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A CONTINUOUS-TIME IDENTIFICATION METHOD FOR PARAMETER ESTIMATION OF NONLINEAR DYNAMIC LOAD MODELS OF POWER SYSTEMS

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Abstract. *More accurate dynamic load models get better description of the dynamic load characteristic and its relation to voltage stability. In this paper, a second order Taylor series expansion model is presented as the simplification of the popular used exponential recovery dynamic load model. Then, a frequency weighted least-squares based Hartley modulating functions (HMF) method is developed to estimate parameters of the load model, which effectively attenuates the effect of noises in the process of parameter identification. Case studies are conducted using simulation data and laboratory measurements to demonstrate the effectiveness of the proposed methods for the identification of the dynamic load model in the presence of noticeable additive measurement noises.*
Keywords: Power systems, Dynamic load models, Parameter identification, Hartley modulating function methods, Continuous-time model, Frequency weighted least-squares

1. **Introduction.** Load models are known to have a significant impact on dynamic simulation and stability analysis of power systems [1,2]. Many research works are focusing on the load modeling of power systems [3,4], including static load models and dynamic load models as two main types in the literature. Generally, the dynamic load models are more accurate than the static load models to capture the load dynamics [5,6]. Since a load bus is usually composed of many different types of load components with diverse characteristics, different load components are taken into account aggregately in the load models to capture the significant part of the overall load behavior.

Parameter identification is a key problem of load modeling of power systems. With a certain load structure, the parameters often appear nonlinearly in the load model and are identified by the data based methods. In the existing literature, many system parameter identification algorithms are proposed to estimate parameters of the dynamic load models. Traditional gradient-based optimization methods [7,8] are first proposed to identify the load parameters, such as Gauss-Newton iteration method and its variants like Levenberg Marquardt (LM) method [9], but these algorithms often bring in local convergence problem in the computation. To overcome such problem, various intelligent techniques are developed to identify the load models, including separable identification algorithm [10], genetic algorithm [11,12], simulated annealing [13] and multistage identification algorithms [14]. These techniques provide a better convergence and are widely used in power systems. However, the effects of measurement noises are ignored in these works.

As all we know, the dynamic load models are expressed as continuous-time (CT) models, while few reported works use continuous-time identification methods directly. To estimate parameters of CT models, the indirect approach is always viewed as a simple method, which converts the CT load equations to discrete-time (DT) counterparts and estimates the parameters of DT model by some usual methods. However, we note that, when obtaining CT model from the estimated DT model, sampling frequency is hard to be determined [15,16], which often brings in model error inevitably. So, the direct identification approaches for CT models are worth taking into account, especially in some important disciplines such as economic, signal processing, and power systems [17-19]. Among the existing CT identification techniques, the Hartley modulating functions (HMF) method is one of the encouraging and widely used approaches [20].

This paper proposes a second order Taylor series expansion model as the simplified load model, which simplifies parameter identification drastically. Then, a frequency weighted least-squares (FWLS) based HMF method is developed to identify the load model. This method can identify the CT load model directly and effectively attenuate the effect of measurement noises. Illustrative simulation studies show the effectiveness of the proposed approaches for the identification of the nonlinear dynamic load model.

2. **Problem Formulation.**

Since a load bus is usually composed of many different types of load components with diverse characteristics, different load components are taken into account aggregately in load models to capture the significant part of the overall load behaviors. This paper is primarily concerned with the exponential recovery load model, which is a widely used aggregate load model and developed from analyzing dynamic load characteristics. However, some parameters appear nonlinearly in the load model, and are hard to be identified by continuous-time identification techniques. In this section, we study how to simplify the model for simplifying the procedure of parameter identification.

2.1. **Exponential recovery load model.**

The exponential recovery load model can capture the dominant nonlinear steady-state behavior of aggregate loads as well as load recovery, and hence is widely discussed and used in literature. It is a mathematical representation of the relationship between load power and voltage:

$$T_p \frac{dP_r}{dt} = -P_r + P_0 \left(\frac{V}{V_0}\right)^{\alpha_s} - P_0 \left(\frac{V}{V_0}\right)^{\alpha_t} \tag{1}$$

$$P_d = P_r + P_0 \left(\frac{V}{V_0}\right)^{\alpha_t} \tag{2}$$

where V is the per-unit magnitude of voltage, T_p is the load recovery time constants, P_r represents the load recovery responses for real power, P_d stands for the real power demands, V_0 and P_0 denote the nominal voltage and real power, respectively, and α_t and α_s represent the transient and steady-state load-voltage dependencies, respectively.

In this model, the total number of parameters to be estimated is three, including α_s, α_t and T_p; the input and output data are the voltage V and the real power demands P_d. Since the dynamic behavior of reactive power is similar to that of real power for an aggregate load, the analysis is limited to real power only.

