A New Estimation Algorithm for Electric Load Forecast Model Identification

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Abstract- This paper presents a new approach for estimating parameters of long term load forecast models. The objective is to reduce the total estimation error by appropriately adjusting the model coefficients. The proposed method is based on particle swarm optimization algorithm that has been getting added attention as a powerful optimization tool in recent years. It is developed to minimize the error associated with the estimated model parameters. Both linear and nonlinear forecast models have been used to perform this study. Actual reported data of Kuwait network is used to analyze the performance of the proposed approach. Results are reported and compared to those obtained using different estimation techniques. Comparison results are in favor of the proposed approach which signifies its potential as a promising estimation tool.

Key-words- Parameter identification, particle swarm optimization, load forecast.

1 INTRODUCTION

Electric power grids are considered the most complex man-made systems mainly due to their wide geographical coverage, various transactions among different utilities, and diversity in individual electric power companies’ layouts, size, and equipment used. Engineers need special tools to optimally plan, monitor, and operate different aspects of such sophisticated systems. Some of these tools are economic dispatch, unit commitment, state estimation, automatic generation control, security analysis, optimal power flow, and load forecast. The latter tool can be categorized into three main categories: long term, medium term, and short term. Results obtained from load forecasting process are used in planning and operation. For example, long-term load forecasting, one to ten years ahead monthly and yearly values, is applied in expansion planning, inter-tie tariff setting and long-term capital investment return problems. Medium term load forecast, covers period of few weeks, is mainly used for scheduling fuel supply. While short-term load forecast results, ahead hourly and daily values, are needed in unit commitment, maintenance and economic dispatch problems. Therefore, the accuracy of load forecasting has significant effect on power system planning and operation. The time horizon for mid and long-term forecasting ranges between few weeks and several years. Unfortunately, it is quite difficult to forecast load demand over a planning period of this length. This fact is due to the uncertain nature of the forecasting process. There are large numbers of influential factors that characterize and directly or indirectly affect the underlying forecasting process; most of them are uncertain and uncontrollable.

Many classic approaches have been proposed to estimate the long term load forecasting model parameters, including static and dynamic state estimation techniques [1-4]. While the least error square (LES) technique has been the most famous conventional static estimation technique and in use for a long time as the preferred technique for optimum estimation in general, some limitations and disadvantages exist in this approach. For example, when the data set is contaminated with bad measurements, the estimates may be inaccurate unless a large number of data points are used. Reference [5] proposed a static method based on non-iterative least absolute value technique. This method has the advantage of detecting bad data.

Different class of estimation is the stochastic dynamic one. Kalman filtering and the least absolute value filtering algorithms are examples of such dynamic approaches. Unlike static approaches, where the whole set of data is used to obtain the optimal solution, dynamic filters are recursive algorithms. In recursive filters, the estimates are updated using each new measurement. Dynamic filters are well suited to on-line digital processing as data are processed recursively. They had been used extensively in estimation problems for dynamic systems [6]. Dynamic filters have the advantage of being able to handle measurements that change with time. Methods based on artificial intelligence such as artificial neural networks (ANN) and expert systems have been also proposed and shown promising and encouraging results [7;8]. Heuristic search methods like Genetic Algorithms (GA) were also proposed and implemented. This method is based on the mechanism of natural selection and natural genetics [9]. Hybrid methods using ANN and GA were also proposed in many references [10;11]. This paper presents a new method for estimating parameters of the long term load forecast model using Particle Swarm Optimization (PSO) technique. PSO is a global optimization algorithm that deals with problems in which a best solution can be represented as a point or surface in an n-dimensional space. The estimation problem is presented in state space form. PSO technique is used to estimate the parameters of different load forecasting models. The proposed method is tested using actual recorded data for the Kuwaiti network.
2 MATHEMATICAL FORMULATION

The goal of load forecasting models is to build a mathematical relationship between electric load and influential variables such as time, weather, seasonal events etc. that may directly impact system demand. Coefficients of the formulated model are identified and used to predict the future loads by extrapolating the relationship to desired lead time. Final accuracy of the forecast process depends on the selected model and accuracy of the estimated parameters. Reported work of load forecasting models have found that techniques almost in use today can be categorized as being of multiple regression, general exponential smoothing and statistical methods [3].

