RESEARCH ARTICLE

Short-Term Load Forecasting with Taguchi-Optimized Single-Layer Feedforward Neural Networks: A MATLAB GUI

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Abstract

This paper proposes a Taguchi-based optimization framework for short-term load forecasting (STLF) using single-layer feedforward neural networks (SLFNs). Although SLFNs are computationally efficient, their accuracy strongly depends on proper hyperparameter configuration, which is often selected through inefficient trial-and-error procedures. The proposed approach applies orthogonal arrays and signal-to-noise analysis to identify robust and reproducible SLFN settings. A MATLAB-based load forecasting interface is developed to support data preprocessing, model selection, parameter tuning, forecasting, and performance evaluation. The methodology is validated using real historical load and meteorological data from the distribution network supplying the municipalities of Kosovska Mitrovica, Zvečan, Leposavić, and Zubin Potok. The Taguchi-optimized SLFN achieves a mean absolute percentage error of 4.32% and a coefficient of determination of 0.991, outperforming all reference methods. More than one year of operational use confirms that forecasting errors consistently remain in the 3–5% range. These results demonstrate that lightweight neural architectures, when systematically optimized, provide a practical, accurate, and computationally efficient solution for real-world STLF applications.

Keywords: MATLAB GUI, neural networks, short-term load forecasting, taguchi method.

1 Introduction

Short-term load forecasting (STLF) plays a crucial role in the secure and economical operation of modern power systems. Accurate forecasts of electricity demand enable system operators to optimize unit commitment, generation scheduling, and market participation, thereby reducing operating costs and improving system reliability [1, 2]. The importance of STLF has grown further in recent years due to the increasing penetration of renewable energy sources, demand-side management, and market liberalization, all of which introduce additional variability and uncertainty into power system operation [3].

Traditional approaches to STLF, such as multiple

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linear regression (MLR) and autoregressive integrated moving average (ARIMA) models, have been widely employed in the past [4, 5]. These statistical models are valued for their simplicity and interpretability, but their predictive capability is often limited when dealing with nonlinear dependencies and strong weather-related effects in electricity demand. To overcome these limitations, researchers have increasingly turned to machine learning methods, including support vector regression (SVR) and Gaussian process regression (GPR), which have shown improved accuracy in capturing nonlinear load patterns [6–10]. However, the performance of these models depends heavily on the selection of kernel functions, hyperparameters, and data preprocessing strategies [11].

Artificial neural networks (ANNs) have emerged as one of the most widely adopted methods for load forecasting, offering strong nonlinear approximation capabilities and adaptability to diverse input features [12]. Multi-layer feedforward neural networks (MLFNs) and deep learning architectures, such as long short-term memory (LSTM) and convolutional neural networks (CNNs), have demonstrated state-of-the-art results in many recent studies [13–15]. In parallel, hybrid methods combining statistical and machine learning techniques, such as CNN-LSTM and SVR-LSTM frameworks, have been proposed to leverage the complementary strengths of different models [3, 16–19]. While such approaches often achieve high accuracy, they usually come at the cost of significantly increased model complexity, high computational requirements, and reduced interpretability. In contrast, single-layer feedforward neural networks (SLFNs) offer a simpler alternative with lower computational burden. Although structurally less complex than MLFNs, several studies have shown that, when properly tuned, SLFNs can still achieve competitive accuracy in load forecasting tasks [20, 21]. For instance, the study in [20] compared a range of machine learning models for STLF, including random forest, decision trees, support vector regression, and feedforward neural networks, and demonstrated that classical methods can perform on par with more sophisticated neural network architectures when their hyperparameters are systematically optimized. These findings highlight the importance of proper hyperparameter selection for SLFNs, particularly the number of neurons, training algorithm, transfer function, and number of epochs. However, selecting these parameters through trial-and-error remains inefficient and risks yielding suboptimal configurations, motivating the need for structured optimization approaches such as the Taguchi method.

To address this challenge, robust optimization techniques have been introduced for ANN hyperparameter tuning. Among them, the Taguchi method [22–24] has attracted particular attention due to its systematic design of experiments (DoE) framework, which allows for efficient exploration of large parameter spaces while minimizing the number of required simulations. By employing orthogonal arrays and signal-to-noise (S/N) analysis, the Taguchi method identifies parameter settings that enhance both accuracy and robustness of the model against noise and variability in training data. This makes it particularly suitable for practical load forecasting applications, where stable and reliable performance is essential.

Building on these insights, this study investigates the application of Taguchi-based optimization for configuring SLFN models in STLF. A MATLAB-based graphical user interface (LF-GUI) is developed to facilitate data preparation, model selection, parameter tuning, forecast execution, and performance evaluation. The tool supports multiple forecasting models, including SLFN, MLFN, SVR, GPR, and MLR, while also providing visualization and statistical diagnostics. The proposed methodology is tested on historical load and meteorological data from four municipalities (Severna Kosovska Mitrovica, Zvečan, Leposavić, and Zubin Potok), which are characterized by strong daily and seasonal demand fluctuations and limited system observability. The results demonstrate that the Taguchi-optimized SLFN achieves superior predictive performance compared to conventional models, confirming the effectiveness of the proposed approach in practical forecasting environments.

1.1 Research Gap and Contributions

Despite the extensive research on STLF using statistical, machine learning, and deep learning techniques, relatively limited attention has been given to the systematic optimization of SLFNs for practical forecasting tasks. Without structured optimization, SLFNs remain underutilized despite their simplicity, computational efficiency, and potential to achieve competitive accuracy. Most existing studies rely on either trial-and-error parameter selection or computationally demanding metaheuristic algorithms, which are often inefficient, difficult to reproduce, and impractical for real-world applications. Furthermore, the application of the Taguchi method, a well-established design of experiments framework, has not been thoroughly explored in the context of load forecasting, particularly for systems with strong seasonal variability and limited observability. This gap motivates the present study.

