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Electricity Demand Forecasting Based On Genetic Algorithm And Extended Nelder Mead

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ABSTRACT

Electricity demand forecasting model based on single algorithm at least have two problems related to local optima and computational cost. We consider to utilised the hybrid genetic algorithm and extended Nelder-Mead to solved local optima and reduced the number of iteration. Through the comparison in model evaluation, our hybrid model produced higher accuracy for electricity demand estimation. The proposed model can be used to assist decision-makers in forecasting electricity demand.

Keywords: genetic algorithm, electricity demand forecasting, local optimal

1. INTRODUCTION

For most electricity demand forecasting models that use evolutionary algorithms (e.g. genetic algorithm); the objective function cannot obtain a good result. In single genetic algorithm, convergence cannot be obtained because the solution is trapped in the near local optimum [1, 2, 3]. This problem cannot be solved even though the single genetic algorithm operations are repeatedly applied. This is difficult to fit into other methods in order to produce a good solution. One attempt to encounter this problem for estimating parameters of electricity demand model, developing a hybrid algorithm that combines genetic algorithm with a stochastic simplex method is needed. The Nelder Mead's simplex method is one of the most popular derivative-free optimization algorithms in the fields of engineering, science, and statistics. Nelder Mead simplex algorithm is widely used because of its simplicity and fast convergence. This method converges really well with small scale problems of some variables. However, for large scale problems with multiple variables, it does not have much success [4]. The existing method needs a high computational cost in term of iterations to reach the global optimum solution because the search is on the wrong direction. A new technique is introduced to improved hybrid algorithm in terms of convergence rate with guidance search on the true direction by improved local search. A procedure using the quasi-gradient method was presented by Pham [4] in their study to improve Nelder Mead simplex algorithm in terms of the convergence rate and the convergence speed. The author has succeeded to obtain the significant improvement of the method compared to the original simplex method.

Section 2 describes the mathematical formulation of the objective function. Section 3 summaries the methodological steps. In Section 4, we describe the electricity demand data that are used in forecasting. Section 5 discusses the results of our experimental evaluation. We provide the comparison of some model and the proposed model. We conclude the research in Section 6.

2. MATHEMATICAL FORMULATION OF THE OBJECTIVE FUNCTION

Objective Function representation of each model is the fitness functions that represent the relation between electricity-demand (ED) with independent variables.

In this research, independent variables are population (X1), gross domestic product (X2), import (X3) and export (X4) in linear and nonlinear forms. In this method, the objective functions are the linear model, the logarithmic model, the exponential model, and the quadratic model. After a model has been developed, this model can be applied according to the range-term of time. Each model was tested using electricity demand data with and without preprocessing and local search.

The mathematical formulas are:

$$\text{Linear ED} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \tag{2.1}$$

Nonlinear i.e. the exponential form

$$\text{Exponential ED} = \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} \tag{2.2}$$

Where β_0, β_1, β_2, β_9 are the weighting parameters.

The objective function in this research is to minimize errors by measuring the least square error of the objective function values. The objective function is the difference between ED actual values and ED forecasting values using least square approach as stated in equation 2.3.

Objective Function:

$$S = \sum_{i=1}^{n} (\text{ED actual} - \text{ED forecasting})^2 \tag{2.3}$$

Where

$$\begin{cases} S = sum\ of\ the\ squared\ prediction\ errors \\ n = the\ number\ of\ data \\ ED\ actual = the\ existing\ recorded\ data \\ ED\ forecasting = approximation\ values \end{cases}$$

The evaluation of the objective function values and fitness is the process to calculate the objective function value's association with the chromosomes. A fitness value is calculated and assigned to each chromosome based on its objective function value through the proposed hybrid algorithm operations. The process of the hybrid genetic algorithm and local search algorithm starts from the initial population of parameter values. Their objective function values are calculated using an objective function through a genetic algorithm process.

