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Nonlinear identification of synchronous generators using a local model approach

Abstract*. A new iterative approach is proposed to model synchronous generators. Different local structures are used for the operating conditions of the synchronous generator with different complexity. Unlike most of the existing methods, which increase the model accuracy based on increasing the number of local model, in the proposed method, there are two choices for increasing model precision at each iteration: (i) increasing the number of local models in one region, or (ii) increasing local model complexity in the same region. The proposed method has been tested on experimental data collected on a 3 kVA micro-machine.*

Streszczenie. *Zaproponowano nową iteracyjną metodę modelowania generatorów synchronicznych. W porównaniu do istniejących metod w zaproponowanej metodzie istnieją dwa wybory zwiększania dokładności iteracji: przez zwiększanie liczby lokalnych modeli lub przez zwiększanie złożoności modelu lokalnego. Metodę sprawdzono na przykładzie generatora 3 kVA. (**Nieliniowe modelowanie generatorów synchronicznych prze wykorzystaniu modelu lokalnego**)*

Keywords: local model, power system modelling, synchronous generator.
Słowa kluczowe: modelowanie loklane, generator synchroniczny

Introduction

Increase in the number of generating units and the complexity of the multiple distribution grids has increased the importance of power system stability and dynamic analysis. System stability is dependent on the performance of the synchronous generators whose behaviour is nonlinear due to such effects as eddy currents, and the magnetic saturation of the rotor and stator iron. Therefore, Synchronous generator modelling is often the critical step in power system stability analysis, design and simulation.

Synchronous generator modelling can be classified into three types: white box [1]-[2], grey box and black box. In the first type, a mathematical model is obtained using physical laws for synchronous generator. The physical parameters of obtained structure are estimated using specific tests. Such tests are specified in IEEE Standards 115 [3]. Such a structure may be obtained by finite element methods, have two main difficulties: i) the computation time in finite element method simulation and ii) the large number of parameters of the electrical machine [4]. Usually, the first category involves difficult and time-consuming tests. These tests can mainly be carried out when the machine is not in service.

In the grey box modelling [5]-[7], a known structure for the synchronous machine is assumed; the physical parameters are estimated from measurements.

In [7], a closed loop subspace parameter identification technique is proposed to estimate Heffron-Phillips model parameters. Such a technique is used instead of open-loop identification to avoid bias errors in the estimated parameters.

In the third type (the black-box modelling) [8]-[10], the structure of the model is not known a priori. The only concern is to map the input data set to the output data set.

Such a model is used either in a predictive control structure for applications such as on-line power system stabilizer design, or used as a simulator to test an off-line design.

Various non-linear models such as; Volterra [8], neural network [9] and wavelet network [10] have been presented in the literature. A difficulty of such models is the large number of parameters required. Therefore, several methods such as, analysis of variance [11], visual inspection method [12], and orthogonal least square with D-optimality design method [13] have been developed for selecting the significant terms.

Another approach for modelling of synchronous generator is local model approach [14]-[15]. In such methods, similar local linear structures are used for all operating conditions. In [15], such an approach is used to model synchronous generator. Partitioning of operating space is obtained using nonlinear optimization. After each iteration of nonlinear optimization, all local linear models' parameters are estimated by global learning. Therefore, the multi-model loses the local interpretability. In such structures using global learning the behaviour of local models may not change smoothly as a function of the operating region. The use of such non smooth models can lead to unreliable control.

The parameters of local models are usually estimated by global or local learning algorithm. The local learning is faster than global learning. The local learning leads to local interpretability which means that the local models reflect the process behaviour at the corresponding operating region, but such property is not satisfied by global learning. The number of effective parameters in model is less with local learning than with global learning (see [16] and references therein).

In this paper, a new iterative identification method is presented. The proposed method uses the local linear structure. At each iteration, the algorithm uses sub optimal local linear models instead of using the same local linear models. The local models' complexity is, therefore, different at different operating regions.

The proposed method includes several iterative steps: First, the worst local model is defined according to local weighted least squares. Then all divisions of this local model on operating space are constructed. The most significant terms of two local models are determined together and their parameters are estimated simultaneously by a novel method. If all determined terms correspond to one of the two local models, one local model is identified instead of the worst local model. Finally the best global model is selected. The parameters are estimated by local learning algorithm in the proposed method.