To address this gap, the present study makes the following contributions:

1. It introduces a Taguchi-based optimization framework for configuring SLFNs in STLF, enabling efficient and robust parameter tuning.
2. It develops a MATLAB-based load forecasting GUI (LF-GUI) that integrates multiple forecasting models (SLFN, MLFN, SVR, GPR, and MLR) with built-in modules for preprocessing, parameter tuning, execution, and evaluation.
3. It provides a comprehensive case study on historical load and weather data from four municipalities, demonstrating that the proposed Taguchi-optimized SLFN achieves superior predictive accuracy compared to conventional methods.

These contributions aim to bridge the gap between lightweight neural network architectures and robust optimization methods, offering both methodological novelty and practical value for real-world forecasting applications.

2 Artificial Neural Networks and the SLFN Model

Artificial neural networks (ANNs) are widely applied in regression and classification problems due to their ability to approximate complex nonlinear relationships between inputs and outputs [11, 12]. Among different ANN architectures, feedforward neural networks (FNNs) are the most commonly used. They consist of an input layer, one or more hidden layers, and an output layer, with information propagating unidirectionally from input to output. A single-layer feedforward neural network (SLFN) represents a simplified form of an FNN, containing only one hidden layer between the input and output layers. Despite its reduced structural complexity, SLFNs have been shown to achieve competitive performance in short-term load forecasting when properly configured and trained [20, 21]. Their simplicity makes them attractive for practical applications where computational efficiency, robustness, and ease of deployment are important.

The output y_j of a hidden neuron in a SLFN can be mathematically expressed as:

$$y_j = \sum_{j=1}^{m} \beta_j f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) + b_o, \tag{1}$$

where x_i represents the ith input feature ($i = 1, 2, ..., n$), w_{ij} denotes the weight connecting the ith input to the jth hidden neuron, b_j is the bias of the ith hidden neuron, $f(\cdot)$ is the activation (transfer) function, β_j is the weight connecting the ith hidden neuron to the output layer, b_o is the bias of the output neuron, and m represents the total number of hidden neurons. The basic structure of a SLFN is illustrated in Figure 1.

As shown in Figure 1, the network output is obtained through weighted summation of the inputs, bias addition, nonlinear activation at the hidden layer, and linear combination at the output layer. The forecasting performance of an SLFN is highly sensitive to the selection of its hyperparameters, including the number of hidden neurons, training algorithm, transfer function, and number of epochs. To systematically tune these parameters and improve accuracy, robustness, and reproducibility, the Taguchi method is employed in this study.

3 Taguchi Method

The Taguchi method [22] is a statistically grounded DoE approach that utilizes orthogonal arrays and S/N ratios to evaluate system performance under uncertainty. Its main advantage lies in the ability to analyze the effect of multiple factors on model performance with a reduced number of simulations, thereby improving efficiency without compromising reliability. For instance, while a full factorial design with 5 factors at 5 levels each would require 3125 experiments, the Taguchi method enables a robust exploration of the parameter space with only 25 runs. In this study, the Taguchi method is employed to systematically tune the hyperparameters of the SLFN, including the number of neurons, training algorithm, transfer function, number of epochs, and random seed. Random or trial-and-error selection of these parameters often results in inconsistent or suboptimal models due to the stochastic nature of neural network training. In particular, the random seed controls the initialization of network weights and data shuffling, and thus directly impacts convergence behavior and