Regression analysis or trend analysis is the study of the behavior of a time series or process in the past and its mathematical modeling so that future behavior can be extrapolated from it [4]. A time variant event such as power system load can be broken down into five components, basic, trends, seasonal variations, cyclic variations and random variations. The last three variations have a long-term zero mean. Regression curves used in power system load forecasting are; linear, polynomial, exponential and power. In general, a multi-variable regression model can be related to \( n+1 \) independent variables and can be written as follows:

\[
P(t) = a_0 + \sum_{i=1}^{n} a_i t^i + r(t) \quad (1)
\]

where \( P(t) \) is the peak load demand at time \( t \); \( a_o, a_i \) are the regression coefficients relating the load \( P(t) \) to time \( t \); \( r(t) \) is the residual load at year \( t \).

In order to build a proper forecasting process, one must construct the model, select the forecasting method and finally evaluate the results. As mentioned before, the regression technique is the most widely used one mainly because of its simplicity and ease of use. Therefore, this technique is considered for modeling. It is very important to emphasize that the primary objective of this paper is to present the application of PSO technique in estimating the parameters of load forecasting models and evaluate the results obtained. The objective is not to present a model comparison.

Parts of data used in this paper are taken from references [5;9]. In these references, the data has been tested and appropriate models have been chosen. Since the scope of this paper is focused on the application of PSO technique for the long-term load forecasting, the models proposed and tested in [5;9] will be used directly here. Therefore, in this paper two models are considered, i.e. linear (i=1) and quadratic (i=2) models. Given the peak load \( P(t) \) at each year \( t \), an equation just like equation (1) can be written for each load. If the data consists of \( m \) sets of years and peak loads, then there will be \( m \) equations with \( n \) unknowns. This system of equation is an overdetermined system \( (m>n) \). Then for \( m \) years, a discrete system of equations in state space form can be written as:

\[
P(t) = H(t) X + r(t) \quad (2)
\]

where \( P(t) \) is the load demand vector; \( X \) is the parameter vector to be estimated; \( r(t) \) is the error vector associated with \( P(t) \); \( H(t) \) is a row vector that relates \( P(t) \) to \( X \).

In this study two models used are:

Model 1: Linear model \( (i=1) \)

\[
T = 1, 2, \ldots m \quad \text{and} \quad X = \begin{bmatrix} \alpha & \beta \end{bmatrix}^T
\]

Model 2: Quadratic model \( (i=2) \)

\[
T = 1, 2, \ldots m \quad \text{and} \quad X = \begin{bmatrix} \alpha & \beta & \gamma \end{bmatrix}^T
\]

Now, the problem is to find an estimate of the parameter vector \( X \) for any model that minimizes the error vector \( r(t) \).

3 PARTICLE SWARM OPTIMIZATION

Two scientists, namely Kennedy and Eberhart, first introduced Particle Swarm Optimization (PSO) in 1995 as a new evolutionary method [12]. The original objective of their research was to graphically simulate the social behavior of bird flocks and fish schools. As their research progressed, they discovered that with some modifications their social behavior model can serve as a powerful optimizer. The first version of PSO was intended to handle only nonlinear continuous optimization problems. However, many advances in PSO development elevated its capabilities to handle a wide class of complex optimization problems involved in engineering and science. It has been applied to different areas of power systems as shown in reference [13].

Different versions of the PSO algorithm were proposed but the most standard one is the one introduced by Shi and Eberhart [14]. Key attractive feature of PSO is its simplicity as it involves only two model equations. In PSO, the coordinates of each particle represent a possible solution associated with two vectors, the position \( (x_i) \) and velocity \( (v_i) \) vectors. The size of vectors \( x_i \) and \( v_i \) is equal to the problem space dimension. A swarm consists of number of particles “or possible solutions” that proceed (fly) through the feasible solution space to explore optimal solutions. Each particle updates its position based on its own best exploration; best swarm overall experience, and its previous velocity vector according to the following model:

\[
v_{i+1} = wn_i + c_1r_1(pbest_i - x_i) + c_2r_2(gbest - x_i) \quad (3)
\]

\[
x_{i+1} = x_i + v_{i+1} \quad (4)
\]
where

- $c_1$ and $c_2$ are two positive acceleration constants, they keep balance between the particle’s individual and social behavior when they are set equal;
- $r_1$ and $r_2$ are two randomly generated numbers with a range of $[0,1]$ added in the model to introduce stochastic nature in particle’s movement;
- $w$ is the inertia weight and it keeps a balance between exploration and exploitation. In our case, it is a linearly decreasing function of the iteration index:

$$w(k) = w_{\text{max}} - \left( \frac{w_{\text{max}} - w_{\text{min}}}{\text{Max. Iter.}} \right) \cdot k \quad (5)$$

- $P_{\text{best}}$ is the best position particle i achieved based on its own experience;
- $g_{\text{best}}$ is the best particle position based on overall swarm experience;
- $k$ is the iteration index.

