On-Line Estimation of Variable Parameters of Synchronous Machines Using a Novel Adaptive Algorithm - Principles and Procedures

*Zhengming Zhao
Member, IEEE

**Longya Xu
Senior Member, IEEE

*Jianguo Jiang

*Department of Electrical Engineering
Tsinghua University
Beijing 100084, P. R. China

**Department of Electrical Engineering
The Ohio State University
Columbus, Ohio 43210

***Abstract*-** A novel adaptive algorithm is presented for on-line estimation of variable parameters of a synchronous machine (SM) as a function of the operating conditions. The concept of Synthesized Information Factor (SIF) is proposed as the core of the novel adaptive algorithm. For continuous process, SIF optimally combines information from the past with that at the present. Adaptive principles based on SIF are discussed and the adaptive estimation procedures are developed. Computer simulation results are given to highlight the advantages of the novel adaptive algorithm over conventional Least Mean Square (LMS) and Recurrence Least Square (RLS) algorithms. Application and experimental verification of this novel adaptive algorithm is presented in detail in the companion paper [1].

1. Introduction

Although widely used and extremely important in dynamic simulation of a power system or in real-time control, valid and accurate parameters of a synchronous machine (SM), such as the transient reactance and resistance, are very difficult to obtain. This is because transient SM parameters are highly nonlinear and operating condition (flux distribution, saturation, rotor slip, etc.) dependent. In fact, it is more accurate to term these parameters as *variable parameters* to emphasize their strong dependence on the operating conditions [1]. Two kinds of well known parameter estimation methods, in frequency or time domain, are presently used, but the estimates only give a set of constant parameters at a time for one specified operating condition. Therefore, it is sometimes not clear whether the estimated parameters can be used in simulation to predict SM dynamic behavior for other operating conditions. This, naturally, has resulted in a reluctant acceptance of the so estimated parameters for many applications.

However, with advanced algorithms and sophisticated computers, it is now possible that the nonlinear, variable parameters of a SM, which were previously unavailable by conventional methods, can be obtained. The contribution of this paper and its companion paper [1] is to develop an on-line adaptive method to estimate the variable parameters of a SM in transient as a function of operating conditions. It is expected that the estimated variable parameters can be applied for dynamic simulation of power systems or on-line control of SMs.

In on-line adaptive estimation of SM variable parameters as a function of operating conditions, the central problem is to find an optimal adaptive algorithm to track the variable parameters promptly and stably during transients. The correct use of the estimated parameters for calculating SM performance is also of great practical importance [2-4]. Frequently used adaptive algorithms include Least Mean Square (LMS) and Recurrence Least Square (RLS). LMS uses the gradient method to estimate parameters based on data sampled at various instants of interest [5]. The ability of the LMS algorithm is limited because of its poor tracking ability and large algorithm noise. On the other hand, the RLS algorithm is based on an accumulated least square weighted by forgetting factors within a sliding time window [6]. Essentially, the error sequence is weighted by the power of a forgetting factor λ, and used as the driving force for the adaptive mechanism. Since this method can take previous data into consideration and emphasize the present data, depending on the selected value of λ, the tracking ability of RLS is improved compared to that of LMS. However, tests in [6] showed that the smaller the λ is (forgetting more), the larger the deviation of trajectory tracking and algorithm noise. On the other hand, if λ is made large (from 0.95 to 1), the tracking ability of RLS is reduced substantially. Although the determination of the optimum weight factor in RLS is left to the user, the importance of the previous data to the on-line adaptive estimation of SM parameters is evident.

In this paper, a concept of *Synthesized Information Factor* (SIF) is proposed to replace the forgetting factor in RLS. A novel adaptive algorithm for on-line estimation of SM parameters is then formulated based on SIF. The paper is organized as follows. First, conventional LMS and RLS adaptive algorithms are reviewed. Then, the novel adaptive estimation algorithm is proposed and analyzed. The concept of SIF and the physical meaning are explained. In particular, the interface of SIF to the adaptive algorithm, and the interface of the adaptive algorithm to the overall estimation process is described. The procedure of SM parameter estimation based on this novel adaptive algorithm is established. Furthermore, the paper presents computer simulation results to highlight the effectiveness of the novel adaptive algorithm. Finally, the paper is completed with a brief summary and conclusion. Additional mathematical derivations are provided in the Appendix as a rigorous proof of the novel adaptive algorithm. In the companion paper, the results of on-line estimation of variable parameters of an actual 100 MVA turbogenerator with experimental verification are detailed [1].

