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Predicting Power Consumption with an Asymmetric Loss and Anomaly Detection Long Short-Term Memory (LSTM) Framework

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Abstract—

To avoid unwelcome power outages caused by insufficient power output, it is critical to construct a reliable load forecasting model with few underpredictions. It is difficult to anticipate household power consumption trends due to the presence of fluctuations and anomalies in this sector. As a means of increasing the penalty for underpredictions, this study suggests a number of Long Short-Term Memory (LSTM) frameworks that use various asymmetric loss functions. Before the load forecasting work, we additionally use a density-based spatial clustering of applications with noise (DBSCAN) anomaly detection technique to get rid of any existing oultiers. Hourly power consumption, weather, and calendar characteristics are part of the three datasets from France, Germany, and Hungary that are subject to seasonality splitting in order to account for the impact of social and meteorological elements. Relocating the outliers effectively lowers the underestimation and overestimation errors across all seasonal datasets, according to root-mean-square error (RMSE) statistics. Furthermore, seasonality splitting and asymmetric loss functions successfully reduce underestimations while slightly raising the overestimation error. In order to avoid potentially disastrous power outages, it is crucial to decrease underestimations of electrical usage.
Index Terms—Anomaly detection, asymmetric loss, DBSCAN, LSTM, seasonality.

INTRODUCTION

Natural resources have been depleted and pollution has worsened due to the dramatic growth in power usage over the last decade. Consequently, there have been extensive efforts to curb the generation of excessive amounts of power [1]. Avoiding power failures and blackouts—which may slow down economic and industrial growth [2] and possibly lead to horrible situations—remains vital, notwithstanding the significance of preventing overproduction of energy. As an example, Lebanon had a severe power outage in 2021, which caused a serious problem in hospitals and other vital sectors. Power companies are always looking for ways to improve their load forecasts and energy use plans in order to prevent electricity from being under- or overproduced [3]. Several machine learning algorithms have been employed in previous work on power consumption estimates, including Recurrent Neural Networks (RNN) [4], the Long Short-Term Memory (LSTM) algorithm [3, 5], or a combination of ANN and SVM approaches [7]. By default, symmetric cost functions are what machine learning models often strive to reduce. When the effects of under- and overestimations are comparable, such loss functions tend to work effectively. To account for the fact that underestimations might have worse outcomes than overestimations in some contexts, several researchers have constructed models with asymmetric goal functions to provide additional leeway [8] [13]. The underpredictions in the power consumption estimate situation, which academics are more concerned in minimizing, are given greater weight due to this imbalance. To avoid an unwelcome power outage or the need to buy power in an emergency, it is best to maintain the produced power slightly higher than the power demand [12], [13]. Power consumption patterns, particularly in the residential sector, are known to fluctuate, making power consumption forecasting a tough task [5]. Climate and societal factors both have a role in these variations [14]. Anomalies or odd numbers in power consumption patterns may also occur as a result of inaccurate measurements, faulty data collection, or uncommon occurrences [15]. According to the authors of [4], the model's error has grown due to the existence of outliers. Our goal in this effort is to make household power consumption forecasts more accurate by lowering the margin of error and doing away with extreme cases. See "Fig. 1" for a visual representation of the suggested structure.

We begin by merging the weather and calendar information with the hourly power usage datasets [16]. Every multi-feature dataset was then divided into three seasonal datasets in order to account for the seasonality component. Next, the power consumption characteristic is subjected to anomaly identification utilizing the density based spatial clustering of applications with noise (DBSCAN) method [15]. To improve the findings, the discovered outliers are replaced with more reasonable numbers. At last, three different LSTM models are given the seasonal datasets: one standard LSTM model with a symmetric loss function, and two LSTM models, one for each season, with their own distinct asymmetric loss function. Both the underestimation and overestimation root-mean-square errors (RMSEs) are used to assess these models. The suggested anomaly identification and replacement method reduced the over- and under-prediction errors across all seasonal datasets, according to the results. In addition, the seasonality splitting and the suggested asymmetric loss functions successfully reduced the underestimating error, but significantly enhanced the overestimation error as compared to the symmetric loss. This work contributes by (1) studying how different asymmetric loss functions integrated into LSTM architectures limit underpredictions and improve load forecasts with and without outliers and (2) studying how seasonality affects the load estimation task. Here is how the rest of the paper is structured: Section II provides an overview of relevant literature, Section III lays out the technique, and Section IV details the experiments and delivers the findings. As a last section, Section V. II. presents the results, limits, and recommendations for further research.

