Short Term Forecasting of Power Quality Distortions in Electrical Energy Systems with LSTM and GRU Networks

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Abstract

Technological development has led to a diversification of loads in transmission and distribution systems. The rise of non-linear loads in the system is one of the biggest effects of this variation as semiconductor technology develops. Nonlinear loads are characterized by current and voltage characteristics that are not purely sinusoidal, also known as harmonics. Harmonics cause the system insulation to degrade and increase energy loss. Therefore, it's crucial to get rid of harmonics before they occur. This study intends to lower the risk of distribution system damage by employing complex harmonic forecasting methods. An RNN-based forecasting algorithm has been created by using actual system power quality data obtained from the Organized Industrial Zone in Bandırma, Turkey. Parameters that are most likely to be neglected in simulation studies are also taken into account in the calculation by using actual data. Active power data, current harmonic data and calendar data were used together to design harmonic forecasting model. Graphs and calculations were used to discuss the results. The obtained minimum values of the RMSE, MAE, and MAPE are 2,116, 0,666 and 11,619, respectively. The convergence as a result of these calculations has allowed high forecasting performance of power quality distortions.

Keywords: Power Quality, Power System Protection, Harmonic Forecasting, Long-Short Term Memory, Power System Analysis.

Nomenclature

θ_n, φ_n : phase angle; x_t : input vector; h_t : output vector; $\hat{h}_t$: activation vector; z_t : update-gate vector ; r_t : reset-gate vector; W,U : parameter matrices; b : vector

1 Introduction

The transmission and distribution network operators' top priorities include providing continuous and uninterrupted energy as well as high-quality energy while avoiding any negative consequences from the facilities. In a precise alternating current power system, electrical energy is produced, transmitted, and distributed at specific voltage levels with a single constant frequency. Waveforms for voltage and current in these systems are fully sinusoidal. These requirements, however, cannot be entirely accomplished in practice. The term "harmonic" refers to fluctuations in alternating current and voltage brought on by abruptly switching loads or generators with non-sinusoidal voltage waveforms [1,2]. In order to reduce harmonics and assure compliance with power quality standards, harmonic analysis is required in power systems. They should be detected and eliminated A.S.A.P. to keep system robust.

A considerable amount of literature has been published on analysis, classification and elimination of power system harmonics [3–6] . Fast Fourier Transform (FFT) is the most known method for harmonic analysis, where the harmonics can be minimized or eliminated by using active - passive harmonic filters and other optimization-based methods, which were widely studied for years [7–9]. These devices are designed to eliminate harmonics to avoid their disruptive effects.

Harmonics have traditionally been studied using signal processing methods that comprehensively reviewed in [10]. FFT has been widely used for analysis of harmonics due to its computational efficiency. In addition, other techniques including discrete wavelet transform (DWT) [11] and s-transform [12] have been used to analyze power system harmonics. On the other hand, in recent years, machine learning based approaches, in which allow researchers to process much more data and obtain more precise results, have been more popular with the rapid development of computing technologies [13]. Machine learning methods including artificial neural networks [14], support vector machines [15], and decision trees [16] have also been widely used. Even if outstanding results have been obtained in practical applications, accuracy and analysis speed still need to be increased to meet the demands of real-time applications [17].

Harmonic studies are evolved to prediction and estimation issues in recent years, as [18–20] are focused on the monitoring and prediction of harmonics. To mitigate the undesirable effects of   harmonics and their variations as sub-harmonics and inter-harmonics, a proper prediction or estimation should be performed. Modern estimation/prediction techniques employ adaptive signal processing approaches [21].

Although prediction and estimation studies include short-term estimations, new planning strategies have begun to be researched in recent years. Harmonic forecasting is one of the most significant current discussions in power system harmonic studies.

Power system operators are able to proactively manage and mitigate harmonic-related issues, assess power quality, ensure compliance with standards and regulations, protect equipment, optimize system operation, make it easier to integrate renewable energy sources, and planning smart grids by using harmonic forecasting studies. [22–24].

Harmonic forecasting helps in predicting the future behavior of harmonics, enabling power system operators to assess power quality and identify potential harmonic-related problems in advance. These studies can aid in grid planning and operation by providing insights into the potential impact of harmonics on the performance of the power grid. It allows for proactive mitigation measures to be taken to minimize the impact of harmonics on the grid, optimize system operation, and avoid costly corrective actions and also can help identify potential harmonic-related issues that could damage or degrade the performance of equipment, enabling timely measures to be taken to protect the equipment from harm and reduce maintenance costs.

Power systems are subject to various standards and regulations related to power quality, including limits on harmonic distortion levels. Harmonic forecasting can assist in monitoring and predicting harmonic distortion levels in power grids, helping to ensure compliance with relevant standards and regulations.

Harmonic forecasting can be useful in the context of smart grid applications, where real-time monitoring and control of power quality parameters are critical. Harmonic forecasting can provide inputs for advanced analytics, decision-making algorithms, and control strategies in smart grids, facilitating efficient and reliable operation of the grid [25].

This paper proposes a harmonic forecasting approach utilizing Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures by using real-data obtained from an industrial feeder. Main motivation of the study is rapidly and accurately forecasting the harmonics before occurrence in accordance with the standards [26]. The main contribution of this article can be summarized as follows:

- While harmonic estimation and prediction studies are well-established and widely researched, harmonic forecasting studies are relatively less common and less mature in the field of power system engineering. Harmonic forecasting techniques are still an active area of research, and there is ongoing development of new methods and approaches for accurate and reliable harmonic forecasting in power grids.
- In the literature, studies show a strong correlation between calendar data and loading values [27–29]. Therefore, in this study, current harmonic prediction was made by using calendar data, active power data, and harmonic data together to observe if a similar correlation exists on the harmonic side.
- In this study, real-world one-year data with 10 minutes of resolution were used for analysis. This allows to take all parameters as unforeseen peak values into account which were possibly to be neglected in simulation studies and achieve more accurate results.
- Two main forecasting models, LSTM and GRU, that widely used in power system studies were compared to obtain the best results.

2 Definition of Power System Harmonics

Sinusoidal waveform distortions occur in energy distribution systems when a sinusoidal voltage source is applied to a non-linear load. The current waveform, which should take the form of a sine wave, is distorted by waveforms that differs from main grid frequency. These additional sinusoidal currents that are distinct from the grid frequency and sourced from the non-linear loads are referred as harmonic currents. Certain mathematical models are used to determine harmonics and inter-harmonics which were summarized in **Table 1**.