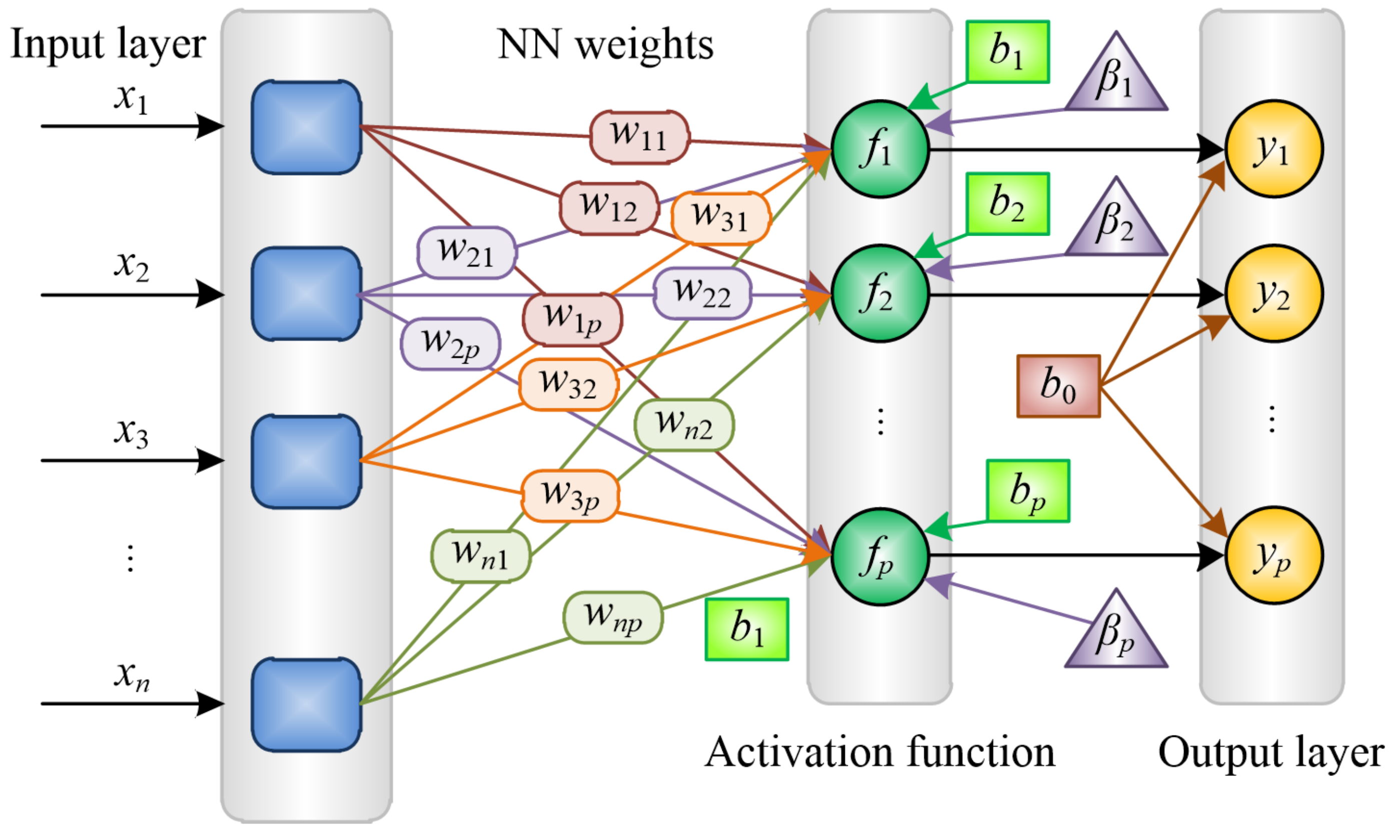

Figure 1. Basic structure of a SLFN.

forecasting accuracy. To overcome these limitations, an orthogonal experimental plan is designed to identify configurations that yield accurate and noise-tolerant forecasting results. The considered factor levels are summarized in Table 1, and the L25 orthogonal array is used to structure the experiments, ensuring that the parameter space is uniformly and efficiently explored.

The proposed methodology follows these steps [23, 24]:

Step 1: Define the performance evaluation metric based on forecasting error indices. In this study, the Mean Absolute Percentage Error (MAPE) is adopted as the objective function to measure forecasting accuracy;

Step 2: Choose parameter levels (Table 2);

Step 3: Construct the L25 orthogonal array (Table 3);

Step 4: Run each of the 25 experiments multiple times to account for training stochasticity;

Step 5: Evaluate robustness using the Smaller-the-Better (STB) S/N ratio:

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}F_i^2\right), \qquad (2)$$

where n is the number of repeated runs per experiment.

This method enables the identification of the most influential control factors affecting both solution quality, as measured by the average MAPE value, and solution robustness, as quantified by the S/N ratio.

4 Solution Software – Load Forecasting GUI

The Load Forecasting Graphical User Interface (LF-GUI) is a custom-developed MATLAB-based software tool for short-term electricity demand forecasting (up to 7 days ahead), created primarily for application in four municipalities (Severna Kosovska Mitrovica, Zvečan, Leposavić, and Zubin Potok). The motivation for its development is the need for reliable forecasts in a power system characterized by pronounced daily and seasonal fluctuations, limited observability, and strong dependence on weather patterns. Although developed for a regional application, LF-GUI has a general design that makes it suitable for broader research, comparative evaluation of algorithms, and teaching. The LF-GUI was developed in MATLAB, since this environment integrates computation, programming, data analysis, and graphical visualization in a single platform, where problems and solutions can be expressed in familiar