RELATED WORK

Many academics have addressed the idea of asymmetric loss, particularly in the context of forecasting applications [8] [13]. In [9], a support vector regression (SVR)-based load forecasting system with an asymmetric linear-linear cost was presented. The economic cost was lowered by a range of 42.19% to 57.39% [9] due to the application of insensitive costs, which include various penalties for over- and under-predictions. Reducing underestimates in load forecasting was achieved in [12] by using a quadratic and asymmetric loss function based on SVR. While the average error rate increased by only 0.3 percentage points, the underpredictions fell from 50% to 1.91% [12]. One more cost-conscious method for load forecasting used a Huber function-based differentiable piece-wise loss [11]. By combining ANN with Multiple Linear Regression (MLR), this cost-oriented approach demonstrated encouraging outcomes in accurately capturing actual costs, particularly in ANN, where it outperformed normal mean squared error (MSE) by 13.74% [11]. For predictive maintenance situations, an asymmetric loss function was suggested in [8] to account for the varying costs of problem detection and premature repair. The loss function, which is linear for overestimates and exponential for underestimates, led to a machine learning model that better reflects real-world business scenarios [8]. Several deep learning models, including Bidirectional LSTM (Bi-LSTM), Deep Neural Networks (DNN), and one-dimensional Convolutional Neural Networks (CNN), were tested using asymmetric loss functions (including quadratic, linear, and logarithmic quadratic formulations) in the study by the authors of [10]. One benefit of using asymmetric loss functions is that they make it easier to estimate how much life an engine has left [10]. By comparing LSTM with other algorithms like SVM and Random Forest (RF), the authors of [4] demonstrated that LSTM with two layers got the lowest RMSE of 11.4299 for predicting the short-term power usage. They noted that the RMSE is still significant because of data abnormalities, even after data preparation was done [4]. In order to identify these outliers in datasets of power consumption, one technique was presented in [17] that used micro-moments and DNN for detection, while another way was introduced in [18] that used a combination of polynomial regression and Gaussian distribution. In order to distinguish between normal and abnormal power consumption patterns, the DBSCAN algorithm was used during the data preparation step in [19]. Next, in order to get more reliable predictions, a hybrid model was trained using a one-dimensional CNN and a Bi-LSTM. Results showed that this method performed well on many assessment parameters when evaluated on a dataset of homes and commercial buildings [19]. Better load forecasting and the elimination of anomalies have so far been the focus of several efforts. Those who wanted to reduce underestimation mistakes used asymmetric loss functions. However, as far as we are aware, the field of power consumption estimation has not yet included both asymmetric loss functions and anomaly detection. To eliminate outliers, the power consumption datasets are processed using the DBSCAN method [16]. Subsequently, the cleaned datasets are input into several LSTM models, which examine different asymmetric goal functions in an effort to decrease underpredictions. Datasets are also divided according to the seasonality factor, and other variables are incorporated to enhance the load forecasting capabilities of the models.

METHODOLOGY

In this work, we begin by separating the power consumption information into three multi-variant seasonal datasets and then removing any noisy data from the combined weather and calendar records. The next step is to predict

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power consumption using a combination of symmetric and asymmetric loss functions from several LSTM algorithms. The goal is to improve prediction accuracy while minimizing underestimation in the load forecasting assignment. Here we take a look at the datasets that were a part of this research, the process for detecting and replacing anomalies, and the various asymmetric loss functions that were utilized. Sets of data We selected three independent datasets on household electricity usage from Germany, France, and Hungary for our study. The European power data portal ENTSO-E Transparency provides these datasets [16]. The hourly power is included in each dataset as a time-series.

