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# Enhancing non-intrusive load monitoring with weather and calendar feature integration in DAE

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The construction of modern power system is key to achieving dual carbon goals, where non-intrusive load monitoring (NILM) plays a vital role in enhancing energy utilization efficiency and energy management. For example, to enable prosumers to better understand the extent of their flexible loads for demand response and peer-to-peer trading, it is essential to be aware of the types and states of loads using the method of NILM. To improve the predictive accuracy and implementation effectiveness of NILM technology, this paper proposes a novel NILM method integrating meteorological and calendar features. It delves deeply into the close connection between external factors such as temperature, precipitation, wind speed, and holidays, and the energy consumption of electrical appliances, constructing additional associative mappings in the training of the Denoising Autoencoder (DAE) model. Test results on the UK-DALE public dataset show that the NILM method proposed in this paper has significant advantages over traditional NILM methods that consider only single-dimensional electrical data features, in terms of load pattern recognition and accuracy in load energy consumption monitoring. This confirms the potential of multi-dimensional feature fusion technology in the application of NILM.

## KEYWORDS

deep learning, non-intrusive load monitoring, denoising autoencoder, weather feature, calendar feature

## 1 Introduction

With the advancement of smart grid technologies and the transformation of global energy structures, the construction of modern power system has become key to achieving decarbonization goals (Sepulveda, 2016). Modern power system leverages up-to-date information technology and communication technology to enable real-time monitoring and management of electrical appliances, characterized by digitalization and decentralization (Voropai, 2020). The characteristics of modern power system have promoted an interactive electricity consumption mode between grid operators and users, where load monitoring plays the critical role (Najmeddine et al., 2008; Abubakar et al., 2017). Load monitoring technology enables grid operators to better understand and predict load variations, optimizing the allocation and utilization of electric power resources.

By gaining deeper insights into user habits, this technology also aids in identifying opportunities for energy saving and emission reduction, thereby enhancing energy efficiency. Meanwhile, to facilitate prosumers in effectively gauging their variable load capacities, crucial for engaging in demand response and peer-to-peer transactions, knowledge about the variety and current conditions of loads is vital. The Hybrid Appliance Load Monitoring System (HALMS) represents a new field in load monitoring research, dedicated to accurately tracking and analyzing energy using at the device level. The establishment of this system is driven by the urgent need for a more connected, efficient electrical grid and an advanced energy infrastructure capable of meeting future energy challenges. With the rapid development of direct current microgrids, standalone energy systems, and distributed energy resources, deploying HALMS has become crucial for effective energy management (Suryadevara and Biswal, 2019).

The Appliance Load Monitoring (ALM) technology encompasses two approaches: Intrusive Load Monitoring (ILM) and NILM. ILM technology requires entering the interior of buildings or homes to gather data. The common approach is to install sensors and communication modules on each electrical device. Sensors are used to collect real-time electrical information of the device, such as current, voltage, and power, while communication modules are responsible for transmitting the collected data. On the other hand, NILM technology does not require entering the interior of buildings. It only involves collecting aggregated electrical information (current, voltage, power, etc.) of the building. By processing and analyzing the collected aggregated data, it is then possible to predict the operational status of the electrical devices inside the building, including the on/off status and power consumption of devices. The advantages and disadvantages of the ILM and NILM systems can be summarized below: ILM is more like straightforward engineering problem, as it only involves the collection and transmission of information without the need for complex computational processing. Furthermore, due to the direct collection of signals from the electrical devices themselves, ILM boasts high accuracy and real-time monitoring capabilities. However, the intrusive method requires the installation of additional transmission and collection devices on each electrical device, making the operation complex, costly, and maintenance difficult. Faults are hard to detect, and even if detected, they are difficult to locate. On the other hand, NILM requires the installation of only a few collection devices outside the building or home, significantly reducing costs compared to the intrusive method. The data collection operation is simpler, and the privacy inside the building is better preserved. However, since the non-intrusive method predicts the condition of electrical devices inside the building through collected aggregated information, its monitoring accuracy is not very high. In terms of practical application, given the large number of electrical devices within buildings, the cost and maintenance difficulties of the intrusive method make it less valuable. In contrast, the NILM system is much more cost-effective, and with the development of algorithms and the advent of neural networks, the accuracy of NILM systems has been increasing. Some models can even achieve real-time monitoring standards, making them increasingly valuable for practical applications.

In 1982, Professor Hart first introduced the concept of NILM. In the early stage, researchers mainly employed mathematical optimization algorithms to transform non-intrusive load

