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Hybrid Real-Value-Genetic-Algorithm and Extended-Nelder-Mead Algorithm for Short Term Energy Demand Prediction

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ABSTRACT

Energy consumption planning of an area is very important. It is essential to accurately predict the amount of short-term power required by an area using a highly effective prediction technique. The real-value-genetics-algorithm (RVGA) is the most effective technique that is currently used. However, the RVGA has some drawbacks, including the fact that it gets caught in premature convergence even when the search is performed over long iterations. This study proposes a hybrid prediction algorithm which comprises the RVGA and the extended-Nelder-Mead (ENM) algorithm. The ENM was implemented to speed up the search for the best among all solutions produced by the RVGA. The RVGA was configured to run under small iterations, and the ENM was used to achieve convergence. Experiments were performed on historical datasets containing the monthly electricity demand of the Gorontalo area, a region in Indonesia. The performance of the hybrid algorithm was compared to the hybrid Genetic Algorithm-Particle Swarm Optimisation (GA-PSO) and Real Coded-Genetic Algorithm (RC-GA) energy demand models based on the mean-absolute-percentage-error (MAPE), mean-square-error (MSE), root-mean-square-error (RMSE), and mean-absolute-deviation (MAD) error rates. The results showed that the proposed hybrid algorithm's MAPE, MSE, RMSE, and MAD errors were 2.95 percent, 0.13 percent, 0.36 percent and 1.29 percent, respectively. Based on the accuracy measure obtained from this study, it implies that the RVGA-ENM hybrid is the best model for forecasting monthly electricity demand.

Keywords: Short term power planning, energy demand prediction, convergence speed, prediction accuracy, exploration and exploitation.

INTRODUCTION

Accurate demand prediction is essential when it comes to national energy planning. However, while the existing model assigned with the task of predicting energy demands could only accurately predict projected long-term demand under different scenarios, there has been an issue of low predictive accuracy and performance with short-term demand predictions (Cascone et al., 2023; Li-Siwei et al., 2023). In addition, the non-iterative structure of the algorithm used in building the existing model significantly affects its predictive accuracy. Larger datasets have been commonly used by previous researchers (Aslam et al., 2021; Gao et al., 2020; Jiang et al., 2020; Johannesen et al., 2019). Various studies have been conducted using different scenarios to forecast future energy demand based on the analysis carried out with these datasets, thus making the predictions of long-term demand quite accurate (Huang et al., 2018; Tan et al., 2019; Ugwu et al., 2022). However, it is also necessary to predict the demand of regions in the short term on a daily or monthly basis (Kartikasari et al., 2018; Li-Ke et al., 2023).

Several approaches using artificial intelligence-based methods have been applied to address energy demand forecasting (Boriratrit et al., 2022; Casteleiro-Roca et al., 2019; Huang et al., 2018; Kazemzadeh et al., 2020). These methods can be classified into two, namely, single algorithm and hybrid algorithm methods. A predictive model built using a single algorithm has some disadvantages, which affect the model's performance. These disadvantages include the stagnation of incorrect solutions when the search approaches the global optimum, low convergence, and high computational cost (Deepa & Venkataraman, 2021; Fernandes et al., 2022; Yadav et al., 2022). Most energy demand-predicting models that use evolutionary algorithms cannot obtain good results because of these problems (Satrio et al., 2019; Xu et al., 2021; Zhou et al., 2020).

Forecasting with genetic algorithms (GA) using linear and non-linear equations was carried out in research conducted by Peng and Xiang (2020), Taghavi et al. (2019), and Yun et al. (2021). These equations are used for optimisation of complex problems that have many variables. Meanwhile, the performance of the optimised GA remains low, and this is due to the large number of iterations, longer running time, high computational cost, and high prediction error (Kim & Kim, 2023; Lu et al., 2023). Implementing GA alone is usually inadequate, especially in the face of complex problems with many obstacles. The biggest limitation of genetic algorithms is that they cannot achieve a global optimum like heuristic methods and their optimisation time is long (Long et al., 2023; Yusran et al., 2020).

