Short-Term Load Forecasting Model Using Flower Pollination Algorithm

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Abstract

Electricity is natural but not a storable resource and has a vital role in modern life. Balancing between consumption and production of the electricity is highly important for power plants and production facilities. Researches show that electricity load consumption characteristic is highly related to exogenous factors such as weather condition, day type (weekdays, weekends and holidays etc.), seasonal effects, economic and politic changes (crisis, elections etc.). In this study, we propose a short-term load forecasting models using artificial intelligence based optimization technique. Proposed 5 different empirical models were optimized using flower pollination algorithm (FPA). Training and testing phase of the proposed models held with historical load and weather temperature dataset for the years between 2011-2014. Forecasting accuracy of the models was measured with Mean Absolute Percentage Error (MAPE) and monthly minimum approximately %1,79 for February 2013. Results showed that proposed load forecasting model is very competent for short-term load forecasting.

Keywords: "Short-Term load forecasting; Nature-Inspired optimization; Flower pollination algorithm; Artificial intelligence"

1.   Introduction

Electric energy is an energy source produced by using various sources and also having a wide variety of consumption fields. Electric energy consumption has a large share in total energy consumption because it can easily be converted into basic energy types such as heat, light, motion. The magnitude of the industrial sector volume, which can be expressed as a measure of development, is directly proportional to the consumption of electric energy.

Load consumption forecasting models are essential and vital for planning and production scheduling of the production facilities. These forecasting models and studies help to make important decisions on purchasing, generating electric power, load switching, and infrastructure development. The forecasting studies are also extremely important for suppliers and other participants in production, transmission, distribution and energy markets [1].

Load demand forecasting is very important for planning and production of power plants and production facilities. Load demand forecasts are generally divided into three main divisions: short-term, medium-term and long-term depending on the time periods [2]. Medium and long-term demand forecasts basically are related to what the electricity consumption is based on in total years, what might be in the future. The establishment of new power generation plants and the planning of large-scale energy investments are planned according to this demand. Short-term based approaches are based on optimum usage of existing resources and profiling the consumption characteristics. Basically, short-term methods are used for security and survival of the main system.

When literature is examined, it is seen that, there are several types of models and methods tried out on load consumption and energy demand forecasting. These studies are divided into two main sections as classical statistical based approaches and artificial intelligence based approaches. These models and methods are classified as time series based (univariate) models which are modelled as a function of historical load data and expert systems which are modelled as systems of exogenous factors especially weather and social variables [3].

Traditional statistical models are based on relation on historical load changes. Some of these univariate studies are auto-regressive models [4, 5], dynamic linear, non-linear models [6, 7], non-parametric regressive model [8], structural model [9], curve-fitting procedural model [10]. These models have lower forecasting errors for the routine periods of consumption.

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Literature shows that statistic based models are not sufficient for non-linear periods of consumption. Thus, researchers leaned to nature inspired and artificial intelligence based non-linear models. Some of these studies are fuzzy logic and artificial neural networks based forecasting models [11-14]. S. Hassan et al. (2016) proposed fuzzy type-2 based load forecasting model. They also used extreme learning machine (ELM) to optimize and finding optimal fuzzy parameters [15]. D.K. Chatuverdi et al. (2015) proposed a model by using generalized neural networks (GNN) [16]. Song Li et al. (2015) used hybrid load forecasting model. They used ELM and modified artificial bee colony (MABC) to optimize input weights of ELM [17].

In Turkey, there are varying types of studies on short-term load forecasting. E. Yukseltan et al. (2017) proposed a linear model using climatic and econometric dataset. They trained and tested forecasting model for the period 2012-2014 and the weekly, daily horizon was estimated [18]. H.H. Cevik et al. (2015) proposed fuzzy and adaptive neuro-fuzzy models to estimate short-term load consumption of Turkey. They used historical weather information and seasonal changes in their study [19]. I Esener et al. (2006) proposed an artificial intelligence based model for short-term load forecasting. They used signal processing techniques and ANN with historical weather condition changes [20].

2. Material and Methods

In this paper, we present a hybrid short-term load forecasting model by using structural mathematical models with nature inspired optimization technic. We used historical load consumption and weather temperature changes data set for the period 2011-2014. We used five different mathematical equation for modelling load consumption and flower pollination algorithm (FPA) was used for finding optimal parameters in equations. Forecasting accuracy of the mathematical models was measured using mean absolute percentage error (MAPE).