2.2. **Simplification.**

The described exponential recovery load model is presented as a set of nonlinear equations, and the power demands P_d has a nonlinear dependency on the voltage V. The nonlinear parameters presented in the model complicate the identification procedure. For simplifying the estimation process, the model has to be simplified firstly.

The exponential recovery load model described in (1) and (2) is simplified around an operating point at steady state. Define the voltage and power of the operating point are V^* and P^*, where $P^* = P_0(V^*/V_0)^{\alpha_s}$. Small deviations around the operating point are denoted by Δ. Using Taylor series expansion and removing all the constant terms, the third order Taylor series expansion of the model is given by:

$$\begin{aligned}\Delta P_d = \Delta P_r + P_0\alpha_t\left(\frac{V^*}{V_0}\right)^{\alpha_t-1}\frac{\Delta V}{V_0} + \frac{1}{2!}P_0\alpha_t(\alpha_t-1)\left(\frac{V^*}{V_0}\right)^{\alpha_t-2}\left(\frac{\Delta V}{V_0}\right)^2 \\ +\frac{1}{3!}P_0\alpha_t(\alpha_t-1)(\alpha_t-2)\left(\frac{V^*}{V_0}\right)^{\alpha_t-3}\left(\frac{\Delta V}{V_0}\right)^3\end{aligned} \tag{3}$$

$$\begin{aligned}T_p\frac{\Delta P_r}{dt} = &-\Delta P_r + P_0\alpha_s\left(\frac{V^*}{V_0}\right)^{\alpha_s-1}\frac{\Delta V}{V_0} + \frac{1}{2!}P_0\alpha_s(\alpha_s-1)\left(\frac{V^*}{V_0}\right)^{\alpha_s-2}\left(\frac{\Delta V}{V_0}\right)^2 \\ &+\frac{1}{3!}P_0\alpha_s(\alpha_s-1)(\alpha_s-2)\left(\frac{V^*}{V_0}\right)^{\alpha_s-3}\left(\frac{\Delta V}{V_0}\right)^3 - P_0\alpha_t\left(\frac{V^*}{V_0}\right)^{\alpha_t-1}\frac{\Delta V}{V_0} \\ &-\frac{1}{2!}P_0\alpha_t(\alpha_t-1)\left(\frac{V^*}{V_0}\right)^{\alpha_t-2}\left(\frac{\Delta V}{V_0}\right)^2 \\ &-\frac{1}{3!}P_0\alpha_t(\alpha_t-1)(\alpha_t-2)\left(\frac{V^*}{V_0}\right)^{\alpha_t-3}\left(\frac{\Delta V}{V_0}\right)^3\end{aligned} \tag{4}$$

Based on the Laplace-transformation, the load variation ΔP_d can be rewritten as:

$$y = \frac{c_1 + d_1 s}{-a_1 + s}u + \frac{c_2 + d_2 s}{-a_1 + s}u^2 + \frac{c_3 + d_3 s}{-a_1 + s}u^3 \tag{5}$$

where $y = \Delta P_d$, $u = \Delta V/V_0$, $c_1 = \frac{1}{T_p}P_0\alpha_s(\frac{V^*}{V_0})^{\alpha_s-1}$, $c_2 = \frac{1}{2T_p}P_0\alpha_s(\alpha_s-1)(\frac{V^*}{V_0})^{\alpha_s-2}$, $c_3 = \frac{1}{6T_p}P_0\alpha_s(\alpha_s-1)(\alpha_s-2)(\frac{V^*}{V_0})^{\alpha_s-3}$, $d_1 = P_0\alpha_t(\frac{V^*}{V_0})^{\alpha_t-1}$, $d_2 = \frac{1}{2}P_0\alpha_t(\alpha_t-1)(\frac{V^*}{V_0})^{\alpha_t-2}$, $d_3 = \frac{1}{6}P_0\alpha_t(\alpha_t-1)(\alpha_t-2)(\frac{V^*}{V_0})^{\alpha_t-3}$, $a_1 = -1/T_p$.

Then, the differential equation of the third order simplified model is obtained:

$$\dot{y} = a_1 y + c_1 u + d_1\dot{u} + c_2 u^2 + d_2\dot{u}^2 + c_3 u^3 + d_3\dot{u}^3. \tag{6}$$

This model represents the load response when a voltage change is occurred in the system, and is characterized by seven parameters: a_1, c_1, c_2, c_3, d_1, d_2 and d_3.

Similarly, the second order and first order simplified models are obtained:

$$\dot{y} = a_1 y + c_1 u + d_1\dot{u} + c_2 u^2 + d_2\dot{u}^2. \tag{7}$$

and

$$\dot{y} = a_1 y + c_1 u + d_1\dot{u} \tag{8}$$

In Section 4, case studies will be conducted to compare the accuracy of the three simplified models (6), (7) and (8). Simulation results show that the second order model (7) is more accurate than the first order model (8). The models (7) and (6) get similar accuracy, while the former one is much simplier than the later one. So in this paper, the second order model (7) is used as the simplified model of the exponential recovery load model.