The combination of GA with another heuristic method can potentially increase the model's ability to achieve global optimal solutions. Hybrid methods consisting of GA and other optimisation algorithms can significantly improve the results, making them better than single algorithms (Boonyopakorn & Meesad, 2017; Chen et al., 2023; Long et al., 2023; Omar et al., 2018). Furthermore, the GA is already being widely used to tackle global optimisation problems (Elaziz et al., 2023; Houssein et al., 2023). When used for parameter optimisation, the algorithm mostly explored solutions globally that need to be exploited to achieve convergence. This exploration process takes a long time and requires many iterations, resulting in lost opportunities to achieve convergence, and sometimes even being trapped in premature convergence (Goldanloo & Gharehchopogh, 2022; Naqvi & Shad, 2021; Rizal & Suyanto, 2020; Xi et al., 2019).

In this study, GA and ENM algorithms were hybridised to develop the hybrid GA-ENM energy demand forecasting algorithm. This study uses the GA-ENM algorithm to solve the short-term energy prediction problem. The GA is used to exploit the parameters in short iterations without requiring the achievement of a convergent solution, while the ENM algorithm is used to optimise the parameters by exploring the results obtained from the GA. The following section presents several models that are related to the proposed hybrid GA-ENM algorithm (in the third section). This is followed by a discussion of the experimental results. The last section highlights the conclusion and future work.

RELATED WORKS

This section describes the work done to forecast monthly electricity demand in several areas, along with a number of exemplary studies (Krstev et al., 2023; Li-Siwei et al., 2023; Neshat et al., 2021; Tarmanini et al., 2023). In decision-making, the role of short-term electricity load demand prediction is crucial. A study by Li-Siwei et al. (2023) developed a hybrid method that uses support vector machine search and manta ray search to optimise parameters in short-term load forecasting. The performance of hybridisation techniques in their research was explored through case studies examining various statistical indicators based on real-world data. The results of the hybridisation technique proved superior to the single method.

The search for the best parameters' values to produce the optimal solution was conducted in a study by Muthana and Ku-Mahamud (2023). This study has successfully used the Pareto Ant Colony System to find a solution to the scheduling problem in generator maintenance. The search for the best parameter values was also carried out in research by Nasir et al. (2019), where it was shown that the values are in a certain range. The best value of each parameter from the experimental results were used for energy consumption, latency and throughput. The results of their research were adopted for the packet routing process in achieving optimal performance.

A hybridisation technique was performed by Tarmanini et al. (2023), by combining Auto-Regressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) to predict electricity demand. The results show that the ARIMA+ANN hybridisation technique is better than ARIMA alone for non-linear load data. Krstev et al. (2023) looked at ANN as a machine learning technique to achieve the model with the best prediction results. They found that ANN, as a machine learning technique, predicts medium-term power consumption more accurately than traditional time series techniques. Neshat et al. (2021) proposed a hybridisation technique between Nelder-Mead (N-M) and other heuristics to predict electricity load. They combined Greedy N-M with Local Adaptive Randomisation. The results show that their hybridisation technique can improve the hyperparameter tuning performance of the prediction model.

In our proposed method, energy demand prediction is performed after the best parameters are obtained from the improved N-M process. This hybridisation technique combines GA and Enhanced N-M (ENM) to calculate energy requirements. These types of proposed hybrid energy demand algorithms incorporate linear, exponential, and mixed models, such as those in (Huang et al., 2018; Piltan et al., 2012). The relationship between electrical energy demand and other variables is expressed by mathematical equations, as shown in Equations 1 and 2. The energy model in Equations 1 and 2 by Piltan et al. (2012), were used for comparison. These models are used during the training and testing of the proposed hybrid energy demand algorithm.

$$y_l = w_0 + \sum_{i=1}^{N} W_i X_i \quad (1)$$

$$y_e = w_0 + \sum_{i=1}^{N} W_i X_i \; X_i^{\,Wi+t} \quad (2)$$

where,

y_l, ye are electricity demand models in linear, and exponential forms.