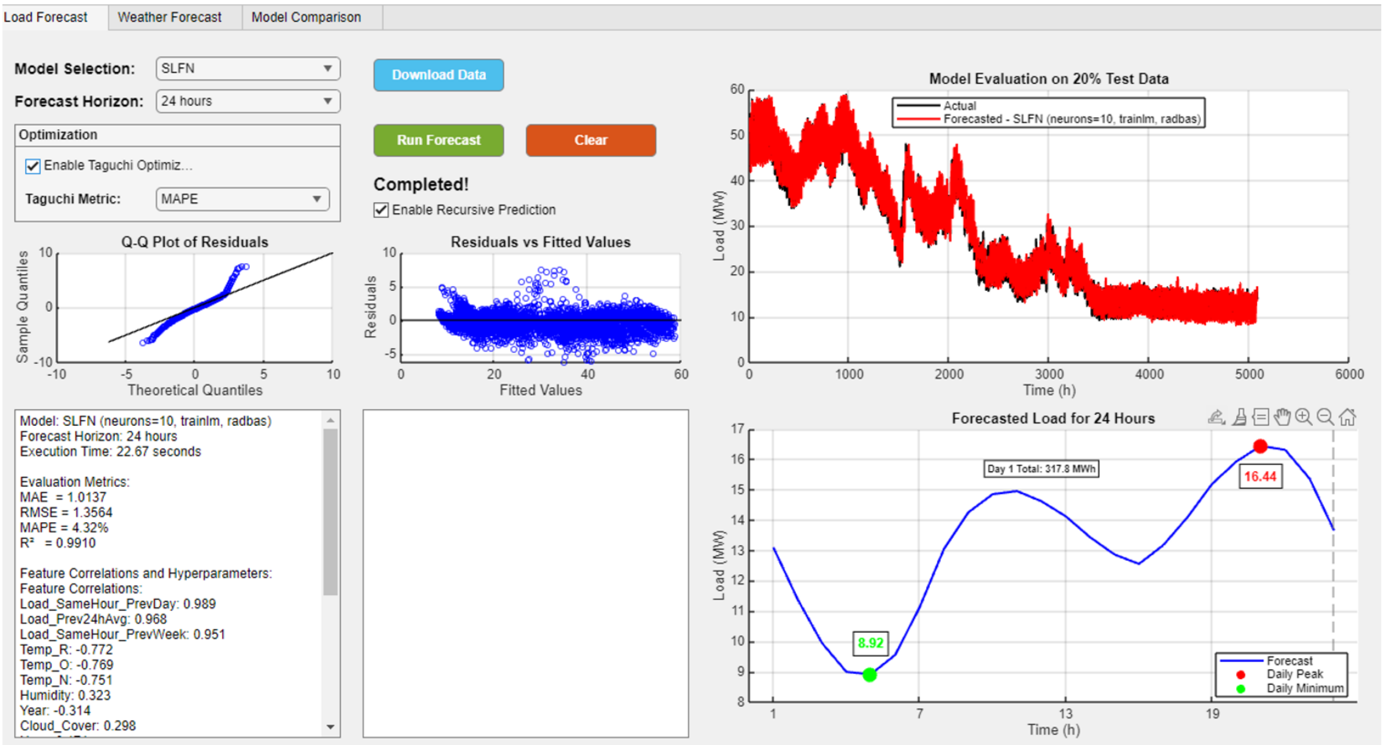

Figure 2. Load Forecast panel of the LF-GUI, showing model selection, forecast horizon definition, Taguchi optimization, and visualization of residual diagnostics, test set evaluation, and a 24-hour forecast profile.

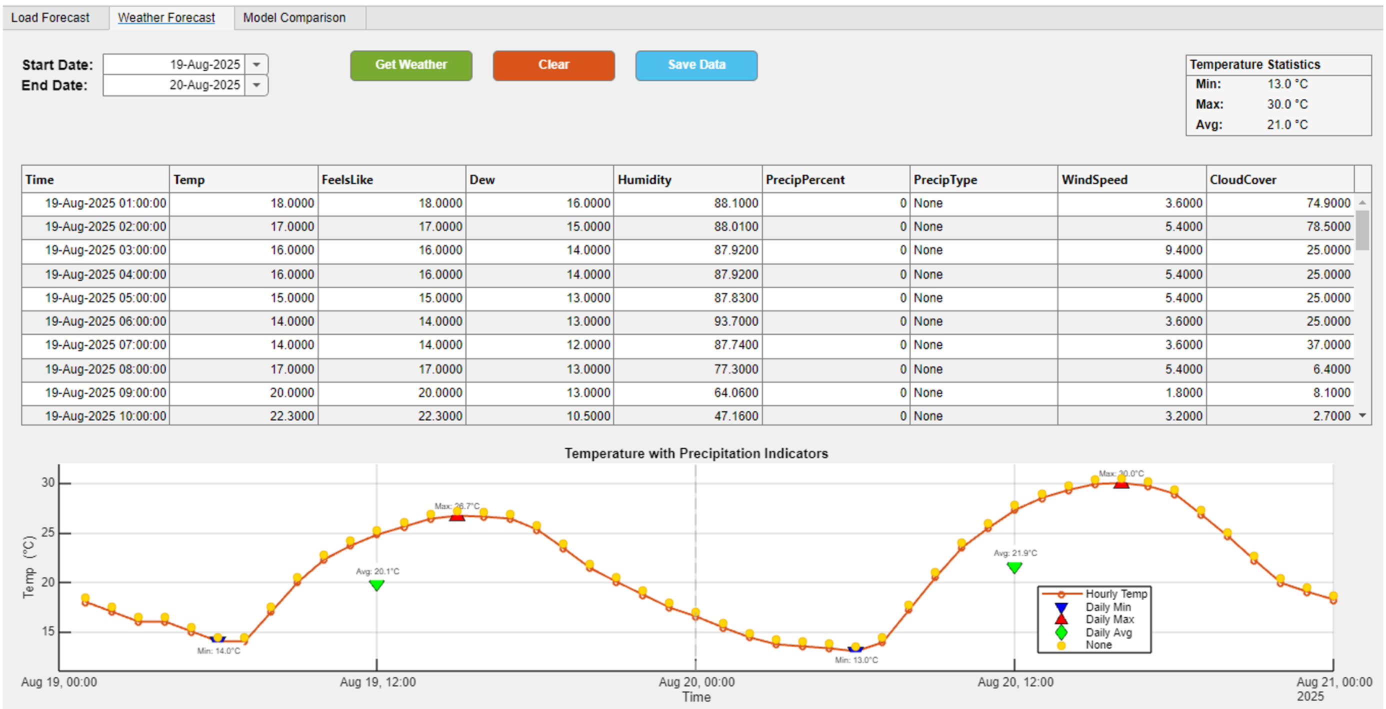

Figure 3. Weather Forecast panel of the LF-GUI, displaying hourly meteorological inputs along with daily statistics.

mathematical notation. During the design process, special care was devoted to its graphical user interface, making the software highly intuitive and user-friendly.

The software integrates the complete forecasting workflow into a single platform, including data preprocessing, model selection, parameter optimization, forecast execution, and performance evaluation. Users can select among several forecasting models, namely SLFN, MLFN, SVR, GPR, and MLR. An optional Taguchi-based optimization module is provided for systematic hyperparameter tuning using standard error metrics (MAE, RMSE, MAPE). The tool supports both recursive and non-recursive prediction modes and provides comprehensive visualization of results, including residual diagnostics, actual-versus-predicted load plots, operational forecast profiles, and statistical performance indicators. Forecast outputs can be exported for reporting and further analysis. Thanks to its modular architecture, LF-GUI can be easily extended with additional forecasting models, feature engineering techniques, or optimization methods, making it suitable for both operational use and methodological research.

4.1 Graphical User Interface structure

The graphical user interface of the LF-GUI consists of three main panels: Load Forecast, Weather Forecast, and Model Comparison, which are illustrated in Figures 2, 3 and 4.

- **Load Forecast panel** – provides model selection, horizon definition (from 24 hours up to 7 days), optimization options, and forecast visualization.
- **Weather Forecast panel** – integrates meteorological forecasts (temperature, humidity, precipitation, wind, cloud cover) and computes daily summary statistics.
- **Model Comparison panel** – enables systematic benchmarking of different models.

4.2 Data Description

The forecasting models operate on a historical dataset covering the period from September 2022 to August 2025, comprising 25,705 hourly records. Each record includes calendar variables (date, hour, holiday indicator), meteorological variables (temperature from three locations, humidity, precipitation, wind speed, and cloud cover), and the system load used as the target variable.

The dataset represents aggregated electricity consumption for the studied region and contains no missing values. Figure 5 illustrates the structure of the dataset, while Figure 6 presents the overall hourly load profile, revealing pronounced seasonal and daily variations. Electricity demand is predominantly residential, with minimal industrial load, resulting in relatively small differences between weekdays and weekends, as shown in Figure 7. The correlation analysis between load and selected explanatory variables (Figure 8) indicates a strong negative correlation with temperature and moderate correlations with humidity and cloud cover.

Meteorological data were obtained via the Visual Crossing Weather API [25], which provides time-aligned historical and forecasted weather information. This ensures consistent input-output pairing for model training, validation, and operational forecasting. Table 1 summarizes the descriptive statistics of the meteorological variables and electricity load.

Table 1. Descriptive statistics of meteorological variables and load, with correlation coefficients relative to load.

Variable	Count	Min	Max	Mean	STD	Correlation
Temperature (°C)	25705	-18	39	11.948	9.179	-0.752
Humidity (%)	25705	8.57	100	72.938	20.932	0.329
Precipitation (%)	25705	0	100	0.097	1.375	0.009
Wind Speed (km/h)	25705	0	111.2	10.958	8.200	0.087
Cloud Cover (%)	25705	0	100	54.24	35.75	0.297
Load (MW)	25705	8.98	77.19	34.619	16.585	1

4.3 Application and research potential

The primary application of LF-GUI is short-term electricity demand forecasting (24-168 hours) for regional power system operators, providing accurate inputs for unit commitment, generation scheduling, and system balancing. By delivering reliable day-ahead and week-ahead forecasts, the tool contributes to more efficient and secure operation of the power system. In addition, the modular design and the integrated set of forecasting models, optimization options, and evaluation metrics make LF-GUI a valuable platform for research and education. It can be used to test and compare different algorithms, benchmark forecasting performance under varying conditions, and serve as a teaching tool in the field of load forecasting and power system planning.

5 Results and Discussion

To evaluate the sensitivity of the forecasting model to different network configurations, a Taguchi design of experiments was applied. The L25 orthogonal array was selected as it enables a balanced exploration of multiple hyperparameter combinations while substantially reducing the number of required simulations compared to a full factorial design. Five key factors were considered: (A) number of neurons in the hidden layer, (B) training function, (C) transfer function, (D) number of epochs, and (E) random seed. Each factor was tested at five levels, as summarized in Table 2, resulting in 25 experiments. The objective function (MAPE), was computed for each run, and the results are presented in Table 3. This setup

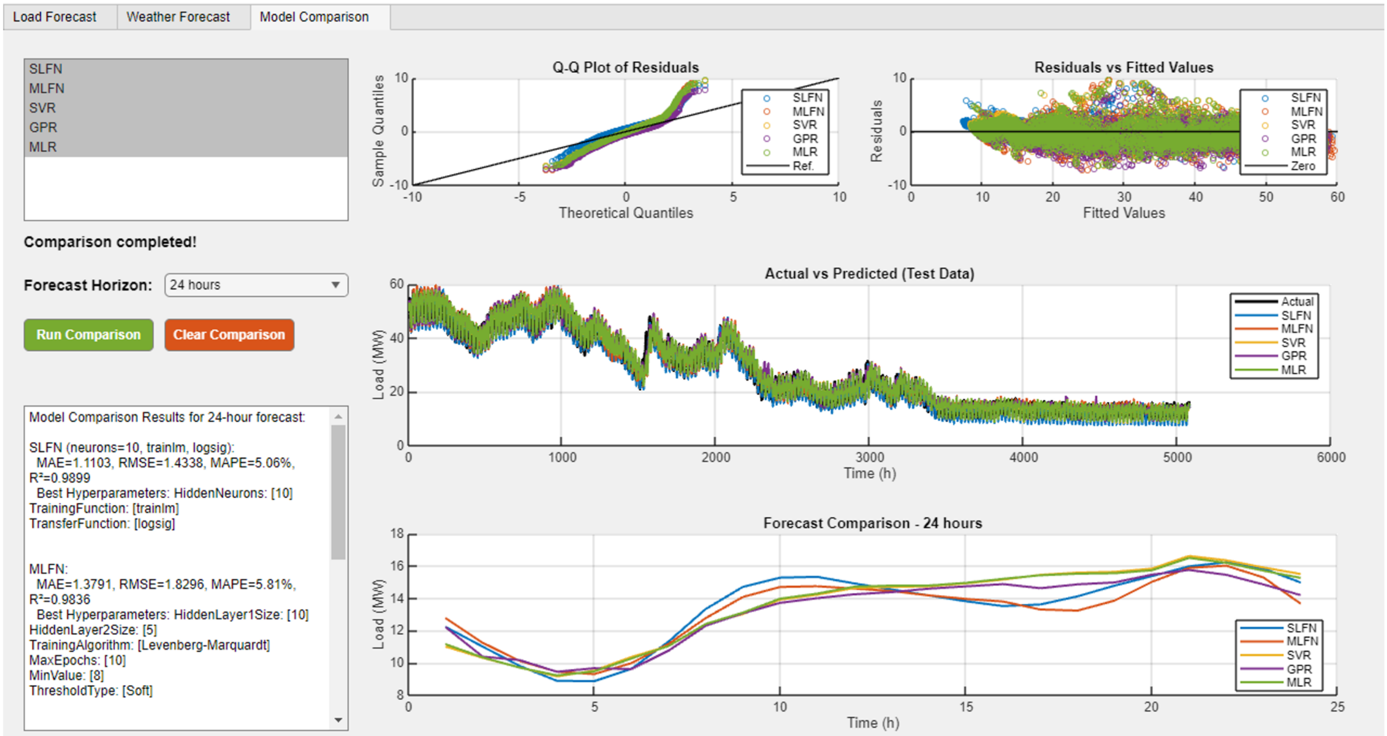

Figure 4. Model Comparison panel of the LF-GUI, illustrating residual diagnostics, actual vs. predicted load evaluation on test data, and comparative results for the selected 24-hour horizon.