2.1. Dataset Preparation

Electricity load consumption has linear and non-linear characteristic. Literature shows that there are several types of input variables used to estimate and define load consumption characteristic. These variables are varying to location, model type and other exogenous factors. While having long-term forecasting, globally scaled factors are used such as economic growth depth and population changing for years, in short-term load forecasting, most of the researchers used hourly changing data such as air temperature, raining period, insolation period etc. In this study, we used 4 different input variables. These variables are;

- Last Day Consumption (LDC)
- Last Week Consumption (LWC)
- Weekly Consumption Trend (LCAL)
- Weekly Temperature Trend (TEFF)

Last day consumption (LDC) – Last week consumption (LWC)

Historical changes of the electricity load consumption are very significant indicator for future demand estimations. Electricity load usually follows a routine path. Actual load consumption values belonging to 2013 is seen in Figure 1. Last day consumption for the time L_{t-24} and last week consumption L_{w-7} may help to estimate future load demand.
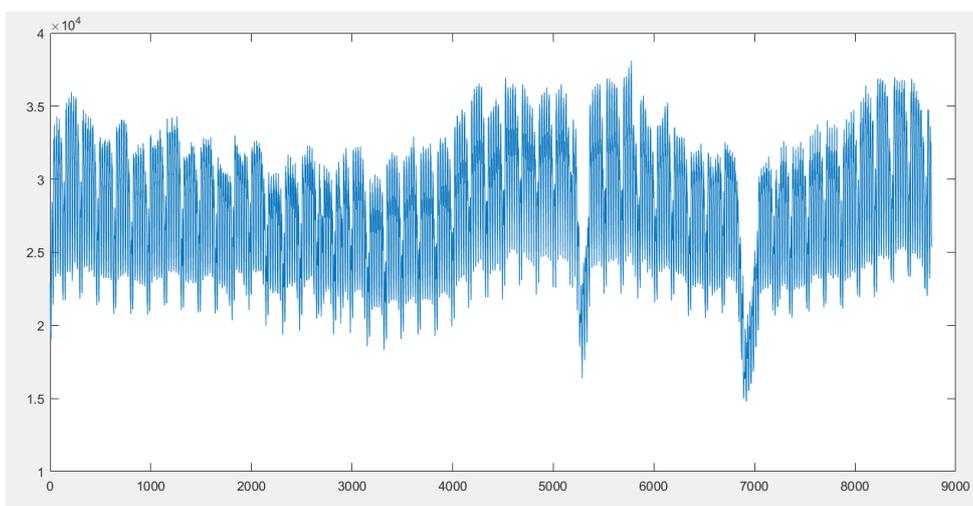

Fig 1. Actual hourly electricity load consumption of 2013

Weekly Consumption Trend (LCAL)

Data obtained with the observations of the amount of consumption for a certain period, may give significant information about the future situation of electricity consumption. These observations are not sufficient information enough for a certain forecasting lonely but may be helpful for an accurate estimation indeed. In this study, we tried to understand consumption characteristic using least square trend analysis for 7 days consumption period and used these results as an input for the mathematical models. Load trend analysis was calculated with using equations 1, 2 and 3.

Load Trend

$$L = a + b_{x_i} \qquad (1)$$

Slope

$$b = \frac{\sum_{i=1}^{n} x_i y_i - n\bar{x}\bar{y}}{\sum_{i=1}^{n} x_i^2 - n\bar{x}^2} \qquad (2)$$

Load Intercept

$$a = \bar{y} - b\bar{x} \qquad (3)$$

Sample load trend data using these equations is seen in Table 1.

Table 1. 25.12.2011 - 31.12.2011 Load consumption data

Date	Time Period (Distance)	Load Consumption (MWh)	x^2	x^2y
25.12.2011	1	26175	1	26175
26.12.2011	2	24386	4	97544
27.12.2011	3	26412	9	237708
28.12.2011	4	26493	16	423888
29.12.2011	5	26345	25	658625
30.12.2011	6	26463	36	952668
31.12.2011	7	26083	49	1278067
1.1.2012		26595		

Weekly Temperature Trend (LCAL)

Literature research shows that, air temperature changes are highly related to hourly based load consumption characteristic. Thus, we used historical temperature data set collected from six different location in Turkey between 2011 and 2014 as an input for proposed forecasting models. The weighted average value of temperature collected from different cities of Turkey calculated with using coefficients. these coefficients were defined by using economic development values according to report published by Republic of Turkey Ministry of Science, Industry and Technology in 2013. The effect of each locations is seen in Table 2.