X_i is the factor affecting the i-th electricity demand. N is the number of electricity demand.

W_i is the corresponding weights.

The proposed hybrid energy demand algorithm is expressed in Equations 3 and 4.

$$y_m = w_0 + w_1^{(w_2 + w_3X_1 + w_4X_2 + w_5X_3 + w_6X_4 + w_7X_5)} \quad (3)$$

$$log\_y_t = w_0 + w_1 \ln X_1 + w_2 \ln X_2 + w_3 \ln X_3 + w_4 \ln X_4 + w_5 \ln X_5 \quad (4)$$

where,

y_m is RVGA-ENM[1] mixed model
$log\text{-}y_t$ is RVGA-ENM[2] linear logarithmic model
w_i is independent variable parameter
X_n is electricity demand at time n.

The following mathematical equation explains the relationship between the proposed energy demand algorithm and the objective function. The mathematical model of the energy demand algorithm is expressed in the form of a function that is calculated in the process of training and testing stages. The best parameters are used to find the error that occurs between actual data and simulation results (predictions). The objective function of the prediction model (S) referring to Equations 3 and 4 is to minimise the squared error, as in Equations 5 and 6.

$$S_1 = \text{Min} \sum_{t=k}^{n} (y - y_m)^2 \quad (5)$$

$$S_2 = \text{Min} \sum_{t=k}^{n} (y - log\_y_t)^2 \quad (6)$$

where,

S_1 = sum of squared errors by RVGA-ENM[1],
S_2 = sum of squared errors by RVGA-ENM[2]
$\boldsymbol{y}$ = actual electricity demand at time t,
$\boldsymbol{y_m}$ = simulated (predicted) value of electricity demand by RVGA-ENM[1],
$\boldsymbol{log\_y_t}$ = simulated (predicted) value of electricity demand by RVGA-ENM[2],
$\boldsymbol{k,n}$ = valid prediction duration.

The relationship between the proposed hybrid energy demand algorithm and the objective function is expressed in Equations 7 and 8.

$$y_t = y_m \quad (7)$$

$$y_t = log\text{-}y_t \quad (8)$$

where,

y_m = simulated (predicted) value of electricity demand by RVGA-ENM[1],

$log\text{-}y_t$ = simulated (predicted) value of electricity demand by RVGA-ENM[2]

The evaluation steps are focused on the demands of the application. Furthermore, the objective function (minimum error) in this study measures mean-absolute-percentage-error (MAPE), and other indicators such as mean-square-error (MSE), root-mean-square-error (RMSE), and mean-absolute-deviation (MAD). These errors are calculated as in Equations 9, 10, 11, and 12.

$$MAPE = \frac{\sum_{i=1}^{n} \left| (y_i - y_i')^2 / y_i \right|}{n} \tag{9}$$

$$MSE = \frac{\sum_{i=1}^{n} (y_i - y_i')^2}{n} \tag{10}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - y_i')^2}{n}} \tag{11}$$