	A	B	C	D	E	F	G	H	I	J	K	L
1	Date	Hour	Holiday	Temp_N	Temp_O	Temp_R	Humidity	Precipitation	Precip_Type	Wind_Speed	Cloud_Cover	Load
25682	17-Aug-25	1	0	21	21	11	52.79	0	0	5.4	61.3	12.1
25683	17-Aug-25	2	0	20	20	10	52.53	0	0	11.2	9.1	10.61
25684	17-Aug-25	3	0	18	18	11	63.61	0	0	1.8	81.6	9.78
25685	17-Aug-25	4	0	18	18	12	67.96	0	0	1.8	97.6	9.38
25686	17-Aug-25	5	0	17	17	11	67.76	0	0	7.6	25	9.3

Figure 5. Example of the historical dataset, including calendar features, meteorological variables, and the system load used as the target variable for forecasting model development.

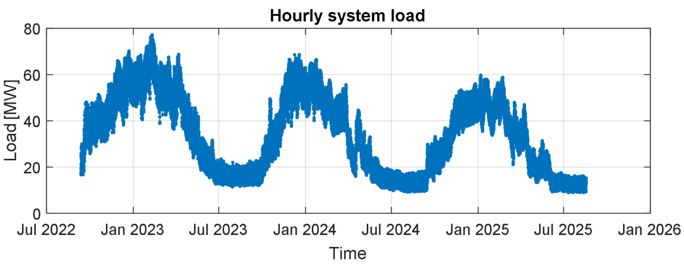

Figure 6. Hourly electricity load for the years 2022–2025.

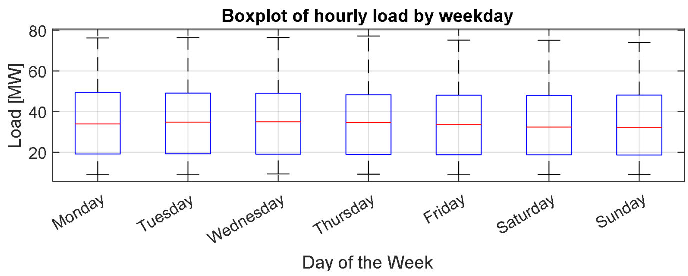

Figure 7. Boxplot of electricity consumption across weekdays.

ensures that the effect of each parameter on the model's performance can be independently assessed while minimizing experimental redundancy.

To evaluate both performance and robustness of the SLFN, the S/N ratios were calculated using the "smaller-is-better" (STB) formulation, as the objective was to minimize the prediction error. The statistical analysis was carried out in Minitab (version 15) [26], where the S/N ratios were computed and the influence of each SLFN parameter was assessed. The results of this analysis are presented in Table 4.

The optimal configuration of SLFN parameters was determined by selecting the levels corresponding to the highest S/N ratios, following Taguchi's robustness principle. As shown in Table 4, the transfer function

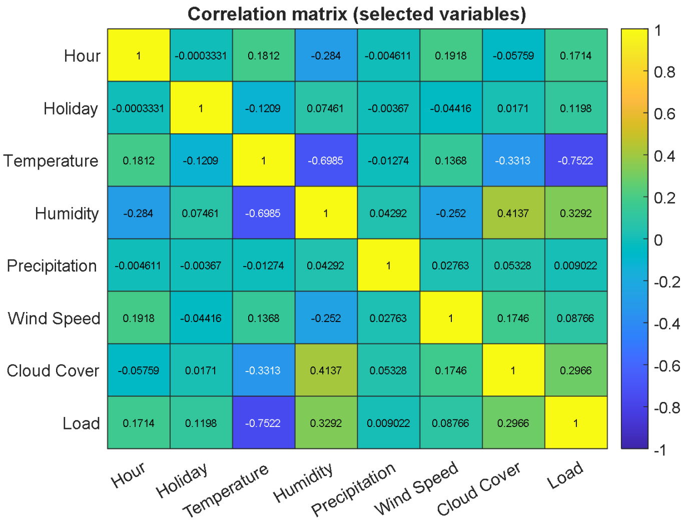

Figure 8. Boxplot of electricity consumption across weekdays.

Table 2. SLFN parameters and levels used in the Taguchi design (L25).

Factor	Level 1	Level 2	Level 3	Level 4	Level 5
Neurons	5	10	15	20	25
TrainFcn	trainlm	trainbr	trainscg	trainrp	traincgb
TransferFcn	tansig	logsig	poslin	radbas	purelin
Epochs	100	200	300	400	500
Seed	0	1	2	3	4

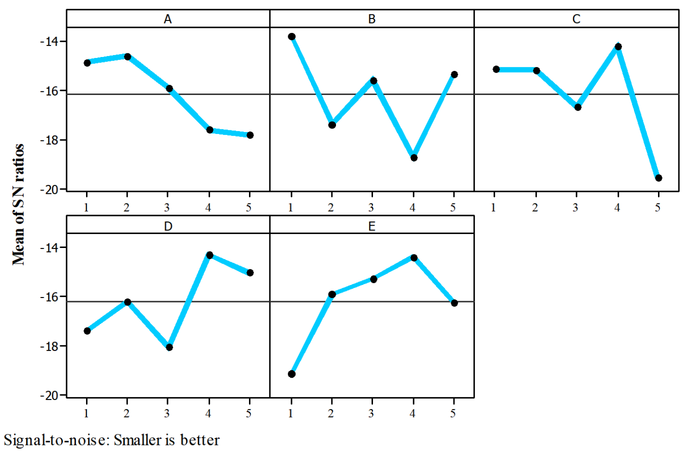

Figure 9. Main effects plot of S/N ratios for SLFN control parameters using the STB criterion.