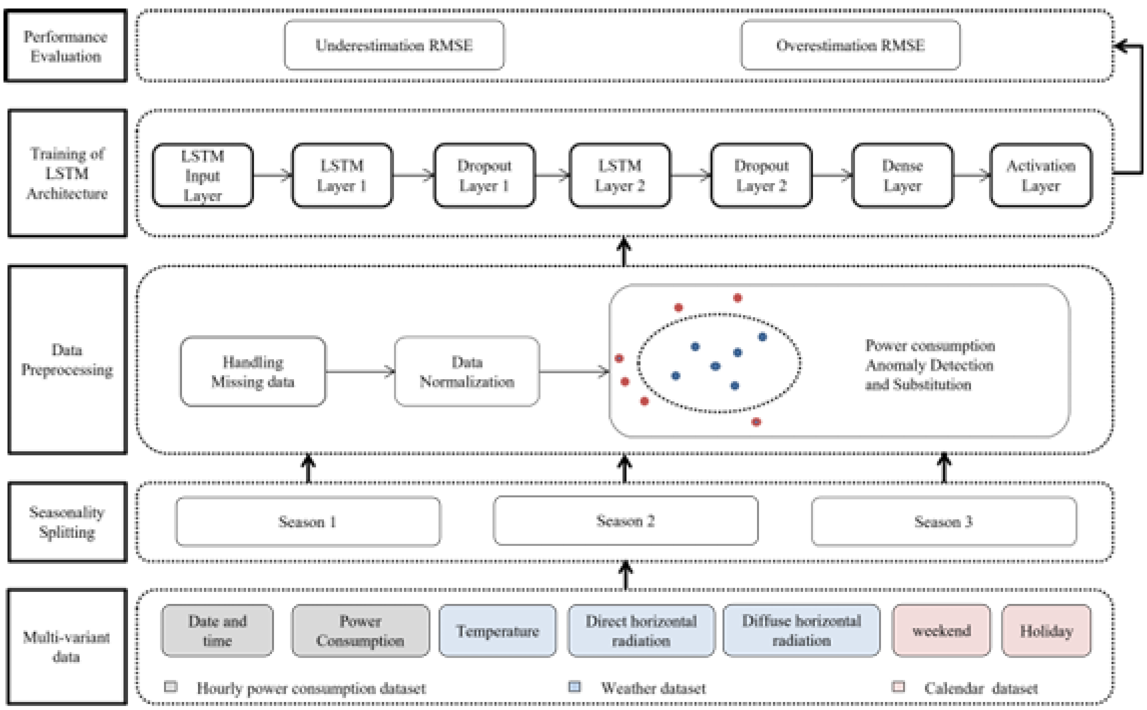

Fig. 1. System framework for power consumption estimation. consumption

starting in 2015 and ending in 2019. To account for the societal and climatic impacts on the electric load, we increased each area's hourly power consumption: This country's weather dataset [16] includes temperature, diffuse horizontal radiation, and vertical radiation; it was retrieved by Renewables.ninja from the NASA MERRA 2 reanalysis. A national calendar dataset containing two months' worth of data: weekends and holidays (with 1 denoting weekends and holidays and 0 denoting ordinary weekdays). In order to better understand the data's seasonal patterns, we split each dataset into three seasonal subsets: Start of Season 1: January – mid-April. Second season: starting in the middle of April and running until the middle of October. October to December marks the third season. B. Finding and Replacing Abnormalities To overcome power consumption anomalies in each seasonal dataset, a standard preprocessing step was taken, which included normalizing the data using the Robust Scaling method and handling missing values. Then, an anomaly detector based on the DBSCAN technique [15] was applied. To demonstrate the efficacy of the anomaly identification method, we manually introduced extra outliers into all of the German and Hungarian seasonal datasets, as there were initially only a small number of them discovered in the power consumption characteristic of the datasets under consideration. Two scenarios were examined, whereby each seasonal dataset had an outlier count of 1% or 2% of the total data points. Because outliers are caused by random occurrences like poor weather or inaccurate measurements, these extra outliers were either added during periods of terrible weather or on dates that didn't make sense. Following the addition of the outliers, the anomaly identification and replacement procedure was used to identify and replace the outliers with their corresponding values in the updated seasonal datasets. The fact that DBSCAN, a clustering method, does not need initializing the number of clusters is one of its benefits. The algorithm sorts the data points into clusters. A maximum neighborhood radius (eps) and a minimum number of samples inside that radius are its sole parameters. Following the implementation of this clustering method, any data point that did not fall into the main cluster (designated as 0) or coincide with a holiday was considered an outlier and its