$$MAD = \frac{1}{n} \sum_{i=1}^{n} | y_i - y_i' | \tag{12}$$

where,

y_i = actual value of electricity demand,

$y_{i'}$ = predicted value of electricity demand

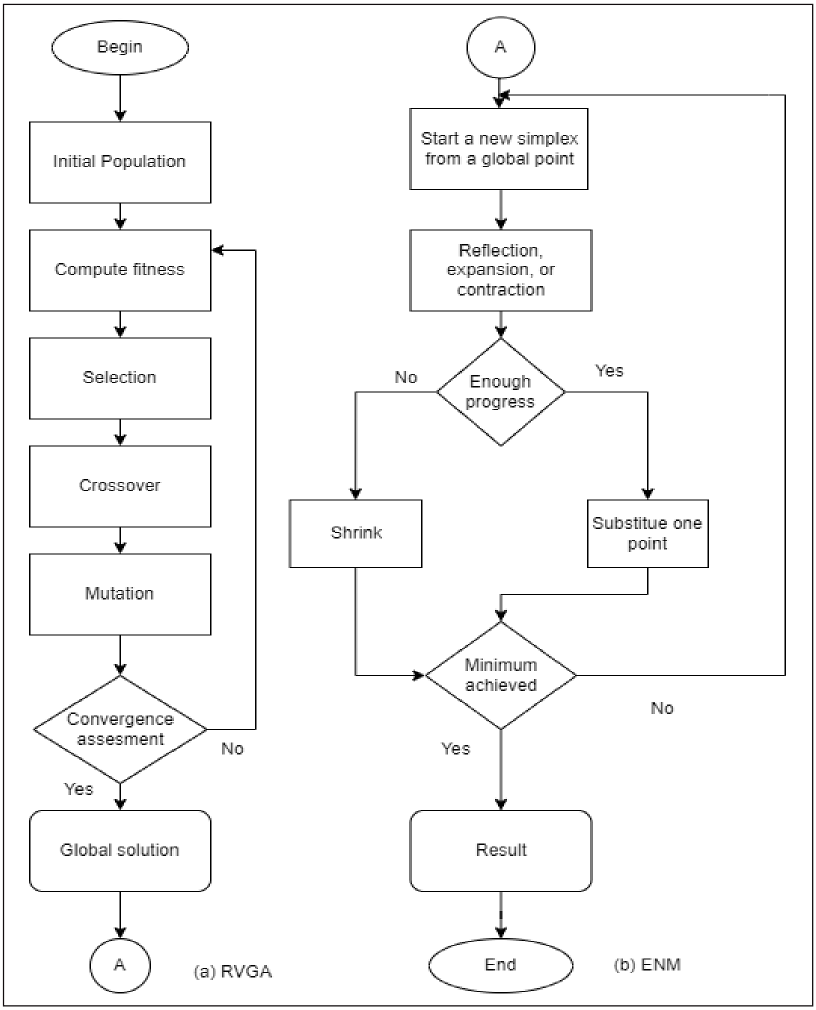
n = number of observations

THE HYBRID PREDICTION ALGORITHM

The flowchart depicted in Figure 1 represents the hybrid RVGA-ENM energy demand algorithm. This algorithm consists of two main parts, i.e., the RVGA followed by the ENM algorithm.

Figure 1

RVGA-ENM Energy Demand Algorithm



RVGA is performed to find the optimal solution. It starts by initialising several parameters including population size, maximum number of generations, mutation and crossover rates, and number of bits. These are the parameters of the objective function. This is followed by fitness computation which is done by mimicking the natural fitness principles of living things. This principle translates into the notion of keeping the high-fitness chromosomes necessary to produce a new generation with a greater chance of survival. A selection process is then performed to rank the chromosomes in a hierarchy based on their objective function values (for error minimisation problems). After that, only the best-ranked chromosomes are kept, while the rest are discarded to make room for a new generation.

The highest- ranked chromosomes are stored and converted from real value to binary form prior to crossover and mutation processes. The crossover and mutation processes are carried out after the selection process. In the crossover process, the descent solution will be produced first. Each individual in the proposed hybrid algorithm uses a 40-bit uniform crossover and the genes between these crossover points are exchanged after they have been randomly selected. In addition, two parents that will contribute genes at each position in extreme cases are selected randomly from points. No new information is introduced at this point since the introduction of new genetic materials solely depends on the mutation. The mutation operator introduces variability by altering some of its genes to randomly select chromosomes.

