Predicting National Gas Consumption in Iran using a Hierarchical Combination of Neural Networks and Genetic Algorithms

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Abstract:
In this paper, we propose an algorithm to predict the monthly national gas consumption. The algorithm is based on a novel combination of Neural Networks (NN) and Genetic Algorithms (GA), and uses temperature and historical recordings as input. Our method is a hierarchical combination of GA and NN: first, a NN is used to generate an initial population for a GA. Given the initial population, the GA is then used to optimize the initial weights of a second NN. Finally, the NN finds the local optima around the initial weights. We compare the proposed algorithm with NN and also with a trivial combination of NN and GA. The experimental results show the efficiency of our algorithm. Given the promising experimental results, we believe the proposed algorithm can be potentially used by the government for energy planning.

Keywords: Artificial Neural network, Genetic Algorithm, Initialization.

1. Introduction

Energy demand is increasing globally as countries need energy for stable growth. Given the importance of environment, natural gas is more desirable compared to other energy resources. Natural gas is used not only to produce heat, but also it is used to generate electricity. Thus, it has a vital role in the economical, social, and technological developments of any country [1]. Gas turbines of electrical power station can be used when the electricity consumption is at its peak. Given the low price of natural gas, electrical power stations that run on gas are appropriate options from an economical point of view [2]. Good prediction of gas consumption can help planners and decision makers to increase the revenue.

Although neural networks are powerful tools in modeling linear and very nonlinear functions, they are sensitive to initial weights. Thus, they can get stuck in a local optima. The focus of this paper is on finding good initial weights that are preferably close to the global optima. Genetic algorithms are effective global search methods [3]. Because of their power in solving nondifferentiable, noncontinuous and discrete functions, they can avoid getting stuck in a local minima and reach a global optima [4].

In the literature, different deterministic and stochastic methods are used to predict the gas consumption. Typically, historical gas consumptions and temperature are used as data in these models [5]. Herbert et al. used linear regression analysis for prediction, but the error was higher than expected [6]. Lin and Liu [7] and Erdogdu [8] used the ARIMA model because of its discrete nonlinear properties, but its weakness was using data from a large time interval to make predictions about a short time interval. Brabec et al. compared NLME with ARMAX and ARX and showed the superiority of ARMAX over ARX [9]. However, ARX has lower complexity compared to ARMAX. Sanchez-ubeda and Berzosa used a new iterative statistical method that improves through least squares minimization [10]. The ANFIS networks are prediction methods that are used by Behrouznia et al. [11] and Azadeh et al. [12]. Dombyci used feedforward neural networks with backpropagation to compare its predictions with actual gas consumptions [13]. Aras used genetic algorithms to improve the domestic gas consumption predictions models. He used genetic algorithms to estimate parameters of the nonlinear regression model that was determining the relation between gas consumption and the input variables [14]. Forouzanfar et al used this logistic approach to predict domestic and business gas consumptions, but used two different techniques to estimate the parameters of these models. The first is based on nonlinear programming and the second is based on genetic algorithms [15]. Chen et al used Grey model as one of six different prediction techniques. They also used regression and mixture models (least squares method, genetic algorithms, etc) to find the best prediction method [16]. Kizilaslan and Karlik used artificial neural networks with seven different objective functions to predict the daily/weekly/monthly gas consumption in Istanbul. The methods that are used are the fast backpropagation method, gradient descent method, quasi-Newton method, quasi-Newton method with limited memory, the Levenberg-Marquardt method, incremental backpropagation, batch backpropagation [17,18].The daily gas consumption in Turkey was predicted using different methods such as Perceptron neural networks, Radial neural networks, multivariable time series, and ordinary least squares [1].In this paper, we use a new combination of neural networks with genetic algorithms, where instead of ordinary random assignment function, the genetic algorithm uses the random function Initnw. In the next sections, we explain the methodology, case study and conclusion.

2. Methodology

2.1. Artificial Neural Networks

Like human brain, artificial neural networks are connections between neurons that transmit signals from input to output. In a feedforward Perceptron network, the input layer consists of known data that are transmitted to output layer through hidden layers. The output is the predicted value. The hidden layer uses an appropriate nonlinear activation function, like the sigmoid function in equation (1), to process the inputs and send them to output. This activations function maps data to [0,1] interval.

$$f\ (x)_{\log sig} = \frac{1}{1+\exp(-x)} \qquad (1)$$

The learning rule that is used in a Perceptron neural network is a type of backpropagation algorithm called Levenberg-Marquardt method. This method is a numerical optimization method that is used for minimization of a function that is a sum of squares of nonlinear functions. In fact, this method is a combination of gradient descent and Gauss-Newton method. When the current point is far from the local minima, while guaranteeing convergence, it moves slowly like the gradient descent, but when current point is close to the local minima it converges fast like Gauss-Newton method [19].