value was substituted with the power consumption value from the preceding week for the same day and hour. But if last week's data point was likewise out of the ordinary or fell on a holiday, we kept going backwards in the same way until we found one that was good enough. Loss Functions that are not symmetrical Our primary goal in this effort is to decrease underestimations and improve forecast accuracy. Therefore, in order to decrease the underestimation mistake, we suggest using the idea of asymmetry to severely punish underpredictions. Different penalties are suggested for overestimates and underestimates in two asymmetric loss functions. For overpredictions and underpredictions, two separate Huber-loss functions are used to build the first asymmetric loss function, AL1. In addition to severely punishing under-estimations relative to over-estimations, the goal of this design is to

$$Underest\_Loss_1 = \begin{cases} a \cdot |E|, & \text{if } -1 < E \leq 0 \\ a \cdot |E|^2, & \text{if } E \leq -1 \end{cases}, \quad (1)$$

$$Overest\_Loss_1 = \begin{cases} b \cdot |E|^2, & \text{if } 0 < E < 1 \\ b \cdot |E|, & \text{if } E \geq 1 \end{cases}, \quad (2)$$

$$Loss_1 = \frac{\sum Underest\_Loss_1 + \sum Overest\_Loss_1}{Total\ number\ of\ estimates}, \quad (3)$$

This is defined as the difference between the actual and expected power consumption at time t, with a and b being constants such that a > b. An insensitive Huber loss function is used for overpredictions in the second asymmetric loss function AL2, while a linear loss function is employed for underpredictions in the first. Furthermore, it uses distinct penalties for overestimates and underestimates, with the underestimation penalty being greater than the overestimation penalty. Nevertheless, there is a consistent penalty for all underestimations. The catch with AL2 is that it uses a Huber loss strategy to penalize larger overprediction mistakes non-uniformly, while letting under-1 overprediction errors stay unaffected. The following examples show the AL2 formulation:

$$Underest\_Loss_2 = a \cdot |E|, \text{ if } E < 0, \quad (4)$$

$$Overest\_Loss_2 = \begin{cases} 0, & \text{if } 0 \leq E < \epsilon_1 \\ b \cdot |E|^2, & \text{if } \epsilon_1 \leq E < \epsilon_2 \\ b \cdot |E|, & \text{if } E \geq \epsilon_2 \end{cases}, \quad (5)$$

$$Loss_2 = \frac{\sum Underest\_Loss_2 + \sum Overest\_Loss_2}{Total\ number\ of\ estimates}, \quad (6)$$

where a, b, and E are defined as previously and $\epsilon_1 < \epsilon_2$.