The amount of total harmonic distortion (THD) is determined by dividing the effective RMS values of the voltage harmonic components by the effective value of the main component. THD for voltage and current can be defined as given in Equation (1) and Equation (2) respectively:

$$THD_V = \frac{1}{U_1}\left(\sum_{n=2}^{\infty} {U_n}^2\right)^{1/2} \quad (1)$$

$$THD_I = \frac{1}{I_1}\left(\sum_{n=2}^{\infty} I_n{}^2\right)^{1/2} \quad (2)$$

The Fourier series can be used to express the instantaneous voltage and current values that have harmonic components in the power system as given in Equation (3) and Equation (4) respectively.

$$v(t) = \sum_{n=1}^{\infty} V_n(t) = \sum_{n=1}^{\infty} \sqrt{2} V_n \sin(n\omega_1 t + \theta_n) \quad (3)$$

$$i(t) = \sum_{n=1}^{\infty} i_n(t) = \sum_{n=1}^{\infty} \sqrt{2} I_n \sin(n\omega_1 t + \theta_n) \quad (4)$$

The DC terms have been deleted to simplify calculation. The instantaneous values of the n^{th} harmonic current and voltage are i_n and v_n. The effective harmonic values for voltage and current are V_n and I_n, ω_1 is the fundamental frequency's angular frequency. θ_n and φ_n are phase angle of the n^{th} harmonic voltage and current.

3 Harmonic Forecasting Methodology

This study is concerned with developing an accurate and reliable model for harmonic forecasting in power systems. Artificial Neural Network (ANN) is the prominent method used for harmonic forecasting. In this context, two Recurrent Neural Network (RNN) based forecasting models with different architectures are proposed in this paper.

RNNs are unsupervised learning techniques that perform remarkably well when used to classify time series data. Compared to other prediction models, RNNs perform significantly better [30]. RNNs use both the samples they are exposed to currently as shown in **Figure 1** and those they perceive over time, in contrast to standard feed-forward neural networks.

The RNNs thus perform better while learning from the events they come across throughout time. RNNs benefit from this capability when anticipating electricity load [29]. The input sequence is supplied as Equation (5) where the value of k can change depending on the length of the sequence in the various samples.

$$[x_1, x_2, x_3, \ldots, x_n]; \quad x_i \in \mathbb{R}^d \quad (5)$$

A hidden state is formed in the array given in Equation (6) at each iteration of the RNN model.

$$[h_1, h_2, h_3, \ldots, h_n] \qquad (6)$$

The hidden state's activation at time t depending on the previous hidden state and the current input can be expressed as given in Equation (7).

$$h_t = f\left(x_t, h_{t-1}\right) \qquad (7)$$

The LSTM is a unique kind of deep learning neural network that has been reported to be state-of-the-art in several time series challenges, including power system analysis issues. As an intelligent approach, LSTM structures are used in various research, including speech recognition, translation, language modeling, short term electricity demand estimation and the forecasting of power quality distortions, which is one of the primary issues with the power systems [31–33]. The internal structure of each module is made up of 4 distinct portions that interact with one another, unlike typical RNNs. There are three distinct gates with labels for forget, input, and output inside the LSTM module as shown in the block diagram of given in **Figure 2**.

Mathematical expressions of forget, input, and output gates can be defined as given in Equations (8)-(10)

$$f_t = \sigma\left(W_f . \left[h_{t-1}, x_t\right] + b_f\right) \qquad (8)$$

$$i_t = \sigma\left(W_i . \left[h_{t-1}, x_t\right] + b_i\right) \qquad (9)$$

$$C = \tanh\left(W_c . \left[h_{t-1}, x_t\right] + b_c\right) \qquad (10)$$

After the determination of candidate values, new state information calculation process and the output of the system can be mathematically expressed as given between Equations (11)-(13):

$$C_t = f_t \otimes C_{t-1} + i_t \otimes C_t \qquad (11)$$

$$o_t = \sigma\left(W_o . \left[h_{t-1}, x_t\right] + b_o\right) \qquad (12)$$

$$h_t = o_t \otimes \tanh\left(C_t\right) \qquad (13)$$

On the other hand, one of the most used alternative techniques for power system forecasting studies, called GRU which was introduced by Cho et.al.[34], is given in **Figure 3**.

The GRU is similar to an LSTM with a forget gate, but because it lacks an output gate, it has fewer parameters than an LSTM.

According to the block diagram, mathematical expressions of fully gated GRU are given between Equations (14)-(17):

$$z_t = \sigma\left(W_z x_t + U_z h_{t-1} + + b_z\right) \quad (14)$$

$$r_t = \sigma\left(W_r x_t + U_r h_{t-1} + + b_r\right) \quad (15)$$

$$\hat{h}_t = \phi_h\left(W_h x_t + U_h\left(r_t \otimes h_{t-1}\right) + b_h\right) \quad (16)$$

$$h_t = z_t \otimes \hat{h}_t + \left(1 - z_t\right) \otimes h_{t-1} \quad (17)$$

LSTM and GRU are types of RNN architectures that are particularly useful for harmonic forecasting. Harmonic forecasting involves predicting patterns that repeat over fixed intervals, such as daily, weekly, or yearly cycles.

LSTM and GRU models are helpful for harmonic forecasting as they have abilities capturing periodic patterns in harmonic data, adapt to the length of the input sequence, making them flexible for different forecasting scenarios, effectiveness at capturing the intricate relationships and cyclic patterns present in harmonic data, help smooth out noisy inputs and make more accurate predictions and generate forecasts for a desired number of time steps ahead.

Overall, the ability of LSTM and GRU models to capture long-term dependencies, handle variable-length sequences, learn complex temporal patterns, handle noisy data, and support multi-step forecasting makes them well-suited for harmonic forecasting tasks. These models have been widely used in various time series prediction applications, including energy load forecasting, stock market prediction, and weather forecasting, where harmonic patterns are prevalent.

Because they are specifically created to prevent long-term dependency issues, the LSTM and GRU models are widely used in time series forecasting. These models are effective machine learning techniques that can reduce the negative consequences of harmonic forecasting long-term dependency issues.