Table 2. Coefficient values of locations

17030 (City-1)	17130 (City-2)	17135 (City-3)	17220 (City-4)	17351 (City-5)	17603 (City-6)
0.02	0.15	0.02	0.10	0.04	0.67

2.2. Mathematical Models

In this study, five different linear and non-linear empirical models were developed for load consumption forecasting. Mathematical models were mostly used empirical models in literature. In this study, five different linear and non-linear empirical models were developed for load consumption forecasting. Mathematical equations were empirical models mostly used by researchers in the literature. These are linear, power, exponential, semi-quadratic and quadratic models.

Linear model

$$Lm = w_1 L_{dc} + w_2 L_{wc} + w_3 L_{cal} + w_4 T_{eff} + w_5 \qquad (4)$$

Power model

$$Km = \quad w_1(L_{dc})^{w_2} + w_3(L_{wc})^{w_4} + w_5(L_{cal})^{w_6} + w_7(T_{eff})^{w_8} \tag{5}$$

Exp. model

$$Em = \quad w_1 e^{w_2 L_{dc}} + w_3 e^{w_4 L_{wc}} + w_5 e^{w_6 L_{cal}} + w_7 e^{w_8 T_{eff}} + w_9 \tag{6}$$

Qua. model

$$\begin{aligned} Qm = \quad & w_1(L_{dc})^2 + w_2(L_{wc})^2 + w_3(L_{cal})^2 + w_4(T_{eff})^2 + \\ & w_5(L_{dc})(L_{wc}) + w_6(L_{dc})(L_{cal}) + w_7(L_{dc})(T_{eff}) + \\ & w_8(L_{wc})(L_{cal}) + w_9(L_{wc})(T_{eff}) + w_{10}(L_{cal})(T_{eff}) + w_{11} \end{aligned} \tag{7}$$

Sem-Qua. model

$$\begin{aligned} Sm = \quad & w_1(L_{dc}) + w_2(L_{wc}) + w_3(L_{cal}) + w_4(T_{eff}) \\ & + w_5\sqrt{(L_{dc})(L_{wc})} + w_6\sqrt{(L_{dc})(L_{cal})} \\ & + w_7\sqrt{(L_{dc})(T_{eff})} + w_8\sqrt{(L_{wc})(L_{cal})} \\ & + w_9\sqrt{(L_{wc})(T_{eff})} + w_{10}\sqrt{(L_{cal})(T_{eff})} + w_{11} \end{aligned} \tag{8}$$

Artificial intelligence based flower pollination algorithm was used to improve forecasting accuracy of the empirical models. Accuracy of the empirical models was calculated by using mean absolute percentage error (MAPE) and mean square error (MSE) methods.

MAPE

$$\frac{1}{n}\sum_{t=1}^{n}\left(\left|\frac{AL_t - FL_t}{AL_t}\right| x100\right) \tag{9}$$

MSE

$$\frac{1}{n}\sum_{t=1}^{n}(AL_t - FL_t)^2 \tag{10}$$

2.3. Flower Pollination Algorithm

Nature inspired optimization algorithms have become very popular in the last 20 years. it can be seen in the literature, these algorithms are frequently used in NP hard problems especially in the solution of complex problems in engineering and industrial field [21]. Flower pollination algorithm (FPA) is a nature inspired optimization algorithm developed by Xie-She Yang in 2012. The algorithm is inspired by pollination process of the flowery plants. Pollination process is having a vital role for the flowery plants. Pollination can take two major forms: abiotic and biotic. About 90% of flowering plants belong to the biotic pollination group. In biotic pollination process, pollens are transferred by natural transporters such as insects, flies or other animals. The abiotic form of pollination is realized with natural effects such as wind and diffusion. Grass is one of the good example of abiotic pollination process. From the aspect of view of biological evolution, the main purpose of flower pollination is the survival of the fittest and the optimal reproduction. This may be expressed like an engineering optimization process of flowery plant species.