EXPERIMENTS AND RESULTS

four, five, six We did many trials on the three datasets from Germany, France, and Hungary to see how well the suggested method worked. The underestimation RMSE and overestimation RMSE were computed to assess the model's performance, and every LSTM method was run on every testing set. Important findings and information about the experimental setup are presented in this section. I. Experimental Establishment The following settings were selected for the DBSCAN algorithm to identify the outliers: A radius of 0.11 was chosen for the neighborhood

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eps, and a minimum of 3 samples were required inside that radius. Following the anomaly identification and replacement technique, a four-width sliding window was used to arrange every seasonal dataset into sequences. Next, the sequences from each dataset were divided into two parts: one for training, which included data from 2015 to 2018, and another for testing, which included data from 2019 onwards. Next, several LSTM algorithms were trained using the training sequences to predict the hourly power usage, allowing enabling short-term load forecasting. The input layer, two LSTM and Dropout layers, dense and activation layers, and lastly the output layers made up all of the LSTM models. Using the Adam optimizer, each model was trained for 100 epochs. We ran this approach on every dataset using every LSTM model, regardless of whether they used symmetric or asymmetric loss functions. To give more weight to underestimations than overestimations, the parameters of AL1 and AL2 were adjusted to a = 5 and b = 2, respectively, after many rounds of hyper-parameter tuning. AL2 also used heuristics to choose 1 and 2 as 0.005 and 0.01 correspondingly. Lastly, we compare the findings obtained using an asymmetric loss function to those obtained using a symmetric MSE loss function in order to test the hypothesis that asymmetric loss functions may reduce underpredictions. In addition, we examine the performance of all the LSTM models with and without seasonality splitting to evaluate the benefits of data splitting into three seasons. As a last step in assessing the suggested anomaly detection method, we compare the LSTM algorithms' performance with and without the anomaly detection and substitution strategy. B. Analysis and Interpretation In order to investigate the effects of the suggested asymmetric loss functions, we compare their performance to that of a symmetric MSE loss function. Compared to the underestimation RMSE of the symmetric loss function in seasons 1, 2, and 3, the underestimation RMSE of the asymmetric loss function AL1 in the French dataset decreased by around 86%, 80%, and 91%, respectively. However, when comparing the underestimation RMSE of the symmetric loss to that of the asymmetric loss function AL2 over the same three seasons, the underestimation RMSE dropped by around 63%, 47%, and 70%, respectively. Figures 2 and 3 show that compared to the symmetric loss function in the French house in season 1, the underestimation RMSE decreases when AL2 is used, and it decreases much more when AL1 is applied. It is worth noting, nonetheless, that the symmetric loss function has a lower overestimation error than the asymmetric loss functions, with AL1 having the largest overestimation error. In both the 1% and 2% additional outlier cases, we compared the LSTM models' performance before and after applying the anomaly detection technique to the seasonal datasets from Germany and Hungary, respectively. We also evaluated the effectiveness of various loss functions. In Table I, we can see the underestimation errors of the suggested loss functions averaged across the three seasonal datasets from Germany, and in Table II, we can see the overestimation errors of the same functions after eliminating the anomalies. Using the symmetric loss, AL1, and AL2 respectively, reduced the underestimating RMSE by 56%, 85%, and 69% after deleting the discovered anomalies in the 1% scenario in the German datasets. Likewise, there was a 66%, 78%, and 80% reduction in the underestimate RMSE,

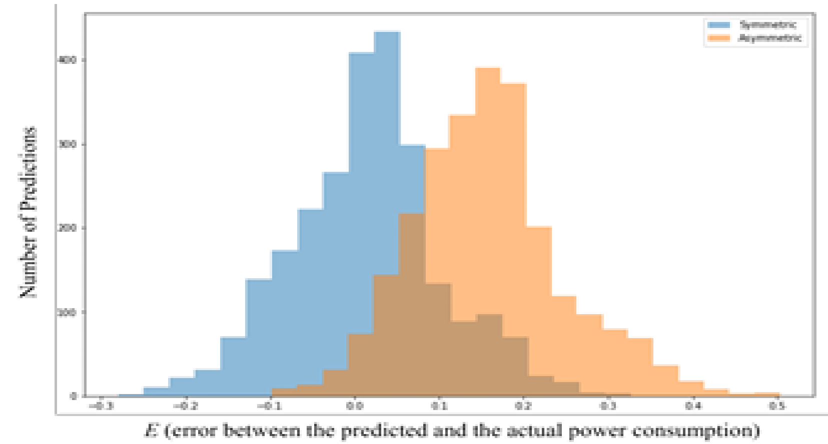

Fig. 2. Histogram of the error for the symmetric loss and asymmetric loss AL_1 in the case of the French residence dataset in season 1.