In a comparison of LSTM and GRU networks for learning harmonic features, GRUs outperform LSTM networks on low-complexity sequences while LSTMs outperform GRUs on high-complexity sequences [35–37] When Autoregressive Integrated Moving Average (ARIMA), LSTM, and GRU models were put side by side to predict time series, another study discovered that the GRU outperformed the LSTM in terms of harmonic forecasting [38]. The major issue is to determine either applying GRU or utilizing LSTM. The LSTM is more specialized and the GRU cell is more responsive to data due to the architecture. This may help to understand why GRUs occasionally perform better than LSTMs and vice versa [39]. Therefore, the purpose of this study is to compare GRU and LSTM models for forecasting the occurrence of current harmonics in a real power system and to examine sensitivity rates as well as accuracy rates.

4 System Setup

This study was focused on forecasting the current harmonics occur in electrical energy systems. In this context, Janitza UMG 512 energy analyzer that measure up to 63 odd and even harmonics, inter-harmonics, positive, negative, and zero components, imbalance, flicker, voltage peak factor, voltage, current, active power, reactive power, and frequency half-wave effective values concurrently, which was located in the Bandırma Organized Industrial Zone distribution center used to obtain the data. Installation was given in **Figure 4**. It also has crucial features like active energy measurement accuracy class 0.2, A-class certified measurement accuracy, continuous sampling of voltage and current measurement inputs at 25,600 Hz, 512 sampling points per period, and recording of more than 2000 measurement values per cycle. The pertinent analyzer logs the electrical characteristics of the local facilities as iron-steel, food, textile, etc.

Data were collected thus analysis was performed separately for L1, L2 and L3. Current waveform for L1 was given in

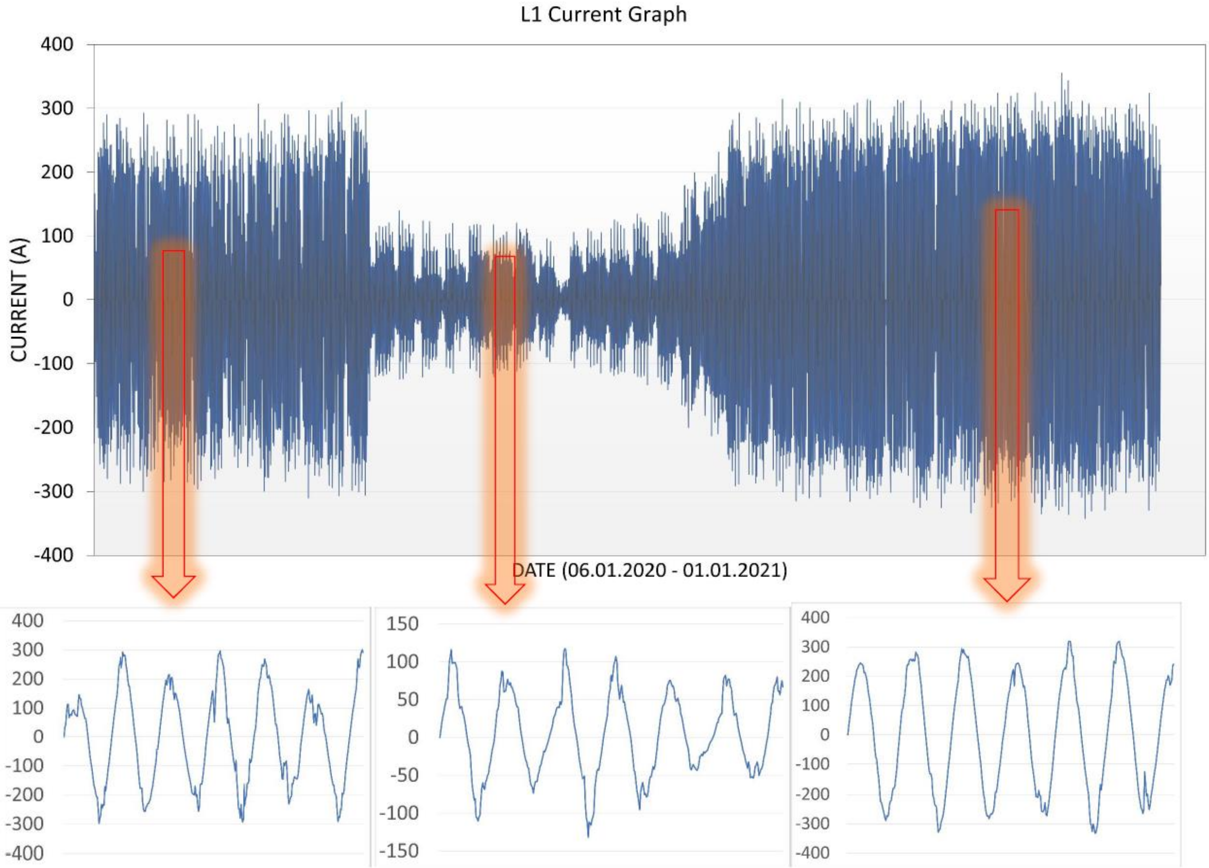

Figure 5 for a better understanding of distortions, where experimental setup block diagram was shown in **Figure 6.**

Relevant dataset was created from recorded data between January 6, 2020, and January 1, 2021. Harmonic value, active power value, year, month, day, weekdays and day of the week data for each line were prepared in the dataset in the appropriate .csv format. 90% of the dataset is reserved for training where 10% is used for testing. There are 45716 total data points during a period of 10 minutes. Active power and current harmonic data for each line were obtained in excel format from the analyzer.

Evaluation metrics are approaches that used to measure the quality of the intelligent models. As there are many different types of evaluation metrics available to test a model, in this paper, Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics were used to evaluate forecasting performance. MAPE, RMSE and MAE values are widely used as error comparison metrics in forecast studies of time series data. The quality of forecasted values has been assessed by statistical measures including MAPE, RMSE and MAE [29]. The forecasting results were evaluated using the MAPE, RMSE and MAE as given in Equation (18), Equation (19) and Equation (20) respectively.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\frac{|e_t|}{|A_t|} \quad (18)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}{e_t}^2} \quad (19)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \quad (20)$$

In these equations, n denotes sample size, e_t is the difference between actual value and the forecasted value and A_t is the total number of forecasting points.

5 Experimental Evaluation and THD_I Forecasting

The main goal of this study is to prevent harmonic-based failures that may occur in the future. Therefore, the short-term harmonic forecasting approach has been applied, and the time-step was set to 1 as target point of forecasting is 10-min ahead.

Artificial neural network models, in which the collected and normalized data were applied, consist of three layers. These sections can be defined as input layer, LSTM or GRU algorithms and output layer. The data contain harmonic value, active power value, year, month, day, weekdays, and day of the week. In this study, active power data, current harmonic data and calendar data were used together for harmonic forecasting.

The model was initially trained using random weights. The forecasting results were recorded after the training process was initiated with various random weights. Because neural network-based methods are so intuitive, different initial values can provide various outcomes.

Layer statement represents the hidden layers in Artificial Neural Networks. The model architecture used for forecasting consists of three layers: input, LSTM or GRU and output. Harmonic data are applied to the input layer with 10 minutes resolution. Various models were tried to obtain best results. Therefore, proposed model includes LSTM and GRU layers consisting of [25-200] nodes with one or two hidden layers after the input. Finally, the forecasted results are obtained from the output layer that formed by one fully-connected neuron.

The study was carried out on a computer with 2 Intel Xeon Gold 6354 processors with a base frequency of 3 GHz and a maximum turbo frequency of 3.6 GHz. The total number of cores of the processors is 36 and the total number of threads is 72. The device is equipped with a total of 128 GB of RAM. It also has a 2TB M2 SSD. In addition to these, there is an Nvidia RTX 3090 graphics card on the computer. Ubuntu 22.04 version is used as the operating system. Python 3.7 version was used together with Anaconda distribution as the programming language in the study. TensorFlow 2.10.0 version is preferred for training machine learning models.

The "epoch" value, which indicates the number of iterations of the training, was applied as a constant 200. These values have been tested separately as single and double layer in LSTM and GRU networks and all test structures with results were summarized in **Table 2**.

RMSE, MAE, MAPE scatter plots of L1, L2 and L3 for both LSTM and GRU were given in **Figure 7**, **Figure 8** and **Figure 9** respectively.

Actual and forecasting THD_I graphs obtained in accordance with RMSE, MAE and MAPE values of L1, L2 and L3 are shown in **Figure 10**, **Figure 11** and **Figure 12** respectively

The peak values appearing in the current harmonics graph of each line, originate from the arc furnace that fed by distribution transformer unit. These changes, which occur depending on the working process of the facility during certain periods of production, can be considered as an important indicator in terms of observing the performance of the model proposed within the scope of this study. When the relevant points in the graphics are examined, it can be seen that the proposed model shows a good forecasting performance at these extreme change points.

It was mentioned in the previous sections that harmonic forecasting studies are a relatively new topic. As a result, it was difficult to find many researches in the literature to compare. In [40], average RMSE indexes obtained from similar studies are given as 5,84; 6,91; 10,06 and 22,53, where the best RMSE value for proposed methodology is 2,116. Considering these results, it is concluded that the error rate in the results obtained in the article is lower than similar studies in the literature, and in this case, the results can be considered acceptable.

6 Conclusion

The financial losses associated with low PQ and harmonics are considerable in both small and large power systems. This situation reveals the importance of detecting the harmonics. Prior knowledge of the harmonics can enable the system-specific actions to be planned from the outset. Although estimation and prediction studies are frequently encountered in the literature within the scope of power systems analysis, harmonic forecasting has been studied less frequently. Harmonic forecasting plays a key role in preventing breakdowns and delivering high-quality electricity. Additionally, forecasting enables the use of harmonic filters as necessary, which helps to increase equipment longevity. In this context, this study was focused on forecasting the THD_I using the LSTM and GRU models.

Studies in the literature show that relatively high performance can be achieved with LSTM and GRU in the forecasting of power quality problems. Therefore, this study was based on these two models. The studied dataset consists of a total 45716 data that collected between January 6, 2020, and January 1, 2021 in 10-minute intervals, and 4572 which was 10% out of total were used for test. This dataset was used to conduct tests on the forecasting of THD_I using 8 different models, including LSTM and GRU networks for each line separately, and the results were compared to select the best forecasting approach. The models were revised in accordance with various scenarios in order to attain the best performance. Following the analyses, the best forecasting values were obtained for the L1, L2 and L3 with 2 layers - 100 nodes, 2 layers- 50 nodes and 2 layers - 25 nodes LSTM models respectively.

The fact that power systems have various characteristics in actual operating conditions has led to obtaining the best results with models that consist of different node and layer structures for each line. This situation can be defined as proof that the proposed model yield results through learning, without memorization.

The dataset contains the data obtained directly from the analyzer, and a cleaning process has been applied only by removing points with zero values that occur due to problems in data transfer. In order to see the performance of the proposed model in different operating conditions the distortions reaching very high levels because of various reasons (fault, sudden loading, etc.) were not removed from dataset during the cleaning process. As a result, it is clear that the model has a high forecasting performance not only in stable operation but also in extreme conditions.

Declarations

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Biographies

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Table 1. Mathematical definitions of harmonics

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Table 1. Mathematical definitions of harmonics

DC Component	$f_\omega = nf_1$; n=0	
Harmonic	$f_\omega = nf_1$	n>0
Inter- harmonic	$f_\omega \neq nf_1$	fω : spectral component frequency
Sub-harmonic	$f_\omega > 0$ Hz and $f_\omega < f_1$	f_1 :fundamental frequency

Table 2. Test results for L1, L2, and L3

Line	Layer	Nodes	**LSTM**			**GRU**		
			Metric Errors			**Metric Errors**		
			RMSE	**MAE**	**MAPE**	**RMSE**	**MAE**	**MAPE**
L1	1	25	2,286	0,734	11,735	2,253	0,698	10,820
		50	2,411	0,760	13,615	2,571	0,963	15,762
		100	2,459	0,804	14,486	2,487	0,780	12,288
		200	2,413	0,739	13,178	2,902	1,599	30,065
	***2**	25	2,534	0,654	10,424	2,334	0,916	17,065