In section 2, the formulation of the local model approach is described. In section 3 the proposed algorithm is presented. Experimental setup and data collection on a micro-machine are discussed in section 4. In section 5 the application of the proposed method is carried out on the micro-machine and the experimental data is compared with the simulated nonlinear model of the synchronous generator. Section 6 concludes the paper.

The local model approach

In the local model approach, each local model shows the behaviour in a region of the synchronous generator's operating space. In these methods, global output $\hat{y}(k)$ is equal to the weighted sum of M local models $y_i(k)=\underline{\varphi}_i^T(k)\underline{\Theta}_i$, $i=1,2,...,M$. In other words, global output is obtained by the average of the local model outputs $y_i(k)$ weighted by local model validity function, that is

(1) $$\hat{y}(k)=\sum_{i=1}^{M} y_i(k)\Phi_i(\underline{z}(k))$$

where $\underline{\varphi}_i(.)$ and $\underline{\Theta}_i$ are the regression and parameter vectors, respectively, and $\underline{z}(k)=[z_1(k),...,z_q(k)]^T$ is the operating space vector. The $\underline{\varphi}_i(.)$ and $\underline{z}(k)$ can be chosen independently. These vectors can be composed of previous model output and input. The validity or weighting function $\Phi_i(\underline{z}(k))$ describes the contribution of the i-th local model to the output. This function causes smooth transition between local models. Usually, the validity function $\Phi_i(\underline{z}(k))$ is chosen as normalized Gaussian function, that is

(2) $$\Phi_i(\underline{z}(k))=\frac{\prod_{m=1}^{q} exp\left(-\frac{1}{2}\frac{(z_m(k)-c_{i,m})^2}{\sigma_{i,m}^2}\right)}{\sum_{j=1}^{M}\prod_{m=1}^{q} exp\left(-\frac{1}{2}\frac{(z_m(k)-c_{j,m})^2}{\sigma_{j,m}^2}\right)}$$

where $c_{i,m}$ and $\sigma_{i,m}$ are, respectively, the centre and the standard deviation of Gaussian function. Normalization means that across the operating space the sum of validity function contributions is unity. Therefore, the contributions of all local models sum up to unity everywhere in the operating space.

The partitioning strategy of the operating space determines the validity functions' parameters. If no a priori knowledge can be utilized for the partitioning of the operating space, either a grid partition or a data-driven method has to be chosen. An overview of existing partitioning strategies is given in [16].

In this paper, the partitioning of operating space is not assumed to be known a priori. The proposed method determines the most significant local models' terms. Also, the local models' and validity functions' parameters are estimated by linear optimization.

The proposed method

Assuming a set of input output data is available; first a global model is fitted to the available input-output dataset $\{y(k),\ u(k)\}_{k=1}^{N}$ where $y(k)$ and $u(k)$ are output and input measurements, respectively. Next, the system operating space is split into two halves along all dimensions of operating space. For each division, a local linear model is considered, that is,

(3) $$y(k)=y_1(k)\Phi_1(\underline{z}(k))+y_2(k)\Phi_2(\underline{z}(k))$$

The parameters of the two local linear models are estimated such that the two models' local weighted least squares are minimized together. The local weighted least squares are as follow

(4) $$\begin{aligned} J_i &=\sum_{k=1}^{N}\Phi_i(\underline{z}(k))(y(k)-y_i(k))^2 \\ &=(\underline{y}-\underline{y}_i)^T Q_i(\underline{y}-\underline{y}_i), \quad i=1,2 \end{aligned}$$

where $Q_i=diag(\Phi_i(\underline{z}(1)),\ \Phi_i(\underline{z}(2)),...,\ \Phi_i(\underline{z}(N)))$.

The local weighted least squares (i.e. J_1 and J_2)are combined to one:

(5) $$\begin{aligned} J &= J_1+J_2= \\ &=(L_1\underline{y}-L_1\underline{y}_1)^T(L_1\underline{y}-L_1\underline{y}_1)+ \\ &+(L_2\underline{y}-L_2\underline{y}_2)^T(L_2\underline{y}-L_2\underline{y}_2) \\ &=(\underbrace{\begin{bmatrix} L_1\underline{y} \\ L_2\underline{y}\end{bmatrix}}_{\underline{y}'}-\underbrace{\begin{bmatrix} L_1U & 0_{N\times n} \\ 0_{N\times n} & L_2U\end{bmatrix}}_{\mathbf{U}'}\underbrace{\begin{bmatrix}\underline{\theta}_1 \\ \underline{\theta}_2\end{bmatrix}}_{\underline{\Theta}'})^T(\underline{y}'-\mathbf{U}'\underline{\Theta}') \end{aligned}$$

In eqn. (5), Q_i, $i=1,2$ is decomposed into $Q_i=L_i^TL_i$ where L_i is an upper triangular matrix with positive diagonal elements and $\underline{y}_i=U\underline{\Theta}_i$, the memory matrix U is composed of candidate regressors.