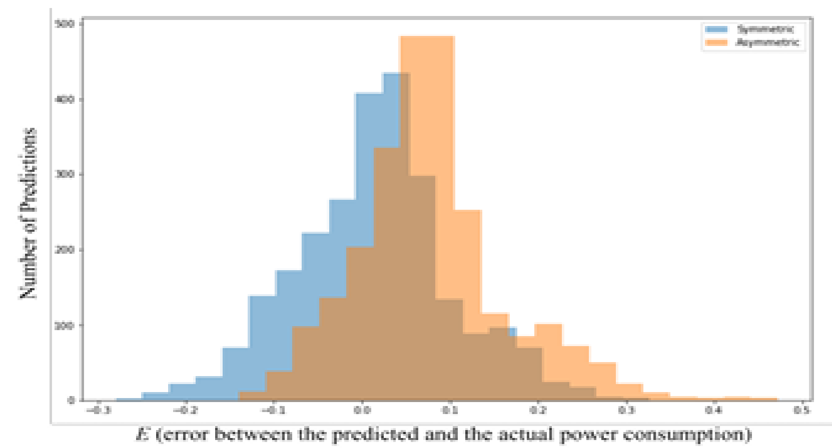

Fig. 3. Histogram of the error for the symmetric loss and asymmetric loss AL_2 in the case of the French residence dataset in season 1.

Fig. 3. Histogram of the error for the symmetric loss and asymmetric loss

Using the symmetric loss, the Hungarian datasets show a 2% Asymmetric loss, 0.584 2% Asymmetric loss after eliminating the 1% extra anomalies, and 75% Asymmetric loss overall in the first season of the French residency dataset. Not only that, for 0.78 0.128 0.141 0.373 0.381 0.136 0.143, the overestimation RMSE decreased by 47%, 16%, and 38% in the German datasets, and by 59%, 64%, and 54% in the Hungarian datasets, respectively. In terms of asymmetric loss, AL2 is 1%, 0.378 is 2%, 0.445 is 0.093, 0.214 is 0.099, and 0.098 is the symmetric loss, AL1. In contrast, after the 2% anomaly removal in the German datasets, the underestimation RMSE for the symmetric loss, AL1, and AL2 fell by 60%, 86%, and 68%, respectively, while the overestimation RMSE fell by 46%, 21%, and 33%. Once the 2% injected anomalies were removed from the Hungarian datasets for the symmetric loss, the RMSE for underestimation fell by 72%, 83%, and 78%, while the RMSE for overestimation fell by 62%, 57%, and 57% for the various loss functions that do not account for seasonality splitting. The French dataset was selected for this examination because it seems that the seasonality element has a significant impact on the trajectory of power consumption in France. Underestimation errors AL1 and AL2 would be the same in the absence of seasonality separation. By comparing the models' output before and after seasonality splitting, we also hoped to examine the impact of factoring in seasonality. Table III displays the mean underestimation and overestimation errors throughout all three seasons in the French dataset subjected to seasonality splitting, as well as the underestimation and overestimation errors

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ABLE I UNDERESTIMATION AND OVERESTIMATION RMSE OF THE THREE LOSS FUNCTIONS AVERAGED OVER THE THREE SEASONAL DATASETS OF GERMANY BEFORE AND AFTER ANOMALY DETECTION FOR THE TWO CASES OF ADDITIONAL OUTLIERS.