monitoring into a mathematical problem-solving exercise. This approach involves calculating the best combination of appliance signals from the aggregated signal data collected, aiming to closely match the actual total measured electricity power. Hart and his colleagues utilized combinatorial optimization algorithms to categorize electrical devices into multiple states, assigning a specific power value to each state. They were the first to propose a method based on the clustering of appliance characteristics for decomposing electrical loads (Hart, 1992). Reference (Lin et al., 2016) presents a NILM method based on quadratic programming to provide adequate load identification accuracy for residential energy monitoring. Reference (Kong et al., 2016) proposes a hierarchical hidden Markov model framework to model home appliances. The model provides better representation for those appliances that have multiple built-in modes with distinct power consumption profiles, such as washing machines and dishwashers. Reference (Chang et al., 2013) utilized particle swarm optimization techniques to optimize the parameters of training algorithms in artificial neural networks for NILM tasks. Reference (Lin and Tsai, 2013) combined transient feature extraction schemes of multi-resolution S transform with an improved 0–1 multi-dimensional knapsack algorithm for load identification, proposing a NILM method based on ant colony optimization algorithm for combinatorial search. Reference (Piga et al., 2015) assuming that the power consumption curves of unknown appliances are piecewise constant, framed the load decomposition problem as a minimization of least square errors, proposing a sparse optimization-based algorithm that provides very accurate estimates of appliance aggregate consumption and accurately characterizes the appliance power consumption curves. However, NILM based on mathematical optimization faces two major challenges: 1) When processing complex electrical load data, mathematical methods often encounter issues with accuracy and robustness, and struggle to perform real-time monitoring as the volume of data increases. 2) Mathematical methods require manual extraction of appliance features, posing challenges in the characteristic identification for electrical appliances with diverse types and multiple states.

As machine learning technology advances, many scholars have also begun to explore the resolution of NILM through pattern recognition methods. Reference (Rahimpour et al., 2017) introduces a Sum-to-k constrained Non-negative Matrix Factorization (S2K-NMF) approach, which represents the aggregated signal as a linear combination of basis vectors within a matrix decomposition framework. Reference (Lin and Tsai, 2014) proposes a novel NILM technique featuring a hybrid classification technology. This method combines fuzzy C-Means clustering, guided Particle Swarm Optimization, and a neural fuzzy classifier that considers uncertainty, addressing the issue of fuzziness in electrical characteristics. Reference (He et al., 2016) designs a NILM approach based on Graph Signal Processing (GSP), offering fresh perspectives for NILM research. Compared to optimization algorithms, these pattern recognition-based NILM algorithms have achieved improvements in identification accuracy. However, they transform the classification problem into a mapping relationship issue of input and output. With the increasing number of devices, the volume of mapping relationships rapidly grows, significantly reducing recognition accuracy.

With the advancement of deep learning technologies, algorithms based on deep neural network models have been proposed and applied to load decomposition, achieving performance superior to traditional optimization algorithms. These algorithms offer improved prediction accuracy and is capable of real-time monitoring in the face of massive data sets. Also, deep neural networks can automatically extract key features from electricity data, enabling intelligent recognition of electrical appliances. Kelly and others (Kelly and Knottenbelt, 2015a) were pioneers in solving the NILM problem using deep learning methods. They applied deep networks such as denoising autoencoders and Long Short-Term Memory (LSTM) networks to NILM tasks. Reference (Zhang et al., 2018) proposes sequence-to-point learning, where the input is a window of the busbar electricity data and the output is a single point of the target appliance. Researchers use convolutional neural networks to train the model and systematically show that the networks can inherently learn the characteristics of the target appliances, which are automatically added into the model to reduce the identifiability problem. Reference (Rafiq et al., 2018) presents two deep recurrent neural networks models: LSTM and GRU and introduces regularization to improve proposed models' performance. Researchers have achieved promising results with proposed regularized LSTM model in terms of accuracy, F1 score and mean absolute error. Reference (Yue et al., 2020) proposes BERT4NILM, an architecture based on bidirectional encoder representations from transformers (BERT) and an improved objective function designed specifically for NILM learning. With the adjusted loss function and masked training, BERT4NILM outperforms state-of-the-art models across various metrics on the two publicly available datasets UK-DALE and REDD. Inspired by the Fully Convolutional Networks (FCN) proposed by Shelhamer and others (Long et al., 2015), reference (Brewitt and Goddard, 2018) further introduced an FCN for sequence-to-subsequence learning, achieving better decomposition performance compared to S2P.

Although deep learning methods have achieved commendable results in NILM, existing algorithms still exhibit shortcomings in the aspect of feature extraction. Specifically speaking, current algorithms typically extract features solely from single-dimensional electrical data, such as active power (Dinesh et al., 2016), reactive power (Valenti et al., 2018), and current waveforms (Shareef et al., 2023), while overlooking the correlations of weather and calendar factors with the energy usage of electrical appliances. For instance, colder weather will increase the usage of heating appliances, and holidays generally lead to more energy consumption in household devices. This neglect of feature interrelation leads to an inadequate mapping between inputs and outputs, ultimately resulting in suboptimal prediction accuracy of deep learning models in NILM, thus influencing the effectiveness of load monitoring and energy management.

