

# Electricity load forecasting using genetic algorithm optimized sigmoid regression

Mustafa Akpinar, Rula Azzawi, Usman Durrani, Kevser Ovaz Akpinar, Shanga Kareem and Mohammed Saleh

## Abstract

**Purpose** – This paper aims to determine an accurate model for forecasting electricity load demand by estimating sigmoid regression parameters using a genetic algorithm.

**Design/methodology/approach** – Meteorological data are used to prepare the city's daily electricity load dataset from February 1, 2014 to November 30, 2019. A genetic algorithm optimizes five parameters of the sigmoid regression.

**Findings** – The study evaluates the usability of the genetic algorithm in sigmoid regression for forecasting electricity load demand. It finds that one of the two seasonal behaviors presented in load consumption is not a good fit for the electricity load models. Winter and summer seasonal models are estimated to increase accuracy. Furthermore, minimum, maximum and average temperatures are used to determine the optimal temperature type for minimizing errors. Test dataset errors are lower than training dataset errors, indicating that the models are sufficiently accurate for forecasting.

**Research limitations/implications** – The findings will be helpful to demand forecasting and energy marketplace experts who want accurate forecasts of their assets.

**Practical implications** – The findings will be helpful to demand forecasting and energy marketplace experts who want accurate forecasts of their assets. The proposed model's relative mean absolute error is 71.8% and 18.1% better in the training and test datasets, respectively, compared with the naïve model, and the proposed model can lead to increased grid stability and cost savings.

**Originality/value** – Previous studies used four parameters, and the authors added one more parameter to the Sigmoid regression. In addition, prior studies employed the Levenberg–Marquardt method to estimate parameters, whereas the authors utilized genetic algorithms with extensive search capabilities.

**Keywords** Genetic algorithm, Electricity load, Load forecasting, Sigmoid linear regression

**Paper type** Research paper

(Information about the authors can be found at the end of this article.)

## 1. Introduction

Electricity demand forecasting has become an essential component of modern power system planning, operation and sustainability. As global energy consumption steadily rises due to population growth, industrial expansion, and the increasing integration of renewable energy sources, accurately predicting electricity load demand has become critical for ensuring grid reliability, minimizing operational costs, and guiding infrastructure investments (Ghalekhondabi et al., 2017; Rostum et al., 2020). Traditional forecasting techniques, such as time series analysis and regression-based models, have provided a solid baseline for load prediction. However, they often struggle to capture the complex, nonlinear behaviors and seasonal variations that characterize modern energy usage patterns. For example, while electricity consumption typically peaks in both winter and summer due to heating and cooling needs, natural gas consumption shows a distinctly different pattern, emphasizing the need for more adaptive forecasting models.

Recent advances in computational intelligence have led to the development of hybrid and evolutionary approaches that combine statistical techniques with machine learning algorithms

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to improve forecasting accuracy (Mystakidis *et al.*, 2024). In particular, genetic algorithms (GAs) have emerged as powerful tools for optimizing model parameters in challenging forecasting environments. Integrating GAs with regression models – especially those based on nonlinear sigmoid functions – can enhance the flexibility and robustness of energy demand estimation. Prior studies by Ravnik and Hriberšek (Ravnik *et al.*, 2021; Ravnik and Hriberšek, 2019) have demonstrated that allowing traditionally fixed parameters to become adjustable can lead to improved performance by reducing forecasting errors and handling outliers more effectively.

In our work, we extend this concept by developing a Genetic Algorithm Optimized Sigmoid Regression model tailored explicitly for electricity load forecasting. By treating the conventional constant (e.g. the fixed value “40” in previous formulations) as an optimizable parameter, our proposed model dynamically tunes its structure to better adapt to seasonal variations and abrupt changes in energy consumption patterns. This improvement is particularly significant for regions where extreme weather conditions cause nonstationary load profiles. The proposed model thereby bridges the gap between conventional load forecasting methods and the need for adaptive, real-time forecasting tools in smart grids and renewable-dominated environments (Rostum *et al.*, 2020).

Furthermore, with the digital transformation and the rise of big data in energy systems, advanced forecasting methods are now not only beneficial but necessary. Improved forecast precision contributes directly to the operational efficiency and economic performance of power systems by ensuring that generation and distribution resources are optimally allocated (Ghalekhondabi *et al.*, 2017). The novel approach presented in this study demonstrates substantial improvements in capturing seasonal shifts and load curve nonlinearities, thereby reducing errors that could otherwise lead to under- or over-provisioning in energy supply.

The remainder of this paper is organized as follows: Section 2 outlines the literature review, and Section 3 shows methods, including sigmoid regression and genetic algorithms. Section 4 gives the proposed model and its detailed formulation. Section 5 presents comprehensive experimental results and discusses the comparative advantages of the proposed method over traditional approaches. Finally, Section 6 concludes with a summary of the findings and potential directions for future research.

## 2. Literature review

Numerous methods have been investigated for demand forecasting, ranging from classical time series techniques to modern artificial intelligence and hybrid approaches. Traditional univariate methods such as ARIMA/SARIMA and Holt-Winters exponential smoothing have been widely used to capture basic seasonal patterns, with studies reporting daily forecast accuracies that achieve a mean absolute percentage error (MAPE) of approximately 24.57% and monthly forecasts with improved performance (Akpınar and Yumusak, 2019). Other time series approaches that employ nonseasonal exponential smoothing – specifically, simple and double exponential smoothing – optimize parameters through one-step-ahead forecasts, with some models reporting a minimal MAPE of 14.1%, thereby underscoring the efficacy of these methods in handling straightforward load trends (Akpınar and Yumusak, 2017). In addition, state space models such as Box-Cox transformation, ARMA errors, Trend and Seasonal components (BATS), and Trigonometric BATS (TBATS) have been assessed, with TBATS showing advantages in short-term forecasting due to its reduced parameter estimation demands (Naim *et al.*, 2018). In addition, BATS and ARIMA are used to forecast passenger market management on Indian Railways (Bhatia and Kalaivani, 2025). However, these traditional approaches often assume stationarity and linearity, require manual parameter tuning, and struggle to accommodate abrupt seasonal shifts and nonlinear load dynamics, highlighting the need for more flexible hybrid models. Econometric and regression-based models have also received considerable attention,

particularly for capturing the effects of exogenous variables and socioeconomic uncertainties. For instance, multiple linear regression (MLR) has been successfully applied to forecast daily electricity consumption in Sulaymaniyah, Iraq, where segmenting data sets based on long-term seasonal trends can enhance accuracy and identify key explanatory variables (Kareem and Akpinar, 2021). Moreover, various regression techniques that involve forward selection, backward elimination, and stepwise methodologies have demonstrated improved performance by incorporating seasonally partitioned data, achieving MAPE values as low as 5.93% with corresponding  $R^2$  values around 0.7965 (Kareem and Akpinar, 2021).