2. RLS Review and SIF

The RLS algorithm is used in on-line estimation of SM parameters to overcome the poor tracking ability and large algorithm noise of LMS [5]. To introduce the SIF concept, the principle of RLS is reviewed as background materials.

A. RLS Review

Fig. 1 shows a typical block diagram for an adaptive parameter estimation system. Note that the various adaptive algorithms can be used to force the estimated model to converge to the physical plant so that the plant parameters can be estimated. The RLS algorithm is

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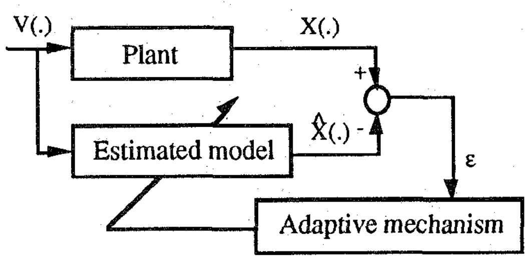

Fig. 1 Typical black diagram of adaptive identification

based on a sequence of least squares within a sliding window weighted by a sequence of exponential forgetting factors to improve its tracking ability [6]. Essentially, the farther the data is away from the moment of interest, the lesser will be the influence of that data as far as the adaptive mechanism is concerned. Written in the form of an object functional, we have

$$J(k)= \sum_{i=k-\ell}^{k} \lambda^{k-i} (Z(i) - h^T(i)\, Q(i)) \tag{1}$$

where k indicates the instant of interest and ℓ is the size of the sliding time window. Z(i) is the system output , h(i) the measured data and Q(i) the parameter matrix to be estimated. Within the sliding window, this method can take previous data (from instants $k-\ell$ to k-1) into account and, at the same time, emphasize present data (at instant k), depending on the selected value of forgetting factor ($0< \lambda <1$). For example, the farther the previous data, at instant "i", is away from the present data, at instant "k", the smaller the value of λ^{k-i}, indicating a weaker contribution to the least square functional and to the adaptive mechanism. The tracking ability of RLS is better than that of LMS because of the averaging effect of the sliding window. However, tests in [6] show that the smaller the λ, the larger the trajectory deviation and the algorithm noise so that the performance of the estimation approaches to that of the LMS. On the other hand, if λ is selected larger (from 0.95 to 1), the tracking ability of RLS deteriorates because the present data is not emphasized. In spite of its weakness, the RLS method does hint that if a piece of optimally synthesized information over the past and present data is used, the adaptive mechanism could be significantly improved.

B. Synthesized Information Factor

To overcome the drawbacks of RLS and substantiate the above stated idea, a new concept of synthesized information factor (SIF) for more advanced adaptive algorithms is proposed in this paper. In processing the data (measured and observed currents) within a sliding window, SIF plays the key role of the weight factors. Since SIFs are constructed by multiplying the correlation factors (characterizing the correlation between two data sampled at different instants) by a proper forgetting factor (characterizing the degree of forgetting), SIFs efficiently synthesize information contained in previous data with that of the present data. The synthesized information then is used as the driving force for an adaptive mechanism. Essentially, SIFs attempt to establish an optimal and balanced relationship between the history and current status of a continuous event.

According to the concept, a complete SIF expression, Γ, is created to relate data sampled at instant "i" (history) to the data sampled at instant "k" (present). Mathematically,

$$\Gamma_j(k,i) = \lambda(k)\, \Gamma_j(k-1,i) \qquad \text{with } (i < k) \tag{2}$$

and $\Gamma_j(i,i) = \Lambda(k-i) \qquad (j = 1, 2, ..., n)$

where n is the dimension of output vector (i.e. the number of state variables), λ the forgetting factor as defined in RLS, and Λ the correlation factor from standard correlation analysis . If λ(k) is a constant at any moment, then Eq. (2) can be written as :

$$\Gamma_j(k,i) = \lambda^{k-i}\, \Lambda(k-i) \tag{3}$$

where the factor Λ(k-i) represents the degree of correlation of the data sampled at instant "i" to those sampled at instant "k"; and λ^{k-i} represents the degree of forgetting. Evidently, the compound factor, $\Gamma_j(k,i)$ represents the collective effects of forgetting and memorizing. Note that whether data will be more forgotten than memorized will be determined by the product of the forgetting factor λ^{k-i} with the memorizing factor Λ(k-i). According to the newly defined Γ, it is generally true that if the data sampled are far away from the moment of interest, the data will tend to be more forgotten. However, once the correlation factor is included, the ultimate effect of the data to the moment of interest will be determined by the inherent correlation between the two moments "k" and "i" as well. The method of obtaining Λ(k-i) is mentioned in Section 4.B.