In this paper, advanced deep learning technology is utilized to conduct NILM research, employing the DAE as the main model. A notable innovation of this paper is the integration of weather and calendar information into the feature selection process, aiming to expand the application potential of deep learning methods in NILM. This approach overcomes the limitation of deep learning models in NILM that solely consider electrical data features. We explore the interrelation between weather, calendar information, and the energy consumption of electrical appliances. The UK-DALE public dataset is

selected as the testing platform for this study. The results demonstrate that our proposed NILM method with multi-dimensional features significantly outperforms traditional NILM methods that consider only single-dimensional electrical data features. This is evident in metrics such as the  $R^2$  score, Explained Variance Score, Mean Absolute Error (MAE), and Normalized Mean Square Error (NMSE), in the NILM performance of various household electrical appliances. NILM considering meteorological features, compared to NILM without such features, has an  $R^2$  Score increase of 0.008, an Explained Variance Ratio increase of 0.008, a decrease in MAE by 0.117, and a reduction in NMSE by 0.008 for the fan appliance test. For the kettle appliance, the inclusion of calendar features resulted in an increase of 0.008 in the  $R^2$  Score and 0.008 in the Explained Variance Ratio, while the Mean Absolute Error (MAE) decreased by 0.231, and the Normalized Mean Square Error (NMSE) decreased by 0.007. This study provides a novel perspective and tools for applying deep learning methods and selecting multi-dimensional features in NILM research.

## 2 Deep learning model architecture for NILM task

### 2.1 The basic autoencoder

An autoencoder processes an input vector  $x$  within the range  $[0, 1]^d$  by initially mapping it to a latent representation  $y \in [0, 1]^d$  using a deterministic function, with parameters given by weight matrix  $W$  and bias  $b$ , the formula is  $y = f_\theta(x) = s(Wx + b)$ . The resulting latent representation is then mapped back to a reconstructed vector  $z$  within the range  $[0, 1]^d$ , the corresponding formula is  $z = g_{\theta'}(y) = s(W'y + b')$ .  $W'$  equal to  $W^T$ , in which case the autoencoder is said to have tied weights. Each training  $x^{(i)}$  is thus mapped to a corresponding  $y^{(i)}$  and a reconstruction  $z^{(i)}$ . The parameters of this model are optimized to minimize the average reconstruction error (Vincent et al., 2008).

$$\begin{aligned}\theta^*, \theta'^* &= \underset{\theta, \theta'}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^n L(x^{(i)}, z^{(i)}) \\ &= \underset{\theta, \theta'}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^n L(x^{(i)}, g_{\theta'}(f_\theta(x^{(i)})))\end{aligned}$$

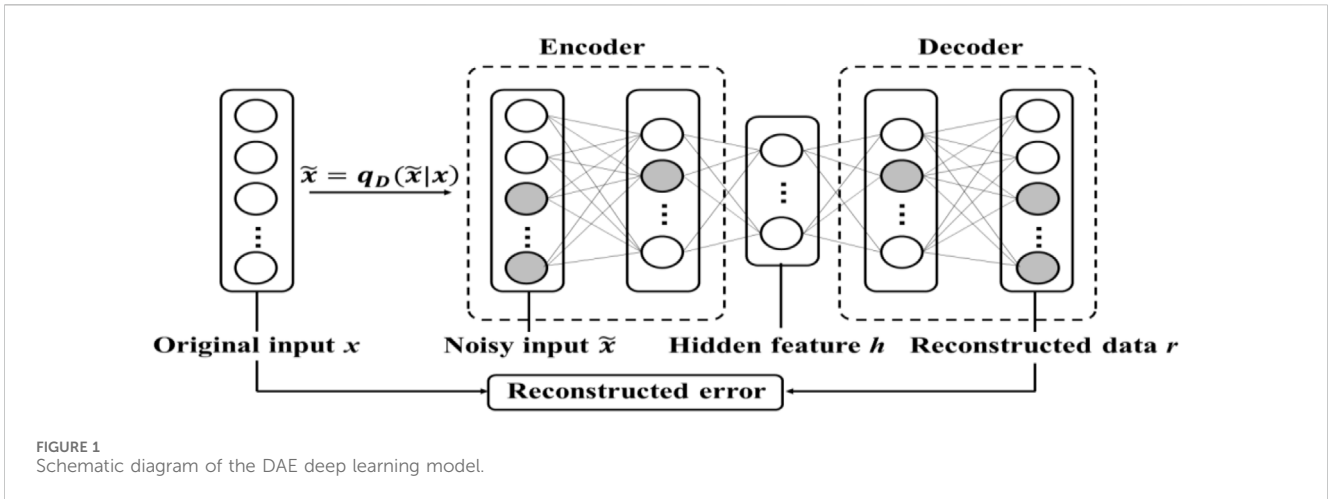
Where  $L$  represents the loss function. Considering  $x$  and  $z$  as bit vectors or vectors of bit probabilities, an alternative loss function proposed is the reconstruction cross-entropy.

$$L_H(x, z) = H\left(B_x || B_z\right) = -\sum_{k=1}^d [x_k \log z_k + (1 - x_k) \log (1 - z_k)]$$

If  $x$  is a binary vector,  $L_H(x, z)$  is a negative log-likelihood for the example  $x$ , given the Bernoulli parameters  $z$ . Equation with  $L = L_H$  can be written by:

$$\theta^*, \theta'^* = \underset{\theta, \theta'}{\operatorname{argmin}} E_{q^0(x)} [L_H(X, g_{\theta'}(f_\theta(X)))]$$

Where  $q^0(x)$  denotes the empirical distribution associated to our  $n$  training inputs. This optimization will typically be carried out by stochastic gradient descent.