		50	2,582	1,455	24,281	2,246	0,962	17,698
		***100**	***2,193**	***0,694**	***12,111**	2,501	0,844	13,202
		200	2,310	0,787	13,953	2,784	1,432	27,572
L2	1	25	2,382	0,680	10,074	2,768	1,460	27,921
		50	2,432	0,765	13,548	2,695	1,104	20,709
		100	2,363	0,792	14,268	2,640	0,610	9,976
		200	2,610	1,292	24,501	2,778	1,526	29,213
	***2**	25	2,700	1,261	23,484	2,489	0,715	11,264
		***50**	***2,354**	***0,759**	***12,329**	2,762	1,372	26,210
		100	2,952	1,717	32,897	2,460	0,944	17,218
		200	2,497	0,838	14,350	2,973	1,553	29,614
L3	1	25	2,277	0,672	12,915	2,527	0,863	15,234
		50	2,548	1,089	23,665	2,872	1,157	24,834
		100	2,648	1,068	22,884	2,520	1,045	22,603
		200	2,515	0,793	16,219	2,508	1,074	23,321
	***2**	***25**	***2,116**	***0,666**	***11,619**	2,173	0,776	13,486
		50	2,326	1,153	25,337	2,503	1,417	27,640
		100	2,447	1,104	21,394	2,159	0,782	15,860
		200	2,639	1,300	27,998	3,064	1,311	28,071