Percentage of outliers	Underestimation RMSE (average)		Overestimation RMSE (average)	
	With outliers	Without outliers	With outliers	Without outliers
Symmetric loss				
1%	0.154	0.068	0.121	**0.064**
2%	0.163	0.066	0.116	**0.063**
Asymmetric loss AL_1				
1%	0.424	**0.062**	0.167	0.141
2%	0.445	**0.063**	0.174	0.138
Asymmetric loss AL_2				
1%	0.209	0.065	0.127	0.079
2%	0.206	0.066	0.128	0.086

TABLE II 0.128 0.086 UNDERESTIMATION AND OVERESTIMATION RMSE OF THE THREE LOSS FUNCTIONS AVERAGED OVER THE THREE SEASONAL DATASETS OF HUNGARY BEFORE AND AFTER ANOMALY DETECTION FOR THE TWO CASES OF ADDITIONAL OUTLIERS.

Percentage of outliers	Underestimation RMSE (average)		Overestimation RMSE (average)	
	With outliers	Without outliers	With outliers	Without outliers
Symmetric loss				
1%	0.311	0.107	0.205	**0.085**
2%	0.383	0.106	0.219	**0.095**
Asymmetric loss AL_1				
1%	0.584	**0.128**	0.373	0.136
2%	0.78	**0.141**	0.381	0.143
Asymmetric loss AL_2				
1%	0.378	0.093	0.214	0.099
2%	0.445	0.098	0.253	0.108

mation mistakes for each loss function in the absence of seasonality splitting. The French dataset was selected for this examination because it seems that the seasonality element has a significant impact on the trajectory of power consumption in France. Underestimation errors AL1 and AL2 would be the same in the absence of seasonality separation. By comparing the models' output before and after seasonality splitting, we also hoped to examine the impact of factoring in seasonality. In table III, we can see that the average underestimation and overestimation errors for the three seasons in the French dataset when seasonality splitting is used are 0.042 and 0.009, respectively. When AL1 and AL2 are used, the underestimation and overestimation errors are 0.019 and 0.042, respectively. As compared to the symmetric loss, this suggests that AL1 reduces underestimates by around 79% and AL2 reduces them by about 55%. In contrast, compared to the symmetric loss, the underestimate RMSE with AL1 was around 87% lower and with AL2 it was about 62% lower throughout the course of the three seasons. Therefore, in both AL1 and AL2, the model that learnt to minimize underestimations also learned to maximize overestimation errors following seasonality splitting. Finally, it should be mentioned that in all the datasets that were taken into consideration, AL1 performed better than AL2 in this regard, although both asymmetric loss functions were able to decrease the underpredictions. Nevertheless, when comparing AL1 and AL2, the overestimation error is larger in the former. Their unique structures might be the cause of such behavior: Underestimations were more severely punished by AL1 than overestimations, but AL2 was less harsh. Not only that, but the three loss functions all had their underestimation errors reduced by the anomaly detection and replacement strategy, with AL1 showing the greatest improvement. Lastly, the seasonality splitting mitigated underestimations while somewhat amplifying overestimations.

CONCLUSION

Underestimations in the power consumption estimate job using an LSTM model are addressed in this study by proposing two asymmetric loss functions, AL1 and AL2. The findings showed that the underprediction error was decreased by the suggested asymmetric loss functions, with the best drop being achieved with AL1. Both AL1 and AL2 saw a rise in the overprediction error, while AL1 had the largest spike. In addition to the load estimate, a clustering method was used to identify outliers in the power consumption data. All of the LSTM models improved their load forecasts after replacing the discovered outliers with more reasonable values. Furthermore, the underprediction error in the French sample was helped by the seasonality component. After the seasonality splitting, however, both asymmetric loss functions showed a little rise in the overstimation error. Although the suggested asymmetric loss functions were successful in significantly lowering underestimations, they were unable to rein in overestimations. Perhaps in the future researchers will try to refine these asymmetric loss functions such that they produce less overestimations and less underestimations overall.

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