Parallel to these statistical methods, machine learning and artificial intelligence models have been explored better to capture the nonlinear and dynamic nature of energy demand. Several studies have applied artificial neural networks (ANNs) and gradient boosting methods, with some hybrid models integrating feature selection techniques such as sensitivity analysis and principal component analysis to improve prediction accuracy by nearly 15% in terms of MAPE reduction (Akpinar *et al.*, 2017; Özger *et al.*, 2019; Sharma *et al.*, 2021). In addition, advanced hybrid strategies combining methods like enhanced singular spectrum analysis with long short-term memory (ISSA-LSTM) networks or integrating convolutional neural networks (CNN) with functional autoregressive methods (FAR-CNN) have been proposed to handle both linear and nonlinear relationships in load data, further demonstrating that hybrid AI approaches often outperform conventional methods in terms of accuracy (Chen *et al.*, 2020; Wei *et al.*, 2019).

Moreover, forecasting studies have been conducted at various scales – from country-level annual energy consumption to city-based or subscriber-based hourly load predictions, which reveal that the performance of forecasting models is highly dependent on the resolution and quality of the input data (Akpinar and Yumusak, 2019; Gao and Shao, 2021). While these diverse methodologies collectively emphasize the importance of model selection and optimization, many rely on regression techniques and incorporate additional algorithms, such as the Artificial Bee Colony algorithm or time series splitting methods, to address issues like overfitting and parameter tuning. Despite these significant advancements, the current literature still reflects a gap in models that can adaptively optimize parameter settings in response to rapid seasonal changes and the inherent nonlinearities of energy demand. This motivates our approach, which introduces a Genetic Algorithm Optimized Sigmoid Regression model that extends conventional sigmoid regression by increasing the number of parameters from four to five and dynamically optimizing these parameters using a genetic algorithm. This approach is designed to capture seasonal variations and enhance forecasting accuracy in complex and rapidly changing demand conditions.

In this research, Sigmoid regression, previously used in two studies, was developed and used in city electricity load forecasting. The novel contributions of the study are outlined as follows:

- The number of parameters used in the Sigmoid regression model was increased to five, and all variables relied on data and parameters.
- The search area was expanded using a genetic algorithm to determine the parameters. The research led to the first application of sigmoid regression in electricity load forecasting.
- Seasonal models were developed, resulting in a reduction in errors.

### 3. Methods

This section will explain the techniques used to forecast electric load. The Sigmoid function, genetic algorithm and proposed hybrid technique are presented in the section “Data,”

which explains the data collection methodology. The last part of this section explains error measurement and terms.

### 3.1 Sigmoid regression

Ravnik and Hribersek propose the first use of the Sigmoid function in demand forecasting (Ravnik and Hriberšek, 2019). Their study compared linear, parabolic and exponential regression methods in addition to Sigmoid regression. Their proposed method is used for forecasting natural gas demand. Their equation [equation (1)] used temperature ( $T$ ) and four parameters ( $A$ ,  $B$ ,  $C$  and  $D$ ). The  $P_g^m$  is gas estimation value using the Sigmoid function:

$$P_g^m = \frac{A}{1 + \left(\frac{B}{T-40}\right)^C} + D \quad (1)$$

In (Ravnik et al., 2021), two different temperatures were used for forecasting. They used one-third of the estimated consumption based on the same-day temperature and two-thirds of the estimated consumption based on the next-day temperature. They added the average annual consumption to their estimations as the intercept point. The second study used simpler Sigmoid Regression (SR) (Ravnik et al., 2021). Their models used all-series average consumption rather than annual average consumption [equation (2)]:

$$P_j = \max \left\{ \overline{P^m} \left[ \frac{A}{1 + \left(\frac{B}{T_j-40}\right)^C} + D \right], 0 \right\} \quad (2)$$

They updated the equation due to the possibility of negative values in the estimations. Also, they removed the weighting of the estimation related to the two days' temperatures and used the same-day temperature to forecast consumption. The Levenberg-Marquardt method was used to find four parameters in the equation (Ravnik et al., 2021; Ravnik and Hriberšek, 2019).

We added one more parameter that is related to temperature to the SR used in (Ravnik et al., 2021; Ravnik and Hriberšek, 2019). We replaced the number 40 with a new parameter,  $E$ , to optimize it [equation (3)]. This update was made due to the possibility of negative values in the estimations. Also, they removed the weighting of the estimation related to the two days' temperatures and used the same-day temperature to forecast consumption:

$$P_j = \max \left\{ \overline{P^m} \left[ \frac{A}{1 + \left(\frac{B}{T_j-E}\right)^C} + D \right], 0 \right\} \quad (3)$$

The five parameters are addressed in the physical interpretation of the model. The first parameter is  $A$ , which multiplies the entire sigmoid fraction before adding  $D$ . When  $A$  increases, the plateau, maximum value of the sigmoid term, grows proportionally. Physically, this corresponds to raising the peak load level that the model can predict, relative to the average consumption  $\overline{P^m}$ .  $B$  and  $E$  are used for inflection and shift. Changing  $E$  shifts the curve left or right along the temperature axis, setting the threshold temperature at which the load begins to climb steeply. Meanwhile,  $B$  scales that threshold effect: larger  $|B|$  makes the inflection region occur at a different distance from  $T_j = E$ . Overall,  $E$  is the temperature pivot around which the load increases (e.g. the "break-even" temperature between heating vs cooling demand), and  $B$  adjusts how far from that pivot the load response starts to accelerate.  $C$  is used for steepness and curvature. As the exponent on the ratio  $[B/(T_j-E)]$ ,  $C$  controls the sharpness of the transition. A higher  $C$  makes the curve more "step-like," meaning load jumps quickly once the threshold is crossed; a smaller  $C$  yields a gentler S-shape. Physically, this reflects how sensitive consumption is to small

changes in temperature around the pivot. Finally,  $D$  is added after the sigmoid fraction. It shifts the entire curve up or down, representing any constant bias in the forecast (e.g. base-load that does not vary with temperature).

### 3.2 Genetic algorithm

GA is one of the most popular algorithms in metaheuristic optimization. Its objective is to maximize, minimize or target fitness functions. The topic has been called *evolutionary computation* (Melanie, 1999). The GA iteratively refines solutions via inheritance, mutation and selection, thereby identifying the best values in each iteration.

The genetic algorithm starts with an initialization process that sets the GA model. In this stage, the first population is created. Then, using the fitness function, the objective of each population is calculated. The end criteria initiated in the beginning are checked for the population and iteration numbers. If the end criteria are unsatisfied, the algorithm continues with the GA components.

The GA components work in the order *selection*, *crossover* and *mutation* are completed to find new populations. Different types of *selection* types are used. Tournament and roulette selections are well-known selection types in GA (Glover and Kochenberger, 2003; Haupt and Haupt, 2004). The second phase of the GA components is *crossover*. Crossover creates a new population related to the selected parents in the *selection* stage by changing some genes (values) with a range of values found in the population (Glover and Kochenberger, 2003). In the *mutation*, the genes' values are swapped randomly from the other children with a probability. After the *mutation*, the objective of each population is calculated using the fitness function to identify the best population and iterate the *selection*, *crossover* and *mutation* processes until the end criteria are satisfied.

### 3.3 Error measurements

Several error measurement terms are used in demand forecasting studies. Our study employed the MAPE, coefficient of determination ( $R^2$ ), and relative mean absolute error (rMAE) to determine the optimal solution. While MAPE and  $R^2$  provide intuition on forecasting accuracy, they are known to exhibit bias (under- or over-penalizing certain errors) and scale dependence. Consequently, we report results with rMAE, in addition to MAPE and  $R^2$ , to ensure a fair comparison across models. Our results indicate that the GA-optimized sigmoid regression consistently outperforms both the Seasonal Naïve and persistence benchmarks under all four metrics.

## 4. Methodology

This section explains the study's data and methodology. The first part shows data preparations. The methodology we proposed is given in Section 2.

### 4.1 The data

The electricity load data prepared in this study was provided by the Sulaymaniyah Electricity Control Center (Kareem and Akpinar, 2021). Hourly-based data was collected from different feeders, along with their locations. The unit used in the study is the ampere (A), which can be converted to kWh using equation (4). In the equation,  $V$  represents voltage,  $h$  represents hours, and kWh represents kilowatt-hours. As shown in equation (4), electricity consumption consists of hourly data. Load consumption was gathered to determine daily load consumption:

$$kWh = \frac{(A \cdot V \cdot h)}{1,000} \quad (4)$$

The second data source used in the study is weather information. OpenWeather is the data source, and hourly temperatures are converted to daily temperatures, and maximum, minimum and mean temperatures are calculated.

## 4.2 Proposed method

In this section, we will present our hybrid model, the Genetic Algorithm–Optimized Sigmoid Regression (GA-SR) model for electricity load forecasting. Our approach departs from prior work in four main ways:

- *Expanded Parameterization:* We augment the classic four-parameter sigmoid function with a fifth temperature-scaling parameter, allowing the model to adjust to different thermal regimes with greater flexibility.
- *Evolutionary Optimization:* Rather than fixing any coefficient a priori, we employ a genetic algorithm to jointly tune all five parameters, dramatically broadening the search space and avoiding manual calibration.
- *First Application to Electricity Loads:* While sigmoid regression has been applied to natural gas forecasting, our study is the first to apply and validate it for daily electricity demand.
- *Season-Specific Models:* To capture the distinct winter and summer consumption patterns, we build and optimize separate seasonal models, yielding statistically significant error reductions compared to a single-model approach.

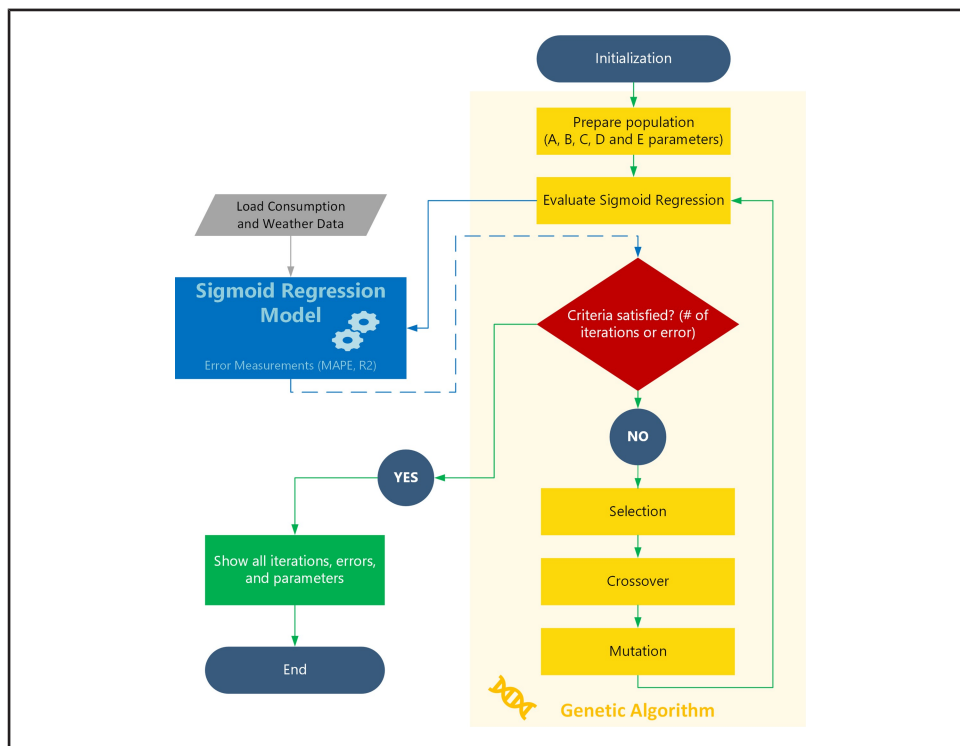
While the Levenberg-Marquardt method was used in determining the parameters in previous studies (Ravnik *et al.*, 2021; Ravnik and Hriberšek, 2019), the genetic algorithm, one of the intuitive approaches, was used in this study. In addition, the optimization set was expanded with an additional parameter assigned the value 40 in the equation in previous studies (Ravnik *et al.*, 2021; Ravnik and Hriberšek, 2019).

The flow of the proposed study is shown in Figure 1. In the initiation phase, fixed values were assigned to the parameters A, B, C, D and E (Table 1), and the initial population was created.

The values in the studies (Ravnik *et al.*, 2021; Ravnik and Hriberšek, 2019) were used as the initial values. Descriptive statistics of the parameters in 217 models obtained by the authors in the same studies were used to determine the maximum and minimum values (Table 2). The minimum and maximum values determined here were rounded, and the values in Table 1 were obtained. Then, the SR errors were calculated for each population.

Next, whether the fitness function value reaches the target value is tested based on the iteration number. The fitness function used in the study is given in equation (7). While the MAPE value is desired to be low in demand estimation, the  $R^2$  value is desired to be high. The fitness value is obtained in the study using these two values. By dividing the MAPE value by  $R^2$ , the fitness value will decrease as the MAPE value decreases and the  $R^2$  value increases. Conversely, the fitness value increases as the MAPE increases and  $R^2$  decreases. While the  $R^2$  value varies between [0 1], MAPE varies between [0  $\infty$ ). In addition, since both error values depend on the estimation results, they exhibit a negative correlation. In the initial rapid preliminary studies, it was observed that using too many iterations was not beneficial in determining the appropriate model. Although it was observed that the first 5 iterations were sufficient to find the appropriate fitness value, the number of iterations, which is one of the stopping criteria, was set to 25 to verify that the appropriate number was determined:

$$Fitness = \frac{MAPE}{R^2} \quad (7)$$

**Figure 1** Proposed hybrid sigmoid regression genetic algorithm model**Table 1** Initial with the maximum and minimum values of the parameters

| Parameters | Initial | Maximum | Minimum |
|------------|---------|---------|---------|
| A          | 1       | 125     | -2      |
| B          | -30     | 20      | -350    |
| C          | 10      | 5,000   | -2,000  |
| D          | 0.1     | 3       | -1      |
| E          | 40      | 200     | -50     |

**Table 2** Descriptive statistics of parameters from (Ravnik *et al.*, 2021; Ravnik and Hriberšek, 2019)

| Statistics | A               | B               | C               | D               |
|------------|-----------------|-----------------|-----------------|-----------------|
| Minimum    | -1.677          | -337.070        | -1937.688       | -0.285          |
| Maximum    | 121.760         | -2.170          | 4819.742        | 2.227           |
| Average    | 4.073           | -40.310         | 19.926          | 0.116           |
| Median     | 2.844           | -37.709         | 5.260           | 0.084           |
| Std dev    | 10.201          | 22.689          | 353.430         | 0.271           |
| Count      | 217 (102 + 115) | 217 (102 + 115) | 217 (102 + 115) | 217 (102 + 115) |

## 5. Results and discussion

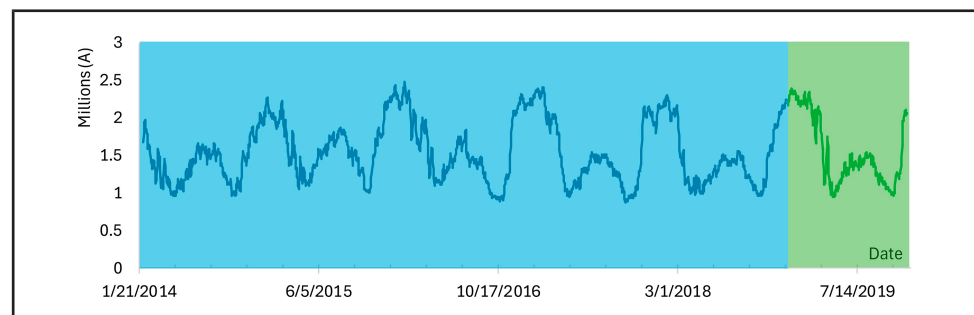
This section will assess the accuracy of determining SR parameters using the GA and attempt to identify the most suitable model. SR has previously been used to estimate natural gas consumption. Natural gas consumption increases in winter and decreases in summer. Electricity load demand differs from natural gas demand. Electricity demand, which is

higher in winter, increases in summer because it is also used for cooling due to hot weather. The most fundamental difference here is that while natural gas consumption exhibits stationary behavior in summer, increased consumption is observed in electricity load consumption (Figure 2). In the first stage of the study, the estimation of both winter and summer consumption behavior with SR will be examined. The load data spans from February 2014 to December 2019. Last year, 2019, was reserved for testing the model, while the remaining data was used for the training phase. In Figure 2, the training data set is represented by the blue area, and the test data is shown in the green area.

For GA to run in the study, some parameters must be determined in advance. All GA parameters used in this study are given in Table 3. Population size was defined as 5 times the chromosome length. The maximum generations and the iteration number were tested with values such as 50, 100, 500 and 1000. The GA found the optimum point of the fitness value in a maximum of 10 iterations (Figure 3). Here, the maximum generations was selected as 25, and the search for the optimum point was carried out for a while. The GA was implemented with Visual Basic Application (VBA), and the SR was implemented with Microsoft Excel functions to perform the study.

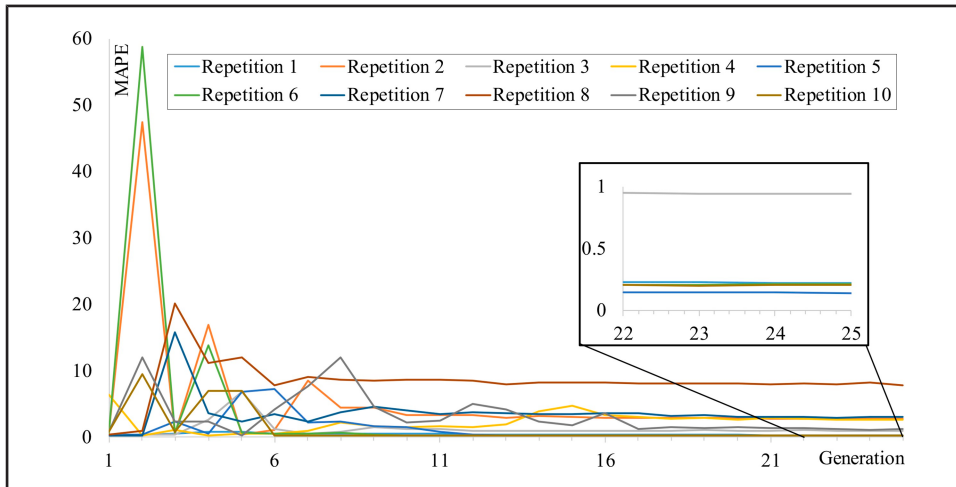
While Bayesian optimization (BO) has gained traction for hyperparameter tuning thanks to its sample-efficient surrogate modeling of the objective function, it can struggle with high-dimensional search spaces and noisy fitness evaluations common in real-world load forecasting (e.g. approximately 10+ parameters) (Alibrahim and Ludwig, 2021). Particle Swarm Optimization (PSO), by contrast, often converges more rapidly than GA on smooth, unimodal landscapes but can be prone to premature convergence and lack GA's robust diversity mechanisms when tackling multimodal, non-convex parameter surfaces (Clarke *et al.*, 2014; Hassan *et al.*, 2005). Genetic Algorithms strike a balance by combining crossover-driven exploration with mutation-driven fine-tuning, which has been shown to yield superior global search performance in power-system applications (e.g. optimal power flow) compared to PSO (Papazoglou and Biskas, 2023). Moreover, hybrid BO-GA frameworks demonstrate that augmenting BO with evolutionary operators can further enhance convergence, but at the cost of increased engineering complexity and computational overhead (Suryawanshi *et al.*, 2023). Given our moderate parameter