had the greatest influence on network performance, followed by the training function, random seed, number of epochs, and finally the number of neurons. Figure 9 presents the main-effects plot for the S/N ratios of the SLFN parameters. Following the Taguchi method with the STB formulation, the optimal setting is obtained by selecting, for each factor, the level with the highest S/N ratio. As shown in Figure 9 and Table 4, the optimal levels are A2, B1, C4, D4, and E4, i.e. Neurons = 10, TrainFcn = trainlm, TransferFcn = radbas, Epochs = 400, and Seed = 3. This configuration

Table 3. Taguchi-based SLFN optimization results.

DoE	A	B	C	D	E	MAPE	SN
1	1	1	1	1	1	4.63	-13.312
2	1	2	2	2	2	4.7	-13.442
3	1	3	3	3	3	5.78	-15.239
4	1	4	4	4	4	5.79	-15.254
5	1	5	5	5	5	7.1	-17.025
6	2	1	2	3	4	3.95	-11.932
7	2	2	3	4	5	4.1	-12.256
8	2	3	4	5	1	4.24	-12.547
9	2	4	5	1	2	11.15	-20.946
10	2	5	1	2	3	5.83	-15.313
11	3	1	3	5	2	6.34	-16.042
12	3	2	4	1	3	6.4	-16.124
13	3	3	5	2	4	5.41	-14.664
14	3	4	1	3	5	8	-18.062
15	3	5	2	4	1	5.36	-14.583
16	4	1	4	2	5	4.38	-12.83
17	4	2	5	3	1	34.22	-30.686
18	4	3	1	4	2	5.31	-14.502
19	4	4	2	5	3	5.52	-14.839
20	4	5	3	1	4	5.86	-15.358
21	5	1	5	4	3	5.44	-14.712
22	5	2	1	5	4	5.32	-14.518
23	5	3	2	1	5	11.3	-21.062
24	5	4	3	2	1	17.03	-24.624
25	5	5	4	3	2	5.24	-14.387

was adopted for the final model to enhance accuracy and robustness.

Analysis of Variance (ANOVA) [23, 24] was conducted at a 95% confidence level to evaluate the relative significance of the SLFN control parameters. The results are summarized in Table 5. Among the examined factors, seed contributed the most to MAPE variation, accounting for approximately 21.5% of the total variation, followed by transfer function (19.49%), train function (13.95%), epochs (12.87%), and neurons (11.85%). The residual error accounted for 20.33%

Table 4. SN ratios for each SLFN parameter at five levels using the STB criterion, along with delta values and ranks.

Level	A	B	C	D	E
1	-14.85	**-13.77**	-15.14	-17.36	-19.15
2	**-14.6**	-17.41	-15.17	-16.17	-15.86
3	-15.89	-15.6	-16.7	-18.06	-15.25
4	-17.64	-18.74	**-14.23**	**-14.26**	**-14.35**
5	-17.86	-15.33	-19.61	-14.99	-16.25
Delta	3.26	4.98	5.38	3.8	4.81
Rank	5	2	1	4	3

