# The gradual learning static load modelling method based on real-time fault recorder data

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**Abstract**

Setting a real-time load model is an effective way to overcome time-variation of power load in course of power load modelling. On the basis of load data sorting, this paper proposes a gradual learning static load modelling method based on power fault recorder data. Firstly, power fault recorder collects and stores valid load data. Secondly, all valid load data will be classified by the time, static load model can be built corresponds to each classification. Thirdly, model parameters of each sort are identified by gradual learning method, for the goal of global fitting optimal for the measured active power and calculated active power, the load model parameters are optimized by using curve fitting method. The identified model parameters can be applied to power system calculation directly without preserving all load data, essential feature of all load data is reserved and modelling operational efficiency is improved greatly. Simulation results show that the gradual learning method is right and effective, which is easier to realize and is of higher precision compared with least squares method, therefore the method has widely applicable value and is prospective in power system on-line static load modelling.

*Keywords:* Fault Recorder, Static Load Modelling, Parameter Identify, Gradual Learning, Curve Fitting

## 1 Introduction

The static load model is commonly employed in power system state analysis, such as power flow computing and some steady analysis based on power flow [1]. Large amounts of simulation results and tests showed: the static load model has great influence on power flow computing, voltage stability computing, frequency stability computing, reactive power compensation equipment planning, long time dynamic process analysing, and so on [2]. Under critical conditions some qualitative conclusions can even be reversed [3]. Therefore, it is highly necessary to research on static load modelling.

At present, the solutions to static load modelling in power system mainly include: statistical synthesis method, steady-state testing method and measurement-based method [4]. In recent years, appearance of various kinds of new electronic devices makes load characteristics become more and more complex, as time goes on, time-variant features of load are increasingly obvious [5]. According to field measurements made by American GE Company [6], static characteristic coefficient of an area changed 20% in 10 minutes. Static load modelling method based on one survey or one test can not reflect time-variant features of power load perfectly [7]. Therefore, to solve the problem above, the best way is on-line and real-time data acquisition, on–line data processing and on-line load model parameters identification. However, until now, on-line or real-time static load modelling method has not being used in power system due to limitation of field measurement equipment.

With the rapid development and prevalence of power fault recorder, recorder makes on-line static load modelling possible [8]. This paper proposes a gradual learning static load modelling method based on real-time fault recorder data, together with the idea of statistical synthesis method. Power load field measured data is classified by their time characteristics, then load model parameters database can be gotten for building static load model corresponded with each class, according to real-time steady-state load data, different time-scale load models can be gotten through on-line correcting load model parameters database. Users choose these models according to their actual need; the time–variant characteristic of power load has been overcome. This paper builds and analyses a load model using measured summer load data of one day in Rizhao, experimental results verify the correctness and effectiveness of the method.

## 2 On-line static load modelling

Static load model is function equation between load power and voltage, frequency in steady-state conditions. The common static load models are polynomial model and power function model neglecting effects of frequency [9], shown in formula (1) and (2).

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$$\begin{cases} P = P_0\left[A_p(U/U_0)^2 + B_p(U/U_0) + C_p\right]\left(1+\left(\frac{\partial P}{\partial f}\right)_{f_0}\Delta f\right) \\ Q = Q_0\left[A_q(U/U_0)^2 + B_q(U/U_0) + C_q\right]\left(1+\left(\frac{\partial Q}{\partial f}\right)_{f_0}\Delta f\right) \end{cases}, \quad (1)$$

$$\begin{cases} P = P_0\left(\frac{U}{U_0}\right)^{p_u}\left(\frac{f}{f_0}\right)^{p_f} \\ Q = Q_0\left(\frac{U}{U_0}\right)^{q_u}\left(\frac{f}{f_0}\right)^{q_f} \end{cases}. \quad (2)$$

Normally, voltage and power fluctuations are keeping small, the static load models are obtained by statistical synthesis method or steady-state testing method, nevertheless, these two methods mentioned above maybe cannot take place often, the static load model based on which cannot accurately describe the time–variant of load [10]. With the development and prevalence of fault recorder, it is possible for on-line real time static load modelling, on-line measuring load inputs and outputs data and building static load model can reflect time-variant feature of load and agree with the actual load [11].

### 2.1 LOAD DATA PROCESSING

Effective information load data through extracting from magnanimity data gathered by fault recorder can be used to build static load model. New-type fault recorder can realize the function of steady-state, transient-state, Long-term continuous dynamic process recording and analysing, can analyse and process the data acquired, and set judgment criterion, then qualitative data can be acquired for static load modelling conveniently.

### 2.2 CHOOSING LOAD MODEL STRUCTURE

There are polynomial model, power-function model and permutations of these two models [12]. With increasingly complex load characteristic, nonlinear functions load model structure has arisen, such as spline functions model, neural network etc [13]. Polynomial model structure is carried out in this paper.

### 2.3 MODEL PARAMETERS IDENTIFICATION ALGORITHMS

Model parameters need to be identified by measured recorder data after load model structure was selected. Fault recorder gathered load data continuously, if each time load data new acquired combined with old load data are used in identifying model parameters, the identifying process will be a long and hard one, the load data got by recorder need refresh constantly, moreover, recorder storing capacity is limit, it is not feasible to identify static load model parameters making use of all the load data. This paper proposes an on-line recurrence revision parameters identifying method: only store load model parameters identified results, when a new set of load data is collected, the results will be revised on basis of original results. The approach need less calculation, compute with high efficiency, and extract essential feature of all load data, through which compose static load model describing all load data samples can be get.

### 2.4 LOAD MODEL PARAMETERS DATABASE CONSTRUCTION UNDER MULTI-SCALE OF TIME

The size and parts of load have been subject to changing formulations. If only one load model revised load data gathered by fault recorder, the revised load model can not reflect time-variant feature of load, which may result in inaccurate or bad presentation for load. This paper classifies power load by time according to load model application scene, time-variant feature of load and statistical synthesis method modelling train of thought, categorizing as follows: short - term load is divided horizontally into morning peak hours, troughs hours, gentle hours, evening peak hours and so on; long-term load can be divided vertically years, seasons, months, workday, weekend and so on. Adopting the above-mentioned categorizing methods, users can choose suited load model as required to do some electric power system calculation for the different profiled scenarios.

## 3 Gradual Learning Method

All measured load data are needed in parameter estimation using least square, without considering the *chronological* order between measured data. Large quantity measurements request computer has a massive storage capacity. When this process occurs, the measurements are given in chronological sequence. Parameter estimation process can carry on in time order too. The estimates $\theta$ can be achieved on the basis of earlier measurements, then estimation results will be revised when new measurements arrive, with it, storage capacity of computer is reduced a lot. This paper identifies model parameters by recursive least square in static load on-line modelling. The identification algorithm comparing with common least square needs little computation, calculates with high speed, doesn't need large amounts of matrix inverse operation, fits in on-line application, and identification results achieved by which are almost the same with calculation achieved by using all measured load data, even better.

The gradual learning method iteration computational equations are given as bellows:

Suppose observation $Y$ is one – dimension, k observations will be achieved by observing k times.

Vectors and matrices expressed by $Y_k$, $H_k$, $\theta$ and $v_k$ showed as follows:

$$Y_k = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{bmatrix} \quad H_k = \begin{bmatrix} h_1(t_1) & h_2(t_1) & \cdots & h_n(t_1) \\ h_1(t_2) & h_2(t_2) & \cdots & h_n(t_2) \\ \vdots & \vdots & & \vdots \\ h_1(t_k) & h_2(t_k) & \cdots & h_n(t_k) \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_k \end{bmatrix}$$

$$v_k = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_k \end{bmatrix}, \quad \theta = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_n \end{bmatrix}, \quad k \geq n .$$

The observing equation can be written in the following matrix form:

$$Y_k = H_k \theta + v_k . \tag{3}$$

The estimate $\hat{\theta}$ can be obtained by the least squares estimation:

$$\hat{\theta}_k = \left(H_k^T H_k\right)^{-1} H_k^T Y_k . \tag{4}$$

Suppose

$$P_k = \left(H_k^T H_k\right)^{-1}, \tag{5}$$

then

$$\hat{\theta}_k = P_k H_k^T Y_k . \tag{6}$$

If $y_{k+1}$ is the observation for $k+1$ times:

$$y_{k+1} = \theta_1 h_1(t_{k+1}) + \theta_2 h_2(t_{k+1}) + \cdots + \theta_n h_n(t_{k+1}) = h_{k+1}\theta . \tag{7}$$

In the Equation (7), $h_{k+1} = \left[h_1(t_{k+1}), h_2(t_{k+1}), \cdots, h_n(t_{k+1})\right]$.

Combine Equation (7) and (3):

$$Y_{k+1} = H_{k+1}\theta + v_{k+1} . \tag{8}$$

In (8)

$$Y_{k+1} = \begin{bmatrix} Y_k \\ y_{k+1} \end{bmatrix}, H_{k+1} = \begin{bmatrix} H_k \\ h_{k+1} \end{bmatrix}, v_{k+1} = \begin{bmatrix} v_k \\ r_{k+1} \end{bmatrix}. \tag{9}$$

According to (4),

$$\hat{\theta}_{k+1} = \left(H_{k+1}^T H_{k+1}\right)^{-1} H_{k+1}^T Y_{k+1}, \tag{10}$$

$$\left(H_{k+1}^T H_{k+1}\right)^{-1} = \left\{ \begin{bmatrix} H_k^T & \vdots & h_{k+1}^T \end{bmatrix} \begin{bmatrix} H_k \\ \cdots \\ h_{k+1} \end{bmatrix} \right\}^{-1} = \left[H_k^T H_k + h_{k+1}^T h_{k+1}\right]^{-1} . \tag{11}$$

Suppose $P_{k+1} = \left(H_{k+1}^T H_{k+1}\right)^{-1}$, then

$$P_{k+1} = \left[H_k^T H_k + h_{k+1}^T h_{k+1}\right]^{-1} . \tag{12}$$

Setting by Equation (5),

$$P_k^{-1} = H_k^T H_k . \tag{13}$$

Based on Matrix Inversion Lemma:

$$P_{k+1} = P_k - P_k h_{k+1}^T \left(h_{k+1} P_k h_{k+1}^T + 1\right)^{-1} h_{k+1} P_k . \tag{14}$$

So Equation (10) can be written as following:

$$\begin{aligned} \hat{\theta}_{k+1} &= \left[P_k - P_k h_{k+1}^T \left(h_{k+1} P_k h_{k+1}^T + 1\right)^{-1} h_{k+1} P_k\right] \cdot \\ &\left[H_k^T Y_k + h_{k+1}^T y_{k+1}\right] = \\ &P_k H_k^T Y_k + P_k h_{k+1}^T y_{k+1} - \\ &P_k h_{k+1}^T \left(h_{k+1} P_k h_{k+1}^T + 1\right)^{-1} h_{k+1} P_k \cdot \left[H_k^T Y_k + h_{k+1}^T y_{k+1}\right] = \\ &\hat{\theta}_k + P_k h_{k+1}^T y_{k+1} - P_k h_{k+1}^T \left(h_{k+1} P_k h_{k+1}^T + 1\right)^{-1} \cdot \\ &h_{k+1} P_k H_k^T Y_k - P_k h_{k+1}^T \left(h_{k+1} P_k h_{k+1}^T + 1\right)^{-1} h_{k+1} P_k h_{k+1}^T y_{k+1} \end{aligned} . \tag{15}$$

In (15),

$$\begin{aligned} &P_k h_{k+1}^T y_{k+1} = P_k h_{k+1}^T \left(h_{k+1} P_k h_{k+1}^T + 1\right)^{-1} \cdot \\ &\left(h_{k+1} P_k h_{k+1}^T + 1\right) y_{k+1} = \\ &P_k h_{k+1}^T \left(h_{k+1} P_k h_{k+1}^T + 1\right)^{-1} h_{k+1} P_k h_{k+1}^T y_{k+1} v + \\ &P_k h_{k+1}^T \left(h_{k+1} P_k h_{k+1}^T + 1\right)^{-1} y_{k+1} \end{aligned} . \tag{16}$$

Equation (16) is substituted in Equation (15),

$$\begin{aligned} &\hat{\theta}_{k+1} = \hat{\theta}_k + P_k h_{k+1}^T \left(h_{k+1} P_k h_{k+1}^T + 1\right)^{-1} \cdot \\ &\left(y_{k+1} - h_{k+1} \hat{\theta}_k\right) \end{aligned} . \tag{17}$$

So recursive formula is found based on recursion least square therefrom:

$$\begin{cases} \hat{\theta}_{k+1} = \hat{\theta}_k + P_k h_{k+1}^T \left( h_{k+1} P_k h_{k+1}^T + 1 \right)^{-1} \cdot \\ \left( y_{k+1} - h_{k+1} \hat{\theta}_k \right) \\ P_{k+1} = P_k - P_k h_{k+1}^T \left( h_{k+1} P_k h_{k+1}^T + 1 \right)^{-1} h_{k+1} P_k \end{cases} . \quad (18)$$

There are two methods for $\hat{\theta}$ and $P$ to get initialization values. In one way, k initial values can be calculated by Equation (4) and (5) straightly, and set k=2n (n is dimension of model parameters). In another way, $\hat{\theta}(0)$ is arbitrary and $P(0)=\alpha I$ ($\alpha$ is a proper scalar), better and proper initial values can be gotten through recursive steps.

## 4 Case Simulations

This paper analysis load data of one summer typical workday of output wire from 200KV/100KV transformer simple secondary in Rizhao, data collecting every 5 minutes, typical load data acquired is shown in the Table 1 below. And length of be confined to, the first 10 groups data are displayed only.

TABLE 1 Measured Load Data

| Time | $U(KV)$ | $P(MW)$ | $Q(MVar)$ |
|---|---|---|---|
| 0:00 | 116.7 | 33.64 | 10.72 |
| 0:05 | 116.9 | 33.64 | 10.72 |
| 0:10 | 116.9 | 32.83 | 10.59 |
| 0:15 | 116.8 | 32.97 | 10.45 |
| 0:20 | 116.6 | 32.57 | 10.45 |
| 0:25 | 116.5 | 32.03 | 10.45 |
| 0:30 | 116.7 | 31.90 | 10.32 |
| 0:35 | 116.6 | 31.76 | 10.05 |
| 0:40 | 116.7 | 31.63 | 10.19 |
| 0:45 | 116.5 | 31.90 | 10.32 |

Since active and reactive power have almost the same expression throughout, only differ in model parameters, this paper builds static load model based on active power load data, employing polynomial II model structure.

$$P(k)=a_p+b_pU(k)+c_pU^2(k) . \quad (19)$$

Error function is shown in (18)

$$J = \sqrt{\sum_{i=1}^{n} \left( \frac{P(i)-P_m(i)}{P(i)} \right)^2} . \quad (20)$$

In the equation, data sampling sites are marked $n$, $P$ is active power based on load model, $P_m$ is measured active power.

### 4.1 PARAMETERS IDENTIFIED BASED ON LEAST SQUARES

Static load model is built on one day's load data, identified parameters using all load data based on Least squares are displayed in Table 2. The measured active power is compared with the calculated active power by load model, and illustrated in Figure 1.

TABLE 2 Parameters Identified by The Least Square

| $a_p$ | $b_p$ | $c_p$ | Error |
|---|---|---|---|
| 0.222755 | 12.921562 | -0.108082 | 2.645554 |

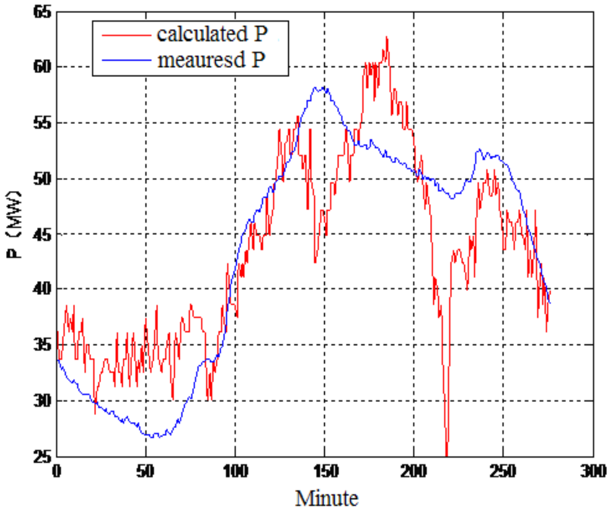


FIGURE 1 Results compared with measured power with calculated power

Table 2 and Figure 1 indicate static load model based on Least squares has weak description, the primary cause is great difference among various times in one day, dispersion and imprecision come to arise when all the load data are used to identify model parameters.

### 4.2 PARAMETERS IDENTIFIED BASED ON GRADUAL LEARNING METHOD

Load model parameters are identified based on gradual learning method using a whole day's load data, the variation of the parameters identified shown in Figure 2, identified results and error are illustrated in Table 3.

TABLE 3 Identified Results and Error Based on Gradual Learning Method

| $a_p$ | $b_p$ | $c_p$ | Error |
|---|---|---|---|
| 0.221429 | 12.921585 | -0.108081 | 2.645554 |

By comparing Table 2 with Table 3, model parameters identified by gradual learning method is almost the same with that of least squares based on load data of all time, it is illustrated that static load modelling method based on gradual learning method is feasible. The modelling method just deal with identified results without all storing load data, and is of high efficiency, quick computing speed. Together, the method can be used in on-line static load modelling based on fault recorder conveniently.

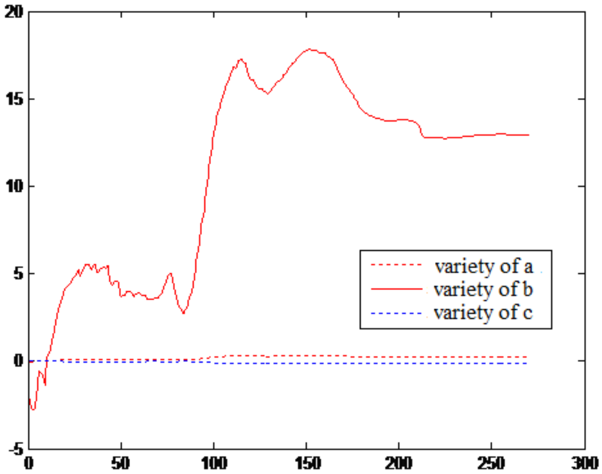


FIGURE 2 The variation of the parameters

As Figure 2 suggests: the trend curve of load model parameters will level off as number of load data increase, as fault recorder operates longer time, model parameters are revised by more measured load data, at the same time, revised parameters are stored only, as time goes by, model parameters become more precisely and static load model is more consistent with practical load.

### 4.3 STATIC LOAD MODELING BASED ON CLASSIFIED TIME

As is stated above, load model based on all load data in one day is not consistent with practical load very well, because power load has time-varying property. This paper divides load data of one day by the hour, builds static load model and identifies model parameters based on measured load data per hour called hour model, finally, load model for one day is composed by hour models.

The identified parameters results and total error based on the method above are illustrated in Table 4, and comparison of measured active power with calculated active power is shown in Figure 3.

By comparing Table 2 with Table 4, static load model is built on classified time, parameters are identified by recursive least squares, the error between measured active power and calculated active power is smaller than before, precision of load model has been improved a lot. It is understood from Figure 3 the calculated active power is successfully simulated with measured active power, so it seems static load modelling based on classified time is very necessary.

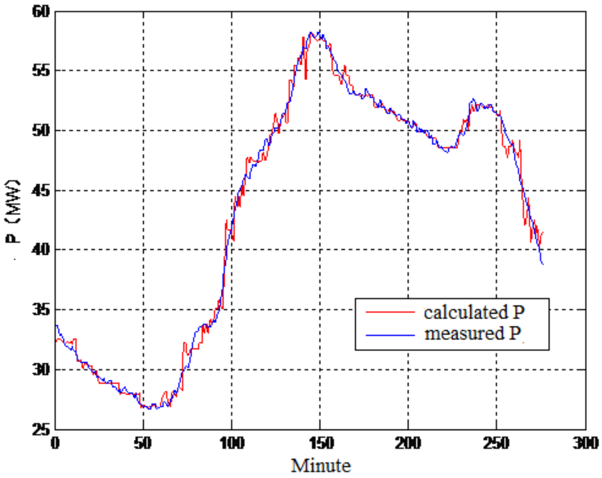


FIGURE 3 Comparison of active power

TABLE 4 Parameters Identified and Total Error Based on Classified Time

| hour | $a_p$ | $b_p$ | $c_p$ | Total error |
|---|---|---|---|---|
| 0:00-1:00 | -0.01 | -0.574 | 0.007 | |
| 1:00-2:00 | 0.04 | 2.347 | -0.018 | |
| 2:00-3:00 | 0.008 | 0.496 | -0.002 | |
| 3:00-4:00 | 0.012 | 0.678 | -0.004 | |
| 4:00-5:00 | 0.015 | 0.869 | -0.005 | |
| 5:00-6:00 | 0.055 | 3.206 | -0.025 | |
| 6:00-7:00 | -0.084 | -4.874 | 0.044 | |
| 7:00-8:00 | 0.08 | 4.676 | -0.037 | |
| 8:00-9:00 | 0.178 | 10.362 | -0.086 | |
| 9:00-10:00 | 0.054 | 3.147 | -0.024 | |
| 10:00-11:00 | 0.088 | 5.072 | -0.040 | |
| 11:00-12:00 | -0.088 | -5.093 | 0.048 | 0.331306 |
| 12:00-13:00 | -0.015 | -0.870 | 0.012 | |
| 13:00-14:00 | -0.055 | -3.175 | 0.032 | |
| 14:00-15:00 | 0.011 | 0.609 | -0.001 | |
| 15:00-16:00 | 0.038 | 2.157 | -0.015 | |
| 16:00-17:00 | 0.040 | 2.300 | -0.016 | |
| 17:00-18:00 | 0.028 | 1.624 | -0.010 | |
| 18:00-19:00 | 0.014 | 0.800 | -0.003 | |
| 19:00-20:00 | 0.069 | 3.997 | -0.031 | |
| 20:00-21:00 | 0.042 | 2.442 | -0.017 | |
| 21:00-22:00 | 0.107 | 6.208 | -0.050 | |
| 22:00-23:00 | 0.093 | 5.404 | -0.043 | |

## 5 Conclusions

This paper proposes a static load modelling method based on real-time data collected by fault recorder. Modern power fault recorder can gather and store plenty of real-time load data, valid load data files is set for on-line static load modelling. All data will be classified by the time, and model parameters database will be built correspond to each classification. Model parameters are identified by recursive least squares, at the same time database is renewed. Simulation results proved the static load modelling method is validity and feasibility.

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