## 2.2 The denoising autoencoder

DAE is an advanced neural network architecture that extends the traditional autoencoder (AE) concept. Unlike standard AEs that focus on learning compressed representations of input data through an encoder-decoder framework, DAEs introduce a significant twist: they are trained to reconstruct original, clean data from corrupted inputs, as shown in Figure 1. In this research, our selection of the DAE model instead of other models is driven by its specific advantages for the NILM task, particularly in handling noisy data and efficiently incorporating external features.

### 2.2.1 Input corruption process

The first step in DAE involves corrupting the original input data  $x$ . This is achieved through a stochastic process, which can be denoted as:

$$\tilde{x} = q_D(\tilde{x} | x)$$

Here,  $\tilde{x}$  represents the corrupted version of the original input  $x$ , and  $q_D$  is the corruption process.

### 2.2.2 Encoding process

The corrupted input  $\tilde{x}$  is then mapped to a hidden representation  $h$  using the encoder. The transformation is given by:

$$h = \sigma(W \cdot \tilde{x} + b)$$

Here,  $W$  represents the weight matrix of the encoder,  $b$  represents the bias vector of the encoder,  $\sigma$  represents non-linear activation function, using ReLU, and  $h$  represents encoded representation of the corrupted input.

### 2.2.3 Decoding process

The hidden representation  $h$  is transformed back to reconstruct the input data. The decoding transformation is:

$$r = \sigma'(W' \cdot h + b')$$

Here,  $W'$  represents the weight matrix of the decoder,  $b'$  represents the bias vector of the decoder,  $\sigma'$  represents the

activation function for the decoder, which is different from  $\sigma$ ,  $r$  represents the reconstructed data, aiming to be as close to the original uncorrupted input  $x$  as possible.

### 2.2.4 Loss function

The objective of the DAE is to minimize the reconstruction error. The loss function used is the Mean Squared Error (MSE):

$$L(x, r) = \|x - r\|^2$$

This function calculates the square of the Euclidean distance between the original input  $x$  and the reconstructed input  $r$ .

### 2.2.5 Optimization

The DAE model undergoes training through backpropagation and optimization algorithms to adjust the weights  $W$ ,  $W'$  and biases  $b$ ,  $b'$  to minimize the loss function. Backpropagation is a method used in artificial neural networks to calculate the gradient of the loss function with respect to the weights by propagating the error backward through the network. It helps in updating the weights to minimize the loss. Backpropagation computes gradients:

$$\frac{\partial L}{\partial W}, \frac{\partial L}{\partial W'}, \frac{\partial L}{\partial b}, \frac{\partial L}{\partial b'}$$

Stochastic Gradient Descent (SGD) is an optimization method used to update the weights and biases of a neural network iteratively. It calculates the gradient of the loss function for a randomly selected subset of data rather than the entire dataset, making the computation more efficient. SGD updates parameters:

$$W = W - \delta \frac{\partial L}{\partial W}$$

$$W' = W' - \delta \frac{\partial L}{\partial W'}$$

$$b = b - \delta \frac{\partial L}{\partial b}$$

$$b' = b' - \delta \frac{\partial L}{\partial b'}$$

Where  $\delta$  is the learning rate.

### 2.2.6 Feature extraction

Through this process, DAE learns to extract robust features from noisy data. The learned weights and biases encapsulate these features, which are crucial for tasks like NILM, where distinguishing between different appliance signatures from noisy aggregate data is essential.

Generally speaking, the application of DAE in NILM is rooted in their proficiency in handling and interpreting noisy, high-dimensional data. NILM tasks involve disaggregating total energy consumption into individual appliance loads, which is inherently a noisy and complex problem. The DAE's capability to denoise input data and extract relevant features is crucial in accurately identifying unique appliance signatures from aggregate energy data. This process involves not only recognizing patterns in the consumption data but also effectively filtering out irrelevant noise and distortions.

## 3 Experiments and results

### 3.1 Data preparation

#### 3.1.1 Electricity data preparation

The UK Domestic Appliance-Level Electricity (UK-DALE) dataset (Kelly and Knottenbelt, 2015b) is a significant resource in the field of NILM. It provides high-resolution energy usage data from domestic environments within the United Kingdom. This dataset is instrumental for us working on algorithms and models to disaggregate total energy consumption into appliance-specific usage. The key characteristics of UK-DALE is: 1) data granularity: UK-DALE offers exceptionally fine-grained power usage data, recorded at a 1/6 Hz temporal resolution. This enables detailed analysis of appliance usage patterns and energy consumption behaviors. 2) duration and diversity: The dataset encompasses a considerable duration, spanning from the year of 2012 to the year of 2015. It includes data from a diverse range of households, thus offering a broad perspective on domestic energy usage. 3) appliance-level detail: It provides disaggregated energy consumption data of five houses in London for individual appliances.

In this paper, four typical appliances from house one are selected: fan, solar thermal pumping, kettle, and dish washer, to investigate the effectiveness of NILM with single-dimensional feature and multi-dimensional features. The dataset for the deep learning model comprises the total electricity consumption data of house one and the consumption data of each appliance, spanning from 15 June 2013, to 20 July 2013. The training and testing sets are divided in a 4:1 ratio.