3. **Parameters Identification.**

In this section, a frequency weighted least-squares based Hartley modulating functions method is firstly proposed to identify the dynamic load model. And then, the parameters of the FWLS-based HMF method are analyzed in Section 3.2.

3.1. **FWLS-based HMF method.** The idea of FWLS-based HMF method is to modulate the simplified load model in time domain to HMF model in frequency domain, which can be solved by a frequency weighted least-squares algorithm. It was motivated by the Laplace and Fourier transformation. The main advantages of this method for estimating CT systems include allowing for arbitrary initial conditions and avoiding approximation of time derivatives from noisy signals.

First, introducing the modulating function $\phi_m(t)$, which is a member of the family of an nth-order HMF,

$$\phi_m(t) = \sum_{i=0}^{n}(-1)^i C_n^i \text{cas}\left((n+m-i)\omega_0 t\right), \quad 0 < t \le T, \quad m = 0, \pm 1, \ldots$$

where $\text{cas}(\alpha) = \cos(\alpha) + \sin(\alpha)$, m is the modulating frequency index, $\omega_0 = 2\pi/T$ plays the role of a resolving frequency, and T is the observation time interval for the given input and output signals.

Define the Hartley transform of $u(t)$

$$H_u(m\omega_0) = \int_{-\infty}^{\infty} u(t)\text{cas}(\omega t)dt$$

Then $\overline{H}_u(m\omega_0)$ and $\overline{H}_u^{(v)}(m\omega_0)$, which are the mth HMF spectral component of the continuous-time signal $u(t)$ and the vth derivative of $u(t)$, respectively, are obtained as follows.

$$\begin{aligned}\overline{H}_u(m\omega_0) &= \textstyle\int_0^T u(t)\phi_m(t)dt \\ &= \textstyle\sum\limits_{i=0}^{n}(-1)^i C_n^i \int_0^T u(t)\text{cas}(n+m-i)\omega_0 t dt \\ &= \textstyle\sum\limits_{i=0}^{n}(-1)^i C_n^i H_u((n+m-i)\omega_0)\end{aligned}$$

$$\begin{aligned}\overline{H}_u^{(v)}(m\omega_0) &= \textstyle\int_0^T u^v(t)\phi_m(t)dt \\ &= \textstyle\sum\limits_{i=0}^{n}(-1)^i C_n^i (n+m-i)^v \text{cas}'(v\pi/2) H_u((-1)^v(n+m-i)\omega_0)\end{aligned}$$

where $\text{cas}'(\alpha) = \cos(\alpha) - \sin(\alpha)$. It can be seen that the approximation of the continuous-time signals' Hartley transform $H_u(m\omega_0)$ is required in the identification process of the HMF method. The extended Simpson's rule is used for better approximation,

$$\begin{aligned}H_u(m\omega_0) &= \textstyle\int_{-\infty}^{\infty} u(t)\text{cas}(\omega t)dt \\ &\approx \frac{T}{3N}\left[\tilde{u}_0 + 4\sum\limits_{l=1}^{k}\tilde{u}_{2l-1} + 2\sum\limits_{l=1}^{k-1}\tilde{u}_{2l} + \tilde{u}_N\right]\end{aligned}$$

where $\tilde{u}_l = u(lT/N)\text{cas}(m\omega_0 lT/N)$, $k = N/2$, and N, an even number, is the number of samples within the fixed time interval.

Modulating the second order simplified model (7) to HMF model

$$\overline{H}_y^{(1)}(m\omega_0) = a_1\overline{H}_y(m\omega_0) + c_1\overline{H}_u(m\omega_0) + d_1\overline{H}_u^{(1)}(m\omega_0) + c_2\overline{H}_{u^2}(m\omega_0) + d_2\overline{H}_{u^2}^{(1)}(m\omega_0) \quad (9)$$

Let

$$z(m\omega_0) = \overline{H}_y^{(1)}(m\omega_0)$$

$\varepsilon(m\omega_0)$ be an equation error. After some arrangement, (9) can be rewritten as a regression equation in the frequency domain

$$z(m\omega_0) = \varphi^T(m\omega_0)\theta + \varepsilon(m\omega_0) \quad (10)$$

where

$$\varphi^T(m\omega_0) = \left[\ -\overline{H}_y(m\omega_0) \quad \overline{H}_u(m\omega_0) \quad \overline{H}_u^{(1)}(m\omega_0) \quad \overline{H}_{u^2}(m\omega_0) \quad \overline{H}_{u^2}^{(1)}(m\omega_0)\ \right]$$

and

$$\theta^T = \left[\begin{array}{ccccc} a_1 & c_1 & d_1 & c_2 & d_2 \end{array} \right]$$