The frequency of next-generation mutated parameters varies depending on the method used. Furthermore, these genes are transferred from the parent to the next generation via different combinations. The blending method finds ways to solve this problem by combining genes from the parents to form new offspring genes. The number of genes in a uniform mutation is determined by the mutation's rate (μM), after which each randomly selected gene has an equal opportunity to process the mutation. Here, the genetic sequence will change from its original state randomly and this is important because it helps prevent premature convergence of bad solutions. For this, some random parts of the genetic sequence will be inverted from 0 to 1 and vice versa.

The convergence assessment process is for checking whether the termination criteria have been met. The process halts either when an optimum solution is found (convergent) or when the maximum iteration has finished execution. This iteration value can be configured to initialise at the beginning of the process. However, convergence can be achieved when the algorithm finds the required solution value. The search for the required value, for a couple of reasons, could fail. These reasons include: (i) when it is trapped in a local optimum and stagnant at an approximate value even though the iteration of the search process is undertaken continuously, (ii) when the data are not properly normalised, leading to an increase in deviations between the data points and, thus, causing the prediction system to respond abnormally. The best value of the optimal solution produced by the crossover and mutation processes is converted, again, from the binary form to the real form as the new generation.

The new generation chromosomes are produced upon completion of the RVGA algorithm. However, the best generation could not be obtained after this process because of the uncertainty of which generation was better in both the previous and the new. According to the configurations, the RVGA will end if any of these two options are met. First, when the value of the objective function is smaller than that of the threshold set before it, this only happens when the RVGA reaches an optimal solution. Second, when the RVGA has executed the total predetermined maximum iteration, this only occurs when the algorithm cannot find an optimal solution. Accordingly, all the best solutions predicted by the RVGA are reported back to the local search process in ENM.

The proposed hybrid algorithm continues with the ENM algorithm which starts by setting up an initial simplex (Barati, 2011). As aforementioned, the best RVGA solution (x0) is the initial solution for ENM. The ENM method begins with a triangle with three vertices: the smallest is the best (B), the second smallest is good (G), and the greatest is the worst (W). The method tries to reduce the triangle until the minimum is reached. The ENM algorithm rescales the (x0) using reflection, expansion, contraction, and shrinkage (see Figure 1). In some cases, GA does not carry out its job properly, and this is because its population is based on meta-heuristics (Lian et al., 2009). A hybrid system consisting of two mechanisms is introduced to solve this problem.

One mechanism (i.e., RVGA) combines local search with a genetic algorithm to find solutions based on objective functions, while the other (i.e., ENM) selects the best solution from all the solutions made available by the first. Accordingly, to improve the unoptimised RVGA results, the ENM local search phase was established. In the proposed mechanism, the best-unoptimised solution provided by the RVGA operation (x0) was selected as the initial solution for the ENM. To supplement non-optimal RVGA results, a local ENM search phase is introduced. This phase is required to aid with a convergence that the RVGA is unable to achieve. The processes involved in this phase include initialising a simplex (x0), selecting an additional vertex, approximating gradients, calculating the new reflected vertex, calculating the newly expanded vertex, and checking convergence.

Furthermore, in the local search process, the individual fitness update process is undertaken in an iteration by successively replacing the current obtained solution with the next best solution in the solutions environment until convergence is reached. The process only terminates when no better solution is found in the environment. The algorithm's performance can be improved by optimising parameters through simultaneous exploration and exploitation. Exploration and exploitation issues to optimise the predictive model's parameters should occur simultaneously during the occurrence of local convergence as they are important and mutually influencing, thus affecting the system's accuracy (Ali et al., 2021; Liu et al., 2019).

EVALUATION AND RESULTS

Monthly regional energy demand datasets from 2012 to 2017 in the Gorontalo region in Indonesia were used to evaluate the performance of the proposed algorithm (see Table 1). In total, there are 72 monthly data and, during the experiment, 76% of the data is used for training and the remaining 24% is used for testing. We used Matlab tools to run the experiments.