#### 3.1.2 Meteorological data preparation

The National Oceanic and Atmospheric Administration (NOAA), a key agency within the United States Department of Commerce, specializes in the study and monitoring of atmospheric and oceanic conditions. Known for its extensive meteorological data collection, NOAA is instrumental in weather forecasting, climate change research, and environmental stewardship. Its comprehensive data repositories, gathered through advanced monitoring technologies like satellites and radar systems, are invaluable for a myriad of scientific endeavors. For NILM research, NOAA's detailed

meteorological data is particularly useful, offering critical insights that can enhance the accuracy of energy usage predictions and analysis, especially in relation to environmental variables.

In this study, due to the location of house one in the UK-DALE dataset being in London, historical meteorological data from the ST JAMES PARK weather station in London was selected (NOAA National Centers for Environmental Information, 2013). ST JAMES PARK station is the nearest station to our test homes within the UK-DALE dataset that offers hourly resolution data encompassing temperature, precipitation, and wind speed. These data points are crucial for our study, and the completeness and clarity of the records at ST JAMES PARK made it the most suitable choice for our research needs. The temporal scope of the data extends from 15 June 2013, to 20 July 2013. The meteorological data types covered include temperature, precipitation, and wind speed. As depicted in Figure 2, during this period, the highest recorded temperature was 30°C, the maximum precipitation reached 71 mm/h, and the highest wind speed was 10.5 m/s.

Besides, due to the inconsistency in time scale of meteorological data and electricity data, we apply cubic spline interpolation to the meteorological data to generate interpolated values at a 6-s resolution, aligning with the electricity consumption data from the UK-DALE dataset. This method allowed us to construct a uniform time scale for both data types, ensuring that our DAE model could effectively incorporate and learn from the combined dataset.

#### 3.1.3 Calendar data preparation

The UK-DALE dataset explicitly specifies the time periods for the electricity data, allowing us to reference the British calendar for June and July 2013 based on these time stamps when conducting deep learning training and testing. This enables the determination of calendar data, including whether the day is a weekday or weekend, a holiday or not, the day of the week, and the week of the month. By selecting these calendar features, we can enrich and refine the original single-dimensional electricity feature.

## 3.2 Evaluation metrics

Assessment is carried out using R<sup>2</sup> Score, Explained Variance Score, Mean Absolute Error (MAE) and Normalized Mean Square Error (NMSE) as four evaluation metrics to compare the performance differences between NILM with multi-dimensional features and NILM with single-dimensional feature. We thoroughly evaluate their accuracy and ability to recognize load patterns.

#### 3.2.1 R<sup>2</sup> score

This metric is used to measure the degree to which the model explains the variance in the dependent variable. Its value ranges from 0 to 1, with values closer to 1 indicating better explanatory power of the model in terms of the dependent variable.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

Where  $n$  is the number of samples,  $y_i$  is the actual value,  $\hat{y}_i$  is the predicted value, and  $\bar{y}$  is the mean of the actual values.