3. Formulation of Adaptive Algorithm

The SIF based adaptive algorithm is formulated according to the following derivation. Take a discrete state difference Eq. (4), derived in the companion paper, as the identified model. The system is expressed as

$$X(k) = A_1\, X(k-1) + B_1\, V(k) \tag{4}$$

where X is the state variable vector, and V the input vector. A_1 and B_1 are parameter matrices. Specifically,

$$X(k) = [x_1(k), x_2(k), ..., x_n(k)]^T \tag{5}$$

$$V(k) = [v_1(k), v_2(k),... ,v_m(k)]^T \tag{6}$$

$$A_1 = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \tag{7}$$

$$B_1 = \begin{pmatrix} b_{11} & b_{12} & \cdots & b_{1m} \\ b_{21} & b_{22} & \cdots & b_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ b_{n1} & b_{n2} & \cdots & b_{nm} \end{pmatrix} \tag{8}$$

Note that in Eq. (4) through (8), n is the dimension of the state variable vector, m the dimension of the input vector and k the instant of concern. Transforming Eq. (4) into least square solution form, one obtains a new parameter vector $Q_j(k)$ to be estimated as:

$$Q_j(k) = (H_k^T \Gamma_{jk} H_k)^{-1} H_k^T \Gamma_{jk} Z_j(k) \qquad (j = 1, 2, ..., n) \tag{9}$$

where

$$H_k = [\, h^T(0), h^T(1), ..., h^T(k-1)\,]^T = [\, X_n V_m \,]^T \tag{10}$$

$$X_n = \begin{pmatrix} x_1(0) & x_2(0) & \cdots & x_n(0) \\ x_1(1) & x_2(1) & \cdots & x_n(1) \\ \cdots & \cdots & \cdots & \cdots \\ x_1(k-1) & x_2(k-1) & \cdots & x_n(k-1) \end{pmatrix} \tag{11}$$

$$V_m = \begin{pmatrix} v_1(1) & v_2(1) & \cdots & v_m(1) \\ v_1(2) & v_2(2) & \cdots & v_m(2) \\ \cdots & \cdots & \cdots & \cdots \\ v_1(k) & v_2(k) & \cdots & v_m(k) \end{pmatrix} \tag{12}$$

$$\Gamma_{jk} = \mathrm{diag}\,[\, \Gamma_j(k,1),\ \Gamma_j(k,2),\ \ldots,\ \Gamma_j(k,k)\,] \tag{13}$$

$$Z_j(k) = [\, x_j(1),\ x_j(2),\ \ldots,\ x_j(k)\,]^T \tag{14}$$

$$Q_j(k) = [a_{j1}, a_{j2}, \ldots, a_{jn}, b_{j1}, b_{j2}, \ldots, b_{jm}]^T \tag{15}$$

Inspecting Eqs. (11) and (12), it is clear that the parameter vector Q_j to be estimated not only depends on the current system input/output but also on the history of the system input/output. More importantly, the system history is related to the current status by Γ, the synthesized information factor. However, it is critical to realize that not all history of the input/output are equally important. Therefore, it is reasonable to truncate the input/output by a time window of finite size. For reducing computing time, a small value of window size ℓ is preferred. On the other hand, for preserving the correlative nature between data, the window size ℓ should be sufficiently large. In this paper the window size is determined by the time-difference characterized by the second largest peak value in the correlation analysis. Detailed discussion on the size of the sliding window is given in [7] and in Section 4.B of this paper. To track the trajectories of the variable parameters in transient, Eq. (9) should be converted into a recurrence form, providing a path to trace back to a set of initial values. Let $\tau = k - \ell - 1$. Then, Eq. (9) is transformed into the form

$$\begin{aligned} Q_j(k) &= [\sum_{i=1}^{k} \Gamma_j(k,i) h(i) h^T(i)]^{-1} \cdot [\sum_{i=1}^{k} \Gamma_j(k,i) h(i) Z_j(i)\,] \\ &= [\sum_{i=1}^{\tau} \Gamma_j(k,i) h(i) h^T(i) + \sum_{i=\tau+1}^{k} \Gamma_j(k,i) h(i)\, h^T(i)]^{-1} \bullet \\ &\quad [\sum_{i=1}^{\tau} \Gamma_j(k,i)\, h(i)\, Z_j(i) + \sum_{i=\tau+1}^{k} \Gamma_j(k,i)\, h(i)\, Z_j(i)] \end{aligned} \tag{16}$$

Define that

$$P^{-1}(\tau) = \sum_{i=1}^{\tau} \Gamma_j(k,i)\, h(i)\, h^T(i) \tag{17}$$

$$P_0^{-1} = \sum_{i=\tau+1}^{k} \Gamma_j(k,i)\, h(i)\, h^T(i) \tag{18}$$

Then,

$$P^{-1}(k) = P^{-1}(\tau) + P_0^{-1} \tag{19}$$

Define that

$$P_1^{-1}(\tau) = \sum_{i=1}^{\tau} \Gamma_j(k,i)\, h(i)\, Z_j(i) \tag{20}$$

$$P_1^{-1} = \sum_{i=\tau+1}^{k} \Gamma_j(k,i)\, h(i)\, Z_j(i) \tag{21}$$

Then,

$$Q(\tau) = P(\tau) \bullet P_1^{-1}(\tau) \tag{22}$$

With the matrix transform identity that

$$(A + BC)^{-1} = A^{-1} - A^{-1} B\, (I + CA^{-1} B)^{-1}\, C\, A^{-1}$$

it can be found from Eq. (19) that

$$\begin{aligned} P(k) &= (\, P^{-1}(\tau) + P_0^{-1}\,)^{-1} \\ &= P(\tau) - P(\tau)\, [I + P_0^{-1} P(\tau)]^{-1}\, P_0^{-1} P(\tau) \end{aligned} \tag{23}$$

Substituting Eqs. (17) through (22) into Eq. (16), it yields that

$$Q_j(k) = Q_j(\tau) + P(\tau)[\, I + P_0^{-1} P(\tau)]^{-1}\, [P_1^{-1} - P_0^{-1} Q_j(\tau)] \tag{24}$$

Further, let

$$K(k) = P(\tau)\, [\, I + P_0^{-1}\, P(\tau)]^{-1} \tag{25}$$

and substitute Eq. (25) into Eqs. (23) and (24), it yields that

$$P(k) = [I - K(k)\, P_0^{-1}]\, P(\tau) \tag{26}$$

and

$$Q_j(k) = Q_j(\tau) + K(k)\ \ [P_1^{-1} - P_0^{-1}\, Q_j(\tau)] \tag{27}$$

Note that P(k) can be approximated by

$$P(k) \approx [\, I - K'(k)\, P_0'^{-1}\,]\ P(\tau) \tag{28}$$

where $K'(k) = P(\tau)\, [\, I + P_0'^{-1}\, P(\tau)]^{-1}$ (29)

$$\text{with}\ \ P_0'^{-1} = \sum_{i=\tau+1}^{k} \lambda^{k-i}\, h(i)\, h^T(i) \tag{30}$$

The difference between Eqs. (18) and (30) is that $\Gamma(k,i)$ in Eq. (18) is replaced by λ^{k-i} . The intention of approximating P(k) will be made clear in later discussion.

In summary, Eqs. (18), (21), (26), (27), (28), (29), and (30) constitute a basis for the SIF based adaptive algorithm. Mathematical proof of two related theorems, uniform convergence and robustness, is given in the Appendix. A brief flow chart describing the relationships among data, vectors, and matrices in the recurrence equations is constructed as shown in Fig. 2.

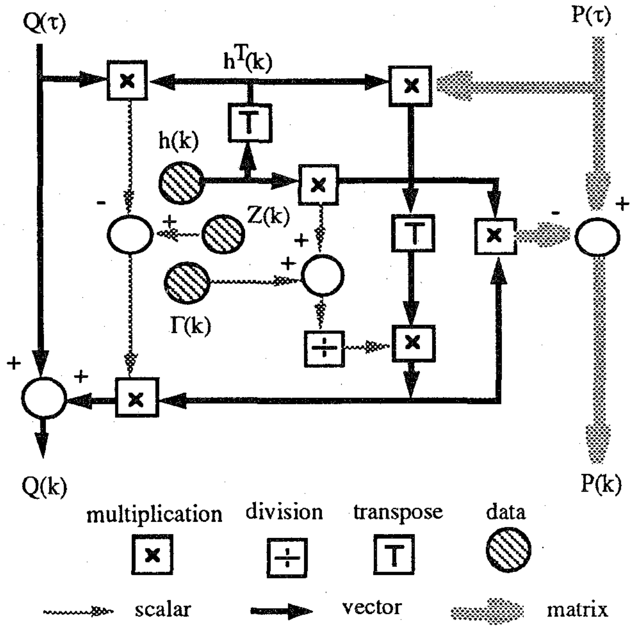

Fig. 2 Flow Chart of the SIF Adaptive Algorithm

Note that in the adaptive algorithm, the following terminology can be used as in a general adaptive algorithm:

$P_0^{-1}Q_j(t)$	the generalized estimated parameter;
P_1^{-1}	the generalized output;
$P_1^{-1} - P_0^{-1}Q_j(t)$	the generalized estimation error;
K(k)	the gain for instant k;
K'(k)	the forecasting gain for the next step.

Since K'(k) is only used for forecasting in Eq. (28) and willl not affect the final estimation accuracy, it is reasonable that Eq. (30), instead of Eq. (18), is used in computing K'(k). In this way, $\Gamma(k,i)$ is replaced by λ^{k-i}, which improves the estimation efficiency.

4. Self-Learning and Correlation Analysis

Before the SIF adaptive estimation starts for parameter estimation in transient, steady state parameters must be known as the initial values. In addition, a knowledge of correlation between two sets of the data sampled at difference instants from the system must be available for constructing $\Gamma(k,i)$. Self-learning is applied to obtain parameter initial values and correlation analysis is used to obtain a knowledge of data correlation.

A. Self-learning Procedure

A self-learning procedure is established to obtain Q(0) and P(0) in steady state with a conventional RLS method with $\lambda=1$. Self-learning involves the following equations:

$$Q(k) = Q(k-1) + K(k)[Z(k) - h^T(k)\, Q(k-1)] \tag{31}$$

$$K(k) = P(k-1)\, h(k)\, [h^T(k)\, P(k-1)\, h(k)+1]^{-1} \tag{32}$$

$$P(k) = [I - K(k)\, h^T(k)]\, P(k-1) \tag{33}$$

where Q, K, h, and P are defined similarly as in the SIF based algorithm. For the steady state parameter estimation, starting values can be arbitrary. The self-learning procedure is usually repeated several times to make Q(0) converge to the true parameter values in steady state. Fig. 3 shows the simulated self-learning results of a_{11}, one element in Q(0), after the first and second times of self-learning, respectively.

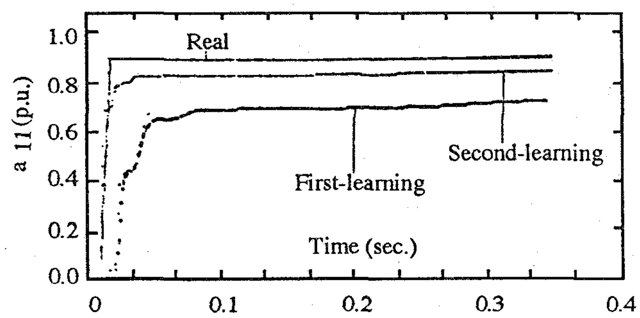

Fig. 3 Self-learning procedure of parameter a_{11}

As seen from the figure, the a_{11} value, after the second round of self-learning, is very close to its real value. However, it is important to realize that it is practically impossible to make Q(0) equal to its real value in a finite amount of time. To accelerate convergence, the designed values of the parameters are often recommended as the initial values for self-learning.

B. Correlation Analysis

Accurate correlation analysis is one of the key steps for SIF adaptive estimation. The correlation function of a SM variable is calculated directly by the standard method with the following definition [8]

$$\Lambda(\tau) = \sum_{i=1}^{k} x(i)\, x(i+\tau) \tag{34}$$

where τ is the time difference between the instants of sampling data in the correlation analysis. Note that the correlation is largely determined by the structure of a model and relatively independent of the values of the system parameters and the type of transient. Once the order of a model is selected, the correlation analysis on the state variables can be calculated by Eq. (34). For example, Figs. 4 and 5 depict the results of the correlation analysis on i_q and damper i_{1q} in a SM with sixth order electrical equations and second order mechanical equations derived in [1].

As seen from Figs. 4 and 5, in each correlation function, there are some peaks, indicating a high degree of correlation between the data separated by the corresponding time difference. Also it is observed that the correlation decays with an increase of the sampling interval. To ensure the generality of observation, further correlation analysis have been conducted for other measured state variables (i_d, i_q, i_{fd}, ω_r, etc.) for an actual SM. The following points are verified: 1) the largest peak value is always the first peak (at Time-Diff. = 0); this is logical because any datum always has the largest correlation with respect to itself; 2) the second largest peak usually appears next in sequence. Then, the third largest peak appears and is about half the size of the second largest one, indicating a quick decay of correlations between the data separated by a time-difference characterized by the second peak (see Fig. 4); 3) if the third largest peak appears before the second largest one, then the third largest peak is about the same size as and is located very near by the second largest peak (see Fig. 5). Hence, the time-difference characterized by the second peak is a good measure to determine the degree of data correlations.

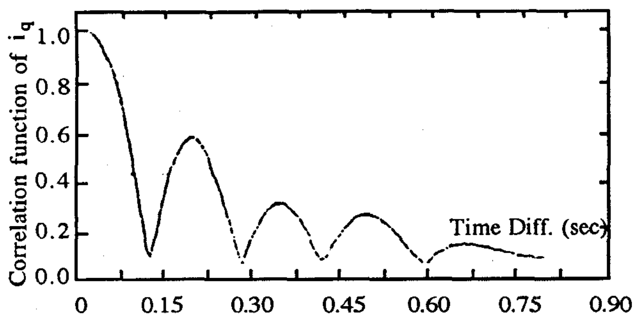

Fig. 4 Correlation function of i_q

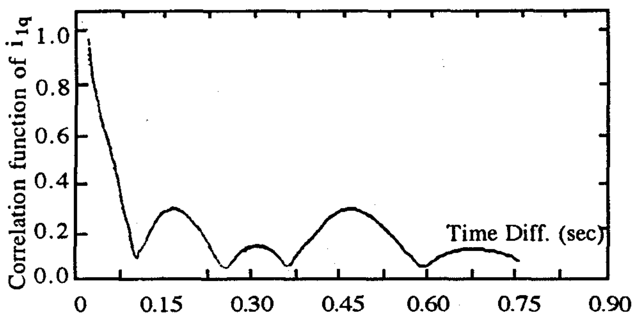

Fig. 5 Correlation function of i_{1q}

Therefore, the results of correlation analysis imply that the SIF with synthesized forgetting and memorizing effects for tracking the trajectories of parameters is very well defined. The results of correlation analysis also answered the question why the second peak in the correlation analysis is used to determine the size of the sliding window, as discussed previously. The principle is that the window size determined in this manner is sufficiently large so that strongly correlated data sampled at different instants will be not missed.

5. Estimation Procedures and Simulation Results

A. Estimation Procedures

In the actual estimation process, two major steps are included: 1) a self-learning is carried out to obtain the initial values of the parameters; and 2) the SIF based adaptive estimation algorithm is fired to track the trajectories of the variable parameters as soon as the perturbation starts. The detailed estimation steps are summarized as follows:

a) Conduct correlation analysis of the output sequences in transient and determine the window size ℓ;

b) Self-learning for initial matrix Q(0) and P(0) by RLS with $\lambda=1$;

c) For each estimation step, pick up the data for $\ell+1$ instants within a window, and assign SIF and λ to the data to form P_0^{-1}, P_1^{-1} and $P_0'^{-1}$;

d) Compute gain matrix K(k) for the current step and forecasting gain matrix K'(k) for the next step;

e) Start estimation of Q(k) and P(k) using matrices Q(k-1) and P(k-1);

f) Repeat Steps c) through e) until estimation is completed. Note that Q and P are updated at each estimation step using the estimated values from the previous step.

B. Simulation Results

In order to compare and verify the estimation performance of the SIF based adaptive algorithm with respect to the other adaptive algorithms, computer simulations have been examined by using three algorithms (LMS, RLS and SIF based) for the same operating conditions in a transient. The SM under estimation is represented by an eighth order, discrete incremental equations as derived in the companion paper. A 30% step change of exciting voltage is imposed to create a transient. The variable parameters x_{ad} and x_{aq} are assumed in the form of

$$x_{ad} = x_{ad0} + C_1 \sqrt{\Delta i_q^2(k) + \Delta i_d^2(k)} + C_2 \Delta \delta(k) \qquad (35)$$

$$x_{aq} = x_{aq0} + C_1 \sqrt{\Delta i_q^2(k) + \Delta i_d^2(k)} - C_2 \Delta \delta(k) \qquad (36)$$

during transient, where x_{ad0} and x_{aq0} are the parameter values prior to the transient. C_1 and C_2 are given constants with $C_1 = 0.1$ and $C_2 = 0.2$. Note that the variable parameters of a SM may not follow Eqs.(35) and (36) in transient. We use these two equations to characterize parameter variations so that we can investigate the performance of the various estimation algorithms by simulation purposes. The variable parameter tracking by three algorithms, LMS, RLS, the SIF based is simulated and the simulation results are shown in Figs. 6 through 8. It is seen that LMS has the poorest tracking ability; RLS improves the tracking performance nicely but with overshoot; and SIF based algorithm shows a superior tracking capability.

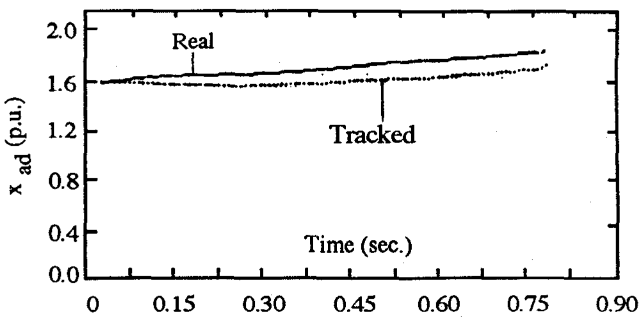

Fig. 6 x_{ad} tracked by LMS algorithm

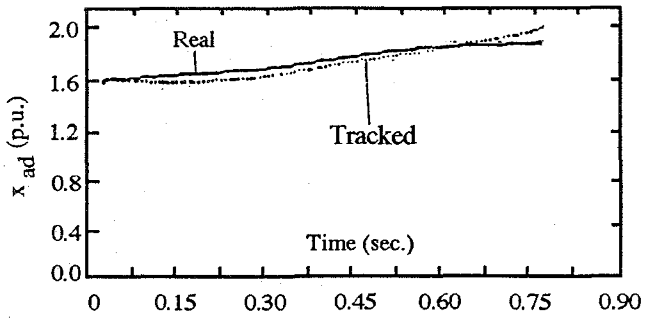

Fig. 7 x_{ad} tracked by RLS algorithm

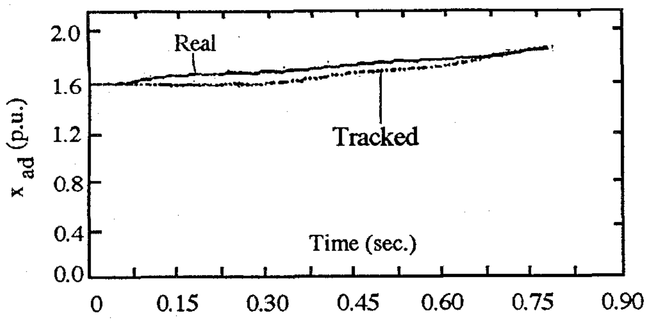

Fig. 8 x_{ad} tracked by SIF based algorithm

As the time increases, the parameter tracking performance of the SIF improves. Other parameters of the SM estimated by the three methods show a similar pattern as indicated by Figs. 6 through 8.

6. Conclusions

The perplexing problem concerning variable parameter estimation of a SM, namely, tracking the trajectories of variable parameters during transients is addressed in this paper. A new concept of SIF for establishing an optimal and balanced relationship between the history and current status of a continuous event is presented. Based on the SIF concept, a novel adaptive algorithm suited for the variable parameter estimation is developed. In particular, the physics of SIF, which combines forgetting effect with memorizing effect, is explored. Also the structure of the SIF based algorithm is given. The following conclusions are reached:

1). For faithful tracking of SM parameters in transients, state variables of the SM from history must be combined with those at present in a balanced way in an adaptive estimation algorithm;

2). Correlation analysis is a proper method to determine the degree of correlation between the past and present data. The results of correlation analysis can be absorbed conveniently by the SIF concept proposed in the paper;

3). The concept of SIF is well developed to implement optimal and balanced information for the novel adaptive algorithm used in tracking SM variable parameters;

4). Compared with conventional adaptive algorithms, LMS and RLS, the proposed SIF based adaptive algorithm possesses the advantages of fast dynamic tracking, robustness, and uniform convergence. The advantages of the SIF based adaptive algorithm are fully verified by matrix theory (see Appendix) and computer simulations.

It should be mentioned that a) the determination of the optimal forgetting factor λ in this paper is largely empirical and will be further investigated in theory; and b) execution of the SIF based algorithm is relatively slow due to its complex ity (about 10 minutes for one transient on a PC-386). Fortunately, quite often only the final estimated parameter functions, other than the algorithm, is used in practical applications.

In the companion paper, the SIF adaptive estimation method is applied to an actual 100MVA turbogenerator for parameter estimation. The estimated parameters are described as functions of transient operating conditions. The experimental results are presented. In addition, the effectiveness of the SIF based adaptive algorithm is demonstrated by comparing the actual SM response to that simulated based on the estimated parameters for a transient condition.

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Appendix : Statistical characteristics of SIF based algorithm

<u>1. Uniform convergence</u>

Theorem 1: Estimated value $\hat{Q}$ by SIF based algorithm is uniform convergence if model noise is zero mean-value sequence and independent of data matrix H_k. That is,

$$E\{\hat{Q}\} = Q_0$$

where Q_0 is the actual value.