Table 1

Monthly Electricity Demand (GWh) From January 2012 to December 2017 Gorontalo Region

	2012	2013	2014	2015	2016	2017
January	19.502	24.085	28.584	31.632	33.690	35.046
February	14.694	22.082	28.198	29.747	35.872	34.618
March	21.120	24.322	27.726	33.173	36.798	36.976
April	19.927	22.854	27.525	33.556	37.323	37.772
May	22.735	23.570	33.891	33.418	38.076	38.970
June	18.817	24.509	31.692	34.603	37.138	36.600
July	22.085	24.688	32.990	33.386	37.037	36.772
August	21.180	23.733	30.338	32.276	37.936	38.418
September	21.336	27.728	29.244	34.018	37.130	37.118
October	22.110	25.771	31.769	31.810	37.033	40.801
November	23.199	25.897	31.104	36.031	37.283	40.256
December	22.188	25.512	33.534	35.164	39.267	43.778

Source: PT. PLN Persero Gorontalo Region

The original data in Table 1 is initially pre-processed so that it can be recognised by the algorithm. Data pre-processing can be done using the simple method of dividing all historical data by a constant value and after prediction, the data is restored to its original value. For example, in Table 1, the maximum value of monthly electricity demand is 43.78 GWh. This value is chosen as the constant (C) for the divisor of each data. All data after dividing by C will be less than or equal to 1 (in the range of 0 to 1). Data that falls within this range will be recognised by the algorithm. The performance of the model is tested through the estimation of the objective function parameter values.

Formulas that show the relationship between parameters and electricity demand are used to calculate fitness values (see Equations 3 and 4). This formula is expressed in the form of the algorithm's objective function (Khazem, 2008). The initial target estimated was 100% accuracy or 0% error (Hussein, 2018). This target was not achievable given the MAPE found during this study, which was around 2.9503% (shown in Table 4). Nevertheless, a value very close to the ideal value was obtained. RVGA played role in improving the accuracy of the prediction system, but to strengthen its accuracy further, a hybrid ENM was introduced.

The objective function parameters are set in Table 2 in the initialisation phase.

Table 2

Initial Values for RVGA-ENM Algorithm Parameters

Parameter	Initial value
Population	50 chromosomes
Maximum generation	100 iterations
Mutation rate	0.02 μm
Crossover rate	1.0 μC
Bit number	40 bits
Simplex size	1.0
Minimum deviation	0.001 %

Output data were obtained from the simulation of the prediction system (see Table 4). Part of this data is used to estimate the parameters of the independent variables, while the rest is used to test the prediction system (Equations 3 and 4). Table 3 shows the results of parameter estimation with the RVGA-ENM algorithm.

Table 3

Parameter Estimation With the RVGA-ENM[1] Algorithm (Equation 3)

Iteration	RVGA best parameter estimations	ENM best parameter estimations
1	3101.069	0.195
2	985.288	0.190
3	155.121	0.189
97	0.201	0.187
98	0.201	0.186
99	0.201	0.183
100	**0.201**	**0.175**

RVGA can extract predictable global solutions as well as solve non-linear stochastic problems (Daraban et al., 2014; Shaiek et al., 2013). However, this algorithm has the drawback that its performance is determined by random coefficients and complicated calculations. This can significantly reduce the convergence speed and lower the prediction accuracy. Therefore, the RVGA algorithm was executed using short iterations, followed by a solution search using the ENM algorithm. Implementing these two processes increased the convergence speed and improved the accuracy of the system. The best fitness objective of this algorithm is zero (to minimise error), but the ideal condition that can be achieved is f(best) = 0.175. The independent variable parameters (w_i) when f(best) is achieved are used in the prediction process.

The prediction results obtained by the RVGA-ENM[1] and RVGA-ENM[2] algorithms through Equations 3 and 4, respectively, are shown in Table 4.