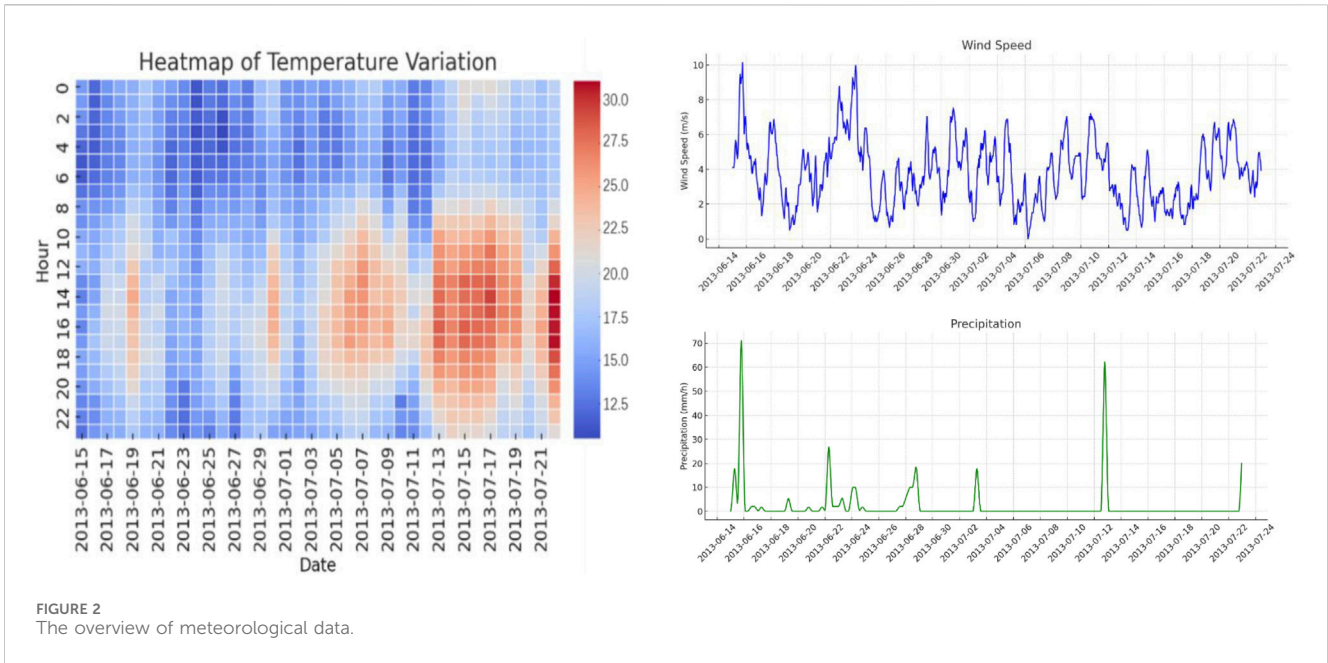


FIGURE 2  
The overview of meteorological data.

### 3.2.2 Explained variance score

This metric measures the degree to which the model explains the variance in the data. Its value also ranges from 0 to 1, with values closer to 1 indicating better explanation of the data variance.

$$EVS = 1 - \frac{\sum_{i=1}^n Var(y_i - \hat{y}_i)}{\sum_{i=1}^n Var(y_i)}$$

Where *Var* represents variance.

### 3.2.3 MAE

This metric measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

### 3.2.4 NMSE

This metric evaluates the predictive error of a model relative to the variance of the observed data. It is a normalized measure that provides insight into the error size in comparison to the variability of the dataset.

$$NMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (\hat{y}_i)^2}}$$

These metrics provide a comprehensive assessment of model performance, including aspects such as model explanatory power, data variance, and prediction error.

## 3.3 Results and discussion

Our experiments initially conducted a comparative study of the NILM implementation effects considering both meteorological and electrical features *versus* considering only electrical features. We selected fan and solar thermal pumping as the two types of electrical appliances and utilized the DAE as the deep learning model. As shown in Figure 3, the blue line represents the actual power consumption of the fan and solar thermal pumping in the test set, while the orange line represents the NILM effect considering both meteorological and electrical features. From the blue line, it is evident that the fan is used infrequently, and data analysis reveals that the fan is only activated at moments of higher temperature. On the other hand, the solar thermal pumping exhibits relatively regular power consumption. However, statistical data indicates that the duration and power consumption of solar thermal pumping are significantly higher on sunny days compared to rainy days. The orange line shows that NILM, when considering both meteorological and electrical features, can closely follow the actual power consumption and accurately predict the start and stop states of the fan and solar thermal pumping appliances. Although there are some minor deviations between the predicted power and the actual power, overall, this method has shown fairly good results in NILM tasks.

We also conducted a comparative study of NILM considering multi-dimensional (electricity and weather) *versus* single-dimensional (electricity) feature. Table 1 presents the results of NILM with and without weather features. The evaluation results indicate that NILM considering meteorological features (temperature, precipitation, and wind speed), compared to NILM without such features, has an R<sup>2</sup> Score increase of 0.008, an Explained Variance Ratio increase of 0.008, a decrease in MAE by 0.117, and a reduction in NMSE by 0.008 for the fan appliance

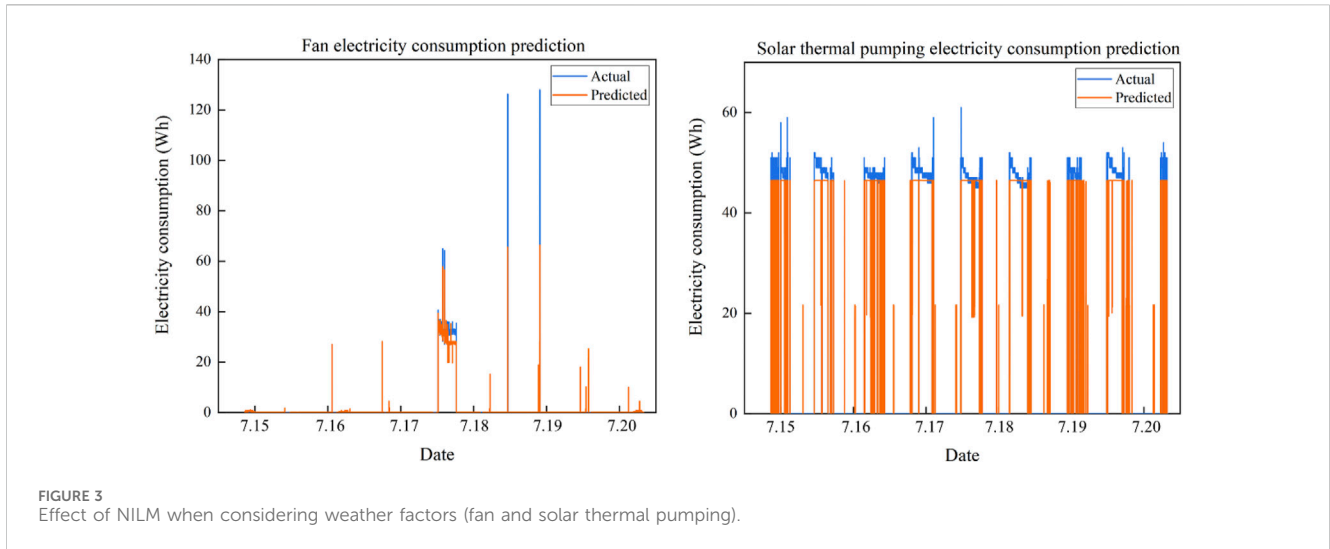


FIGURE 3 Effect of NILM when considering weather factors (fan and solar thermal pumping).