Proof: rewrite Eq. (9)

$$\hat{Q}_j(k) = (H_k^T \Gamma_{jk} H_k)^{-1} H_k^T \Gamma_{jk} Z_j(k)$$

and let $$Z_j(K) = H_k Q_0 + n_k$$

where n_k is noise with a zero mean -value.

Then, the expectation value

$$E\{\hat{Q}_j(k)\} = E\{ (H_k^T \Gamma_{jk} H_k)^{-1} H_k^T \Gamma_{jk} Z_j(k) \}$$
$$= E\{ (H_k^T \Gamma_{jk} H_k)^{-1} H_k^T \Gamma_{jk} (H_k Q_0 + n_k)\} = Q_0$$

2. Robustness

Theorem 2: Let error $\varepsilon = Q_0 - \hat{Q}(k)$, λ_{min} is the minimum eigenvalue of gain matrix K(k), and V_{min} the corresponding eigenvector. Then, the co-square error is

$$Cov[\varepsilon] = E\{[Q_0 - \hat{Q}(k), [(Q_0 - \hat{Q}(k)]^T\}$$
$$= \frac{\lambda_{min}^{-1} V_{min} V_{min}^T}{t+1}$$

Proof: SIF and RLS algorithm gain matrices are

$K_1(k) = P_1(k)\, \Gamma_k\, h(k)$ for SIF

$K_2(k) = P_2(k)\, h(k)$ for RLS,

Corresponding $P_1(k)$ and $P_2(k)$ are

$$P_1(k) = [H_k^T \Gamma_k H_k]^{-1}$$
$$P_2(k) = [H_k^T H_k]^{-1} .$$

For the dispersion of synthesized information factors, the value of λ_{min} in $P_1(k)$ is greater than that in $P_2(k)$. Then, $Cov[\varepsilon_1]$ for SIF is less than $Cov[\varepsilon_2]$ for RLS algorithm [9].

Zhengming Zhao received the B.S. and M.S.degrees from Hunan University,PR China in 1982 and 1985 respectively, the Ph.D. degree from Tsinghua University, PR China in 1991, all in electrical engineering.

He worked in the Dept. of Electrical Engineering, Hunan University during 1985-1987 as a lecturer. He is an Associate Professor in Tsinghua University since 1993 and currently on leave in the Department of Electrical Engineering, The Ohio State University as visiting scholar. His areas of interest include parameter identification and signal processing, transient analysis of power system, and design, analysis and control of electric machines.

Longya Xu was born in Hunan, China. He graduated from Shangtan Institute of Electrical Engineering in 1970. He received the B.E.E. from Hunan University, China, in 1982, and M.S. and Ph.D. from the University of Wisconsin, Madison, in 1986 and 1990 both in Electrical Engineering.

From 1982-1984, he worked as a researcher for linear electric machines in the Institute of Electrical Engineering, Sinica Academia of China. Since he came to the U.S., he has served as a consultant to several industry companies including Raytheon Co., US Wind Power Co., Pacific Scientific Co., and Unique Mobility Inc. for various industrial concerns. He joined the Department of Electrical Engineering at the Ohio State University in 1990, where he is presently an Associate Professor. Dr. Xu received the 1990 First Prize Paper Award in the Industry Drive Committee, IEEE/IAS. In 1991, Dr. Xu won a Research Initiation Award from National Science Foundation for his research project "A High-efficiency, Low-cost Flexible Variable Speed Wind Power Generating System." His research and teaching interests include dynamic modeling and converter optimized design of electrical machines and power converters for variable speed generating and drive system. He is an active IEEE member, currently serving as the Secretary of Electric Machine Committee of IEEE/IAS and an Associate Editor of IEEE Transaction on Power Electronics.

Jianguo Jiang received B.S. and M.S. degrees from Tsinghua University in 1961 and 1965, respectively, all in Electrical Engineering.

From 1965-1988, he worked in the Dept. of Electrical Engineering of Tsinghua University as a lecturer and Associate Professor. In 1989, he was a visiting scholar at the Toronto University in Canada, working on fault diagnosis of electric machines and digital signal processing. He is currently a Professor in the Dept. of Electrical Engineering of Tsinghua University. His areas of interest include machine fault diagnosis and dynamic analysis, signal processing, design and control of electric machines.

Discussion

[For a discussion of this paper, please see the discussion following the companion paper in this issue, "On-Line Estimation of Variable Parameters of Synchronous Machines Using a Novel Adaptive Algorithm — Estimation and Experimental Verification" (96 SM 355-8 EC) by L. Xu, Z. Zhao, and J. Jiang.]