_{j=1}^{m}\sum_{i=1}^{n}(l_i^j - l_i^j)^2} \tag{14}$$

(3) Mean Absolute Error (MAE):

$$MAE = \frac{1}{mn}\sum_{j=1}^{m}\sum_{i=1}^{n}\left| l_i^j - l_i^j \right| \tag{15}$$

where l_i^j and l_i^j represent the real load and predicted load of EVCS_i at time j; m is number of time samples; n is number of modes. L and $\hat{L}$ represent the set of l_i^j and l_i^j respectively.

III. MPC BASED OPTIMIZATION SCHEDULING STRATEGY FOR EVPP

A. Intraday Load Declaration Model for EVPP

The intraday load declared by the EVPP is defined as follows:

$$P_{g,t} = \begin{cases} P_{pre,t}^{EVCS} - P_{pre,t}^{ren}, & \text{if } P_{pre,t}^{ren} < P_{pre,t}^{EVCS} \\ 0 & \text{, otherwise} \end{cases} \tag{16}$$

where $P_{g,t}$ is the declared load of the EVPP at time t; $P_{pre,t}^{EVCS}$ represents the forecasted load of EVCS at time t; $P_{pre,t}^{ren}$ denotes the forecasted output of renewable energy at time t.

The forecasted times for $P_{pre,t}^{EVCS}$ and $P_{pre,t}^{ren}$ can be adjusted, allowing the model to determine the forecasted load and output for specific future time periods. This flexibility enables the adjustment of the optimization scheduling intervals and durations accordingly.

B. Uncertainty Analysis

In this study, the uncertainties in the EVCS forecasts and renewable energy output are discussed in Chapter II. For the uncertainty in renewable energy output, it is represented as a confidence interval at a given confidence level, as follows:

$$P_{true,t}^{ren} = P_{pre,t}^{ren} + z_t \quad z_t \in [-P_{h,t}^{ren}, P_{h,t}^{ren}], \forall t \in S_T \tag{17}$$

$$P_{pre,t}^{ren} - P_{h,t}^{ren} \le P_{true,t}^{ren} \le P_{pre,t}^{ren} + P_{h,t}^{ren} \quad \forall t \in S_T \tag{18}$$

where $P_{true,t}^{ren}$ is the actual output of renewable energy at time t; Z_t represents the forecast deviation; S_T is the set of all time intervals considered.

To avoid excessive conservatism in forecasting and to consider the temporal smoothness of forecasts, a smoothing coefficient Γ_{S_T} is introduced, defined as:

$$\sum_{t \in S_t}\left| \frac{P_{true,t}^{ren} - P_{pre,t}^{ren}}{P_{h,t}^{ren}} \right| = \sum_{t \in S_t}\left| \frac{z_t}{P_{h,t}^{ren}} \right| = \sum_{t \in S_t} y_t \leqslant \Gamma_{S_T} \tag{19}$$

The selection of Γ_{S_T} is as follows:

$$\Gamma_{S_T} = T\mu + \Phi^{-1}(\alpha)\sqrt{T}\sigma \tag{20}$$

where z_t represents the uncertainty factor for forecast deviations, and μ and σ are the mean and standard deviation, respectively. $\Phi(\cdot)$ is the cumulative distribution function of the normal distribution, and α is the confidence level.

For renewable energy output, different forecast time intervals may cause sustained random fluctuations, as shown in Table I:

TABLE I. NEURAL NETWORK PARAMETER VALUE

Time Scale (min)	Confidence Level
15	99%
30	98%
60	95%

C. EVPP Optimization Model

The EVPP includes each EVCS, renewable energy DER, the distribution network, and a gas turbine for balancing power within the region. The objective function aims to minimize the operational cost of the EVPP:

$$\min_x \quad y = \sum_i C_{EVCS,i} + C_{mt} \tag{21}$$

where $C_{EVCS,i}$ is the optimized dispatch cost of each EVCS, and C_{mt} is the operational cost of the gas turbine.

Since EVCSs have *energy storage* attributes, the cost of EVCS dispatch is inherently the sequential cost of using the stored energy, expressed as:

$$C_{EVCS,i} = \sum_t \delta \cdot \Delta P_{EVCS,i,t} - (\tau_{t+1} - \tau_t) \cdot \Delta P_{EVCS,i,t} \tag{22}$$

where δ is the cost coefficient associated with the load adjustment of the EVCS alliance, and $\Delta P_{EVCS,i,t}$ is the load adjustment degree of EVCS i, τ_t reflecting the charging cost at time t.

The expression of C_{mt} is as follow:

$$C_{mt} = a \cdot P_{mt}^2 + b \cdot P_{mt} + c \tag{23}$$

where P_g represents the power purchased by the EVPP from the power grid to balance the load, and P_{mt} represents the output power of the EVPP's gas turbine. The solution space of the optimization problem is defined accordingly.

The solution space for the optimization problem is $x = \{\mathbf{\Delta P_{EVCS,t}}, P_{mt,t}\}$, in which $\mathbf{\Delta P_{EVCS,t}} = \{\Delta P_{EVCS,i,t}\}$.

In the EVPP, each EVCS adopts a cooperative game approach to achieve the minimum objective function as defined in (14).

The constraints are as follows:

$$\Delta \underline{P}_{EVCS,t} \le \Delta P_{EVCS,t} \le \Delta \overline{P}_{EVCS,t} \tag{24}$$

$$\Delta P_{EVCS,t-1} + P_{mt,t} + P^{ren}_{true,t} = P^{EVCS}_{true,t} + \Delta P_{EVCS,t} \tag{25}$$

where $P^{EVCS}_{true,t}$ is the actual load of the EVCS at time t.

From (25), it can be observed that the load variations in the previous time period of the EVPP will have a cumulative impact on the load in the current time period.

D. The Solution Process of the TGCN-MPC Model

The application of MPC technology to the real-time rolling optimization scheduling of EVPP is illustrated in Figure 3.

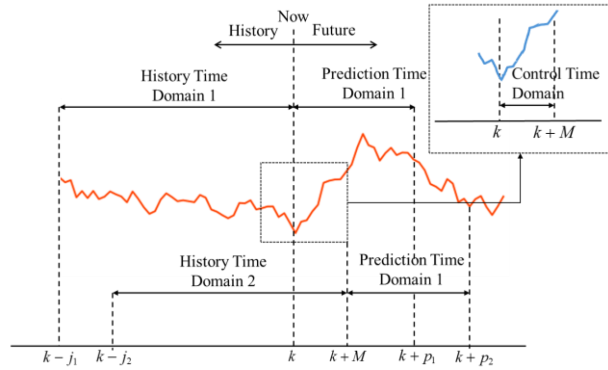

Fig. 3. Overall structure

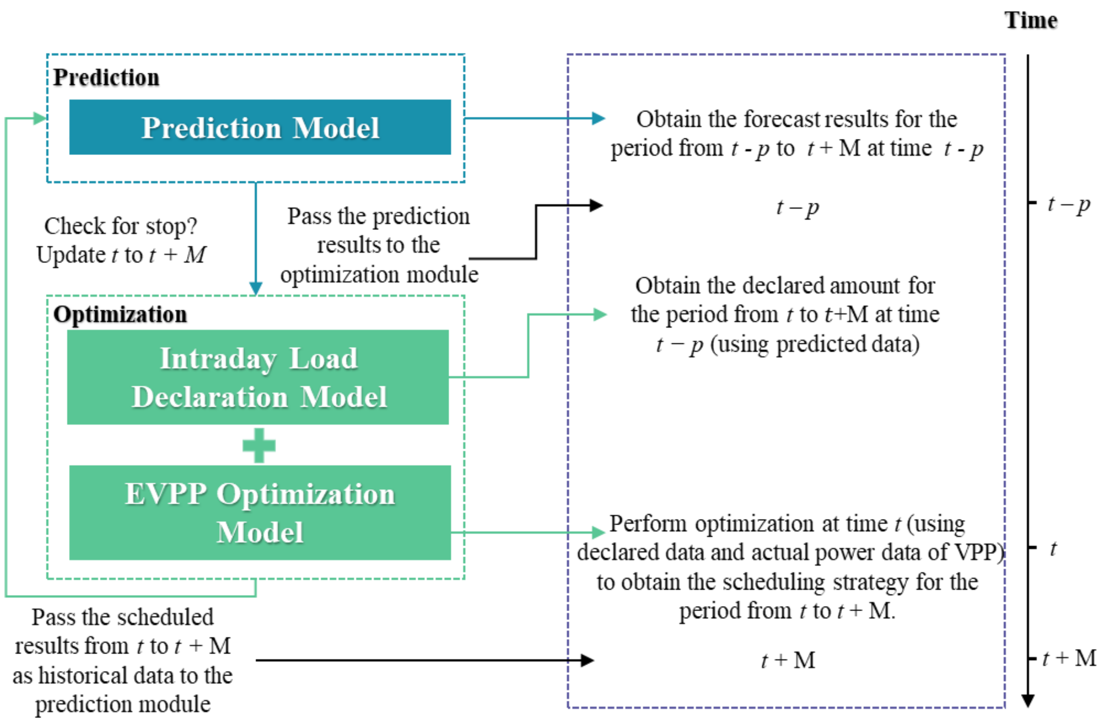

Fig. 4. Model Solution Process

The strategy mainly includes the following phases: (1) At the current time k and current state, based on a certain predictive model, forecast the future state of the system while considering current and future constraints, and obtain a sequence of control commands for future moments by solving an optimization problem. (2) Apply the first value of the control command sequence to the control system. (3) At time k+1, update the state and repeat the above steps.

The model solution process is illustrated in Figure 4.

Step 1: At time t−p, the Prediction Model forecasts the future load and renewable energy output for the period t to t + M using historical and real-time data.

Step 2: Using the forecast data from the Prediction Model, the Intraday Load Declaration Model declares the anticipated load for the period t to t + M.

Step 3: At time t, the EVPP Optimization Model receives the declared data and the actual power data of the virtual power plant, using the MPC optimization algorithm to generate the optimal scheduling strategy for t to t + M.

Step 4: The optimized scheduling strategy is implemented over the interval t to t + M in the EVPP system.

Step 5: The results from the period t to t + M, along with any new real-time data, are fed back into the Prediction Model to continuously improve future forecasts and scheduling decisions.

Step 6: Check whether the process is finished. If not, update t to t + M.

IV. Case Study

The data set utilized in this study comprises load data from nine neighboring charging stations in the Shenzhen region, collected over a three-day period. Figure 5 shows the load curve of EVCSs within 72 hours. Figure 6 shows the EV's charging price.

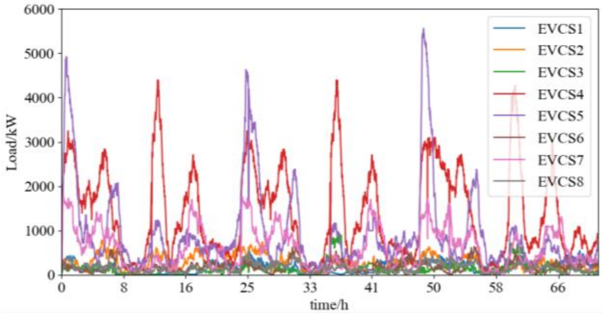

Fig. 5. EVCSs' load curve

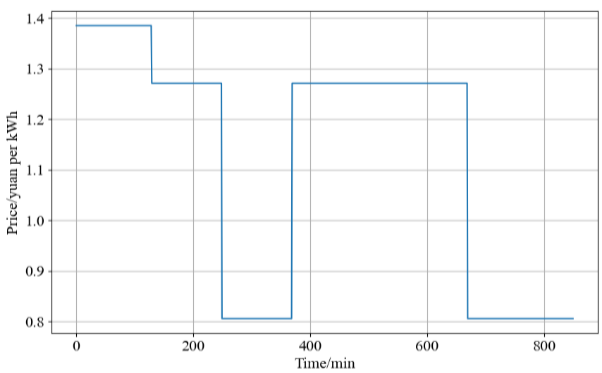

Fig. 6. EV's charging price

Table II shows the parameters chosen in neural network's training and testing.

TABLE II. NEURAL NETWORK PARAMETER DESIGN

Parameters	Value
Number of Hidden Units	32
Learning Rate	0.001
Batch Size	64
Training Epoch	2000
Train Set Proportion	0.8
T (predicted time length)/min	15/30/60
t (historical time length)/min	60

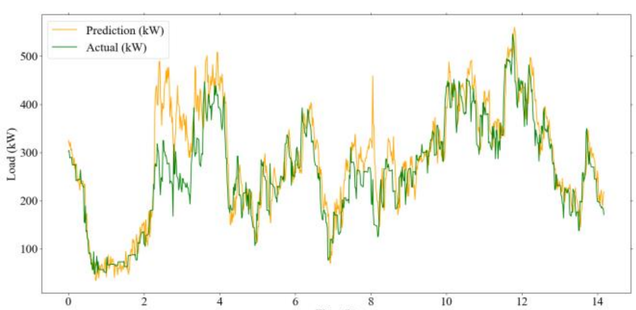

Fig. 7. T=15min EVCS1 load prediction results for 14.4h

The data cleaning strategy adopted in this paper is as follows: missing data is filled with the average of adjacent positions, while outliers are either removed or replaced with the average of preceding and succeeding time sequences.

The load of EVCS1 is employed as an illustrative case. Figure 7 demonstrates the predicted outcomes for EVCS1 over 14.4 hours (20% of 72 hours), in comparison to the actual loading, at T=15 min.

Figure 8 illustrates the load variation, scheduled power, and wind curtailment in the EVPP after optimized scheduling. The optimized EVPP demonstrates high flexibility and adaptability in load management and renewable energy utilization.

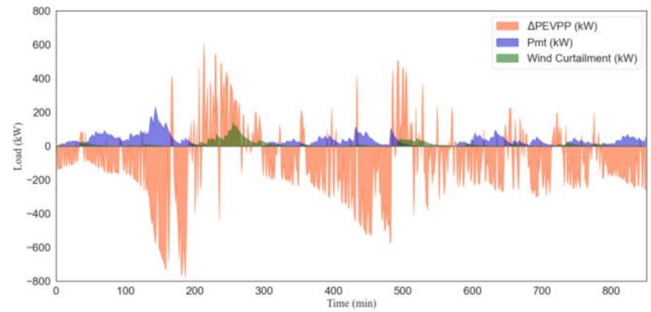

Fig. 8. EVPP optimized scheduling results

Figure 9 shows the load forecast for EVCS1 after optimization using the EVPP scheduling optimization model proposed in Chapter 3. The forecasting accuracy is 91.54%, with RMSE and MAE values of 54.40 and 37.90, respectively, compared to prediction model without MPC optimization, which accuracy is 91.30%, with RMSE and MAE values of 56.02 and 38.56 This indicates that the EVPP optimization operation model has a positive impact on the TGCN forecasting model, and, to some extent, the EVPP optimization model smooths the load curve of the EVCS, resulting in improved forecasting performance. The total operational cost of EVPP is reduced from 14382.96 yuan to 12347.57 yuan.

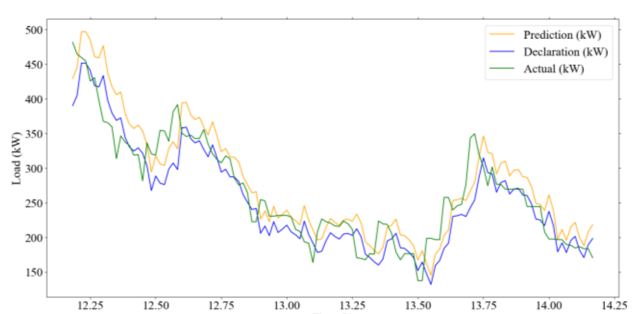

Fig. 9. EVCS1 load forecast changes

V. CONCLUSION

This paper proposes an optimized scheduling method for EVPP that enhances management efficiency through load forecasting of EV charging stations. Using TGCN to predict the load of charging stations, the model captures spatial correlations between different stations and temporal dynamics, thus improving forecasting accuracy. Combined with MPC technology, an optimized scheduling strategy based on forecasted load data is developed, achieving efficient EVPP management and significantly reducing operational costs.

Future research can explore the following direction: Investigate EV users' willingness to participate in scheduling and how incentives can encourage more users to charge during off-peak times, thereby better managing load fluctuations.

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