TABLE 1 Results of NILM with and without weather features.

	R <sup>2</sup> score	Explained variance ratio	MAE	NMSE
Fan with weather features	0.982	0.982	0.323	0.017
Fan without weather features	0.974	0.974	0.440	0.025
Solar thermal pumping with weather features	0.946	0.946	1.688	0.037
Solar thermal pumping without weather features	0.936	0.938	2.395	0.045

test. In the solar thermal pumping appliance test, NILM considering meteorological features saw a significant improvement in both R<sup>2</sup> Score and Explained Variance Ratio over NILM not considering meteorological features, with a notable decrease in both MAE and NMSE. This demonstrates that the NILM approach proposed in this study, which takes into account meteorological features, can achieve higher prediction accuracy and more precise non-intrusive load monitoring effects compared to traditional NILM methods.

Hence, from the above experiments, we can conclude that for the two types of electrical appliances, fan and solar thermal pumping, NILM that considers both meteorological and electrical features as opposed to just electrical features is better at capturing the characteristics of load variations, achieving superior prediction accuracy, and is more conducive to the implementation of energy-saving, emission reduction, and energy management strategies. The reason for this outcome is that traditional NILM, which only considers electrical features, overlooks the correlation between household electrical appliances and meteorological factors. Consequently, a deep learning model constructed solely from electrical features has an incomplete and insufficient mapping relationship between its inputs and outputs, thus limiting the predictive accuracy of NILM based on deep learning methods. By considering the three categories of meteorological features—temperature, precipitation, and wind speed—during feature selection, the model training can account for the relationship between meteorological factors and energy consumption, thereby better implementing NILM. This conclusion is not only applicable to the two types of typical electrical appliances proposed but also to high-power appliances such as air conditioners and

heaters in users’ homes. The novel NILM approach based on meteorological and electrical features can further enhance predictive performance over traditional NILM methods.

In our subsequent investigations, we expanded our focus to explore the effectiveness of NILM when integrating both calendar data and electrical consumption metrics as opposed to solely relying on electrical data. For this purpose, kettle and dish washer were chosen as the representative appliances, with DAE continuing to serve as our chosen deep learning framework. The data, as illustrated in Figure 4, reveals through a blue line the real-time consumption patterns of these appliances within the test dataset. In contrast, the orange line denotes the outcomes of NILM when it synthesizes information from both calendar events and electrical usage. A notable observation from the blue line is the heightened use of these appliances, particularly during holidays, suggesting a marked uptick in energy usage compared to regular workdays. The orange line, on the other hand, showcases NILM’s adeptness at mirroring these consumption patterns, precisely indicating the operational status of kettle and dish washer. While minor variances are noted between the forecasted and actual energy usage, the overall results point to the robustness and effectiveness of this approach in NILM applications, especially in capturing regular energy use behaviors linked to calendar-specific influences.

Table 2 presents the results of NILM implementation with and without calendar features. For the kettle appliance, the inclusion of calendar features resulted in an increase of 0.008 in the R<sup>2</sup> Score and 0.008 in the Explained Variance Ratio, while the Mean Absolute Error (MAE) decreased by 0.231, and the Normalized Mean Square