3. METHODOLOGICAL STEPS

Hybridisation genetic algorithms with local search are commonly implemented in solving many complex problems where each new generated offspring follows local optimisation procedures to lead the solution towards a local optimum area before continuing to the next generation. In the improved version of binary genetic algorithm, the genetic algorithm involves binary genetic sequences that are converted from real valued variables before the crossover and mutation processes. After these processes, the binary genetic sequences are converted back to real-valued variables. It can handle real-valued variables while processing the crossover and mutation process. In this work, it is named the real-value genetic algorithm (RVGA). The improved local search performs local exploitation around individuals in the local neighbourhood, while genetic algorithms make global explorations in a population.

The proposed approach is known as hybrid real-value genetic algorithm and extended Nelder-Mead (RVGA-ENM). In order to take advantage of both, these hybrid algorithms basically use the way to hybridise the RVGA and ENM. The results solution from RVGA is returns as the initial solutions of the ENM. Individual solutions will experience both evolution from RVGA and the exploitation of local neighbourhood solutions from ENM in every iteration. To better exploit the ENM and real-value genetic algorithm, advance discussion of the hybrid mechanism is presented in Fig. 1.

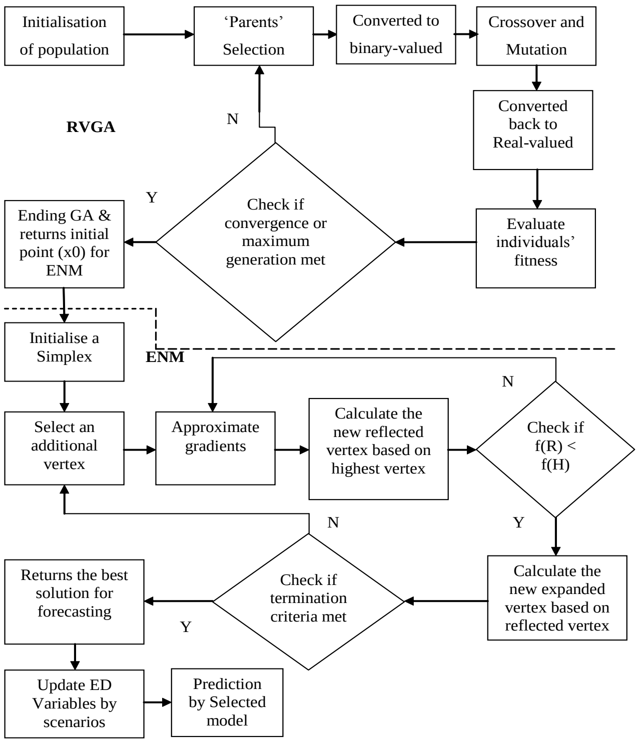

Fig.1. Proposed RVGA-ENM flowchart

The hybrid algorithm steps are presented as following:

- Step 1: The initialisation step is to generate the first generation of individuals for starting the algorithm. To initialise the algorithm, every variable of an individual will be randomly generated within their defined range. In this study, the range is a two-element vector specifying to converted decimal number. The range of the initial population will have to cover the entire space of possible solutions. Depending on the nature of the problems, the population size can be from several to hundreds. In this study, the population is set to 50.
- Step 2: Selection. As one of the evolution progress steps, the proportion of the existing population is selected to breed a new generation during each succesive generation. Usually, individual solutions are selected through a fitness-based process, which means that fitter chromosomes have high possibility to be selected as 'parents' to produce offspring (solutions).
- Step 3: Converted to binary-valued. The 'parents' solutions will come from those individuals selected to survive from last generation. The 'children' solutions will be first generated by crossover process which all the variables of an individual solution will be clustered and converted into a binary form with ones and zeros. Its encode the individuals.
- Step 4: Crossover and Mutation (Reproduction). The reproduction step consists of crossover and mutation process. It will produce new born 'children' solutions which share the characteristics of their 'parents' solutions.