Now an orthogonal least squares with D-optimality algorithm is used in order to determine the most significant terms and to estimate the local models' parameters, $y_1(k)$ and $y_2(k)$. See the Appendix for more details of the Orthogonal Least Squares with D-optimality algorithm.

If all chosen terms correspond only to one of the two local models (for example, $y_1(k)$), the other model along with the corresponding membership function can be eliminated. In such a case it is recommended the orthogonal least squares with D-optimality algorithm be implemented once more to determine the most significant terms of $y(k)=y_1(k)$ i.e.

(6) $$\begin{aligned} J &= J_1=(\underline{y}-\underline{y}_1)^T Q(\underline{y}-\underline{y}_1) \\ &=(L\underline{y}-LU\underline{\theta}_1)^T(L\underline{y}-LU\underline{\theta}_1) \end{aligned}$$

where Q is the validity function corresponding to the worst model. The matrix Q is decomposed into $Q=L^TL$, where L is an upper triangular matrix with positive diagonal elements.

With the above-mentioned method, new local linear models are obtained for all operating dimension $m=1,2,...,q$. Among all partitions, the partition with the smallest output error is chosen. Then, the local loss functions for each local linear model $(S_j,\ j=1,...,nl)$ are computed by weighting the squared model errors with the corresponding value of validity function

(7) $$S_j=\sum_{k=1}^{N}\Phi_j(\underline{z}(k))(y(k)-\hat{y}(k))^2,\ j=1,...,nl$$

where nl denotes the number of local linear models.

Next the local linear model with the maximum local loss function is chosen. Now the algorithm is repeated with regard to the operating region of the chosen local linear model. The proposed algorithm is outlined below:

1- Identify a global model using the orthogonal least squares with D-optimality algorithm.

2- Calculate the local loss function in eqn. (7) for all local linear models. Choose the worst local linear model with the highest local loss function.

3- Split the rectangle of the worst local linear model into two halves with an axis-orthogonal split. Try divisions in all dimensions. Carry out the following steps for each division:

3-a-Construct membership functions for rectangle. The centers of these membership functions are the centers of the rectangle. The standard deviation in each dimension is calculated as $\sigma_m=k\Delta_m$, where Δ_m is the width of the hypercube in the dimension $m=1,...,q$ and k a factor which is chosen a priori.

3-b- Construct all validity functions.

3-c-Using eqn. (5) of the orthogonal least squares with D-optimality algorithm determine a number of $y_1(k)$ and $y_2(k)$

terms as most significant terms and estimate their parameters.

3-c-1- If all the chosen terms are only corresponding to one of the two local models, implement the orthogonal least squares with D-optimality algorithm for eqn. (6).

3-d - Calculate the sum of square errors for the global model (global loss functions).

4- Among all divisions constructed in step 3, select the one with the smallest global loss function.

5- Check the termination criterion: if satisfied, algorithm is stopped. Otherwise go to step 2.

In the proposed algorithm, the significant terms of both local models at each dimension are estimated together. The local models' complexity is different at different operating regions. Complex (or simple) model is used for the operating condition of the synchronous generator with more (or less) complex. In this method, it is decided which of the two selections is better to achieve a more precise model: Increasing the number of local models (if the selected parameters belong to both regions), or increasing the number of terms (if the selected parameters belong to one of the regions).

Experiment on synchronous generator

The system under consideration is a 3 kVA, 208 V, 3 phase micro-machine, driven by a DC motor. The micro machine can represent dynamic response of much larger synchronous machines when the parameters and variables are considered in a normalized version (per unit system [17]). The main problem with a micro-machine can be the field time constant, which is much lower than that of the larger machines. This problem has been overcome using a time constant regulator, which is used to increase the effective field time constant to match that of the larger units. The experimental setup used for the experiment is shown in Fig. 1. The synchronous generator is driven by a DC motor. The exciter input signal is applied to the synchronous machine through a D/A converter. The field voltage, terminal voltage (v_t) and the electrical power (P) are measured and sampled by the data acquisition system. The machine is connected to a constant voltage bus by a double circuit transmission line modelled by lumped elements. Each circuit consists of six π sections and simulates the performance of a 300 km long 500 kV transmission line.

The sampling time was selected to be 50 ms. This sampling time proved to be fast enough to capture the required dynamics.

A pseudo random binary sequence (PRBS) signal with 25% of the nominal value was applied. The initial operating condition was selected to be P=0.6p.u., Q=0.53 p.u., $v_t=1.22$p.u..

The field voltage, terminal voltage and electrical power measured are shown in Fig. 2.

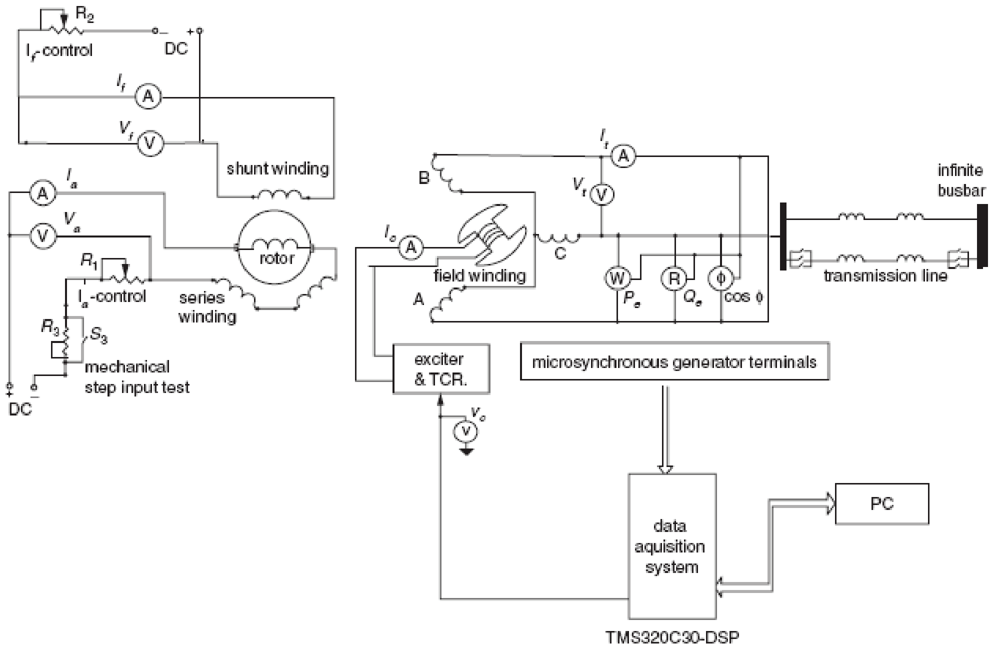

Fig. 1. Experimental setup for micro-machine

Simulation Results

Now that the system under study is explained, the proposed method is applied on the synchronous generator.

The order of local linear models is considered to be equal seven. In this study, the input is the sampled field voltage and the outputs are the sampled terminal voltage and electrical power. For convenience of implementation, the input-output data is subtracted by their mean values, respectively. The outputs of an identified model can be recovered to the original system operating region. The converted input and output are denoted by $u(k)$ and $y(k)$, respectively.

The operating space is chosen as $\underline{z}(k)=[u(k-1),\ y(k-1)]^T$. The proposed algorithm with $\alpha=0.005$ is applied for electrical power and terminal voltage.

Partitioning of operating space ($\underline{z}$) based on the proposed method for modelling terminal voltage and electrical power are shown in Fig.3 and 4, respectively.

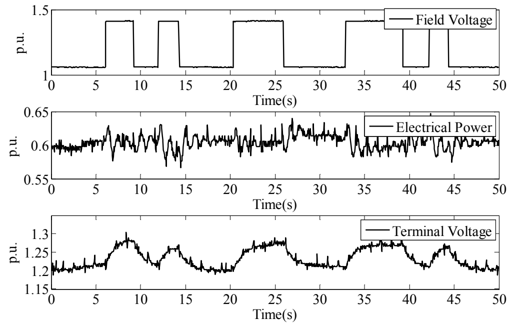

Fig. 2. Experimental data with a PRBS signal applied to the field.