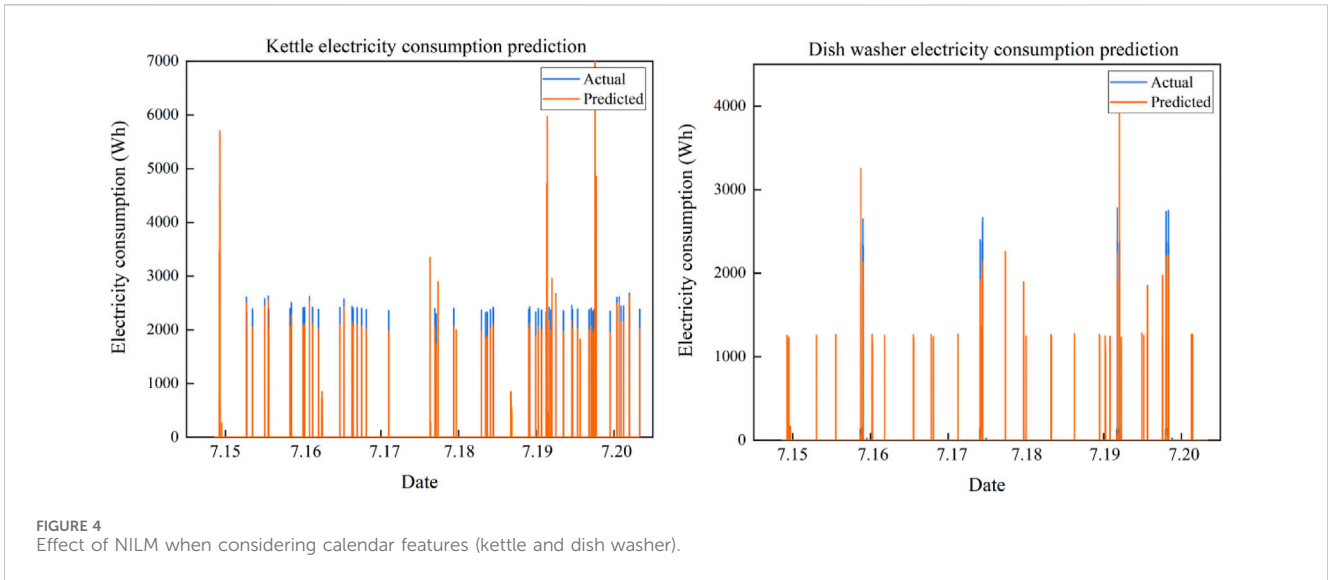


TABLE 2 Results of NILM with and without calendar features.

	R <sup>2</sup> score	Explained variance ratio	MAE	NMSE
Kettle with calendar features	0.834	0.834	7.349	0.165
Kettle without calendar features	0.826	0.826	7.118	0.172
Dish washer with calendar features	0.735	0.736	11.543	0.262
Dish washer without calendar features	0.731	0.731	11.618	0.267

Error (NMSE) decreased by 0.007. In the case of the dish washer appliance, incorporating calendar features led to an increase of 0.004 in the R<sup>2</sup> Score and 0.004 in the Explained Variance Ratio, with a decrease of 0.075 in MAE and 0.005 in NMSE. This demonstrates that for these two types of appliances, considering calendar features enhances the accuracy and reliability of NILM implementation, marking a significant advancement over traditional NILM methods.

In summary, NILM implementation considering calendar features further captures the relationship between users' daily routines and power consumption of electrical appliances. During holidays and weekends, users spend more time at home compared to workdays, leading to more frequent use of various household appliances and consequently higher electricity consumption. This conclusion is not only applicable to kettle and dish washer appliances but also extends to a broader range of household devices.

It is evident that the improved NILM method outperforms the traditional approach across all evaluation metrics for the four types of electrical appliances we focused on (fan, solar thermal pumping, kettle, and dish washer). In fact, the start-stop actions and energy consumption of household appliances are closely linked to user activities, which in turn are significantly influenced by external factors. Therefore, our proposed NILM method, incorporating meteorological and calendar features, can more comprehensively capture the factors influencing household appliance energy consumption and accurately establish correlations. By conducting

training and testing in this manner, we achieve superior load monitoring results compared to the traditional NILM approach.

## 4 Conclusion

The NILM method proposed in this paper, integrating meteorological and calendar features, surpasses traditional non-intrusive load monitoring techniques in capturing load characteristics and establishing comprehensive energy consumption correlations for tested appliances. Specifically, for the fan, enhancements include a 0.008 increase in both R<sup>2</sup> Score and Explained Variance Ratio, with MAE decreasing by 0.117 and NMSE by 0.008. For the kettle, the addition of calendar features similarly boosts the R<sup>2</sup> Score and Explained Variance Ratio by 0.008 each, while MAE and NMSE decrease by 0.231 and 0.007, respectively. This approach offers a novel perspective and tools for research in the NILM domain and provides more reliable and efficient technical support for energy management and demand response in smart grids.

In future research, we will consider integrating the NILM software algorithms proposed in this paper with advanced hardware measurement technologies (such as smart plugs) to further enhance the effectiveness and capabilities of load monitoring. Smart plugs act as a complementary innovation, improving the cost-effectiveness and precision of energy monitoring. The potential functions of smart plugs to benefit load monitoring and management include (Suryadevara and Biswal, 2019): 1) device identification. 2) device



scheduling and control. 3) occupancy detection. 4) thermal and overload safeguards. By combining advanced software algorithms with hardware devices, we will achieve improved energy management efficiency.

## Data availability statement

The original contributions presented in the study are included in the article/[Supplementary Material](#), further inquiries can be directed to the corresponding author.

## Author contributions

ZP: Conceptualization, Data curation, Investigation, Methodology, Software, Supervision, Writing—original draft, Writing—review and editing. YH: Formal Analysis, Funding acquisition, Project administration, Resources, Validation, Visualization, Writing—original draft, Writing—review and editing. MW: Writing—original draft, Writing—review and editing. YM: Writing—original draft, Writing—review and editing. YZ: Writing—original draft, Writing—review and editing. GH: Writing—original draft, Writing—review and editing.

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## Conflict of interest

Authors ZP and YH were employed by Electric Power Research Institute of Guizhou Power Grid Co., Ltd. Authors MW and YZ were employed by Guiyang Power Supply Bureau of Guizhou Power Grid Co., Ltd. Author YM was employed by Duyun Power Supply Bureau of Guizhou Power Grid Co., Ltd.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenrg.2024.1361916/full#supplementary-material>

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