**Figure 2** Daily electricity load (in million amperes) data from 2014–2019



**Table 3** Genetic algorithm parameters

| Parameter           | Value |
|---------------------|-------|
| Population size     | 50    |
| Chromosome length   | 5     |
| Maximum generations | 25    |
| Mutation rate       | 0.05  |
| Crossover rate      | 0.85  |

**Figure 3** MAPE - generation graph for model 2014

dimensionality (five parameters) and the need to robustly navigate seasonal, nonlinear demand patterns, we selected GA for its well-established convergence reliability, ease of parallel implementation, and proven track record in energy forecasting studies (Nazari *et al.*, 2015).

In the first model prepared in the study, load estimation was performed using data from February 2014 to December 2014. Since this model was based on 2014 data, it was named Model 2014. The genetic algorithm was repeated 10 times with the same initial values to determine the appropriate model and consistency. The generation-MAPE change of each different trial is shown in Figure 3. The reason why the fitness value is not used here is that it reaches very large values. Genetic algorithm fitness values depend on the MAPE and  $R^2$  values. When the  $R^2$  value is very low, the fitness value increases significantly. For example, in the first generation following the initial situation, the MAPE value was 0.2799, and the  $R^2$  value was  $7.77 \times 10^{-30}$ . In this case, the fitness value was obtained as  $3.6 \times 10^{28}$ . As seen in Figure 3, there has been no major progress in training since the 10th generation. The detailed graph shows the results of the last 4 iterations for a maximum MAPE value limited to 1. Four out of 10 different trials had an MAPE value below 0.22. The best fitness value obtained here is the 25th generation in 5 trials. The fitness value, corresponding MAPE and  $R^2$  values were 0.2479, 0.1445 and 0.583, respectively.

In the next stage of the study, the model was executed again, starting from January 2015, assuming that the missing data for January 2014 could increase the error of the obtained model. The lowest fitness value in this model, Model 2015, occurred in the 20th generation in the 8th trial. This trial's fitness, MAPE and  $R^2$  values were 0.2085, 0.1365 and 0.655, respectively. The estimated parameters for both models are given in Table 4. While the difference between the A and D parameters is low, the B, C and E parameters have entirely different values. Another critical point is that the E parameter added to the SR yields very different results from the value of 40. This difference shows that adding the E parameter positively contributes to the model.

**Table 4** Estimated parameters for model 2014 and model 2015

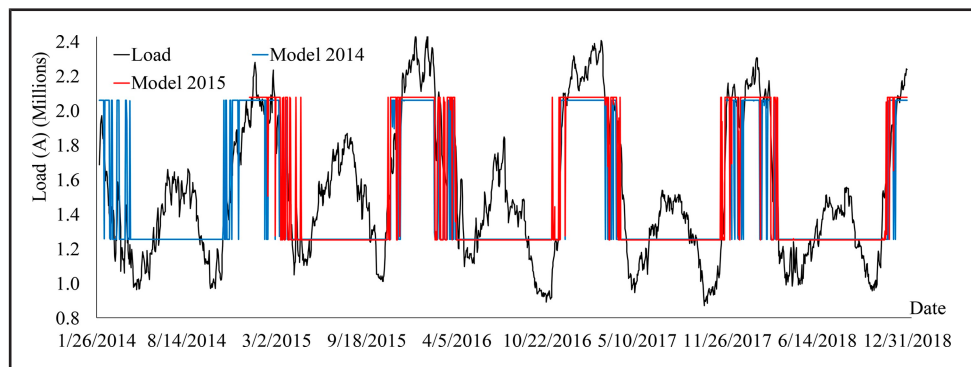
| Model      | A      | B       | C     | D      | E      |
|------------|--------|---------|-------|--------|--------|
| Model 2014 | 0.5235 | -71.60  | 2,170 | 0.8162 | 82.37  |
| Model 2015 | 0.5249 | -128.64 | 1,399 | 0.7985 | 140.77 |

When the MAPE and  $R^2$  values of Model 2014 and Model 2015 are examined, the 2015 model yields better results than the 2014 model, with 0.1365 and 0.655. When the obtained models and load estimations are compared for the training data set, it is seen that they make higher consumption estimates in the winter season (Figure 4). The most fundamental difference between the load demand graph and the estimate graph is the differences between seasonal consumption behaviors. While both the 2014 and 2015 models estimate the consumption in the winter season more accurately, they ignore the consumption behavior in the summer. This graph shows us that the study needs to be developed in two ways.

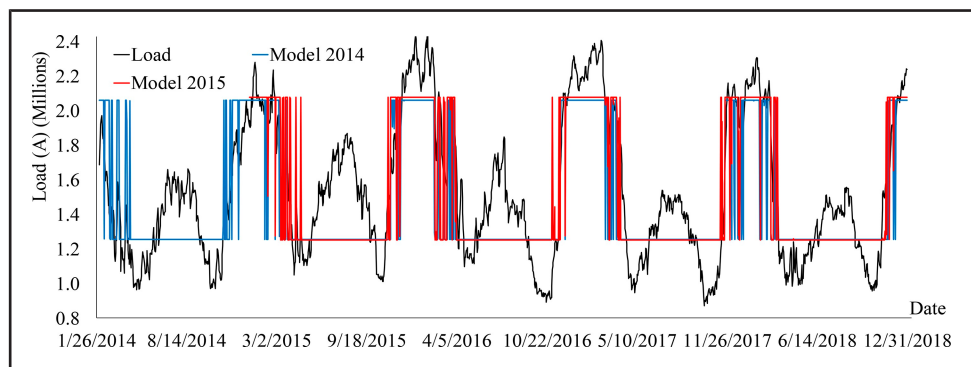
In the study, the load behaviors of the summer and winter seasons are different. It is hypothesized that creating models based on winter and summer seasons, informed by these behaviors, can increase the accuracy of load estimation. When the consumption behavior in Figure 5 is examined, the models are determined by separating the summer and winter seasons. Accordingly, consumption between April 22nd and October 31st is included in the Summer model, while consumption outside these dates is included in the Winter model. In the Winter and Summer models, the dates outside their specified dates should be filtered to avoid affecting the model estimates and the parameter values obtained. Accordingly, in the Winter models, the consumption in the summer season is taken as the average of the consumption in the summer model (Figure 6). In the summer model, the lowest consumption values in the summer season are used to remove the effect of winter data.