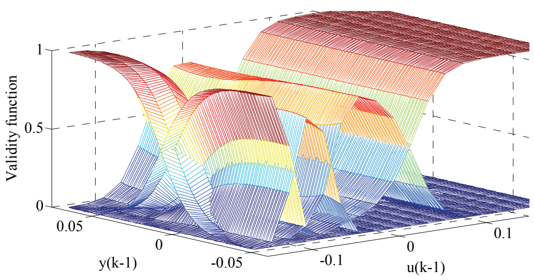

Fig.3. operating space partitioning is generated by the proposed algorithm for terminal voltage.

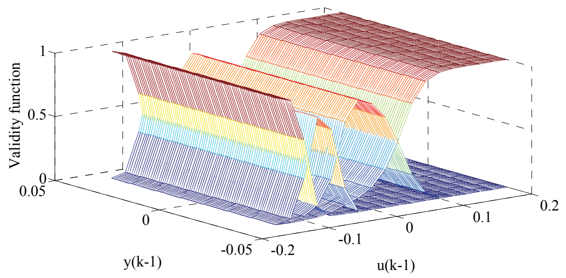

Fig.4. operating space partitioning is generated by the proposed algorithm for electrical power.

The number of partitions is dependent on behaviour of synchronous generator in each region. The number of partitions in regions with complex behaviour is more than regions with simple behaviour.

Identification results with the identified model and measured output are shown in Fig.5.

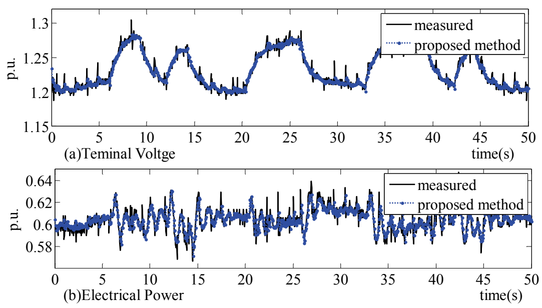

Fig. 5. Identification results with the identified model and the micro-machine outputs

It can be seen from fig. 5 that the proposed method can predict the synchronous generator behaviour well, despite the fact that the generator operating conditions change significantly.

Conclusions

Nonlinear identification of a synchronous machine using local structure is described in this paper. In the proposed method, to obtain a precise model for synchronous generator's operating space, the operating space is divided into several regions. The number of partitions in regions with simple behaviour is fewer than regions with complex behaviour. Also, the proposed method uses different local linear models for different operating regions. To obtain a more precise model, at each iteration, a choice is made between increasing the number of optimal local models or increasing the complexity of each local model.

The proposed method has been verified by studies using actual data obtained on a physical synchronous machine.

In this paper, terminal voltage and the active power are considered as the outputs of the system and the field voltage as the input of the system. The obtained model can be used for system analysis and controller design, and is planned to be used for designing a power system stabilizer in a predictive on-line control structure.

Appendix: The Orthogonal Least Squares with D-optimality algorithm

A linear-in-parameters model can be formulated as

$$y(k)=\sum_{i=1}^{n}\theta_i\phi_i(k)+e(k),\ k=1,2,\dots,N \tag{8}$$

where $\varphi_i(k)$, $i=1,2,\dots,n$ are all candidate model terms, $e(k)$ is an uncorrelated model residual sequence with zero mean and variance of σ^2 and θ_i ,$i=1,2,\dots,n$ are the unknown parameters to be estimated.

Eqn. 8 can be represented in matrix form as

$$\underline{y}=\mathbf{U}\underline{\theta}+\underline{E} \tag{9}$$

where $\underline{y}=[y(1),\dots,y(N)]^T$, $\mathbf{U}=[\underline{\varphi}_1,\dots,\underline{\varphi}_n]$, $\underline{\varphi}_i=[\varphi_i(1),\dots,\varphi_i(N)]^T$, $\underline{\theta}=[\theta_1,\dots,\theta_n]^T$, $\underline{E}=[e(1),\dots,e(N)]^T$.