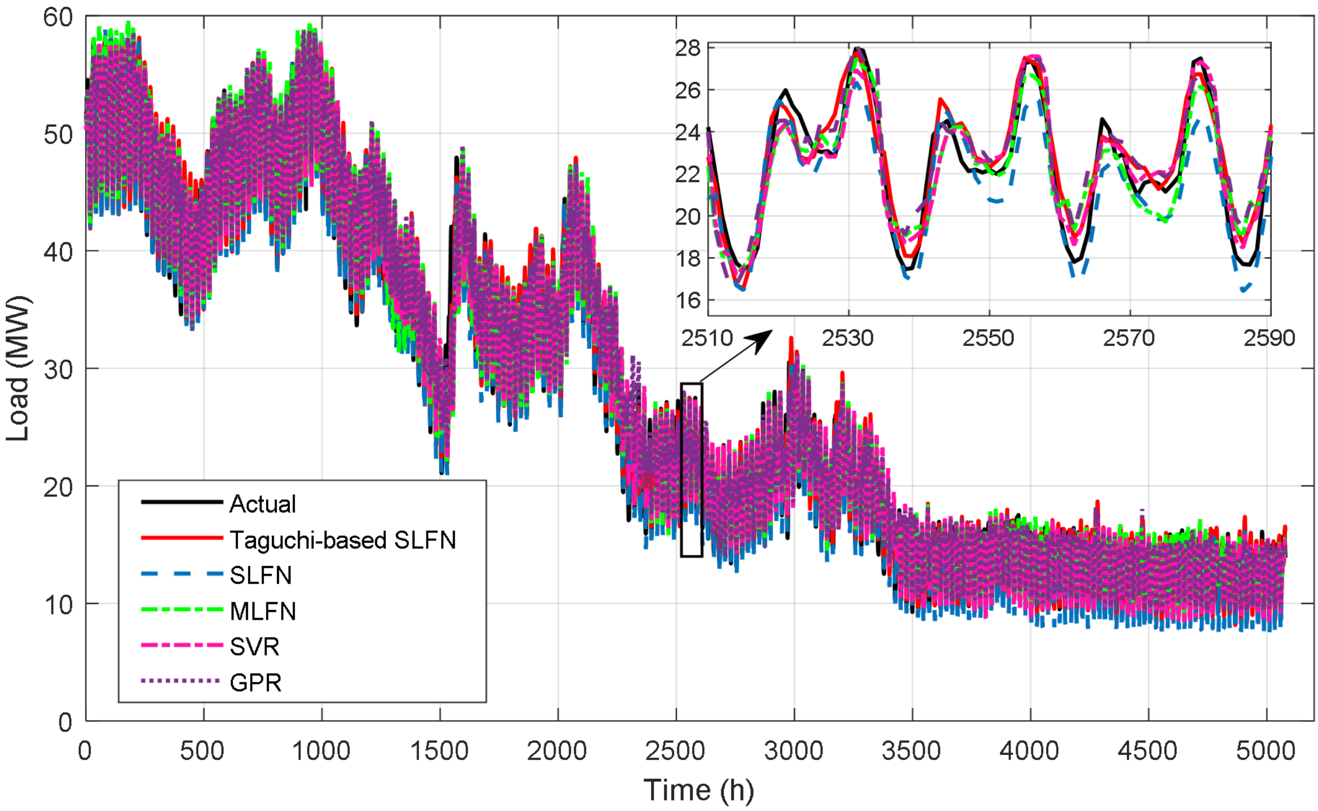

Figure 10. Comparison of actual and predicted hourly load values on the 20% test dataset.

Table 5. ANOVA results for S/N ratio analysis of SLFN parameter tuning.

Source	DF	Seq. SS	Adj. MS	F-value	P-value	Contribution (%)
A	4	111.37	27.84	0.58	0.693	11.85
B	4	131.05	32.76	0.69	0.638	13.95
C	4	183.08	45.77	0.96	0.516	19.49
D	4	120.77	30.19	0.63	0.666	12.87
E	4	201.95	50.49	1.06	0.479	21.50
Error	4	190.98	47.75	-	-	20.33
Total	24	939.21	-	-	-	100

of the total variation. Despite these differences, none of the factors were statistically significant ($P > 0.05$), indicating that variations in MAPE could not be conclusively attributed to any single parameter. Nevertheless, the contribution analysis highlights which parameters have a relatively greater impact on network performance, with seed and transfer function showing the strongest influence among the tested factors.

Once the optimal SLFN configuration was identified using the Taguchi method, the model's performance was benchmarked against alternative approaches, including the standard SLFN, MLFN, SVR, and GPR models. The comparative analysis was conducted on the 20% test dataset, while the remaining 80% was used for training and validation. Figure 10 presents a visual comparison between actual and predicted hourly load values for the different models. As shown in Figure 10, all models are generally able to follow the main seasonal and daily oscillations of the load profile; however, noticeable discrepancies appear during peak and valley periods. The Taguchi-based SLFN consistently demonstrates closer tracking of the actual load, particularly under sudden transitions.

The statistical performance indices of the models are summarized in Table 6. The Taguchi-based SLFN achieved the lowest error values (RMSE, MAE, MAPE) and the highest coefficient of determination (R^2), confirming its superior predictive accuracy. In contrast, the standard SLFN, MLFN, SVR, and GPR models exhibited higher error magnitudes and lower R^2 values, indicating relatively weaker generalization capability on unseen data. These results validate the effectiveness of Taguchi-based optimization in enhancing model robustness and accuracy. By systematically tuning hyperparameters, the SLFN model outperformed both conventional neural networks and statistical learning approaches, demonstrating its suitability for STLF in the studied region.

6 Conclusion

This study presented a Taguchi-based optimization framework for configuring SLFNs in STLF. By

Table 6. Performance evaluation of the forecasting models on the 20% test dataset.

Model	RMSE	MAE	MAPE	R^2
SLFN	1.4338	1.1103	5.06%	0.9899
MLFN	1.8296	1.3791	5.81%	0.9836
SVR	1.7819	1.3542	5.72%	0.9844
GPR	1.6828	1.2356	5.10%	0.9861
Taguchi-based SLFN	**1.3564**	**1.0137**	**4.32%**	**0.9910**

systematically exploring the effects of five key parameters, i.e. number of neurons, training function, transfer function, number of epochs, and random seed, the Taguchi method enabled efficient hyperparameter tuning while substantially reducing the number of required simulations compared to conventional approaches. The results demonstrated that the optimized SLFN achieved superior predictive accuracy (MAPE = 4.32%, R2 = 0.991) compared to standard SLFN, MLFN, SVR, and GPR models. These findings confirm that lightweight neural architectures, when properly tuned, can match or even outperform more complex forecasting models while offering reduced computational cost and improved interpretability.

A MATLAB-based graphical user interface was developed to support the complete forecasting workflow, including data preparation, parameter tuning, forecast execution, and performance evaluation. The tool has been tested on historical load and meteorological data from four municipalities, a power system characterized by high daily and seasonal variability and limited observability. The application of LF-GUI in operational practice for over a year has validated its robustness, with forecasting errors consistently maintained in the range of 3–5%. This confirms the practical value of the proposed approach for system operators in real-world environments.

Overall, the study bridges the gap between robust optimization techniques and lightweight neural networks, demonstrating that the Taguchi method offers a structured, reliable, and reproducible framework for SLFN parameter selection in STLF. Beyond the presented case study, the methodology is generalizable and can be applied to other power systems facing uncertainty, variability, and data limitations.

Future work will extend the LF-GUI with additional data sources, advanced forecasting algorithms, and more sophisticated optimization strategies, further enhancing its role as a user-friendly and reliable platform for power system operators and researchers.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Milorad M. Dragičević and Nebojša R. Krečković are affiliated with the Elektrokosmet, Belgrade 11000, Serbia. The authors declare that this affiliation had no influence on the study design, data collection, analysis, interpretation, or the decision to publish, and that no other competing interests exist.

Ethical Approval and Consent to Participate

Not applicable.

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