Based on a sequence of observations for $m = 0, \pm1, \ldots, \pm M$, $(2M + 1)$ regression equations can be represented as a vector equation

$$Z(M\omega_0) = \Psi^T(M\omega_0)\theta(M\omega_0) + \varepsilon(M\omega_0) \tag{11}$$

where

$$\begin{aligned} Z^T(M\omega_0) &= \left[\begin{array}{cccccc} z(-M\omega_0) & \cdots & z(-\omega_0)z(0) & z(\omega_0) & \cdots & z(M\omega_0) \end{array} \right] \\ \Psi^T(M\omega_0) &= \left[\begin{array}{ccccccc} \varphi(-M\omega_0) & \cdots & \varphi(-\omega_0) & \varphi(0) & \varphi(\omega_0) & \cdots & \varphi(M\omega_0) \end{array} \right] \\ \varepsilon^T(M\omega_0) &= \left[\begin{array}{ccccccc} \varepsilon(-M\omega_0) & \cdots & \varepsilon(-\omega_0) & \varepsilon(0) & \varepsilon(\omega_0) & \cdots & \varepsilon(M\omega_0) \end{array} \right] \end{aligned}$$

Define a positive definite diagonal frequency weighting matrix

$$W = \text{diag}(\begin{array}{ccccccc} w_{-M} & w_{-M+1} & \ldots & w_0 & \ldots & w_{M-1} & w_M \end{array})$$

where $w_m = 1/(|m\omega_0| + 0.1)$, $m = 0, \pm1, \ldots, \pm M$. Introducing W in the cost function

$$J = \frac{1}{2}\varepsilon^T(M\omega_0)W\varepsilon(M\omega_0) \tag{12}$$

a frequency weighted least-squares based HMF method is obtained for estimating the unknown parameters vector $\theta(M\omega_0)$:

$$\hat{\theta}(M\omega_0) = [\Psi^T(M\omega_0)W\Psi(M\omega_0)]\Psi^T(M\omega_0)WZ(M\omega_0) \tag{13}$$

In the expression of the frequency weighting matrix W, m is the modulating frequency index. It can be seen that W is inversely proportional to the modulating frequency. At the same time, the mth diagonal elements of W multiplies the mth spectral component of the regression matrix (13), which leads to the effectiveness of the mth regression matrix elements decreasing with frequency. Hence, the frequency weighting matrix W can be interpreted as a kind of low-pass filter for the parameters estimation.

3.2. **Analysis of parameters of the FWLS-based HMF method.** Some parameters of the FWLS-based HMF method should be examined, such as the optimal choice of the sampling time t_s or the number of input and output data points N within a certain record length, and the mode number M of numerically significant spectral elements in the parameters estimation. These variables are important for the computational considerations associated with the proposed method. In this section, the performance of the proposed method for different values of N and M is analyzed, and good suggestions for optimal choices of these variables are proposed.

For simulation purpose, the dynamic load model should be considered with known parameters. In general, the parameters α_s, α_t and T_p are not known exactly for a given load of power systems. However, average values for many load types have been predetermined in literature [13]. Here practical values of these parameters are given as $T_p = 1.2$ s, $\alpha_s = 0.5$, $\alpha_t = 1.5$; the nominal voltage and real power are given as $V_0 = 1$ p.u. and $P_0 = 12$ MW. Based on the relationship between the exponential recovery load model and the third order simplified model (6), the parameters of the simplified model are obtained as $a_1 = -1$, $c_1 = 6.3246$, $d_1 = 17.0763$, $c_2 = -1.7568$, $d_2 = 4.7343$, $c_3 = 0.9760$ and $d_3 = -0.8784$.

In the simulation, measurements are generated by setting the voltage of operating point as $V^* = 0.9$ p.u., and the voltage variation range as 0.9 p.u. to 0.95 p.u., which means the system operating in a normal voltage level. The corresponding voltage deviations around the operating point used as the input signal is shown in Figure 1. The output signal is generated by using the second order simplified model (7) with the known parameters

$a_1 = -1$, $c_1 = 6.3246$, $d_1 = 17.0763$, $c_2 = -1.7568$, $d_2 = 4.7343$, and then mixed with Gaussian noises according to a selected value of noise-to-signal ratio (NSR). The time interval is 5 seconds. The investigation is done in two cases, and estimation results are all obtained based on 25 Monte Carlo runs.