An orthogonal decomposition of U is

$$\mathbf{U}=\mathbf{PA} \tag{10}$$

where $\boldsymbol{A}$ is an $n\times n$ unit upper triangular matrix and $\boldsymbol{P}$ is an $N\times n$ matrix with orthogonal columns $\underline{p}_i$ such that

$$\mathbf{P}^T\mathbf{P}=diag\{p_1^T p_1, p_2^T p_2,\dots,p_n^T p_n\} \tag{11}$$

so that eqn. 9 can be expressed as

$$\underline{y}=\mathbf{PA}\underline{\theta}+\underline{E}=\mathbf{P}\underline{\theta}^o+\underline{E} \tag{12}$$

The orthogonal least squares solution $\underline{\theta}^o$ can be estimated from

$$\hat{\underline{\theta}}^o=(\mathbf{P}^T\mathbf{P})^{-1}\mathbf{P}^T\underline{y} \tag{13}$$

or

$$\hat{\theta}_i^o=\frac{\underline{p}_i^T\underline{y}}{\underline{p}_i^T\underline{p}_i}\qquad ,i=1,2,\dots,n \tag{14}$$

The original parameters $\underline{\theta}$ can be estimated from

$$\mathbf{A}\underline{\theta}=\underline{\theta}^o \tag{15}$$

The mean squares error (J) is computed as

$$\begin{aligned}J&=\frac{1}{N}\underline{y}^T\underline{y}-\frac{1}{N}\sum_{i=1}^{n}\theta_i^{o^T}\underline{p}_i^T\underline{p}_i\\&=\frac{1}{N}\underline{y}^T\underline{y}-\frac{1}{N}\sum_{i=1}^{n}\frac{(\underline{p}_i^T\underline{y})^2}{\underline{p}_i^T\underline{p}_i}\end{aligned} \tag{16}$$

To enhance model robustness, eqn. 16 is combined with D-optimality criterion. Such a criterion is defined as:

$$max\left\{ det(\mathbf{P}^T\mathbf{P}) = \prod_{i=1}^{n}(\underline{p}_i^T\,\underline{p}_i) \right\} \quad (17)$$

Eqn. 16 and D-optimality are augmented as

$$\begin{aligned} J &= \frac{1}{N}\underline{y}^T\underline{y} - \frac{1}{N}\sum_{i=1}^{n}\frac{(\underline{p}_i^T\underline{y})^2}{\underline{p}_i^T\underline{p}_i} + \alpha\, log(\frac{1}{\prod_{i=1}^{n}\underline{p}_i^T\underline{p}_i}) \\ &= \frac{1}{N}\underline{y}^T\underline{y} - \frac{1}{N}\sum_{i=1}^{n}\frac{(\underline{p}_i^T\underline{y})^2}{\underline{p}_i^T\underline{p}_i} + \alpha\sum_{i=1}^{n} log(\frac{1}{\underline{p}_i^T\underline{p}_i}) \end{aligned} \quad (18)$$

where positive number α regulates the trade off between model approximation ability and robustness. Note that the net contribution of each term $\underline{p}_i$ can be computed independently as $(\underline{p}_i^T\underline{y})^2 \big/ N\underline{p}_i^T\underline{p}_i + \alpha\sum_{i=1}^{n} log(1\big/\underline{p}_i^T\underline{p}_i)$.

Eqn. 18 can be expressed as

$$J^{(i)} = J^{(i-1)} - \frac{1}{N}\frac{(\underline{p}_i^T\underline{y})^2}{\underline{p}_i^T\underline{p}_i} + \alpha\, log(\frac{1}{\underline{p}_i^T\underline{p}_i}) \quad (19)$$

At the i-th iteration, a candidate term is selected as i -th term if it produces the smallest $J^{(i)}$ [13]. The selection procedure is terminated if $J^{(n^o+1)} \geq J^{(n^o)}$.

The identified model is expressed as

$$y(k) = \sum_{i=1}^{n^o}\theta_i^o p_i(k) + e(k), \;\; k = 1,..,N \quad (20)$$

The model output is represented by means of the non-orthogonal model terms

$$y(k) = \sum_{i=1}^{n^o}\theta_{\gamma_i}\phi_{\gamma_i}(k) + e(k), \; k = 1,..,N \quad (21)$$

where the parameters $\underline{\theta} = \left[\theta_{\gamma_1}, \theta_{\gamma_2}, ..., \theta_{\gamma_{n^o}}\right]^T$, $\gamma_i =\{1,2,...,n\}$ can be calculated from eqn. 15. $\{\gamma_1, \gamma_2,..., \gamma_{no}\}$ is the index set of non-zero components of $\underline{\theta}$ where $\theta_{\gamma i}$ is the γ_i-th component in the parameter vector $\underline{\theta}$.

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