Optimization process of the FPA is based on four rules. These rules are:

1. Biotic and cross-pollination can be considered processes of global pollination, and pollen-carrying pollinators move in a way that obeys Lévy flights.
2. For local pollination, abiotic pollination and self-pollination are used.
3. Pollinators such as insects can develop flower constancy, which is equivalent to areproduction probability that is proportional to the similarity of two flowers involved.
4. The interaction or switching of local pollination and global pollination can be controlled by a switch probability p ∈ [0, 1], slightly biased toward local pollination

These rules are converted into proper mathematical equations. In biotic process of the pollination, flower pollen gametes are transferred and carried by pollinator animals such as insects and used for global search in algorithm. Therefore rule 1 and rule 3 are represented mathematically as below equation 11.

$$x^{t+1} = x_i^t + \gamma\, L(\lambda)(g_* - x_i^t) \tag{11}$$

x_i^t is the pollen i, solution vector x_i at iteration t. g_* is the best current solution among all solutions. γ is the scaling factor and used for controlling the step size for each iteration. $L(\lambda)$ is a Lévy-flights based step size parameter and corresponds the strength of the pollination. Levy-flights can be used for mimic of global pollination which is realized by bio-natural agents mentioned before. The local pollination, both Rule 2 and Rule 3 is represented in equation 12.

$$x^{t+1} = x_i^t + \epsilon(x_j^t - x_k^t) \tag{12}$$

$x_j^t - x_k^t$ are pollens from different flowers of same species and ϵ is drawn from uniform distribution [0-1]. The working process of FPA may be represented with pseudo code as below.

1. Initialize a population of n flowers/pollen gametes with random solutions
2. Find the best solution g_* in the initial population. Define a switch probability $p \in [0, 1]$
3. **while** (t <MaxGeneration)
    for $i = 1 : n$ (all n flowers in the population)
        if rand < p,
            Draw a (d-dimensional) step vector L from a Levy distribution
            Global pollination via $x^{t+1} = x_i^t + \gamma\, L(\lambda)(g_* - x_i^t)$
        else
            Draw from a uniform distribution in [0,1]
            Do local pollination via $x^{t+1} = x_i^t + \epsilon(x_j^t - x_k^t)$
        end if
        Evaluate new solutions. If new solutions are better, update them in the population
    end for
    Find the current best solution g_*
  end while
4. Output the best solution found

3. Results and Discussion

In this study, we trained and tested 5 different empirical models with historical load consumption and temperature data set. Flower pollination optimization algorithm was used to optimize mathematical models and having accurate load forecasting values. Parameters and pre-defined constraints of the optimization method FPA are given in Table 3.

Table 3. Parameters and constraints for FPA.

Population Limit (Np)	30
Probability Density	0.80
Beta	3/2
Step Size	0.01
Maximum Iteration Limit	2000

Training and testing of the proposed models was used for monthly horizons. Proposed models trained with data of 2012 and 2013 then tested with data of 2014. Training and testing results for the period 2013 and 2014 are seen in Table 4.

Table 4. Training and testing mape results for FPA.

	February 2013	February 2014	March 2013	March 2014	April 2013	April 2014
Linear	1,871	1,816	2,015	2,146	3,436	2,932
Exponential	11,257	11,919	10,156	11,148	10,206	11,141
Power	2,302	2,576	2,938	2,865	3,573	2,949
Quadratic	9,29	10,33	9,241	10,042	9,634	9,924
Semi-Quadratic	1,794	2,068	1,796	1,953	2,535	2,279

As it seen in Table 3, semi-quadratic model generally gives the better forecasting values than the other empirical models. Obtained results of the proposed models for the 12-hour period of 1 February 2013 is given in Table 4 and comparative results for the period between 1-5 February 2013 is seen in Figure 2.

Table 5. Training and testing mape results for FPA

| Real (MWh)	Linear	Exp.	Power	Quad.	Sem-Quad.	Error Linear	Error exp.	Error power	Error quad.	Error semi-quad
27114	27654	27814	26865	26918	26822	1,991	2,582	0,917	0,722	1,075
25480	26002	27816	25290	25375	25175	2,048	9,167	0,746	0,411	1,196
24374	24958	27821	24374	24486	24292	2,395	14,142	0,000	0,459	0,335
23783	24416	27815	23632	23981	23637	2,661	16,952	0,633	0,834	0,613
23574	24327	27810	23463	23884	23579	3,195	17,968	0,473	1,315	0,023
24040	24758	27809	23860	24218	23971	2,986	15,679	0,751	0,742	0,285
24376	25434	27813	24538	24806	24631	4,341	14,101	0,666	1,764	1,046
25122	26630	27823	25734	25874	25959	6,001	10,750	2,437	2,993	3,330
29277	30599	27908	29921	30286	30472	4,514	4,676	2,199	3,447	4,082
32054	33055	27970	32597	33218	33000	3,124	12,742	1,695	3,633	2,951
33032	33793	28047	33552	34104	33682	2,303	15,091	1,574	3,245	1,967
33805	34152	28037	33975	34437	33925	1,028	17,064	0,502	1,869	0,354
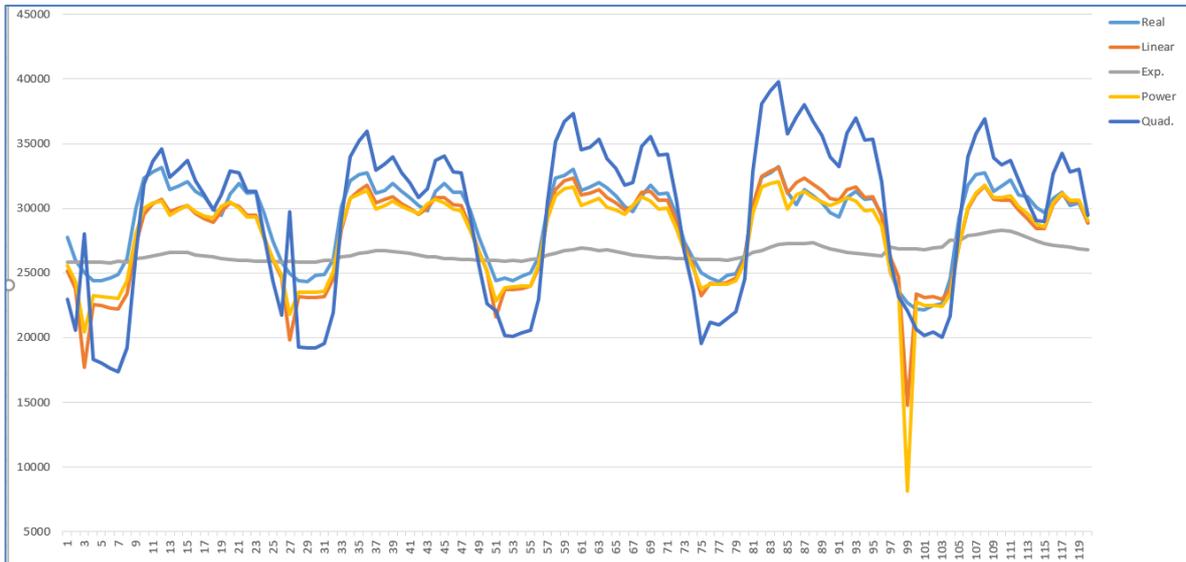
Fig 2. Comparative results of the proposed empirical models for the period between 1-5 February 2013

4. Conclusion

Electricity load consumption estimation is having a vital role for official and non-official environments which are responsible for generation and distribution of the resources. From the aspect the view of literature, short-term load forecasting is becoming very popular research area recent years. There are several types of studies and varying of models have been developed for aiming accurate load forecasting. These models and techniques are basically divided into two main categories: classical statistical based models and artificial intelligence or nature inspired models.

In this study, we proposed a hybrid forecasting model which composed classical structural based empirical models and nature-inspired optimization techniques. We used flower pollination algorithm for optimizing empirical models. Proposed forecasting models were trained and tested by using historical load consumption and weather temperature data. Obtained results show that, proposed empirical models give promising results on hourly based short-term load forecasting. Proposed semi-quadratic model is having more accurate forecasting values than other models. Best result was obtained for February 2013 with %1,79 forecasting accuracy.

Acknowledgements

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