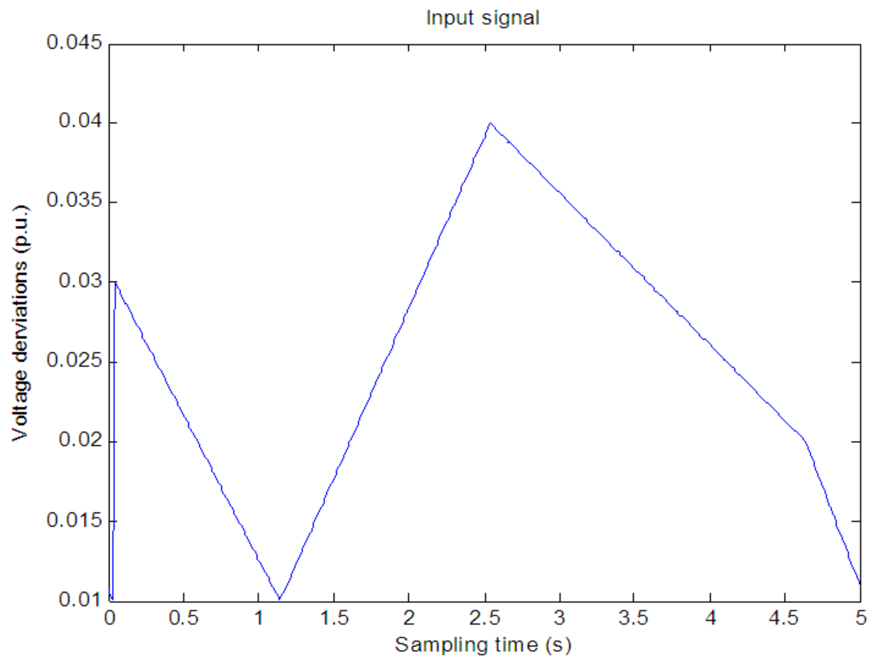


FIGURE 1. Input signal

Case 1: In this case, the output signal for noise free and 10% noises are used respectively. Given $M = 4$, the FWLS-based HMF method is applied to identify the paramters of the load model as N increases from 50 to 1000. The estimation loss J is observed and recorded in Table 1. The results show that the accuracy of the estimated paramters increases as N increases. It is because that smaller sampling time is selected ($t_s = T/N$). In general, N should be chosen carefully for good estimation accuracy.

TABLE 1. Estimation loss for different values of N

N	50	100	400	500	1000
0%	6.2638e-5	2.4334e-5	1.9609e-6	1.3609e-6	7.2941e-7
10%	3.0408e-3	9.2338e-4	8.6252e-5	4.7596e-5	4.0681e-6

Case 2: In this case, Gaussian random noises are imposed on measurements with three different NSRs. Given $N = 500$, the FWLS-based HMF method is used to estimate the parameters by setting different values of M. As all we know, the ture paramters of aggregate load models are not known exactly in practical. So, the lost function for different values of M is computed, and the value of M which gives the minimum loss can be selected as the optimum value. The minimum value of M required for identification can be obtained from $2M + 1 - n \geq n_\theta$, where n_θ is the number of parameters to be estimated. For the second order simplified model, the minimum value of M is 3.

The simulation results are shown in Figure 2. Clearly, from the observation of the results, the optimal value of the mode number M is 3 in this case. This is because for the simplified model which is a high-pass system, noises have a more important effect than the relevant data does for a bigger M.

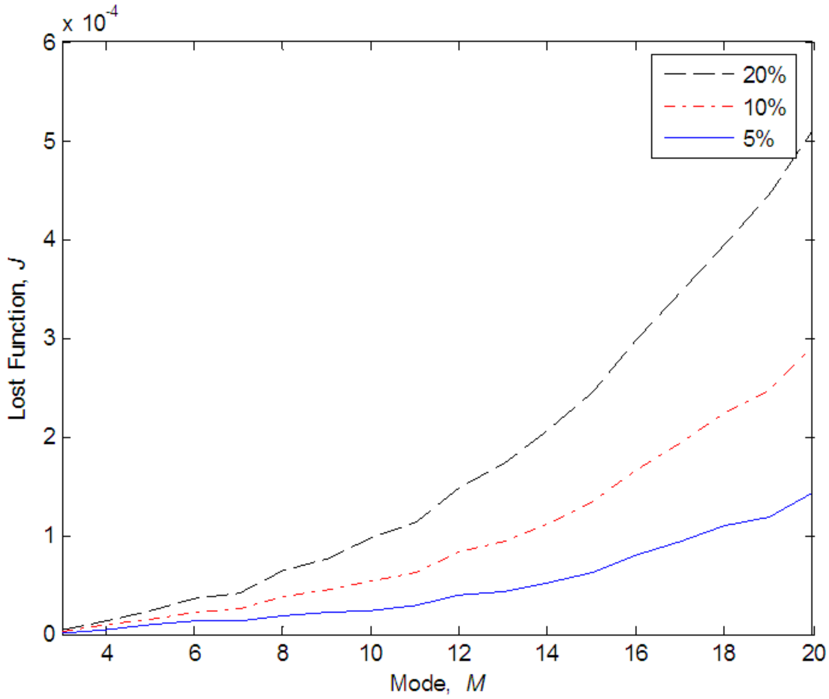


FIGURE 2. Lost function J versus mode number M

4. **Results of Parameter Identification.**

The proposed simplified models and FWLS-based HMF method are tested using simulation data and laboratory measurements.