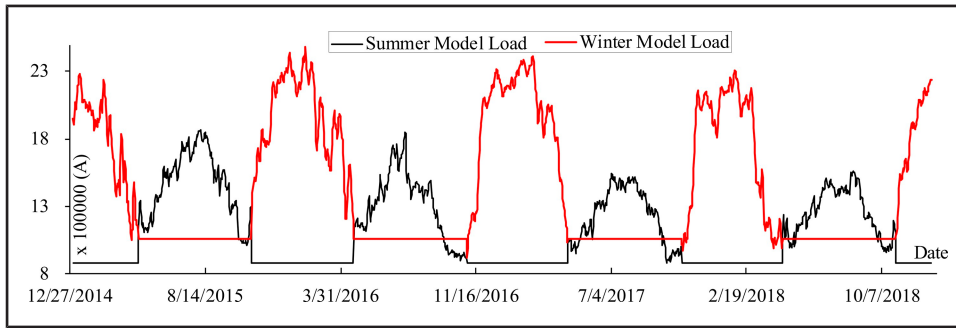
Another dimension the study will expand is changing the temperature value used. In previous studies, the average temperature value was used (Ravnik *et al.*, 2021;

**Figure 4** Load estimations for model 2014 and model 2015 on training data



**Figure 5** Load estimations for model 2014 and model 2015 on training data



**Figure 6** Winter and summer models load data

Ravnik and Hriberšek, 2019). In our study, winter and summer models will be created. In this case, it is thought that the minimum temperature may be more effective for the winter model. On the contrary, the maximum temperature is expected to have a greater effect on consumption for the summer model. To examine both seasonal and temperature effects, 6 models were developed, and the proposed SR-GA method was tested. The names of these models are given in Table 5.

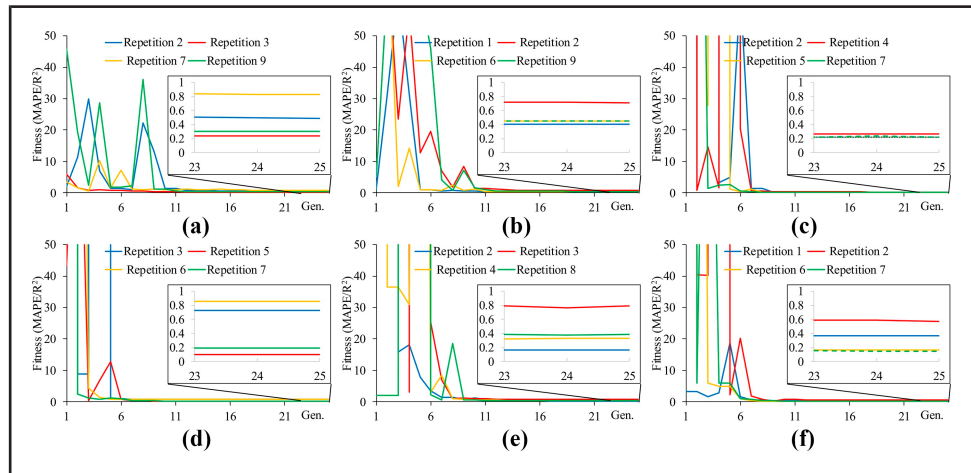
The fitness function calculations of the models depend on the coefficients. Some of the parameter values assigned by GA may cause unexpected situations, such as the error of dividing by zero originating from the equation itself, and the fitness value being too high due to the  $R^2$  value being too low. A few corrections were made here, and the results were redeemed from errors. For example, when there was a zero error division, the consumption estimate was obtained by copying the previous day's estimate. Another correction at this stage was to use only the MAPE and  $R^2$  values of the estimates between the relevant seasonal dates in the fitness function. Thus, lower MAPE and higher  $R^2$  values were obtained, and the fitness function value was minimized. Figure 7 displays the values of the four repetitions with the lowest fitness function value in each generation for the models listed in Table 5. The success of GA is evident in identifying the five parameters with a wide range of values in the appropriate form. In the winter models, the model using the maximum temperature to predict had the lowest fitness function value (MAPE = 0.1208,  $R^2$  = 0.554). In contrast, in the summer model, which used the average temperature to predict, had the lowest fitness function value (MAPE = 0.0748,  $R^2$  = 0.721).

The fitness, MAPE and  $R^2$  values of the seasonal models with the lowest fitness values, along with the determined parameter coefficients are given in Table 6. The examined values show that parameter  $A$  remains below the minimum boundary in two cases (Model W-TAvg, Repetition 7, and Model S-TAvg, Repetition 3). This is due to the GA crossover and mutation components, which is an expected condition. The fact that the parameter  $E$  added to the model takes very different values (minimum -7.419, maximum 187.976, average 108.85, standard deviation 59.217) than a fixed value of 40 in (Ravnik *et al.*, 2021; Ravnik and Hriberšek, 2019) shows that the approach here has a positive effect on the result. Obtaining similar MAPE and  $R^2$  values with different parameter values in each repetition shows that the solution space is broad and that GA has high space exploration capabilities. As shown in Table 6 (f), in cases where two different repetitions yield the same MAPE value, the model

**Table 5** Model naming for seasonal models with temperature types

| Models       | Average temperature | Minimum temperature | Maximum temperature |
|--------------|---------------------|---------------------|---------------------|
| Winter model | Model W-TAvg        | Model W-TMin        | Model W-TMax        |
| Summer model | Model S-TAvg        | Model S-TMin        | Model S-TMax        |

**Figure 7** Fitness - generations training process for six models: (a) Model W-TAvg, (b) Model W-TMin, (c) Model W-TMax, (d) Model S-TAvg, (e) Model S-TMin, (f) Model S-TMax