PSO is a population-based evolutionary technique that has many key advantages over other optimization techniques like:
- It is a derivative-free algorithm unlike many conventional techniques.
- It has the flexibility to be integrated with other optimization techniques to form a hybrid tool.
- It is less sensitive to the nature of the objective function, i.e. convexity or continuity.
- It has less parameters to adjust unlike many other competing evolutionary techniques.
- It has the ability to escape local minima.
- It is easy to implement and program with basic mathematical and logic operations.
- It can handle objective functions with stochastic nature.
- It does not require a good initial solution to start its iteration process.

The PSO algorithm can be best described in general as follows:

1. For each particle, the position and velocity vectors will be randomly initialized with the same size as the problem dimension.
2. Measure the fitness of each particle ($P_{\text{best}}$) and store the particle with the best fitness ($g_{\text{best}}$) value.
3. Update velocity and position vectors according to (3) and (4) for each particle.
4. Repeat steps 1-3 until a termination criterion is satisfied.

### 4 PRACTICAL APPLICATION AND RESULTS

Real peak demands of Kuwait network are used in this study [15]. The data set is used to establish an overdetermined system of equations. This system of equations is solved using the proposed PSO technique to find the optimal parameters for different forecasting models. A series of experiments were conducted to fine tune the proposed PSO. Key parameters of PSO algorithm used in this study are presented in Table 1. Both linear and nonlinear models are used in the given test system and results obtained using PSO are compared with those of LES method.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>10 Particles</td>
</tr>
<tr>
<td>Stop Criterion</td>
<td>1000 Iterations</td>
</tr>
<tr>
<td>Velocity</td>
<td>$V_{\text{max}} = 2.0$, $V_{\text{min}} = 0$</td>
</tr>
<tr>
<td>Acceleration Constants</td>
<td>$C_1 = 3$, $C_2 = 3$</td>
</tr>
<tr>
<td>Inertia Weight</td>
<td>$W_{\text{max}} = 0.9$, $W_{\text{min}} = 0.4$</td>
</tr>
</tbody>
</table>

Peak demands of Kuwait power network during 1992-2005 are used to estimate the parameters of both linear and nonlinear long term forecasting models. Fig. 1 shows the annual peak loads of Kuwait network. PSO and LES techniques are used to estimate models’ parameters for the same time horizon and the computed parameters are tabulated in Table 2. The corresponding forecasted demands based on the estimated parameters of linear and quadratic models are shown in Tables 3 and 4 respectively. Calculated estimation errors are given in Table 5. This table reveals that PSO on average performed better than LES in minimizing the error associated with the estimation process. Thus, the parameters estimated using PSO are better correlated with the actual measurements recorded.

![Fig. 1. Kuwait Annual Peak Demands.](image-url)
The solution framework is implemented and tested. The estimation problem is formulated as an optimization for representing the available data in terms of total error. Parameter estimation using the PSO method has been compared with that obtained using the LES method. From total error point of view, it is found that PSO method has produced better estimates than the LES method. This indicates that the PSO approach is quite promising and deserves serious attention as a new tool for parameter estimation.

References:


5 CONCLUSIONS

A PSO algorithm is presented for optimal parameter estimation of long term load forecasting in power systems. The estimation problem is formulated as an optimization one. The solution framework is implemented and tested using actual recorded data. Real network data for Kuwait network is used to validate the performance of the proposed approach and test its potential. Two different models are used and the quadratic model is proven to more suitable for representing the available data in terms of total error. Parameter estimation using the PSO method has been compared with that obtained using the LES method. From total error point of view, it is found that PSO method has produced better estimates than the LES method. This indicates that the PSO approach is quite promising and deserves serious attention as a new tool for parameter estimation.

References:


