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MULTIPLE-DAY FORECAST OF RESIDENTIAL POWER CONSUMPTION

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Аннотация. Прогнозирование нагрузок является ключевым этапом для обеспечения оптимального энергообмена и надежной работы энергосистем, особенно при активной интеграции распределенных возобновляемых источников энергии (DRES). Методы глубокого обучения получили широкое распространение среди исследователей благодаря их способности обобщать сложные нелинейные колебания электропотребления. В частности, рекуррентные нейронные сети наиболее подходят для моделирования электрического потребления, так как хорошо отражают временные зависимости. Данная работа направлена на дальнейшее совершенствование моделей RNN, построенных на основе исходных и вручную созданных признаков. Горизонт прогнозирования был расширен в соответствии с практическими требованиями. Сравнены два подхода многодневного прогнозирования, при этом предложенный метод показал лучшие результаты по сравнению с альтернативным рекурсивным методом прогнозирования.

Ключевые слова: прогнозирование нагрузок, глубокое обучение, RNN нейронные сети, ручные признаки, горизонт прогнозирования, рекурсивное прогнозирование, многодневное прогнозирование.

Аннотация. Жүктөлүүнү болжолдоо оптималдуу энергия алмашууну жана энергетикалык системалардын ишенимдүү иштешин камсыз кылуунун негизги кадамы болуп саналат, өзгөчө бөлүштүрүлгөн кайра жаралуучу энергия булактарын (ДРЭС) активдүү интеграциялоо менен. Терең үйрөнүү методдору электр энергиясын керектөөнүн татаал сызыктуу эмес термелүүлөрүн жалпылоо жөндөмдүүлүгүнөн улам изилдөөчүлөр арасында кеңири таралган кабыл алынган. Атап айтканда, кайталануучу нейрон тармактары электр энергиясын керектөөнү моделдөө үчүн өзгөчө ылайыктуу, анткени алар убакыттан көз карандылыкты жакшы кармашат. Бул иш оригиналдуу жана кол менен түзүлгөн функцияларды колдонуу менен курулган RNN моделдерин андан ары өркүндөтүүгө багытталган. Болжолдоо горизонту практикалык талаптарга жооп берүү үчүн кеңейтилген. Сунушталган метод альтернативалуу рекурсивдүү болжолдоо ыкмасына караганда жакшыраак натыйжаларды көрсөткөн эки көп күндүк болжолдоо ыкмалары салыштырылды.

Ачкыч сөздөр: жүктү болжолдоо, терең үйрөнүү, RNN нейрондук тармактары, колго жасалган функциялар, болжолдоо горизонту, рекурсивдүү болжолдоо, көп күндүк болжолдоо.

Abstract. Load forecasting is a crucial step in achieving optimal power exchange and ensuring the robust operation of utilities, particularly in the active integration of distributed renewable energy sources (DRES). Deep learning methods have gained popularity among researchers due to their capability to generalize complex nonlinearity in power consumption fluctuations. Especially, recurrent neural networks are suitable for modeling electricity consumption as they have strong temporal patterns. This work aims to continue enhancing RNN models, which are built on base and manual features. The forecasting horizon has been extended to meet the requirements of practical application. Two approaches of multiple-day forecasting have been compared, and the proposed method outperformed the alternative recursive forecasting method.

Keywords: Load forecasting, deep learning methods, RNN model, manual feature, forecasting horizon, recursive forecasting, multiple-day forecasting.

Introduction

Accurate residential load forecasting is essential for power system operation, demand-side management, and the integration of renewable resources. Multi-day forecasts, in particular, support scheduling and planning over horizons longer than a single day, yet remain a challenging task due to the nonlinear dependence of consumption on weather conditions and user behavior.

Traditional statistical approaches such as ARIMA and SARIMA provide limited capability in modeling nonlinear temporal dependencies. Deep learning methods, including Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and Bidirectional recurrent models, have shown superior performance in capturing complex load dynamics. However, most studies focus on one-day-ahead prediction, with multi-step forecasting typically achieved by recursive strategies. Such approaches suffer from error accumulation, leading to degraded accuracy across longer horizons.

This paper addresses the problem of multiple-day residential load forecasting by leveraging historical consumption, daily average temperature, and a manually engineered temperature-based feature. We propose a framework that extends LSTM, GRU, and Bidirectional architectures with a TimeDistributed dense layer, enabling direct multi-output prediction and reducing error propagation. A comparative analysis with recursive day-ahead forecasting demonstrates the advantages of the proposed method in terms of accuracy and robustness for multi-day horizons.

Related works

Many studies have been conducted on forecasting residential aggregate load over multiple days. However, it remains a challenging problem, owing especially to nonlinear temporal dependencies, exogenous influences (such as temperature), and error accumulation in multi-step forecasting. The network architectures using recurrent neural networks (RNNs), including LSTM, GRU, and bidirectional LSTM networks, strategies for multi-day or multi-step forecasting, especially recursive versus direct forecasting, and the use of engineered features or auxiliary variables such as weather, temperature, to improve performance. Recurrent neural networks, particularly LSTM and GRU, are widely used in electrical load forecasting because of their ability to capture temporal dependencies over time. For example, Tang et al. (2019) propose a short-term power load forecasting model based on multi-layer bidirectional RNNs combining LSTM and GRU [1]. The proposed method outperformed simpler RNNs and classical statistical models on multiple datasets. Cai et al. (2021) presented a stacked bidirectional LSTM model for short-term load forecasting in Applied Sciences, demonstrating that bidirectional layers capturing both past and forward temporal context help reduce forecasting error [2]. More recent work has focused on combining bidirectional recurrent architectures with attention mechanisms, convolutional components, or feature extraction modules. For instance, "Adaptive Bi-Directional LSTM Short-Term Load Forecasting with Improved Attention Mechanisms" (Yu et al., 2024) adds clustering and pattern recognition to distinguish load patterns before forecasting [3]. Another example is "Multi-feature Short-Term Power Load Prediction Method Based on Bidirectional LSTM Network" (Xiong et al., 2023), which integrates multiple input features and uses feature mining and deep convolutional layers to extract high-dimensional input features before feeding them into a BiLSTM [4]. Ke, Hongbin, Chengkang et al. (2019) apply stacked auto-encoding to pre-process load data before a GRU network to improve short-term forecasting [5]. Also, "Short-Term Aggregated Residential Load Forecasting using BiLSTM and CNN-BiLSTM" (Bohara et al., 2023) compares plain BiLSTM and CNN-BiLSTM for day-ahead horizons, showing that adding convolutional layers to extract local temporal features can improve performance in residential settings [6].

A key issue in forecasting over multiple days (or multiple steps) is how to structure the problem: whether to forecast one day ahead recursively, or to forecast the full horizon. Recursive methods are simple to implement. The model forecasts one step, then feeds that output back as input, and repeats for n steps. But several studies warn of "error accumulation" when doing so, especially over longer horizons.

Some works explore direct or multi-output forecasting. For example, the "Hybrid Distribution Feeder Long-Term Load Forecasting Method Based on Sequence Prediction" (Dong & Grumbach, 2018) investigates using LSTM and GRU in different sequential configurations against traditional bottom-up ARIMA methods for longer time horizons [7]. Also, in the forecasting literature more generally, methods combining direct and recursive strategies (i.e. ensembling or averaging) have been proposed to balance bias and variance over different horizons. For instance, "Simple averaging of direct and recursive forecasts via partial pooling using machine learning" was used in the M5 competition to improve robustness and accuracy of multi-period forecasts [8].

More recently, there are hybrid designs combining sequence prediction (multi-step) with auxiliary features, sometimes attention weights or TCN (Temporal Convolutional Network) components, to improve direct forecasts. For instance, a 24-step forecasting model "KOA-BiTCN-BiGRU-Attentions" builds on bidirectional temporal convolutional networks and attention to produce accurate multi-step load predictions [9].

Temperature is one of the most important exogenous variables in load forecasting, especially in residential settings (heating/cooling demand). Many works use daily average temperature or similar aggregated weather variables. Feature engineering (e.g., extracting degree-days or manually created transformations) has been shown in several cases to improve forecast accuracy by capturing nonlinear effects, thresholds, or interactions with other variables.

A recent paper, "Hybrid feature-based neural network regression method for load profiles forecasting" (2025), explicitly incorporates correlations with air temperature along with clustering and feature selection, resulting in substantial error reductions in a regional dataset [10].

Problem statement

In recent years, increasing attention has been directed toward time series forecasting, yet most studies remain focused on one-step-ahead predictions, which have limited practical significance. For multi-step forecasting, two main approaches are commonly employed: iterative (recursive) and direct methods.

The iterative method uses the model output at time step t as part of the input for the next step t+1. The main drawback of this approach is that forecast errors accumulate over multiple steps, potentially leading to significant deviations. In contrast, the direct method trains a separate model for each forecast horizon: one model predicts the next step, another predicts two steps ahead, and so forth. While this avoids error accumulation, its major limitation lies in the substantial computational resources required [11].

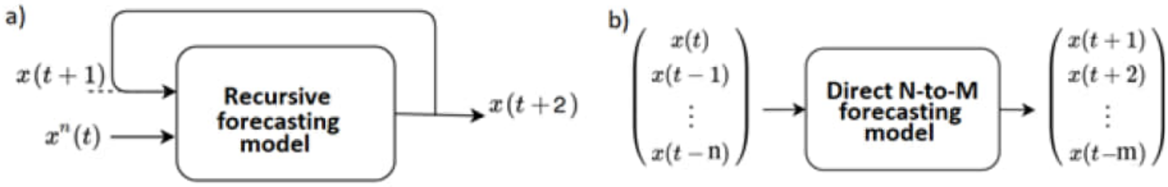

Figure 1. Principal view of recursive (a) and direct N-to-M (b) forecasting models.

This work improves the architecture of an RNN-based neural network proposed in our previous work [12]. RNN variants examined in this study employ gating mechanisms to preserve sequential dynamics across multiple time steps, enabling prediction of the subsequent value (*N+1*) given *N* inputs. For instance, an input of shape (10,3) yields an output of (1,1) when only the final hidden state of the second RNN layer is forwarded. This was implemented in Keras via return_sequences=False. To extend the model for multi-step forecasting, the second RNN layer is configured to return full sequences, allowing each hidden state to be passed to subsequent dense layers. This is achieved using the TimeDistributed wrapper, which applies a specified layer (e.g., Dense, Conv2D, LSTM) independently at each time step without introducing additional computations. By treating temporal sequences stepwise rather than as a whole, the TimeDistributed mechanism enhances the model's ability to capture time-dependent features [13].

The neural network was trained using the Adam optimization algorithm with a learning rate of 0.002, as described above. The performance of the improved architecture was evaluated in both recursive and direct multi-day point forecasting settings, using MAE and MAPE metrics. The results of the models are presented in Table 1.

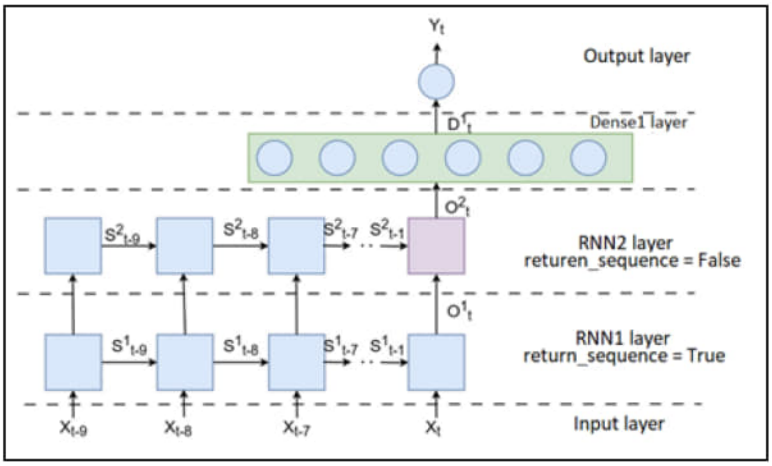

Figure 2. A many-to-one RNN network of the recursive forecasting model.

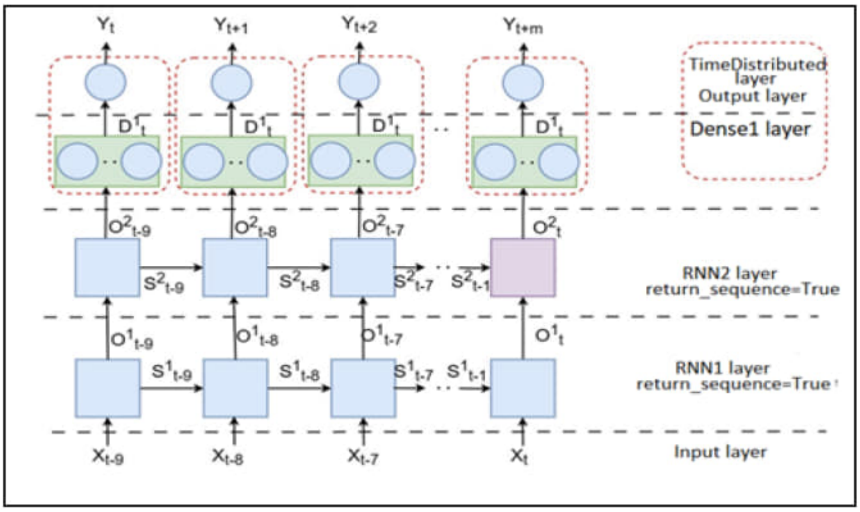

Figure 3. A many-to-many RNN network of the proposed forecasting model.

Results and discussions

The many-to-one architecture achieved strong performance in one-day-ahead forecasting, with an average deviation of 74–76 kWh from the actual daily consumption. However, in recursive forecasting, the error was observed to grow exponentially with the forecasting horizon. This growth can be expressed as:

$$E(n) = E_0 r^n \tag{1}$$

where, $E(n)$ is the error at time step n, E_0 is the initial one-day-ahead error, r is the error growth rate, and n is the time step. Indeed, analysis of 10-day forecasts showed that the error accumulation in all models closely followed an exponential trend, with a growth rate of approximately $r \approx 1.55$ (Fig. 4).

Table 1 presents a side-by-side comparison of recursive and direct forecasting errors for LSTM, GRU, and Bidirectional LSTM models. As illustrated in Fig. 4, all three models exhibit nearly exponential error growth under recursive forecasting. By contrast, in direct multi-day forecasting, the error was considerably smaller. Although the initial error was higher than that of one-day-ahead forecasting (99.9, 154.9, and 116.9 kWh for LSTM, GRU, and BiLSTM, respectively), subsequent errors increased more gradually, following a near-linear trend with a small coefficient.

Table 1. Error accumulation in recursive and direct forecasting methods.

Metrics	Forecasting length, days	LSTM		GRU		Bidirectional LSTM	
		Recursiv	Direct	Recursiv	Direct	Recursiv	Direct
MAE, kW*soat	1	76,21	99,90	76,90	154,90	73,65	116,90
	2	183,23	200,80	204,55	210,40	166,02	207,50
	4	579,91	369,50	630,72	388,00	516,52	337,80
	6	1074,71	524,30	1114,27	557,00	897,04	500,70
	8	1656,96	615,70	1701,43	709,50	1438,01	582,60
	10	3173,54	761,60	3227,57	844,60	2601,41	654,50
MAPE, %	1	0,48	0,80	0,49	1,25	0,43	0,94
	2	1,36	1,61	1,63	1,69	1,30	1,67
	4	4,61	2,97	4,94	3,12	4,05	2,72
	6	7,94	4,22	8,05	4,48	6,85	4,03
	8	13,50	4,95	13,72	5,71	11,70	4,68
	10	23,40	6,12	25,82	6,79	18,80	5,26

The results showed that the recursive approach can be considered reliable only for short horizons of 2–4 days, where the deviation between predicted and actual consumption ranges from 516 kWh to 630 kWh. Beyond this limit, the error increases exponentially with longer forecasting horizons. In contrast, direct forecasting demonstrates a slower error growth rate as the prediction window extends. Specifically, for a 10-day horizon, the average percentage error ranges between 5.5% and 6.8%, which can be considered acceptable in practice and implies significant potential for energy savings.

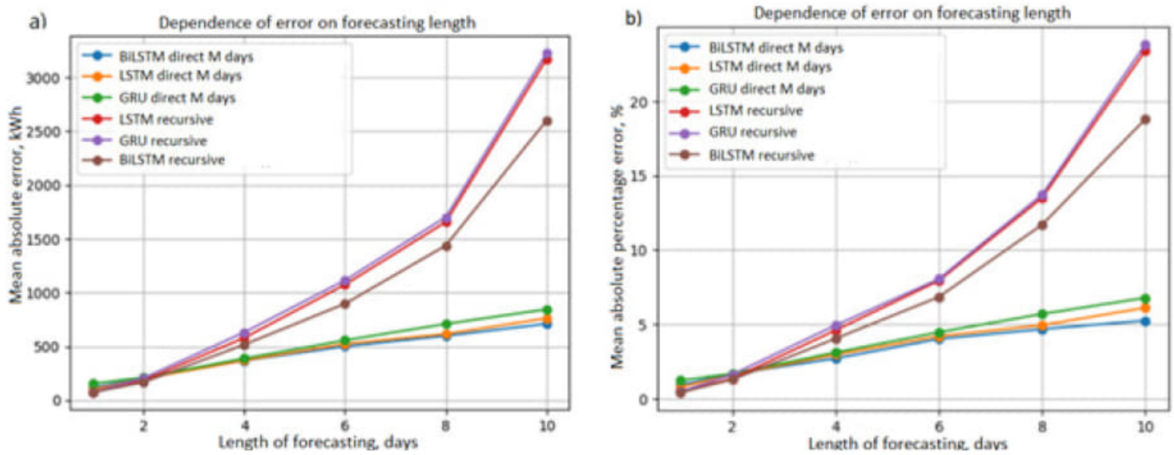

Figure 4. Change of MAE and MAPE values of recursive and direct models.

The error growth curve in direct forecasting slowed as the prediction horizon increased. Among the models, the Bidirectional LSTM consistently outperformed GRU and LSTM models, yielding lower errors. When the horizon was extended to 20 days, the Bidirectional LSTM model achieved an average absolute error of approximately 800 kWh, corresponding to 6.4% deviation from actual consumption. In comparison, the GRU and LSTM models exhibited slightly higher errors of 975–1025 kWh, or 7.8–8.25% in percentage terms.

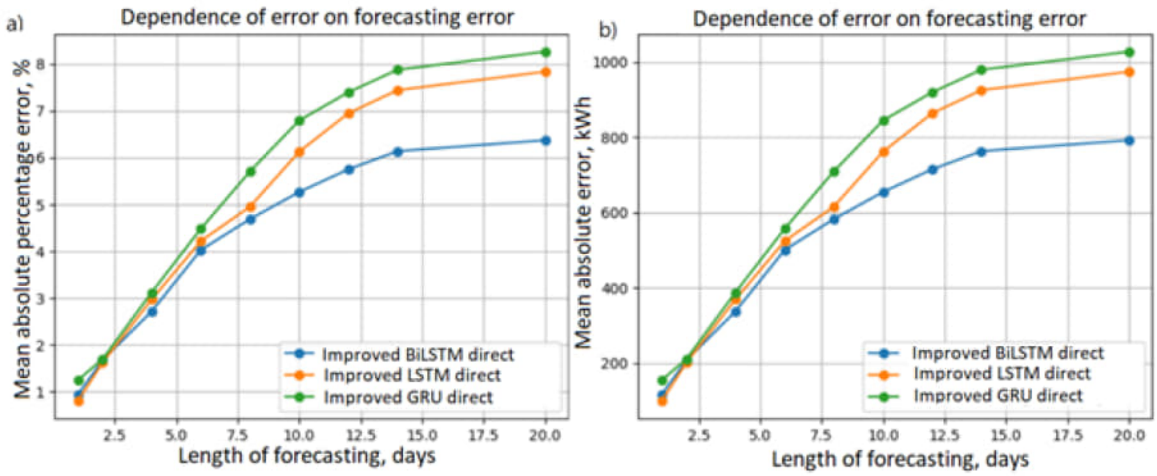

Figure 5. Change of MAE and MAPE values of the direct model.

Conclusions

In this work, manual feature-enhanced RNN models proposed in our previous studies have been improved to extend the forecasting horizon. Forecasting several days of electricity consumption has been implemented in two ways. The first method is using a recursive deploying LSTM, GRU, and bidirectional LSTM day-ahead models, where we observed exponential deviation of predicted values from actual power consumption. However, the extended architecture of the neural network allowed for a direct many-to-many forecasting. Distributing neurons of a dense layer to outputs of the RNN layer at each time successfully modelled the appropriate expected power values. Thus, MAE and MAPE of the best model on Bidirectional LSTM for the 10-day forecast decreased from around 2600kWh to 654.5 kWh and 18.8% to 5.26%respectively.

References used:

1. Tang, X., Dai, Y., Wang, T., & Chen, Y. *Short-term power load forecasting based on multi-layer bidirectional recurrent neural network.* IET Generation, Transmission & Distribution, 2019. IET Research Journal
2. Cai, C., Tao, Y., Zhu, T., & Deng, Z. *Short-Term Load Forecasting Based on Deep Learning Bidirectional LSTM Neural Network.* Applied Sciences, 2021. MDPI
3. Yu, K., *et al. Adaptive Bi-Directional LSTM Short-Term Load Forecasting with Improved Attention Mechanisms.* Energies, 2024. MDPI
4. Xiong, N., Li, M., Li, K., Xiao, Z., Liao, L., & Wang, L. (2023). *Multi-feature Short-Term Power Load Prediction Method Based on Bidirectional LSTM Network.* In: ICNC-FSKD 2022. Lecture Notes ... Springer.
5. Ke, K., Hongbin, S., Chengkang, Z., Sun, H., & Brown, C. *Short-Term Electrical Load Forecasting Method Based on Stacked Auto-encoding and GRU Neural Network.* Evolutionary Intelligence, 2019.
6. Bohara, B., Fernandez, R. I., Gollapudi, V., & Li, X. *Short-Term Aggregated Residential Load Forecasting using BiLSTM and CNN-BiLSTM.* arXiv preprint, 2023.

7. Dong, M., & Grumbach, L. S. *Hybrid Distribution Feeder Long-Term Load Forecasting Method Based on Sequence Prediction.* arXiv preprint, 2018.
8. In, Y., & Jung, J. Y. *Simple averaging of direct and recursive forecasts via partial pooling using machine learning.* International Journal of Forecasting, 2022.
9. *24-Step Short-term Power Load Forecasting Model Utilizing KOA-BiTCN-BiGRU-Attentions[v1].* Preprints.org, 2024.
10. Hybrid feature-based neural network regression method for load profiles forecasting. Energy Informatics, 2025.
11. G. Chevillon, "Direct multi-step estimation and forecasting," 2007. doi: 10.1111/j.1467-6419.2007.00518.x.
12. Abdurazakov, Nosirbek N., et al. "Feature Engineering for Short Term Residential Load Forecasting Using RNN-Based Neural Networks." *International Conference on Environmental Design, Material Science, and Engineering Technologies*. Cham: Springer Nature Switzerland, 2024.
13. Keras documentation on Time Distributed Layer. https://keras.io/api/layers/recurrent_layers/time_distributed/ .