**Table 6** Estimated parameters with fitness, MAPE and  $R^2$  values for Six models: (a) model W-TAvg, (b) model W-TMin, (c) model W-TMax, (d) model S-TAvg, (e) model S-TMin, (f) model S-TMax

| Repetition              | Fitness | MAPE  | $R^2$ | A      | B       | C         | D     | E      |
|-------------------------|---------|-------|-------|--------|---------|-----------|-------|--------|
| <i>(a) model W-TAvg</i> |         |       |       |        |         |           |       |        |
| 3                       | 0.240   | 0.167 | 0.693 | 12.42  | -296.83 | 3.21      | 0.77  | 122.90 |
| 2                       | 0.489   | 0.182 | 0.371 | 42.19  | -113.83 | 23.66     | 0.87  | 101.44 |
| 9                       | 0.302   | 0.209 | 0.692 | 112.45 | -97.05  | -17.78    | 1.30  | 173.72 |
| 7                       | 0.828   | 0.477 | 0.576 | -24.01 | 19.62   | 1,911.99  | 1.07  | -7.42  |
| <i>(b) model W-TMin</i> |         |       |       |        |         |           |       |        |
| 1                       | 0.408   | 0.150 | 0.368 | -0.45  | -31.24  | -1,971.40 | 1.50  | 33.25  |
| 6                       | 0.447   | 0.154 | 0.344 | 0.42   | -48.55  | 1,627.27  | 1.09  | 49.57  |
| 9                       | 0.446   | 0.164 | 0.368 | 0.24   | -24.69  | 630.68    | 1.23  | 26.68  |
| 2                       | 0.706   | 0.210 | 0.297 | 25.38  | -82.55  | 17.25     | 0.93  | 65.51  |
| <i>(c) model W-TMax</i> |         |       |       |        |         |           |       |        |
| 2                       | 0.218   | 0.121 | 0.554 | 0.52   | -155.19 | 4,146.11  | 0.94  | 173.15 |
| 5                       | 0.221   | 0.122 | 0.551 | 0.49   | -59.14  | 3,312.79  | 0.96  | 77.11  |
| 7                       | 0.222   | 0.121 | 0.543 | -0.60  | 14.88   | 1,496.78  | 1.46  | 4.00   |
| 4                       | 0.265   | 0.127 | 0.480 | -0.61  | -166.66 | -1,714.58 | 1.43  | 187.98 |
| <i>(d) model S-TAvg</i> |         |       |       |        |         |           |       |        |
| 5                       | 0.104   | 0.075 | 0.721 | 0.39   | -103.16 | -64.23    | 0.96  | 130.35 |
| 7                       | 0.191   | 0.119 | 0.622 | -0.53  | -100.97 | 1,969.38  | 1.49  | 128.60 |
| 3                       | 0.730   | 0.413 | 0.566 | -13.97 | -99.91  | 1,222.30  | 1.29  | 124.71 |
| 6                       | 0.856   | 0.437 | 0.510 | 1.63   | -154.50 | 1,328.60  | -0.59 | 185.05 |
| <i>(e) model S-TMin</i> |         |       |       |        |         |           |       |        |
| 2                       | 0.164   | 0.098 | 0.597 | -1.19  | -81.44  | 12.76     | 1.55  | 92.98  |
| 4                       | 0.328   | 0.176 | 0.536 | -0.06  | -158.55 | -938.35   | 1.21  | 174.38 |
| 8                       | 0.383   | 0.204 | 0.533 | 102.47 | -189.84 | 11.00     | 1.00  | 118.77 |
| 3                       | 0.797   | 0.386 | 0.484 | 0.83   | -60.08  | 2,019.26  | 0.22  | 79.11  |
| <i>(f) model S-TMax</i> |         |       |       |        |         |           |       |        |
| 7                       | 0.145   | 0.093 | 0.639 | -0.27  | -119.04 | 79.71     | 1.27  | 153.81 |
| 6                       | 0.163   | 0.093 | 0.573 | -0.37  | -149.57 | 479.57    | 1.34  | 184.55 |
| 1                       | 0.366   | 0.155 | 0.422 | 64.22  | -62.52  | -33.20    | 1.13  | 148.67 |
| 2                       | 0.574   | 0.242 | 0.422 | 33.78  | -139.51 | 4.96      | 0.99  | 83.52  |

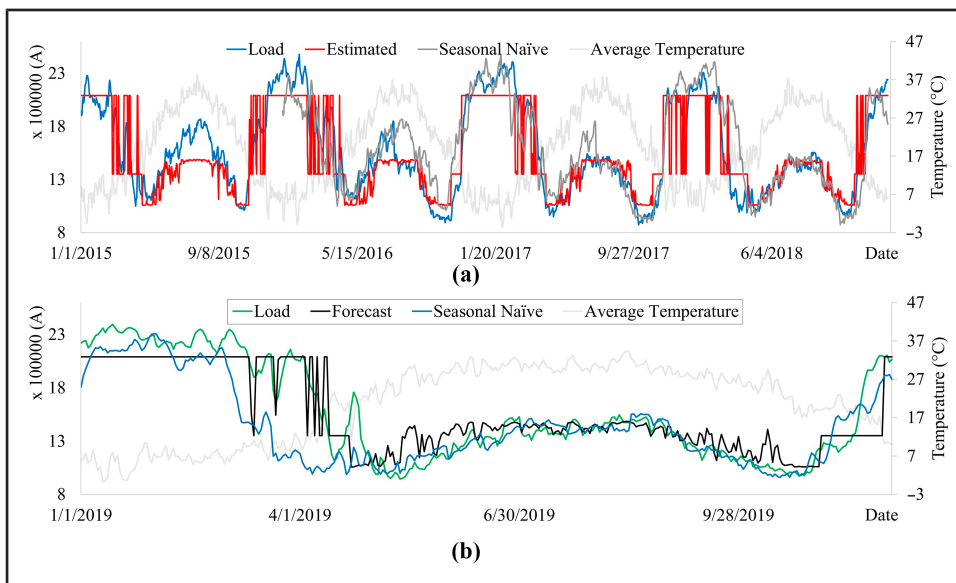
with the higher  $R^2$  value makes more accurate predictions, indicating that the fitness function is selected appropriately.

Figure 8 shows the estimation and forecasting values performed on the train and test data sets and the temperature. The gray line with the right axis of the graph show the temperature. The blue line in Figure 8(a) represents the actual consumption, the red line represents the estimations, the black line in Figure 8(b) represents the actual consumption, and the green line represents the forecasting values. The final forecast model graph for the training data set using the obtained parameters is shown in Figure 8(a). While it is evident that the three estimates in the winter model cannot be accurately estimated and the temperature changes are not reflected in the model, it is observed that the effect of the temperature change is reflected in the model in the summer model. According to the estimations made in the test data set, it is observed that the summer model estimations accurately capture the consumption trend. In contrast, in the winter model, it is seen that the estimation of the summer and short transition zones is not performed correctly.

The estimation errors of the study are shown in Table 7. The proposed model is compared with the Seasonal Naïve model in the table. The first point that draws attention to the errors is that the error values in the test data set are lower than in the training data set in the proposed model.