4.1. **Comparative performance analysis.**

In order to select an optimum simplified load model, the performance of the proposed three different order simplified models are compared in this section.

In the simulation, given the same parameters and input signal as in Section 3.2, the output data are generated by simulating the orignial exponential recovery load model with the given parameters. Based on the input and output data, the Hartley spectra of the input and output signals and some of their derivatives are computed first. Then for $M = 4$, the parameters of the HMF model (9) are estimated using the FWLS algorithm. Finally, perform the above two steps for 25 Monte Carlo runs, and calculate the average value of the parameters. The estimation results are shown in Table 2.

TABLE 2. Parameter values of different simplified models with the first input signal

	a_1	c_1	d_1	c_2	d_2	c_3	d_3	J
	-1	6.3246	17.0763	-1.7568	4.7343	0.9760	-0.8784	
First order model (8)	-1.0039	6.3014	17.3613	–	–	–	–	0.3750
Second order model (7)	-1.0002	6.3235	17.1305	-1.7546	4.7393	–	–	1.3694e-5
Third order model (6)	-1.0002	6.3249	17.1217	-1.7538	5.1201	1.7845	-5.0726	1.3780e-5

It can be seen that the accuracy of the first order simplified model (8) is much less than that of the models (6) and (7). Comparing the estimation results between the second order model and the third order model, it can be observed that the two models get similar accuracy of J, while the parameters c_3 and d_3 of the higher order model are not accurate enough. Further more, the second order model is much simpler than the third order model. From what has been discussed, it can be concluded that higher than second order models are not very useful and accurate as the simplified model. In this paper, the second order simplified model is chosen for the simplification of the exponential recovery load model.

The proposed simplified models are also tested by using another input signal different from that in the last subsection, that is $u(t) = 0.05\sin(2\pi t) + 0.05\cos(3\pi t)$ over 2 seconds. The obtained parameters and estimation loss of the three different order simplified models are shown in Table 3. It can be observed that the proposed second order simplified model is the optimal one for its accuracy and simplication.

Table 3. Parameter values of different simplified models with the second input signal

	a_1	c_1	d_1	c_2	d_2	c_3	d_3	J
	-1	6.3246	17.0763	-1.7568	4.7343	0.9760	-0.8784	
First order model (8)	-1.0049	6.4217	17.0727	–	–	–	–	2.1023
Second order model (7)	-0.9999	6.3277	17.0709	-1.7480	4.7914	–	–	1.2581e-4
Third order model (6)	-0.9985	6.3001	17.0758	-1.7622	4.7453	0.8492	-0.8897	1.1368e-6

4.2. **Presence of output noises.** In this section, the performance of the proposed FWLS-based HMF method in the presence of output noises is analyzed.

Just as in Section 3.2, for the given input signal shown in Figure 1, $V_0 = 1$ p.u., $P_0 = 12$ MW, $V^* = 0.9$ p.u., the output signal is generated based on another set of practical parameters: $T_p = 1.2$, $\alpha_s = 0.67$ and $\alpha_t = 2.8$. In the simulation, Gaussian random noises are imposed on output measurements with different NSRs. The paramteres are estimated using the proposed FWLS-based HMF method and the Levenberg-Marquardt (LM) method [9], respectively.

The LM method identifies the original exponential recovery load model directly, and the input and output signal of the original model are the voltage and real power of the load, while the input and output data of the simplified models are deviations values. Hence, for the LM method, the input and output data should be added V^* and P^*, respectively. In the simulation, the finite difference method (central difference) is used to denoise the data first. In order to conveniently compare the performance of the two methods, relative error is introduced in this paper:

$$\zeta = 100 \times \frac{\left(\frac{1}{N}\sum_{k=1}^{N}\left(P_d(k) - \hat{P}_d(k)\right)^2\right)^{1/2}}{\left(\frac{1}{N}\sum_{k=1}^{N}P_d(k)^2\right)^{1/2}} \tag{14}$$

where $P_d(k)$ and $\hat{P}_d(k)$ are the measured and simulated output data, respectively.

Based on the relationship between the parameters of the simplified load model and these of the exponential recovery dynamic load model, it can be easily calculated α_s, α_t and T_p from the estimated values of a_1, c_1, d_1, c_2 and d_2.

The estimation results of the LM method for NSR increasing from 0 to 2% are shown in Table 4. The performance of the proposed FWLS-based HMF method for NSR increasing from 0 to 30% are shown in Table 5 ($M = 3$, $N = 500$). The results show that the FWLS-based HMF method is able to estimate parameters of the dynamic load model in the presence of additive measurement noises precisely, while the LM method can get acceptable results only for the data with few noises. Besides, as all we know, the LM method is initial-sensitive and suffers from finding a local optimal solution, instead of a global optimal solution.

From what has been disscussed above, it can be concluded that the proposed FWLS-based HMF method shows more advantages for identification of the dynamic load model.

Table 4. Estimation results using the LM method

NSR In %	α_s	α_t	T_p	$\zeta(\%)$
0	0.6700	2.8253	1.2017	0.0027
0.01	0.6700	2.8254	1.2029	0.0100
0.1	0.6704	2.8364	1.1062	0.0967
0.5	0.6774	2.8673	1.0951	0.4306
1	0.6874	3.7264	0.9808	0.6613
2	0.6967	6.1647	0.7278	0.8280

Table 5. Estimation results using the FWLS-based HMF method

NSR In %	α_s	α_t	T_p	$\zeta(\%)$
0	0.6683	2.8209	1.2025	0.1348
1	0.6683	2.8216	1.2029	0.1351
2	0.6687	2.8140	1.2048	0.1496
5	0.6689	2.8267	1.1885	0.1756
10	0.6714	2.8969	1.1696	0.3224
20	0.6690	2.8697	1.0940	0.4476
30	0.6736	3.0415	1.0023	0.5485

4.3. **Laboratory experiments.** In this section, the proposed model and identification method are verified through laboratory experiments. The laboratory measurements are carried out on a laboratory test system shown in Figure 3, which is modeled as a dynamic load. The load contains various types of lightings, which are expressed as R and X, a direct current (DC) machine and an induction machine. The voltage source is the supply voltage source at the laboratory facilities in University of Alberta, and is considered as an infinite bus.

In the dynamic measurements, the voltage changes are created by quickly turning the adjustable transformer T, which results in a voltage step with a rise time of approximately

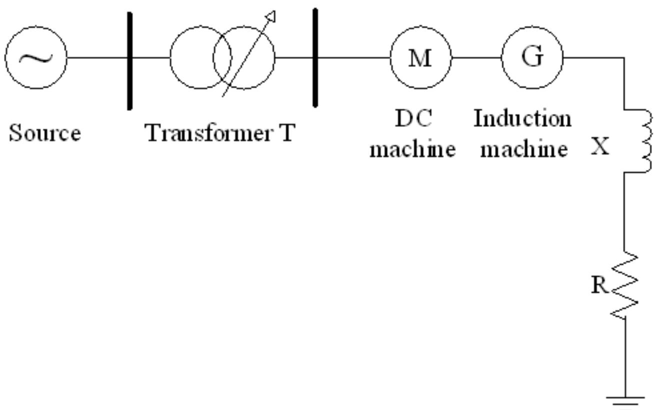


Figure 3. A laboratory test system

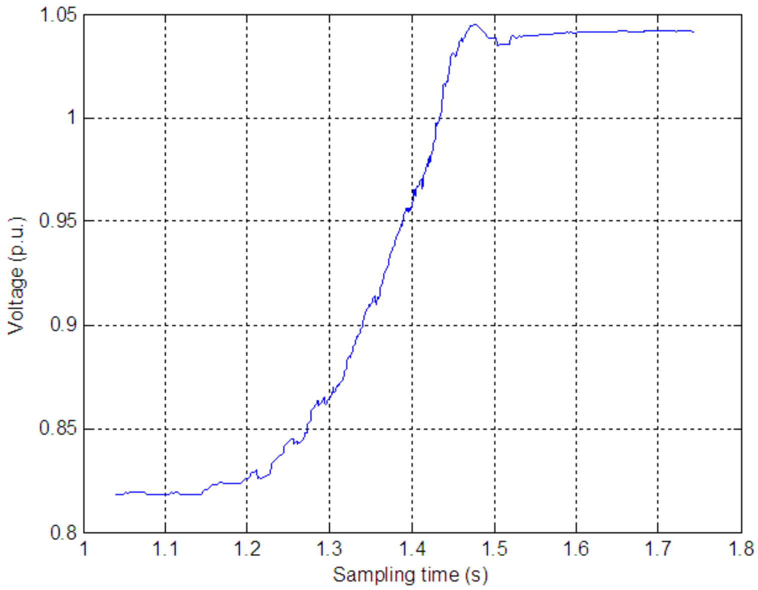


FIGURE 4. Measured load voltage profile

0.2 to 0.3 seconds. Figure 4 shows the measured voltage profile for 0.7 seconds. The voltage changes are applied to the system. Three-phase voltage and current of the load bus are recorded and stored on a computer, and then transformed into phasor form using the discrete Fourier transform technique. The voltage and current phasors are then used to compute the load power. Finally, the voltage and power signals are used as the input and output data to estimate parameters of the load model.

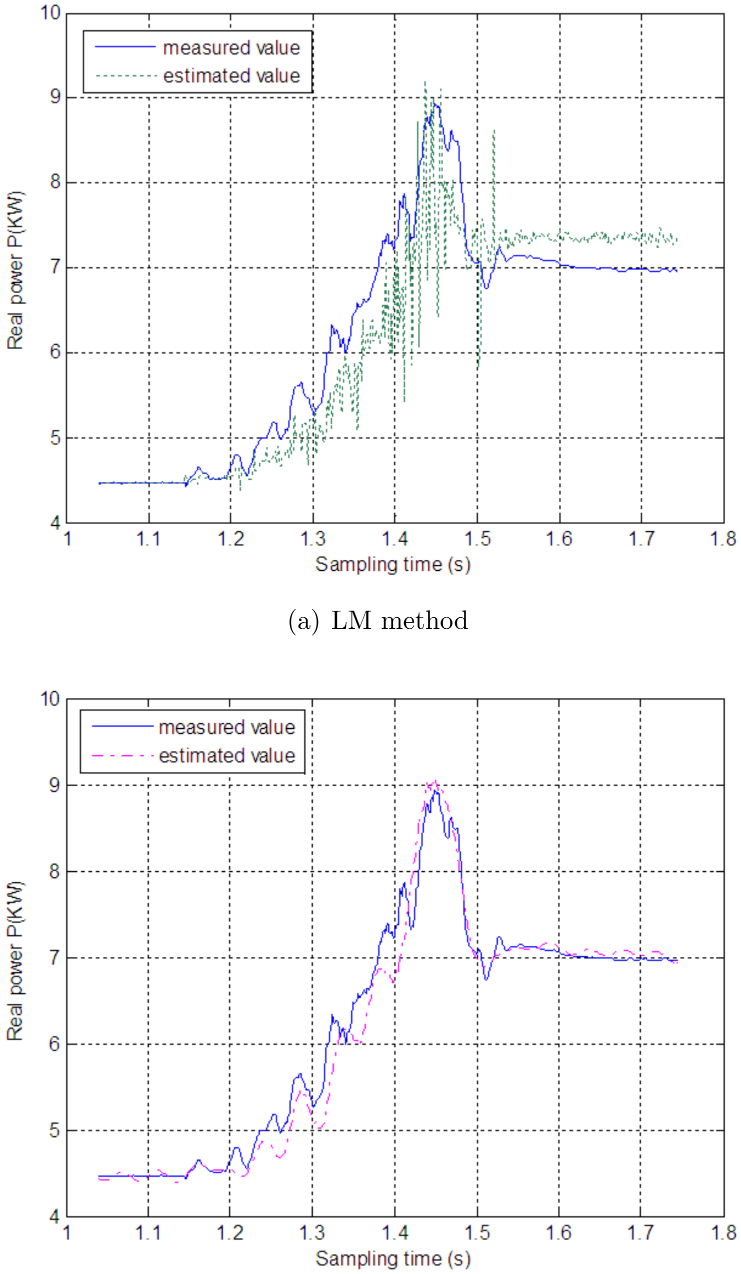
Based on the optimum value of $M = 3$, the FWLS-based HMF method is used for identifying the load model. The estimated parameters and relative error are obtained as $\alpha_s = 1.8992$, $\alpha_t = 5.5431$, $T_p = 0.0201$ and $\zeta = 0.2042\%$.

The LM method is also used to estimate the load parameters based on the laboratory measurements. The estimated parameters and relative error are got as $\alpha_s = 2.0667$, $\alpha_t = 8.8916$, $T_p = 0.0024$ and $\zeta = 2.0177\%$.

The measured and simulated real power profiles using the FWLS-based HMF method and LM method are shown in Figure 5. It can be observed that, for the laboratory measurements, which contain measurement noises, the FWLS-based HMF method is more effective than the LM method to estimate the parameters of the dynamic load model of power systems.

5. **Conclusions.**

In the paper, a second order Taylor series expansion model has been presented as the simplification of the popular used exponential recovery dynamic load model. Then a FWLS-based HMF method has been proposed to estimate the parameters of the simplified load model. Several case studies using simulation data and laboratory measurements have been conducted to illustrate the performance of the proposed load model and identification method. The estimation results have showed the effectiveness of the proposed method for the identification of the continuous-time dynamic load model even in the presence of noticeable additive measurement noises. The proposed simplified model and method are of considerable practical importance in problems of parameter identification of dynamic load model in power systems.



(a) LM method

(b) HMF method

FIGURE 5. Estimation results for laboratory measurements

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