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Theory guided deep-learning framework for load forecasting

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ABSTRACT

Electricity constitutes an indispensable source of secondary energy in modern society. Accurate and robust short-term load forecasting is essential for more effective scheduling of load generation, minimizing the gap between generation and demand, and reducing electricity waste. This study proposes a theory guided deep-learning load forecasting (TgDLF) framework to predict the future load through load ratio decomposition, in which dimensionless trends are obtained based on domain knowledge, and the local fluctuations are estimated via data-driven models. The historical load, weather forecast and calendar effect are considered in the model, and the model's robustness to inaccurate weather forecast data is improved by adding synthetic disturbance during the training process. Experiments demonstrate that TgDLF is 23% more accurate than LSTM, and the TgDLF with enhanced robustness can effectively extract information from weather forecast data with up to 40% noise.

Keywords: load forecast, domain knowledge, neural network, theory guided, physics informed

1. INTRODUCTION

Electricity, as one of the most important secondary energy sources, plays a vital role in social development, the global economy, and people's daily lives. Accurate and stable short-term load forecasting (STLF) for future demands is critical in the daily operations of power systems [1]. It not only provides electricity network operators and retailers with timely information to make optimal plans for economic power generation, but is also crucial for detecting vulnerable situations of systems in advance [2]. It was estimated that a 1% increase in forecast accuracy in a thermal power system will save up to 10 million pounds in operating costs annually [3].

Load forecasting has constituted an active research area for decades. In regards to the knowledge-based models, Rahman and Bhatnagar have proposed an expert system which yields superior results compared to the simple regression-based forecasting techniques [1]. But many complex nonlinear relationships between different factors and the load cannot be effectively described by either rules or simple equations. In response to this problem, researchers have attempted to employ machine learning algorithms. The neural networks are particularly promising and achieve superior performance. Park et al. has proven that the ANN is suitable to interpolate among load and temperature pattern data of training sets to determine the future load pattern [2]. Their model, however, only utilize temperature information. To solve this problem, the calendar effect is studied [4-6]. ANN is a point-to-point mapping and cannot use its reasoning about previous events to inform later ones. For sequence data, the long short-term memory (LSTM) performs better [7, 8]. Bedi and Toshniwal used LSTM to forecast electricity demand and achieved good results in 2019 [9]. The LSTM has been proven to be the state-of-the-art model, and it is taken as one of the baselines in this study.

A number of challenges exist for load forecasting. For example, domain knowledge is usually only used for feature engineering in load forecasting models, and has not been fully integrated with machine learning algorithms. The influencing factors considered by the models are also not comprehensive. In addition, because many models use different sub-models for different scenarios (e.g., seasons and weather), the models are frequently complicated. Considering these problems, a salient question becomes: is it possible to build a model

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that can effectively combine domain knowledge and machine learning algorithms, fully consider influencing factors, have a simple structure, and be suitable for a variety of seasons and weather? The objective of this study is to answer this question and build a theory guided deep-learning model with high accuracy.

2. METHODOLOGY

In this study, the theory guided deep-learning load forecasting (TgDLF) is used to predict the load ratio based on EnLSTM algorithm [10], and the desired grid load can be obtained based on the load ratio and historical load. The inputs of the TgDLF include historical load, weather data, and calendar effect. The TgDLF comprises two parts, which are the dimensionless trend and the local fluctuation obtained by load ratio decomposition. The dimensionless trend is determined based on domain knowledge, and the local fluctuation is modeled and predicted by the EnLSTM. The architecture of the TgDLF is illustrated as Fig. 1.

2.1 Load ratio decomposition

In the problem of load forecasting, the direct use of machine learning models can accurately predict the trend of the load, but there are always deviations in the prediction. Considering the continuity of grid load, we can convert the load sequence data with large differences into load ratio sequence data with similar data distributions. The conversion essentially utilizes known historical load data to correct the deviations, so that the predictions in different time periods are in a similar value interval and have similar data distributions. In order to accurately predict the load ratio, we decompose it into two parts: the dimensionless trend and local fluctuation, as shown in Eq. (1).

$$
\begin{aligned}
L_{t+1} &= Ratio_{t+1} \cdot L_t \\
&= f(x,t) \cdot L_t \\
&= \left(f_1(x,t) + f_2(x,t) \right) \cdot L_t \\
f_1(x,t) &= DT_{t+1} \\
f_2(x,t) &= \delta_{t+1} = EnLSTM(x,t)
\end{aligned}
\tag{1}
$$

where L_{t+1} and L_{t+1} is the load at time t+1 and t, respectively; $Ratio_{t+1}$ is the load ratio at time t+1; $f_1(x,t)$ is the dimensionless trend (DT); $f_2(x,t)$ is the local fluctuation; $EnLSTM(x,t)$ represents the prediction of the neural network; and x represent the input variables.

The specific process of load ratio decomposition is presented in Fig. 2. The dimensionless trend f_1 is determined in advance based on the physical mechanism and domain knowledge, according to specific problems and scenarios. It describes the amount of change in the load ratio that has a certain periodicity and regularity, reflecting the role of a priori knowledge. The dimensionless trend is similar to the load trend characterization proposed in previous studies. These methods use the periodicity and regularity of the data to extract information as the base value of the prediction, which captures the behavior of load patterns. The local fluctuation f_2 is more complicated, however, and is related to various input variables on the forecast day. Therefore, we use data-driven models with greater expressiveness to predict the local fluctuation. Ultimately, the load forecasting problem is simplified to the problem of predicting the local fluctuation.

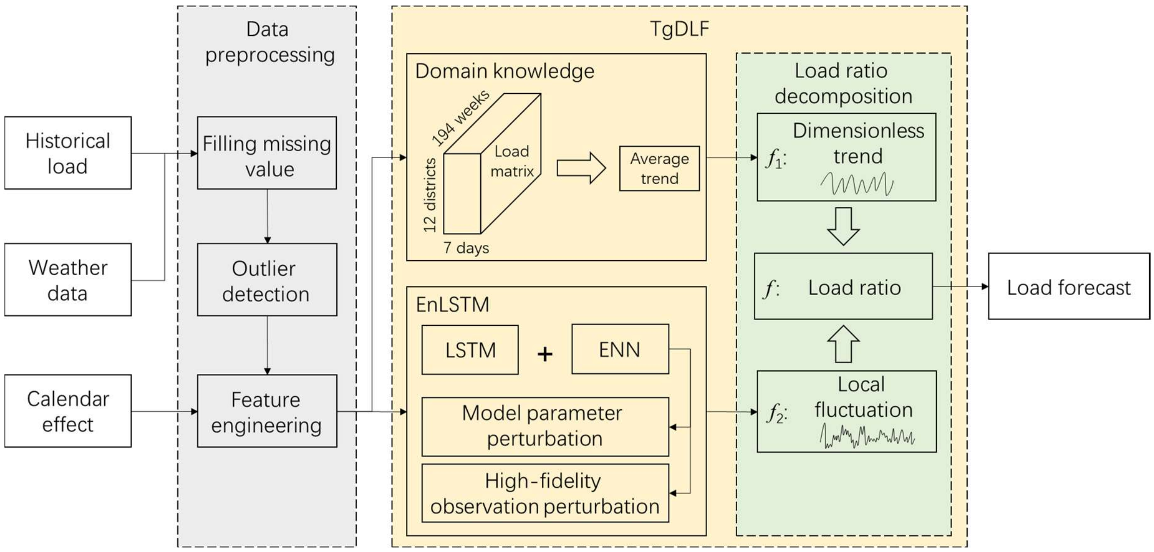

Fig 1 Flow chart of load forecasting based on TgDLF.

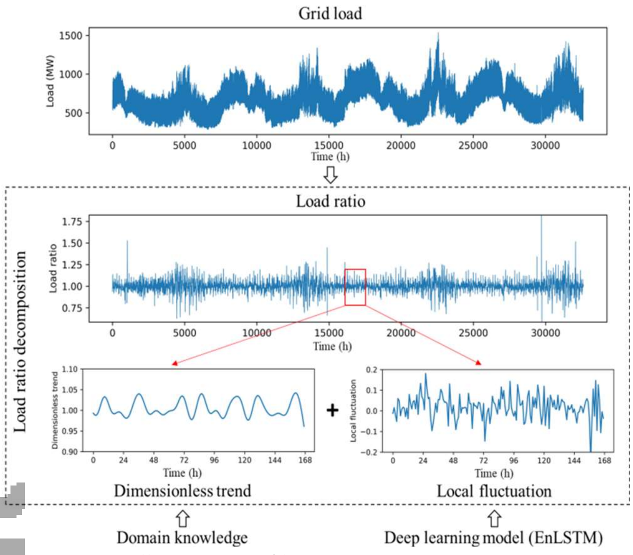

Fig 2 Illustration of load ratio decomposition.

In this study, we use the EnLSTM algorithm to model the local fluctuation based on historical load data, weather data and calendar effect, and further combine the dimensionless trend to reconstruct the load ratio. As long as the load ratio can be accurately predicted, the one-day ahead load can be accurately predicted based on the load of the previous day. The load ratio decomposition method disassembles the parts related to historical data and domain knowledge in the complex load forecasting problem, and uses the neural network to predict simplified local fluctuations, which can simplify the problem and improve the model performance.

2.2 Ensemble long short-term memory (EnLSTM)

The EnLSTM is a novel neural network constructed based on the ensemble neural network (ENN) and LSTM, in which the covariance, rather than the gradient, is used to update the model parameters in the feedback process [10, 11]. The essence of the EnLSTM is to maximize the posterior probability of model parameters given the observations according to the Bayes' theorem. The EnLSTM combines the advantages of LSTM and ENN, i.e., it can not only process sequence data, but also provide accurate prediction results with uncertainty quantification. Previous investigations have shown that the EnLSTM achieves better performance than the vanilla LSTM [10]. In addition, this kind of covariance-based ensemble algorithm is more robust when there are measurement errors in the data [11].

Since the grid load is sequence data, and the weather forecast information in the independent variables inevitably has measurement errors, the EnLSTM is particularly suitable for the load forecasting problem. Intuitively, the EnLSTM is similar to data augmentation in the field of image recognition, for which random disturbances are added to observations of the training data to generate an ensemble of realizations.

The update process of EnLSTM might encounter the problems of over-convergence and disturbance compensation in practice, which always cause failure in training. The model parameter perturbation method and the high-fidelity observation perturbation method, respectively, are proposed to resolve these problems [10]. The EnLSTM is introduced in detail in [10, 11].

3. DATA PREPROCESSING

In this study, the load data and meteorological data of 12 districts in Beijing, China are used. The data set contains 1,362 days of data from Jan. 1, 2008 to Sep. 23, 2011. The 12 districts are as follows: Chaoyang district (CY), Haidian district (HD), Fengtai district (FT), Shijingshan district (SJS), Pinggu district (PG), Yizhuang development Zone (YZ), Changping district (CP), Mentougou district (MTG), Fangshan district (FS), Daxing district (DX), Miyun district (MY), and Shunyi district (SY).

This study also utilized meteorological data in the 12 districts through observation stations of the China Meteorological Administration. The meteorological data set has four variables, including temperature, humidity, wind speed, and precipitation rate in the past hour. In addition, the calendar effect is considered in the inputs. By observing the load trend, it can be seen that the load always changes greatly on Saturday and Monday, i.e., the change caused by the conversion of working days and rest days. Therefore, whether the day to be predicted is Saturday or Monday is also added to the inputs. Finally, the inputs of the model have the following nine dimensions: load (L), temperature (T), humidity (H), wind speed (W), precipitation rate for the past hour (R), date information (D), whether it is a weekend (E), whether it is Saturday (S), and whether it is Monday (M).

The calendar effect of the forecast day can be obtained directly from the calendar, but the weather information depends on the availability of the weather forecasting. Therefore, the first five variables (L, T, H, W, and R) in the inputs are the data from day t-l to day t, and the last four input variables (D, E, S, and M) and the output load are the data from day t-l+1 to day t+1, where t+1 represents the day to be predicted and l+1 is the sequence length of the training data. When weather forecasting is available, the weather data (T, H, W, and R) can also use the information on the forecast day (from day t-l+1 to day t+1).

4. EXPERIMENTS

In this section, we verify the performance of TgDLF based on EnLSTM and the theory guided dimensionless trend through three experiments. We first use the vanilla LSTM and EnLSTM to perform one-day-ahead prediction on the load, and the results are used as the baselines of this study. We then introduce the load ratio decomposition and analyze the performance of the TgDLF. Finally, this study evaluates the robustness of the TgDLF in the presence of varying scales of errors in weather forecast data.

The four-fold cross-validation method is applied in all of the experiments in order to make full use of the data. In the four-fold cross-validation, each experiment uses three folds as training data and one fold as test data. In other words, the proportion of training data and test data in each experiment is 75% and 25%, respectively. In order to cover all types of districts in each fold to make the model more broadly applicable, group sampling is adopted in generating the four folds according to the correlation analysis on the load data of 12 districts.

In section 3.1, we discussed the method of load ratio decomposition. Although we can construct complicated and accurate dimensionless trends by counting the load shapes of different regions in different seasons, we extracted the filtered weekly average trend of the load ratio from the training data as the dimensionless trend for simplicity in this study. We first extract the average ratio trend based on the historical data, and then perform low-pass filtering to smooth the dimensionless trend and enhance the generalization ability. The obtained dimensionless trend can capture a more rigorous and deep understanding of the behavior of load ratio patterns.

4.1 Load forecasting based on vanilla LSTM and EnLSTM

In this section, we directly use the vanilla LSTM and EnLSTM to predict load data. The LSTM uses a deeply optimized model in Pytorch, so it can represent the performance of conventional machine learning models that process sequence data. In this experiment, the LSTM and EnLSTM use the same network architectures, in which both of the models have an LSTM layer containing 30 neurons and a fully connected layer with 15 neurons. In order to avoid overfitting, a dropout with a ratio of 0.3 is used in the LSTM layer, and batch normalization is performed between the fully connected layer and the output layer. The ReLU is chosen as the activation function. The default values of the hyperparameters are used in EnLSTM, i.e., the ensemble size is 100, the smoothing factor is 1, and the disturbance added to the observations is 2%. The mean squared error (MSE) of the prediction results is used to evaluate the performance of the model, in which a smaller MSE indicates better model performance.

The experiment shows that the average MSE over all of the 12 districts of the vanilla LSTM is 0.079 and that of the EnLSTM is 0.075. This indicates that EnLSTM can obtain higher prediction accuracy by using covariance instead of gradient for optimization, which is in line with previous research [10]. Furthermore, the EnLSTM is embarrassingly parallel and it does not depend on derivative calculation, which removes the constraint that the activation function and loss function must be derivable in the neural networks, and makes the model more applicable and expandable. The EnLSTM can also provide uncertainty quantification for sequence prediction results. Therefore, EnLSTM is adopted as the basic model for the load forecasting problem, and a more accurate theory guided model is constructed by combining domain knowledge and physical mechanism in subsequent experiments.

4.2 Load forecasting based on TgDLF

This experiment assesses the performance of TgDLF after introducing dimensionless trends (DT) and weather forecast data into EnLSTM. The load (L_t) in the inputs and the load at forecast day (L_{t+1}) in the outputs are converted into the dimensionless trend (DT_t and DT_{t+1}). The dimensionless trend is then decomposed into two functions, in which the base trend can be obtained from domain knowledge, and the local fluctuations are predicted by the neural network (EnLSTM).

Table 1. Prediction MSE of different models.

	DT	LSTM	EnLSTM	EnLSTM-DT	TgDLF
PG	0.121	0.102	0.095	0.090	**0.077**
SJS	0.116	0.115	0.119	0.111	**0.106**
CY	0.065	0.052	0.046	0.041	**0.032**
YZ	0.126	0.091	0.089	**0.077**	0.080
MTG	0.123	0.111	0.120	0.115	**0.107**
FT	0.064	0.058	0.053	0.046	**0.030**
MY	0.078	0.072	0.065	0.060	**0.049**
FS	0.096	0.093	0.091	0.089	**0.075**
CP	0.056	0.059	0.053	0.048	**0.040**
SY	0.100	0.078	0.070	0.065	**0.055**
HD	0.081	0.064	0.053	0.053	**0.042**
DX	0.062	0.059	0.051	0.045	**0.035**
Ave	*0.091*	*0.079*	*0.075*	*0.070*	***0.061***

The experimental results of introducing dimensionless trend and weather forecast data are shown in Table 1. The DT represents a model that predicts the load only based on the dimensionless trend, and does not use machine learning models to predict the local fluctuations. The LSTM shows the performance of the conventional machine learning methods. The EnLSTM-DT means an EnLSTM model with dimensionless trend. The contribution of the dimensionless trend can be evaluated by comparing the EnLSTM and the EnLSTM-DT. It is also shown that the introduction of weather forecast data can further improve the accuracy of the model. The last column in Table 1 shows the result of using TgDLF based on dimensionless trend and weather forecast data, which is significantly better than the conventional machine learning models (LSTM). It is shown that the prediction error of TgDLF is 33% lower than that of using domain knowledge directly (DT), and it is 23% and 19% lower than the LSTM and EnLSTM, respectively, which are the most advanced machine learning models. This experiment validates the effectiveness of TgDLF and reflects the advantages of combining domain knowledge with machine learning algorithms.

In order to show the model performance in detail, the prediction results of the TgDLF in the Fengtai district is taken as an example and shown in Fig. 3. The ordinate represents the load, and the abscissa represents time. The black lines are the observations (targets) of the load, the red lines indicate the prediction results of TgDLF based on the dimensionless trend and weather forecast data, and the gray region is the uncertainty interval. In order to show the experimental results in detail, five local areas marked by the dashed boxes are enlarged and shown in Fig. 3a to Fig. 3e. The enlarged area basically covers the entire prediction of three years. It can be seen that the predictions are close to the observations.

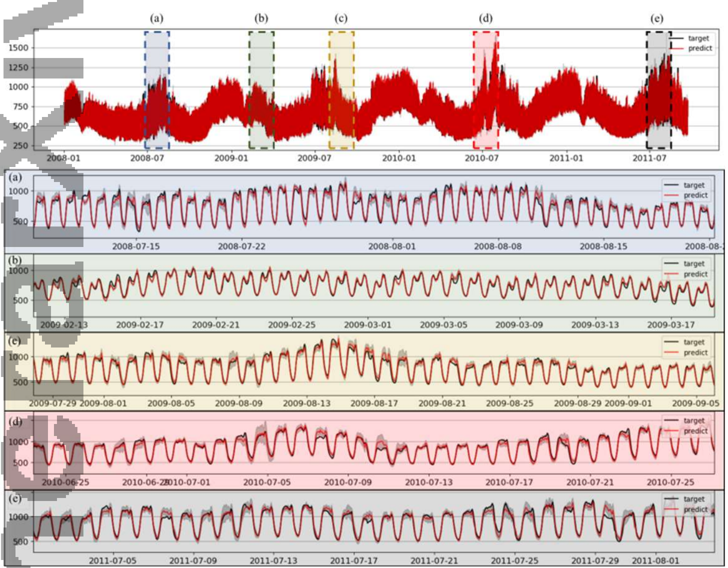

Fig 3 Load forecasting of TgDLF in the Fengtai district.

Moreover, the uncertainty is greater where the model prediction is not accurate, and the uncertainty interval contains most of the true values of the load. Therefore, due to the introduction of domain knowledge, the TgDLF decomposes the complex mapping relationships, and the model prediction accuracy is improved through theory guided dimensionless trends.

4.3 Influence of noisy weather forecast data on TgDLF

The experiments in the previous sections demonstrate that the weather forecast data can effectively improve the prediction accuracy of the model. However, since it is impossible for weather forecast data to be absolutely accurate, the impact of noisy weather forecast data on load forecasting accuracy is evaluated in this section.

Specifically, in order to simulate an inaccurate weather forecast, normally distributed random errors are added to the temperature (T_{t+1}), humidity (H_{t+1}), wind speed (W_{t+1}), and precipitation rate for the past hour (R_{t+1}) when we predict the load on the forecast day (t+1). In the experiment, the standard deviations of random errors are set to 10%, 20%, 30%, 40%, 50%, and 60%, respectively, to simulate scenarios with different weather forecast accuracy.

In order to improve the robustness of the model to noisy weather forecast data, we add 5% disturbance to the weather-related variables in the training data. The disturbed training data make the model gradually adapt to noisy weather data during the training process, which means that the final model is more insensitive to noise compared with the model obtained based on clean training data. It should be emphasized that the noise added here is different from the noise added in EnLSTM. The noise added here is to enhance the robustness of the model, and the noise added in EnLSTM is to construct an ensemble to optimize model parameters. In addition, this method adds noise directly to the input variable, while EnLSTM adds noise to the observations and model parameters.

It can be seen from Fig. 4 that, as the scale of noise in the weather forecast data increases, the performance of the model gradually deteriorates, but it is still better than the model without the weather forecast data when the noise is less than 30%. Furthermore, by adding disturbances to the training data, the robustness of the model can be further improved, so that the model can accept weather forecast data with up to 40% error. The synthetic disturbance in the training data makes the model insensitive to the errors in the weather forecast data, and ensures that the model works well in the

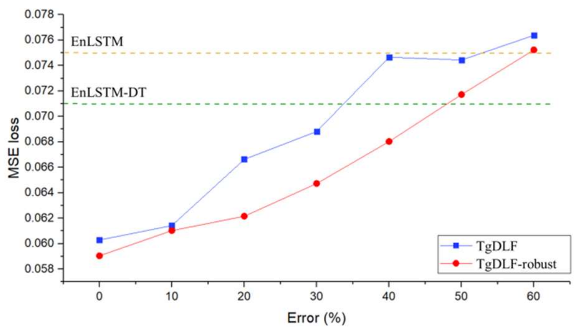

Fig 4 The prediction MSE of TgDLF and TgDLF-robust with different scales of noise in the weather forecast.

presence of errors in the weather forecast data. Indeed, the robustness-enhanced TgDLF model will not blindly trust weather forecast data, and thus it is more stable and less sensitive to inevitable noise.

5. CONCLUSIONS

In this study, we proposed TgDLF, a short-term load forecasting model that combines domain knowledge and machine learning algorithms. The model can predict future load based on historical load, weather forecast data, and calendar effect. Specifically, the grid load is first converted into a load ratio to avoid the impact of different data distributions in different time periods in the same district. The load ratio is then decomposed into dimensionless trends that can be calculated in advance based on domain knowledge, and local fluctuations that are estimated by machine learning models. Essentially, the dimensionless trend in TgDLF is a load trend characterization. Studies have shown that the short-term load data of a specific region have significant approximate periodicity, which is due to the regular work and life mode of people [12]. The load trend characterization can be used to capture a more rigorous and deep understanding of the behavior of electricity consumption patterns [9]. However, this trend based on domain knowledge is not sufficient to support accurate forecasting in practice. Therefore, we predict local fluctuations through neural networks to adjust the final prediction in the TgDLF.

In order to verify the performance of TgDLF, experiments are carried out in this study via cross-validation. First, we obtained the baselines of the load forecasting problem based on vanilla LSTM and EnLSTM. The performance of TgDLF with different sets of hyperparameters is then compared. Subsequently, the TgDLF is compared with the baselines. It is shown that the prediction error of TgDLF is 33% lower than that of using domain knowledge directly (DT), and it is 23% and 19% lower than the LSTM and EnLSTM, respectively, which are the most advanced machine learning models. Finally, a method for adding synthetic disturbances to the training process to enhance the robustness of the model is proposed, and the effectiveness of the method is verified by adding observation errors to the weather forecast data. The experiment demonstrates that the model with enhanced robustness can extract effective information from the weather forecast data with up to 40% noise.

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