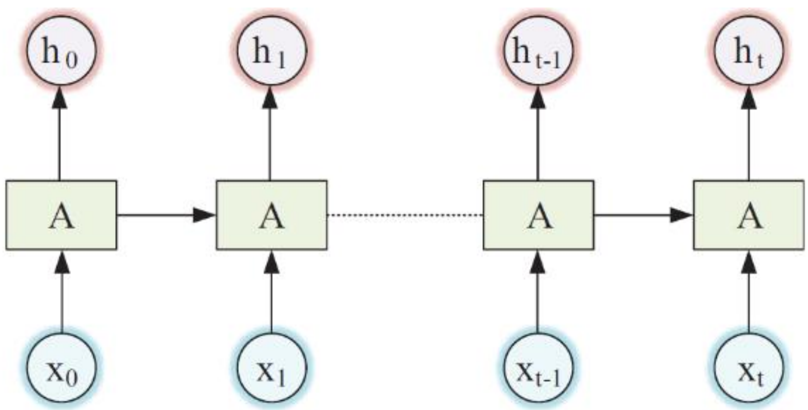

Figure 1. RNN Architecture

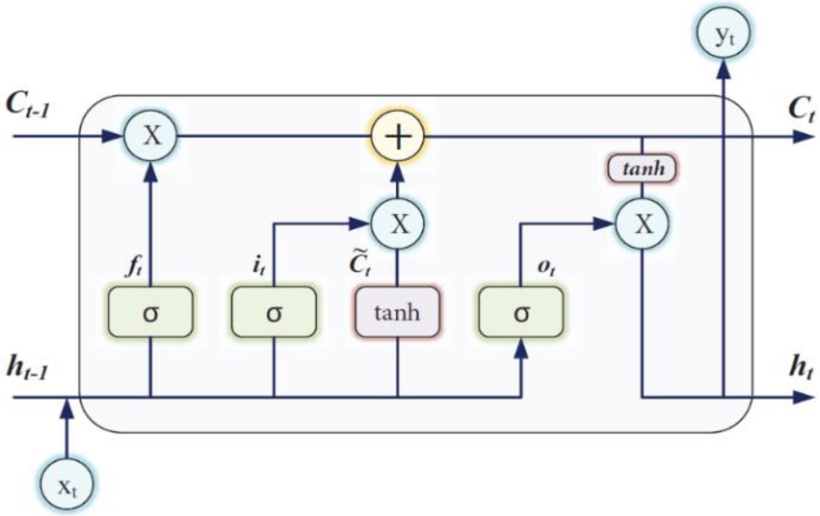

Figure 2. Block diagram of LSTM

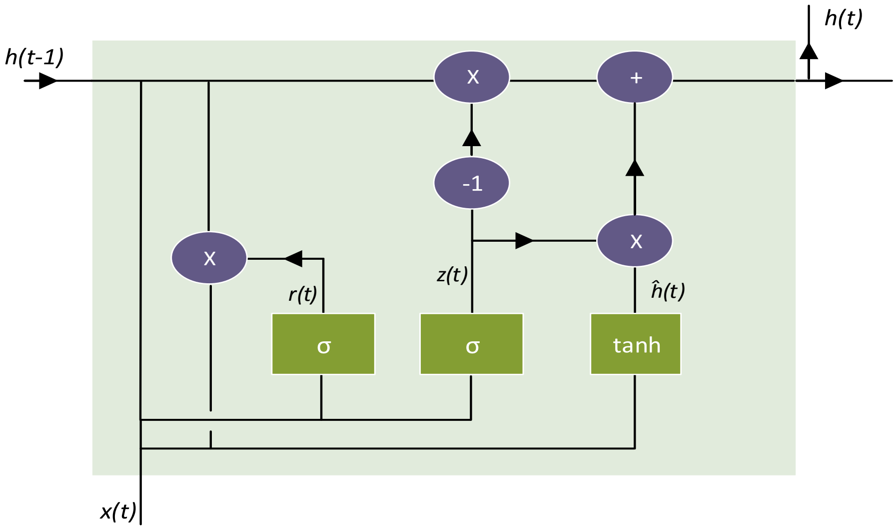

Figure 3. Fully gated version of GRU

Figure 4. Installation of data collecting unit

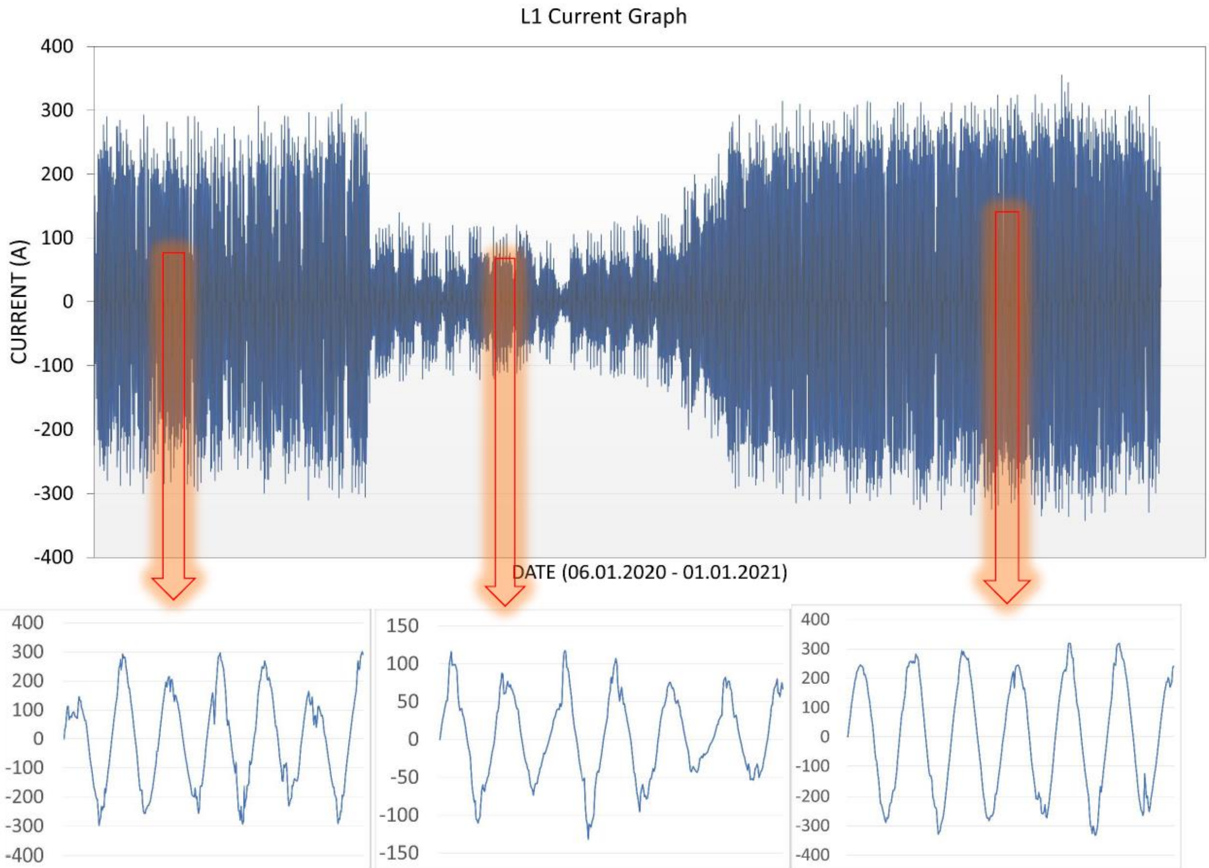