In addition, the seasonal naïve tends in the same direction as MAPE and rMAE. While the MAPE in the test data set showed a 1.69% improvement compared to the training data set, the  $R^2$  value improved by 6.36%. The proposed and seasonal naïve models are compared,

**Figure 8** Estimated and forecasted load consumptions (a) estimation on training data, (b) forecasts on test data



**Table 7** Error comparison of the models

| Model          | Dataset | MAPE (%) | $R^2$ | $\rho$ | MSE                  | RMSE     | rMAE        |
|----------------|---------|----------|-------|--------|----------------------|----------|-------------|
| Proposed       | Train   | 9.652    | 0.761 | 0.872  | $4.32 \cdot 10^{10}$ | 207851.4 | 4.486103706 |
|                | Test    | 9.488    | 0.809 | 0.899  | $4.08 \cdot 10^{10}$ | 202105.7 | 3.671892369 |
| Seasonal naïve | Train   | 11.451   | 0.751 | 0.867  | $5.48 \cdot 10^9$    | 74054.2  | 15.91267348 |
|                | Test    | 10.235   | 0.69  | 0.831  | $6.63 \cdot 10^{11}$ | 814204.1 | 4.480839005 |

and MAPE,  $R^2$  and rMAE are improved by 18%, 1% and 225%, respectively. In MSE, the proposed model's performance is 87% worse than that of the seasonal naïve model. Overall, the proposed model outperforms the seasonal naïve model in training and testing across four out of six error measurements. It was seen that the results of the obtained model were consistent. In the study conducted by Kareem and Akpinar, where the same data set was used, the lowest MAPE value in the training data set was 8.83%, and the  $R^2$  value was 0.8188, while the lowest MAPE value in the test data set was 12.4%, and the  $R^2$  value was 0.7133 (Kareem and Akpinar, 2021). In our study, the MAPE value in the training data set was 8.5% lower than the MAPE value in the compared study, while this rate was 30.7% better in the test data set. A similar situation occurred for  $R^2$ , and  $R^2$  in the test data set was higher. Compared with the study conducted by Ravnik and Hriberšek, the correlation coefficient value in the model they used for workdays varied between 0.35 and 0.82. In contrast, it varied between 0.2 and 0.84 in the model used for weekends (Ravnik and Hriberšek, 2019). The correlation coefficient value varied between 0.3 and 0.83 in the model used for the entire data set. In our study, the correlation coefficient values for the train and test sets were 0.872 and 0.899, respectively, yielding better results. Again, in the same study, normalized RMSE was obtained and varied between 0.36 and 1.58. To make the comparison, RMSE was normalized in our study and was found to be 0.092. Here, it is seen that our study improved the results. In another study, Ravnik *et al.* obtained a correlation coefficient with Sigmoid regression that varied between 0.01 and 1, while the normalized RMSE value ranged between 0.15 and 1.5 (Ravnik *et al.*, 2021). Here, the normalized RMSE value we obtained was lower.

## 6. Conclusions

This study presented an innovative approach to forecasting electricity load demand by optimizing the parameters of a sigmoid regression model using a genetic algorithm. Introducing an additional parameter that depends on temperature and utilizing a genetic algorithm to enhance the model's ability to capture seasonal variations in electricity consumption. The research demonstrated that while a single model struggled to accurately predict both summer and winter demand patterns, separating the seasonal models significantly improved forecast accuracy.

The winter and summer models were further refined by testing different temperature types – average, minimum and maximum – revealing that the maximum temperature was the most effective for winter predictions. In contrast, average temperature yielded the best results for summer. These refinements enabled the model to more accurately reflect consumption behaviors during these seasons, resulting in lower MAPE and higher  $R^2$  values in both the training and test data sets.

The successful application of the hybrid sigmoid regression-genetic algorithm model underscores the value of combining traditional regression techniques with advanced optimization algorithms. The improved accuracy of load forecasts has important implications for energy demand management, as it enables more precise predictions of electricity consumption, leading to more efficient resource allocation and operational planning.

In closing, we note that electricity-load forecasting in real-world settings often benefits from incorporating a wider range of calendar and meteorological variables, such as day-of-week and holiday indicators, humidity, wind speed and other weather extremes, to capture demand anomalies and special-event patterns. While our current work focuses on temperature-driven sigmoid regression with seasonal segmentation, extending the GA-SR framework to include these additional exogenous factors represents a promising direction for future research. Specifically, integrating holiday flags and multi-weather inputs into the fitness function could further reduce forecasting errors and improve responsiveness to non-temperature shocks. Building on our demonstration of GA-SR's flexibility, we plan to explore hybrid models that jointly optimize a richer feature set, thereby bridging the final gap between our theoretical contributions and the operational demands of grid operators and energy planners. Apart from incorporating exogenous factors, we will expand our study by

including other metaheuristic algorithms, such as Particle Swarm Optimization (PSO), Simulated Annealing (SA) and Artificial Bee Colony (ABC), to further optimize the forecasting model. By comparing these algorithms with the genetic algorithm, the research aims to identify the most effective method for optimizing the sigmoid regression model in various scenarios. The broader exploration of optimization techniques is expected to yield further improvements in accuracy, particularly in capturing complex patterns in electricity demand.

Overall, this study contributes to the growing body of knowledge on energy demand forecasting by introducing a novel approach that enhances forecasting accuracy through the use of metaheuristic algorithms. The proposed model holds promise for applications beyond the specific city data set used in this research and could be adapted for other regions or industries that require precise energy forecasting. The continued development of this model will further solidify its potential to contribute to the efficient management of energy resources, reduce operational costs, and support sustainability efforts.

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#### Author affiliations

Mustafa Akpınar is based at the Department of Computer and Information Science, Higher Colleges of Technology, Dubai, United Arab Emirates, and Department of Software Engineering, Sakarya University, Sakarya, Turkey.

Rula Azzawi and Usman Durrani are both based at the Department of Computer and Information Sciences, Higher Colleges of Technology, Dubai, United Arab Emirates.

Kevser Ovaz Akpınar is based at the Department of Cybersecurity, Rochester Institute of Technology - Dubai Campus, Dubai, United Arab Emirates, and Department of Computer Engineering, Sakarya University, Sakarya, Turkey.

Shanga Kareem is based at the Department of Computer and Information Engineering, Sakarya University, Sakarya, Turkey.

Mohammed Saleh is based at the Department of Computer and Information Sciences, Higher Colleges of Technology, Dubai, United Arab Emirates.

### Corresponding author

Mustafa Akpınar can be contacted at: [mustafakpinar@gmail.com](mailto:mustafakpinar@gmail.com)

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