One or more crossover point on both ‘parents’ organism string is randomly selected. All data beyond that point in either organism string is swapped between the two ‘parents’ organisms. The ‘children’ will be the resulting organisms. In this study, uniform crossover is used for 40 bits of each individual. After crossover, the mutation process will prevent the premature convergence on poor solutions.

- Step 5: Converted back to real-valued. A parameter of mutation rate will be defined so that the higher the rate is, the more likely the ‘children’ will mutate. The newborn individual data will be evaluated by the fitness values after the reproduction process. After crossover and mutation, the individuals will be converted back to real form.
- Step 6: Evaluation of fitness This step focuses on the application demands. In this study, MSE, RMSE, MAD, and MAPE are used as the fitness evaluation functions to measure the least error between the actual electricity demand and the forecasting values. The solution obtained from RVGA is returns as initial point (x0) for extended Nelder Mead (ENM).
- Step 7: Initialise a simplex with (n+1) random vertices x1, x2,…, xn
- Step 8: Select an additional vertex XA with its coordinates composed from n vertices in the simplex. Coordinates of the selected vertex are a diagonal of the matrix X from n vertices in the simplex. XA = [x1,1, x2,2 , …, xn,n].
- Step 9: Approximate gradients based on the additional vertex A with other n vertices in the selected simplex. To illustrated how this method works, a two dimensional case which has a triangular simplex ΔHSL, highest (xH), second highest (xS) and the least (xL) vertices is shown in Figure 2.
- Step 10: Calculate the new reflected vertex R’ based on the highest vertex H, where XR’ = XH – σS. Parameter σ is the learning constant or step size. In this work, σ = 1.
- Step 11: If the function value at R’ is smaller than the function value at H, it means that HR’ is on the right direction of the gradient.
- Step 12: Calculate the new expanded point E’ based on the new reflected point R’. The R’ can be expanded to E’ using the formula XE’ = (1 – γ) XH + γ XR’. γ is the expansion coefficient (in this work, γ=0.5). R’ and E’ are rely on the right direction towards global optimum point (Fig. 2).
- Step 13: Check if the termination criteria has been achieved. If convergence or termination criteria not met, go back to step 9 with (n+1) vertices.
- Step 14: Returns the best function evaluation values and parameter values for forecasts the electricity demand.
- Step 15: Update the electricity demand (ED) variables using scenarios based on the economic and the population growth. Step 16: Prediction for future electricity demand using selected model.

4. ELECTRICITY DEMAND DATA

The experiment used the Turkish data for electricity demand and economic indicators as tabulated in Table 1. The Turkish data for electricity demand were obtained from IEA (International Energy Agency) as Turkey is a member of the IEA at www.eia.gov/countries/data.cfm, and the data for economic indicators was obtained from Turkey Statistical institution (TSI).

Table 1. Electricity Demand Data

Years	Electric Consumption (Billion KWh)	GDP (10^9 U.S.$)	Population (10^6)	Import (10^9 $)	Export (10^9$)
1980	21.84	94.26	42.17	7.91	2.91
1981	22.49	95.5	43.12	8.93	4.70
1982	24.90	86.77	44.28	8.84	5.75
1983	26.15	82.91	46.97	9.24	5.73
1984	29.63	80.64	48.07	10.76	7.13
1985	32.57	90.38	49.17	11.34	7.96
1986	31.73	101.8	50.27	11.10	7.46
1987	35.02	117.18	51.37	14.16	10.19
1988	40.37	122.13	50.53	14.34	11.66
1989	40.19	144.03	51.25	15.79	11.62
1990	47.84	202.38	52.44	22.30	12.96
1991	50.46	202.72	53.52	21.05	13.59
1992	55.51	213.58	54.55	22.87	14.71
1993	60.45	242.14	55.59	29.43	15.35
1994	62.79	174.45	56.55	23.27	18.11
1995	68.39	227.51	57.51	35.71	21.64
1996	75.27	243.9	58.48	43.63	23.22
1997	82.73	255.07	58.1	48.56	26.26
1998	88.67	269.13	59.01	45.92	26.97
1999	91.63	249.82	59.91	40.67	26.59
2000	98.57	266.44	62.76	54.50	27.77
2001	97.39	195.55	63.82	41.40	31.33
2002	102.55	232.28	64.85	51.55	36.06
2003	110.43	303.26	65.89	69.34	47.25
2004	120.04	392.21	66.9	97.54	63.17
2005	129.01	482.69	67.9	116.77	73.48
2006	141.46	529.19	68.13	139.58	85.53
2007	153.66	649.13	68.89	170.06	107.27
2008	160.37	730.32	69.66	201.96	132.03
2009	155.19	614.47	70.54	140.93	102.14

In this study, all data have been normalised to the same ranges of values. Normalisation is simply dividing all values of a set by an arbitrary reference value, usually the maximum value. However, this process carries with it the potential for loss of information as it can distort the data if one or a few values are larger than the rest of the data.

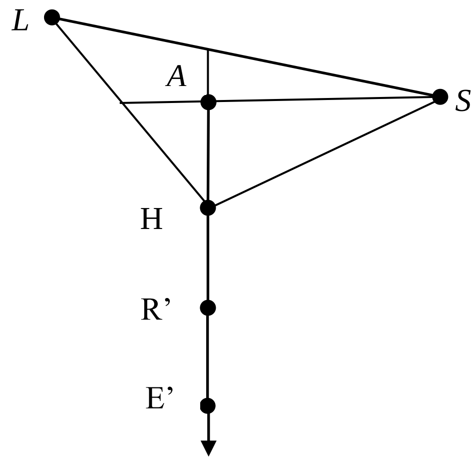

Figure 2. The Simplex ∆HSL with additional vertex

5. EXPERIMENT RESULT

Table 2 presents the comparison of proposed models based on hybrid RVGA and the extended NM simplex (ENM) local search with hybrid GA and the original local search. The comparison between the proposed RVGA-ENM models and the hybrid GA-original simplex local search are summarized below. From Table 2, a conclusion can be draw that the proposed hybrid RVGA-ENM algorithm shows its better performance than the original simplex method in terms of errors and convergence rate.

TABLE 2. THE COMPARISON OF PROPOSED RVGA-ENM MODELS AND GA-OLS MODELS FOR TURKEY ELECTRICITY DEMAND

Methods		Models		Fitness Functions			
			Max Iter	MAPE	RMSE	MSE	MAD
Proposed Hybrid	RVGA+ENM	Mix	50	1.03	0.64	0.41	1.32
		Quad		3.67	0.67	0.45	4.72
Original Hybrid		Log	2194	1.77	0.25	0.06	2.27
		Exp		2.95	1.89	3.57	3.78
	GA+ OLS	Mix		8.58	7.13	50.83	4.17
		Quad		7.76	5.01	25.09	3.78
		Log		3.42	2.44	5.93	1.66

Figure 3 shows the fitness evaluation by proposed RVGA-ENM algorithm. Ideally, its converged fast at zero (minimum error) measured from the difference between forecasting values and actual values of electricity demand. But in this study, the minimum deviation required for termination was set initially to 0.0001.

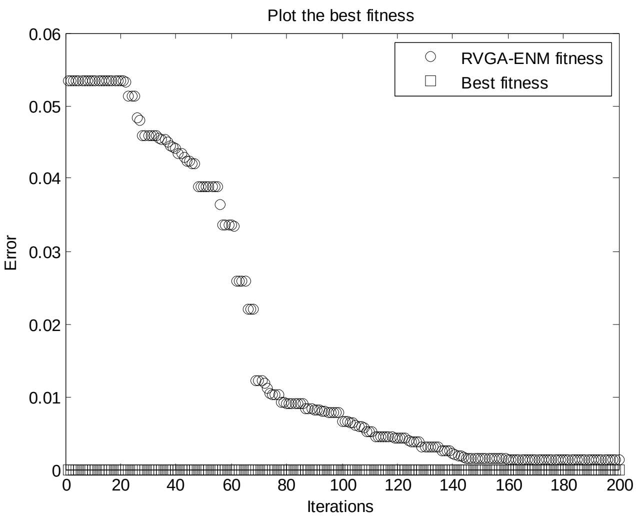

Figure 3. RVGA-ENM fitness evaluation

In RVGA-ENM, the best value of fitness have been reached in minimum iteration, it’s the significant improvement in convergence rate compare to single genetic algorithm. Figure 4 presented the forecasting result by RVGA-ENM for Turkey electricity demand data.

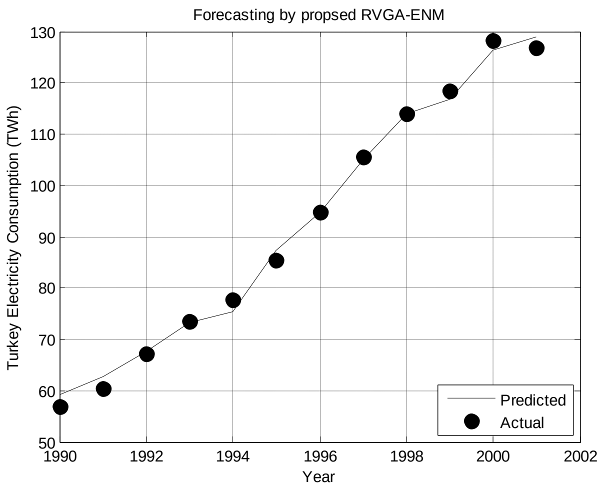

Figure 4. RVGA-ENM demand forecasting

In five times of RVGA-ENM process, the best value of fitness have been reached by the hybrid algorithm (iteration=2, Minimum value of f = 0.00096588), it means that the ENM process have been reached 62.85 time less than optimisation value obtained by RVGA in 100 generations.

```
Generation 99: f(0.0302 0.0503 0.0951 1.2635 1.8742 1.0955 1.8062)=0.060711
Generation 100: f(0.0302 0.0503 0.0951 1.2635 1.8742 1.0955 1.8062)=0.060711
x0 = 0.0303    0.0503    0.0951    1.2636    1.8743    1.0956    1.8063
Iteration = 1; Minimum value of f = 0.0024306
located at x = [-0.13143   0.21153   -0.56203    0.4248    2.4978    -1.4075   6.4775].
Iteration = 2; Minimum value of f = 0.000965;
located at x = [-0.0576   0.0221    0.2693    0.2669    7.7153    -0.2584    2.9479]
act_pred_err =
   56.8100      60.2221      3.4121
   60.5000      63.8661      3.3661
   67.2200      68.8178      1.5978
   73.4300      71.9428      1.4872
   77.7800   `75.7123   2.0677
   85.5500      89.2974      3.7474
   94.7900      93.5093      1.2807
  105.5200     105.6721      0.1521
  114.0200     116.5410      2.5210
  118.4800     116.6038      1.8762
  128.2800     123.6716      4.6084
```

126.8700 128.5275 1.6575
MAPE =1.0295; MAD =1.3206; MSE =0.4134; RMSE =0.6429

6. Conclusion

Linear and nonlinear models based on genetic algorithm and extended Nelder Mead were utilised to forecast electricity demands in Turkey. These models were tested over several benchmark problems of electricity demand forecasting models, and show better performance than the original algorithm methods in terms of error rates and the number of iterations.

Based on the extensive experiments and obtained results, it appears that the proposed RVGA-ENM is more accurate than the conventional genetic algorithm approach. In the proposed RVGA-ENM, improved hybrid algorithms and normalising of available data and variables have more effect towards the forecasting process, therefore, the obtained results proved to have the best accuracy.

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