Figure 5. L1 current waveform

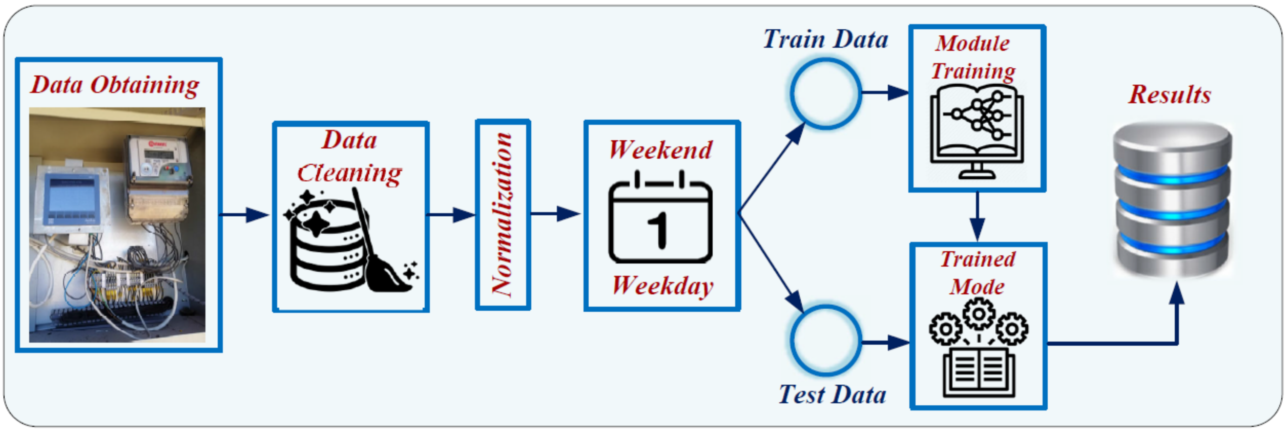

Figure 6. Experimental Setup

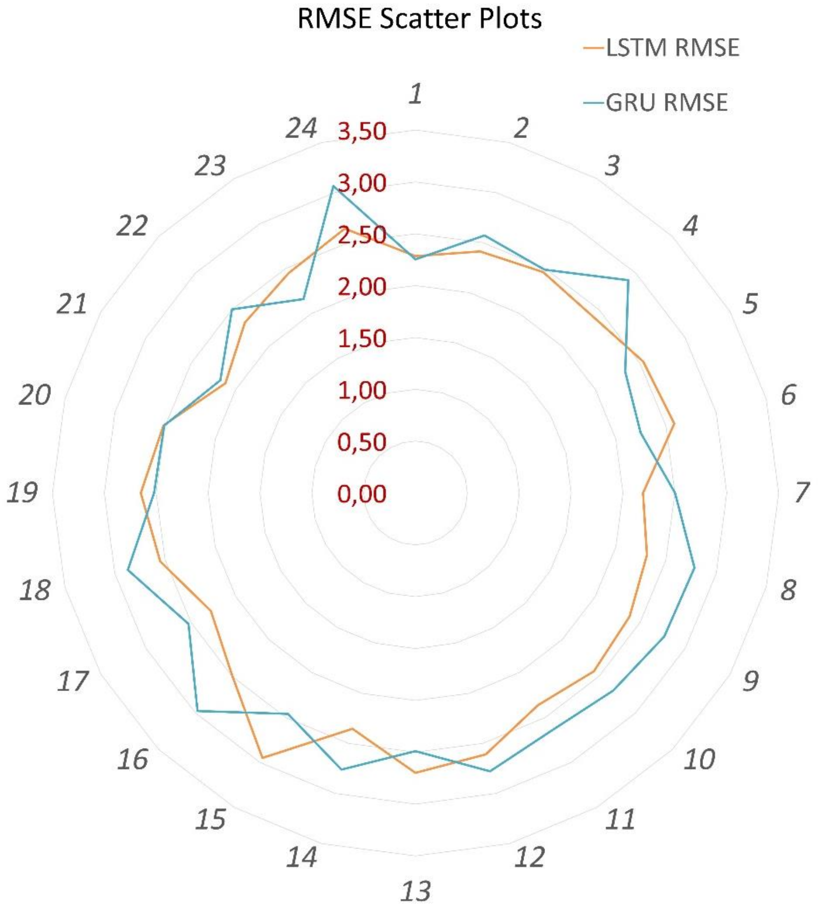

Figure 7. RMSE scatter plots

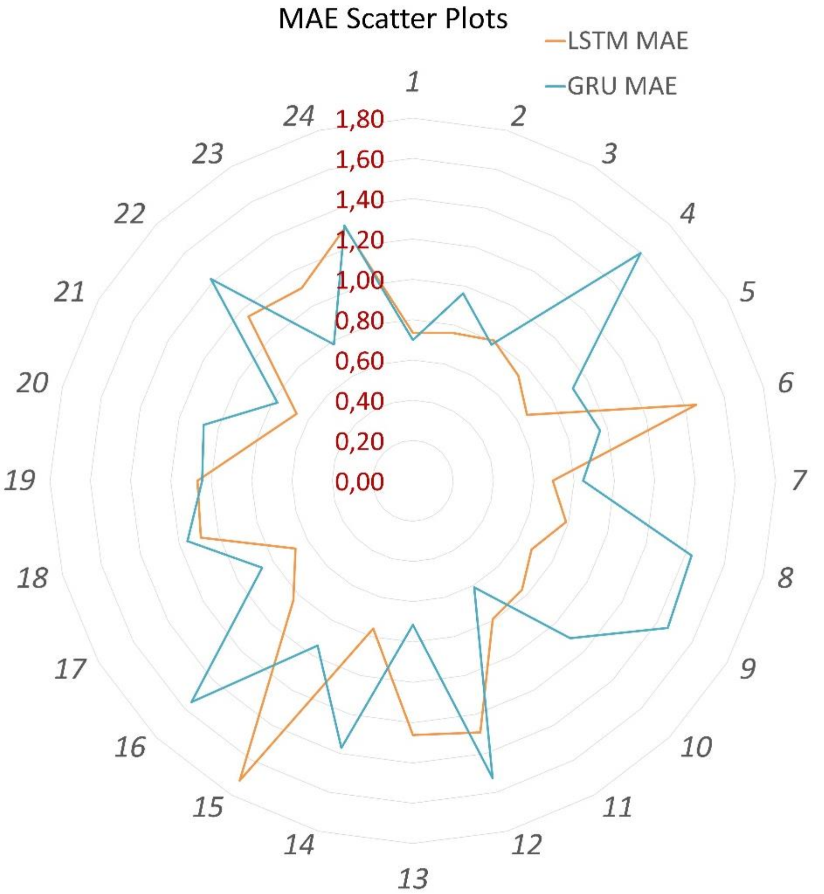

Figure 8. MAE scatter plots

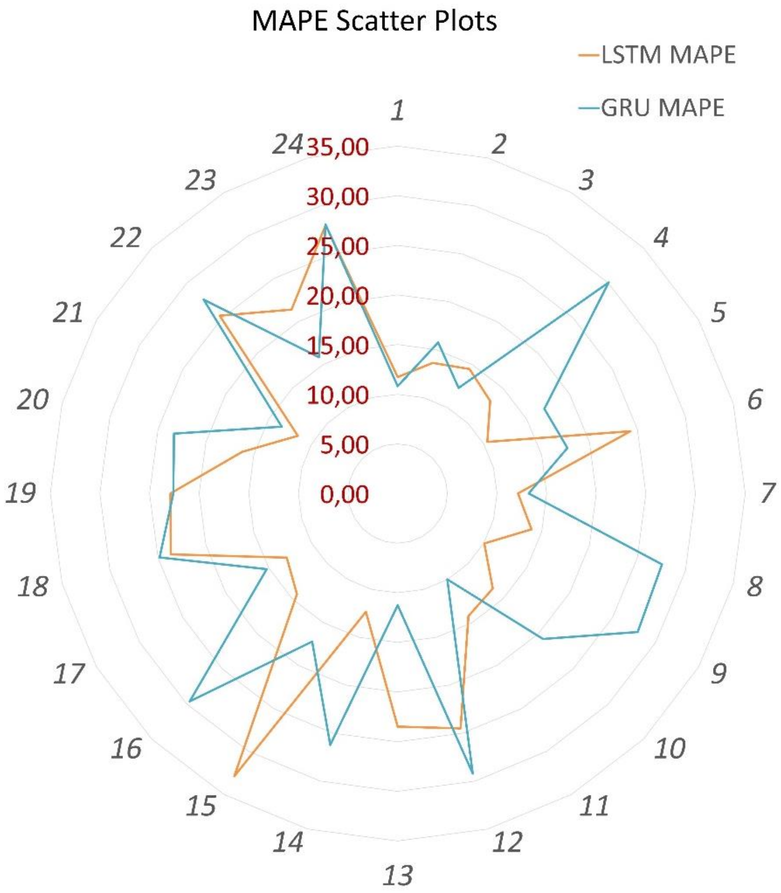

Figure 9. MAPE scatter plots