2.2. Combination of Genetic Algorithms with Neural Networks

The genetic algorithms are members of family of computational models that are inspired by evolution in nature and are proposed by John Holland in 1975 [20]. The idea of combining genetic algorithms with neural networks was introduced first in 80^{th}. As Figure 1 shows, the method of choosing initial weights of the neural network is a combination of a genetic algorithm and Levenberg-Marquardt method. Based on figure.1, the genetic algorithm performs a global search to find the minimum. The advantage of the genetic algorithm is that it reaches the minimum faster. The genetic operators create a bigger diversity in the population and so they can create a larger solution space. The back propagation Levenberg-Marquardt method performs a local search in the vicinity of the optimal point. In fact, the genetic algorithm collects information about the search space in the generations and these information guide the Levenberg-Marquardt method in the next stage [21].

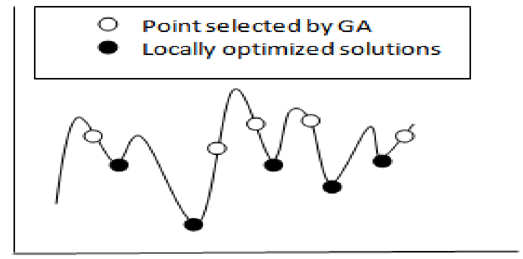

Figure 1: The Hybrid Approach (GA+NN) [21]

2.3. The Nguyen-Widrow Initialization Function

Initnw is the main algorithm used in Matlab to initialize a neural network and is based on the Nguyen-Widrow method. The main idea behind Initnw is to choose small random values for the initial weights. Weights are modified such that the corresponding region divides into small intervals. It is logical that if we associate each node to its own interval, the learning process becomes faster. In the learning process, the nodes can still change the size and the location of their interval, although most of these changes are small [22].

3.Case Study

The data is daily readings from 2005 to 2012. We transformed this data to monthly averages to decrease the noise level. Then, data is mapped to [0.35, 1] interval to further decrease the noise and also have a reasonable output interval for the activation function of neural network. After normalization, data is split into training and test sets, so that the first 80% of data is used for training and the remaining is used for test. As can be seen in Figure 2, first, the initial population of the genetic algorithm is generated by Initnw. This function acts according to the structure that is chosen for the neural network, i.e. type of the activation function. This is so that the activation space of neurons is spread over the input space. When the genetic algorithm finds the best solution (best weights and biases), the neural network modifies the solution of genetic algorithm and improves the weights by a local search. The cost of each member of genetic algorithm is the Mean Squared Error (MSE) that is computed by Levenberg-Marquardt method. The chosen parameters are obtained by trial and error. In Table 2, the number of generations is 50 and the size of population and the values of the mutation and crossing operators are

200, 0.03, and 0.9, respectively. In Table 3, in different nodes, different parameters for the genetic algorithm are chosen.

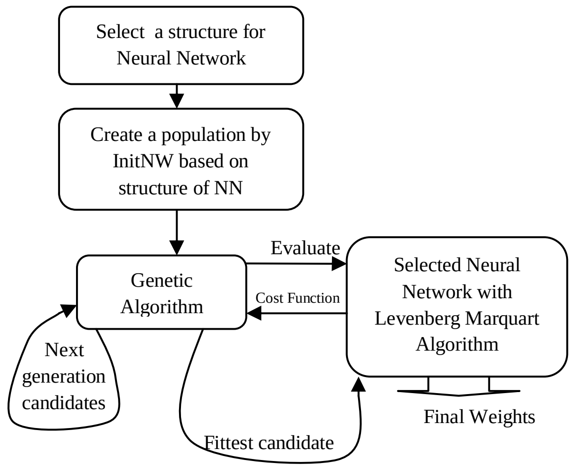

Figure 2: The architecture of proposed approach

We consider two models to predict the gas consumption over the next 12 months in Iran. The first model uses temperature, the total gas consumption, and the domestic and industrial gas consumptions in the current month and the same month last year. The second model uses temperature, the total gas consumption, and the domestic and industrial gas consumptions in the current and one month ago.

Table1: The results RMSE, MAPE, MSE for the models

Model No.	Train			Test		
	RMSE	MAPE	MSE	RMSE	MAPE	MSE
1	.0414	.0514	.0032	.0567	.0560	.0054
2	.0329	.0402	.0011	.0432	.0431	.0019

The comparison results of these two models in the neural network are shown in Table 1. These are results for 10 different runs and report performance measures RMSE, MAPE, and MSE. Based on results in Table 1, we choose model 2 as it performs better on test data and is less subject to over fitting problem.