Table 4

RVGA-ENM[1] and RVGA-ENM[2] Predictions

Month number	Actual (GWh)	RVGA-ENM[1] Predictions (GWh)	RVGA-ENM[2] Predictions (GWh)
56	37.93	37.63	37.61
57	37.13	38.35	38.56
58	37.03	38.02	37.84
59	37.28	37.64	37.49
60	39.26	37.85	38.17
61	38.04	39.32	38.83
62	34.61	38.89	38.41
63	36.97	36.26	36.31
64	37.77	37.18	38.17
65	38.97	38.41	38.85
66	36.60	39.01	37.55
67	36.77	37.53	37.53
68	38.41	37.53	37.48
69	37.11	37.38	39.28
70	40.80	38.17	37.69
71	40.25	40.19	39.20
72	43.77	40.92	40.44
MAPE		**3.1521%**	**2.9503%**

Figure 2

RVGA-ENM[1] Prediction

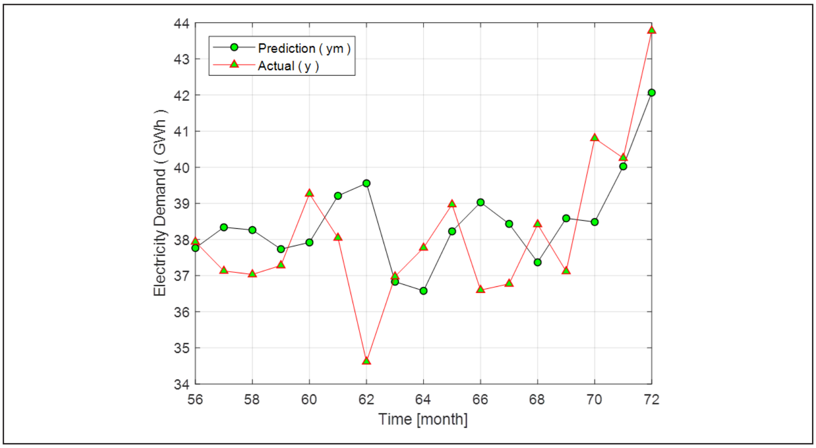
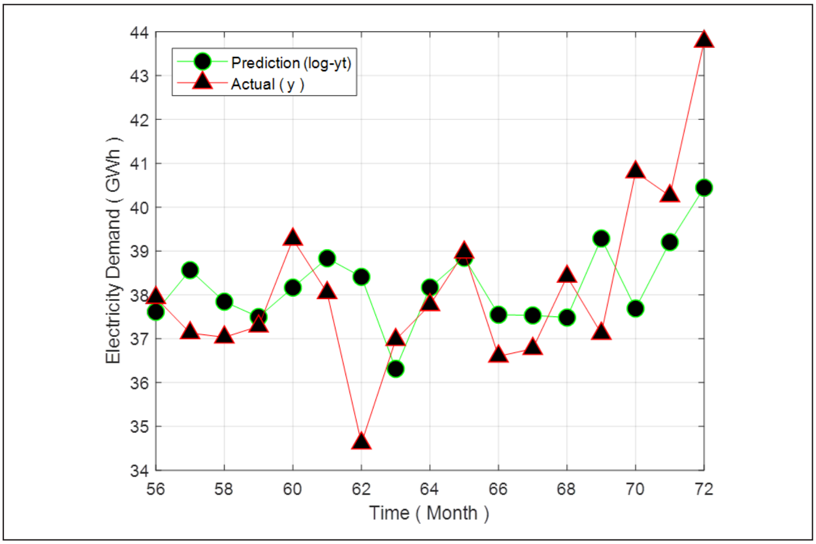


Figure 3

RVGA-ENM²Prediction



The results obtained from the proposed hybrid prediction model are compared with the best results from Piltan et al. (2012) as a reference model. The performance metrics used for comparison are MAPE, MSE, RMSE, and MAD. See Table 5 for the performance of RVGA-ENM¹ and RVGA-ENM².

Table 5

Prediction Errors for the Proposed RVGA-ENM, GAPSO and RCGA Models

Error (%)	Piltan et al. 2012		Proposed Model	
	GAPSO	RCGA	RVGA-ENM¹	RVGA-ENM²
MAPE	4.93	8.31	3.15	**2.95**
MSE	35.94	4.46	0.57	**0.13**
RMSE	5.99	4.71	0.75	**0.36**
MAD	6.33	6.43	1.38	**1.29**

The analysis in Table 5 shows that the proposed RVGA-ENM hybrid's prediction estimation approach for electricity demand provides better-predicting accuracy than the other prediction algorithm. This is due to the overall estimation capability settings in the proposed hybrid algorithm.

DISCUSSIONS

Based on Figures 2 and 3 and Table 4, we can calculate the relative absolute error of the forecast results for RVGA-ENM^1 and RVGA-ENM^2 per month. The results of this calculation are shown in Table 6.

Table 6

A Relative Error by RVGA-ENM^1 and RVGA-ENM^2

Month Number	Relative error by RVGA-ENM^1 (%)	Relative error by RVGA-ENM^2 (%)
56	0.3907	0.7339
57	2.7610	3.2778
58	2.8102	1.8559
59	1.0317	0.4846
60	3.0777	2.5138
61	2.6581	1.8007
62	**11.2814**	**8.6643**
63	**0.3276**	1.5130
64	2.7220	0.9086
65	1.6981	**0.2822**
66	5.5523	2.1669
67	3.7946	1.7369
68	2.3953	2.1352
69	3.3566	4.9530
70	5.2913	7.1080
71	0.5281	2.4051
72	3.9092	7.6147

The superiority of each model can be seen from the calculation results. From the observations, the RVGA-ENM^2 model is superior, with the smallest prediction error (0.2822%) for the 65th month and the largest (8.6643%) for the 62nd month. The RVGA-ENM^1 model excelled in forecasting the following months, excelling with the smallest error (0.3276%) in month 63, and month 62 had the largest prediction error (11.2814%).

Using Table 5 to compare the errors of the two proposed models (RVGA-ENM[1] and RVGA-ENM[2]) with other models used for comparison (GAPSO and RCGA), we find that RVGA-ENM[1] and RVGA-ENM[2] are superior. The superiority of the two proposed models is illustrated by the four types of errors measured: MAPE, MAD, MSE and RMSE. The RVGA-ENM[2] model has an error range of 0.13 % to 2.95 %. The RVGA-ENM[1] model has an error range of 0.77 % to 3.7 %. Meanwhile, the two comparison models (GAPSO and RCGA) had their respective error ranges, with GAPSO having a minimum error of 4.93 % to a maximum of 35.94 %, and RCGA from a minimum of 4.46 % to a maximum of 8.31 %. Based on the accuracy measures (i.e., MAPE, MAD, MSE, and RMSE) obtained from this study, it can be concluded that RVGA-ENM[2] is the best model for forecasting monthly electricity demand. It should be noted that the error of the proposed hybrid model is smaller compared to that reported in other studies on the best model.

CONCLUSION

In conclusion, the proposed algorithm has accurately forecasted energy demand and demonstrated that it has outperformed other short-term energy demand forecasting algorithms. The hybridisation of RVGA and ENM is able to enhance the exploration and exploitation capabilities resulting in better prediction accuracy. Furthermore, the pre-processing of the algorithm's input data, the tuning of short iterations in RVGA, and the exploration of the results by ENM have greatly and positively affected the precision of the system. For future work, this algorithm can be applied to solve various real-life optimisation problems with minimal customisation. It is recommended for future development that the proposed hybrid algorithm be applied to medium- and long-term energy planning. For that, it is necessary to pre-process the data according to the type of medium- and long-term data.

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