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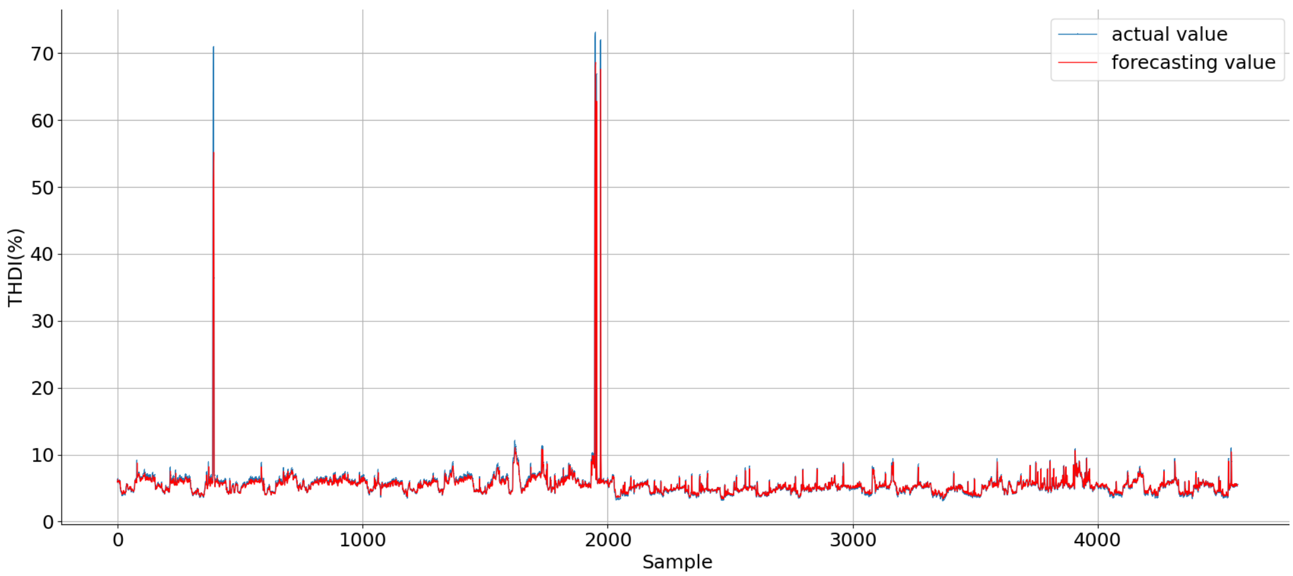

Figure 10. Actual and forecasting values for L1

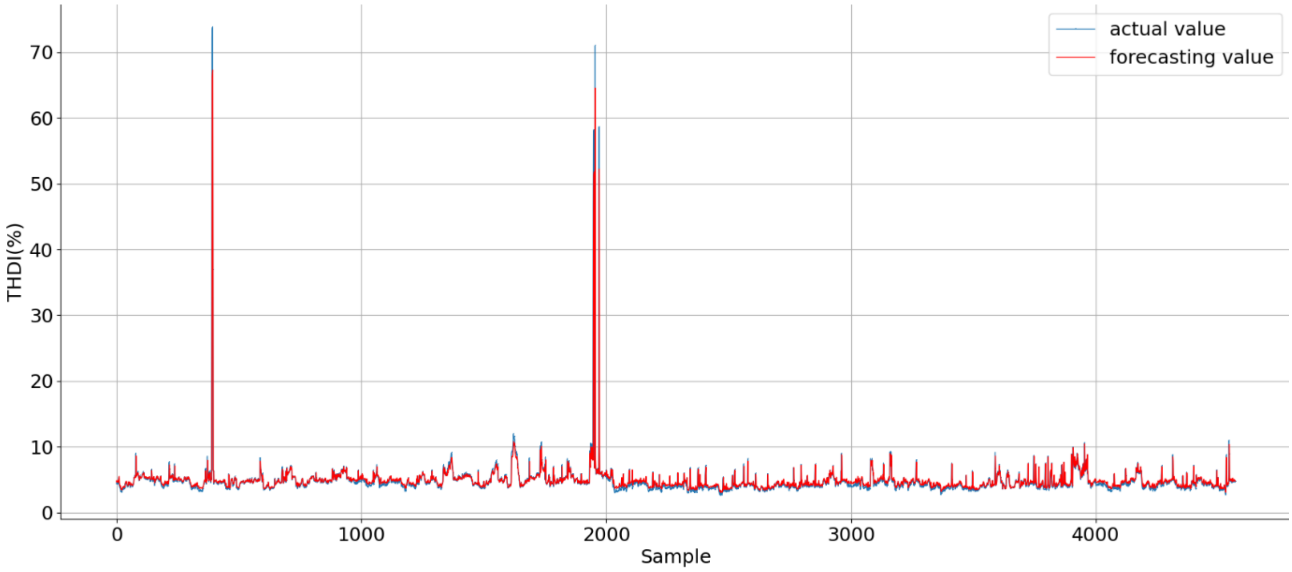

Figure 11. Actual and forecasting values for L2

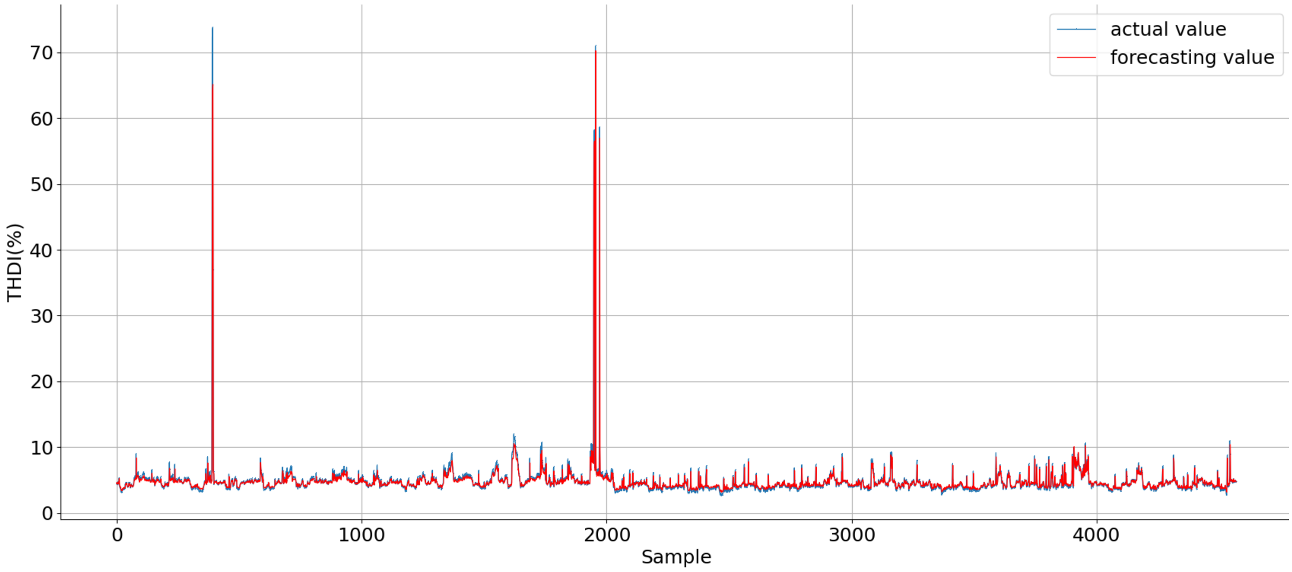

Figure 12. Actual and forecasting values for L3