Our proposed approach to predict the gas consumption in Iran is based on a combination of neural networks and genetic algorithms. In this model, the genetic algorithm uses Initnw instead of simple random function to generate initial values of the population. This function is the default function in Matlab to choose the initial weights in a neural network. The proposed approach is compared with the typical way of combining neural networks and genetic algorithms. The results are shown in Tabel 2. The results in Table 2 and Figure 3 show that all three methods can predict the gas consumption within an acceptable prediction error. The genetic algorithm performs well in decreasing the error of neural network. In Table 3, the performance of the genetic algorithm that is initialized by Initnw is compared over five different nodes with the performance of typical implementation of genetic algorithms. The performances are similar only in one node (node 3). In other nodes, the proposed method is more effective in dealing with over fitting problem, i.e. the proposed method has more generalization power compared with the existing approach. In the existing combination, the genetic algorithm uses the Rand function that is totally random, but the proposed method uses the Initnw function that uses information from activation function of the neural network. The initial weights are chosen such that the activation space of neurons in the first layer is spread over the input space. This is why its results on test data are more acceptable. Parameter tuning in genetic algorithms is not easy, but the proposed method finds parameter values that are more reliable. The performance in different runs is similar.

In this project, we use artificial neural network and genetic algorithm toolbars of Matlab version 2012a. The hardware is two 64bits Intel 2.53 GH processors on Windows 7 operating system.

Table2: The results according to figure 3.

Model	Node No	Train			Test		
		RMSE	MAPE	MSE	RMSE	MAPE	MSE
ANN	2	.0312	.0389	9.7e-4	.0316	.0324	9.9e-4
ANN+GA	3	.0269	.0318	7.2e-4	.0245	.0268	6.04e-4
Proposed	4	.0255	.0306	6.5e-4	.0213	.0215	4.5e-4

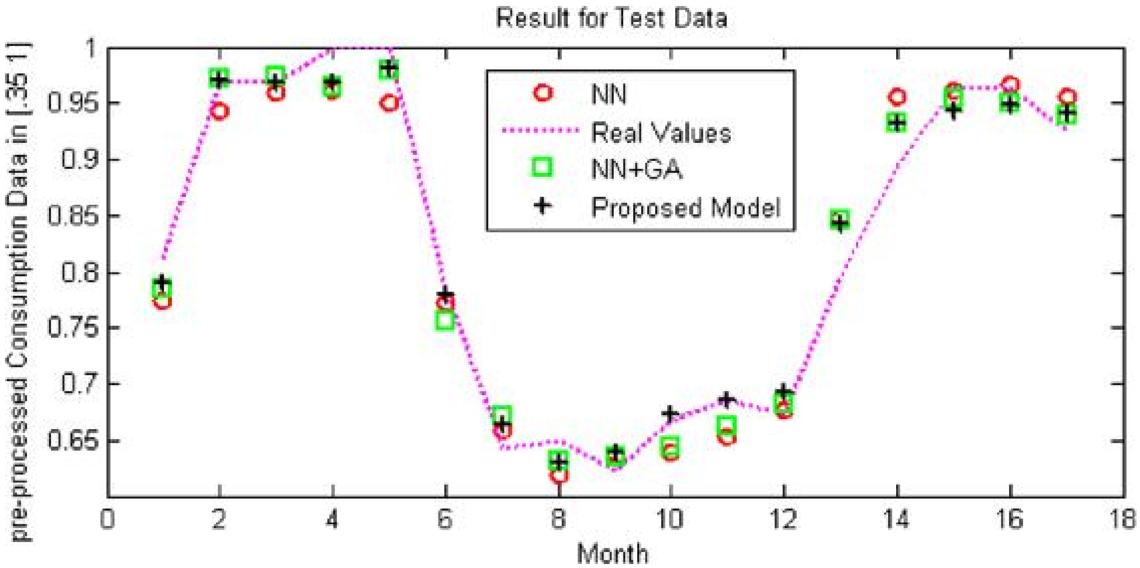

Figure 3: Performance of proposed approach compare with ANN and (GA+NN).

Table3: The Results with various nodes for two different type of initialization

Node	Function Type For GA Population	Test Data		
		RMSE	MAPE	MSE
3	Initnw	.0244	.0269	5.9e-4
	rand	.0246	.0269	6.03e-4
4	Initnw	.0213	.0215	4.5e-4
	rand	.0821	.0670	.0067
5	Initnw	.0229	.0239	5.2e-04
	rand	.0269	.0251	7.2e-4
6	Initnw	.0204	.0216	4.1e-04
	rand	.0802	.0639	.0064
8	Initnw	.0235	.0252	5.5e-4
	rand	.0482	.0402	.0023

4. Conclusion

The proposed method is less subject to over fitting compared to existing combinations of genetic algorithms and neural networks. Parameter tuning is easier as, compared to existing methods, its convergence space is larger. Moreover, it can deal with larger parameter space more effectively. In the existing combination, the genetic algorithm uses the Rand function that is totally random, but the proposed method uses the Initnw function that uses information from activation function of the neural network. The initial weights are chosen such that the activation space of neurons in the first layer is spread over the input space. For our data, using information from current and one month ago gave better results compared to using information from current month and the month from last year. The proposed technique is more accurate than the neural network based on MAPE, RMSE, and MSE performance measures. The genetic algorithm is effective in reducing the error of neural network. Based on these results, the proposed approach is an effective method to deal with complexity, uncertainty, and nonlinearity.

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