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*PAPERS*

# A novel measurement-based procedure for dynamic equivalents of electric power systems for stability studies using improved sine cosine algorithm

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Dynamic equivalent (DE) is an important process of multi-area interconnected power systems. It allows to perform stability assessment of a specific area (area of interest) at minimum cost. This study is intended to investigate the dynamic equivalent of two relatively large power systems. The fourth-order model of synchronous generators with a simplified excitation system is used as equivalent to the group of generators in the external system. To improve the accuracy of the estimated model, the identification is carried in two stages. First, using the global search Sine Cosine Algorithm (SCA) to find a starting set values, then this set is used as starting point for the fine-tuning made through the Pattern Search (PS) algorithm. To increase the reliability of the model's parameters, two disturbances are used to avoid the identification based on a specific event. The developed program is applied on two standard power systems, namely, the New England (NE) system and the Northeast Power Coordinating Council (NPCC) system. Simulation results confirm the ability of the optimized model to preserve the main dynamic properties of the original system with accuracy.

K e y w o r d s: dynamic equivalents, model order reduction, parameter estimation, power system dynamics, transient stability

## 1 Introduction

Despite the fast growth of renewable energy resources such as wind energy and solar energy which can be integrated with the conventional resources [1, 2], the synchronous machine is still the most applied equipment used for energy conversion. Stability studies are an important part of assessing transmission system security and are defined as the system's ability to withstand large disturbances such as faults or/and loss of system elements. In fact, Transient Stability (TS) studies are essentially related to the simulation of the synchronous machine's behavior; this behavior might be precisely reproduced by computer programs based on numerical integration techniques [3].

Nowadays, to meet with the increasing demand in power and energy, modern power systems contain a large number of interconnections, generating units and control systems. Therefore, when dealing with stability studies, a set of numerous Differential and Algebraic Equations (DAEs) are solved [3]. Analysis of this High Order System (HOS) can be costly and time consuming that requires considerable computational effort. The high order and complexity of such system cannot be ignored anymore, whereas fast and accurate TS studies are mandatory for online stability assessments. For these reasons, researchers focus their efforts on developing a reduced order system to the higher order system under the so-called dynamic equivalents [4–8].

So far, many efforts are devoted to reduce the power system model using classical approaches based on modal analysis [4–9], coherency concept [10, 11], or a combination of both [12]. However, using classical approaches may not be a good choice due to the continuous growth of the network and the non-availability of neighbors' system parameters and configurations that are the key information of these analytical approaches [13, 14]. To overcome these shortcomings of classical approaches, measurement based approaches have been proposed [15, 16].

In measurement based approaches, the goal is to preserve the main signals in the internal area (area of interest) while replacing the remaining parts of the system by an equivalent. This equivalent is usually in the form of virtual generator placed at boundary buses, that is, those buses that form the link between the area of interest and the external areas. Unknown parameters of the dynamic equivalent model can be determined using identification and parameter estimation methods using only dynamic responses within the internal system [17]. The only concern in measurement based approaches is their need for fast and accurate dynamic responses of the power system. Fortunately, current power systems are equipped with Wide Area Measurement System (WAMS) that utilize Phasor Measurement Units (PMUs) to collect data in real time, so with the aid of GPS and high-speed

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communication links, signals recorded by PMUs may be used to achieve online identification of dynamic equivalents [18, 19].

Taking the complexity of power system dynamics into consideration, parameter identification of the equivalent model is an optimization problem with a discontinuous multimodal and non-convex landscape. The traditional programming technology is fast and reliable, but it is often unable to find the best solution to the highly complex multimodal search space and may get easily trapped into a local optimum [20, 21]. Metaheuristics, on the other hand, are simple, flexible, derivation-free and local minima avoidance. These techniques combine the rules of randomness and the mimicry of several physical phenomena such as animals' behavior or evolutionary concepts [22]. Over the past two decades, metaheuristic algorithms have been attracting significant attention. Theses algorithms along with their variants proved their efficacy to solve real-world complex problems [23]. Some of the eminent population-based optimization algorithms such as genetic algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) were successfully applied to the parameter identification problem [24–27].

In [16], the second and third order models were used to identify the dynamic equivalent model for the 13 machines system. At first, an initial equivalent is calculated. Then, the equivalent parameters are adjusted based on how well the equivalent fits the original system, using an adaptive step size. The procedure is iteratively repeated until the objective function is minimized. In [28], Artificial Neural Networks (ANNs) were used as an equivalent to the 16 machines system. As famous as they are, ANNs need a large set of inputs measurements for the training. Once the network is well trained, it can operate to model complex nonlinear relationships including power system dynamic equivalents [29, 30]. Artificial neural networks with multiple hidden layers between the input and output layers are called Deep Neural Networks (DNNs), and they have a higher ability to model nonlinear systems. However, they require high processing time when the number of hidden layers increases. In addition, ANN-based equivalents have no physical meaning [31].

Reference [32] presents two graph-theoretic algorithms for PMU placement in a multi-area power system for the purpose of identifying equivalent models. In [24], the linearized model computed from the machine's transfer function was used to estimate the synchronous generator model. The main drawback of these methods is that they do not reflect precisely the nonlinear model of the machine in transient stability applications due to linearization error.

The performances of recently developed metaheuristic algorithms to solve the dynamic equivalence problem are addressed in [14, 33–36]. Although optimization algorithms such as PSO [34], Grey Wolf Optimizer (GWO) [35] and Salp Swarm Algorithm (SSA) [36], are able to solve the dynamic equivalence problem, accuracy of the solution is not guaranteed. To overcome the shortcomings of existing identification approaches, a more precise and flexible dynamic equivalent model is proposed in this paper. By incorporating two optimization algorithms for the evaluation of the model's parameters in cascade, it is expected that the accuracy of the equivalent model will be improved. Furthermore, it is possible to make the equivalent system more flexible and precise by using additional operation cases to avoid the identification based on a specific event. In this paper, the identification is carried out in two stages. First, using the global search Sine Cosine Algorithm (SCA) to find a starting set of values, then this set is used as the starting point for the fine-tuning made through the Pattern Search technique. This new algorithm is referred to in this paper as the hybrid Sine Cosine Algorithm Pattern Search (h-SCAPS).

## 2 Proposed approach

### *2.1 Dynamic equivalent model structure*

The power system is always partitioned into an internal system, an external system and a group of boundary buses; the external system is often a large system with certain electrical distance or geographical extent. The detailed information of the external system is not necessary and its influence on the internal system is the only interest. Therefore, its detailed model can be replaced by an equivalent. The equivalent is allocated at boundary buses, that is, those buses which are directly connected to the internal system through tie lines. In this paper, the 4$^{\text{th}}$ order model of synchronous generators with an excitation system is used as an equivalent to the group of generators in the external system. Notice that, the equivalent generator can be of any dynamic order [24]. However, the 4$^{\text{th}}$ order model offers considerable computational simplicity without any significant loss of accuracy compared to the sixth order used in [36]. This equivalent generator describes the transient dynamics on the $d$ and $q$ axes with four state variable $\delta$, $\omega$, $E'_d$ and $E'_q$. A common representation is given in

$$\begin{aligned}
\frac{\mathrm{d}\delta}{\mathrm{d}t} &= \Omega_b(\omega-1)\,,\\
\frac{\mathrm{d}\omega}{\mathrm{d}t} &= \frac{P_m-P_e-r_aI^2-D(\omega-1)}{2H}\,,\\
\frac{{}'_q}{\mathrm{d}t} &= \frac{-f_s(E'_q)-(x_d-x'_d)i_d}{T'_{d0}}\,,\\
\frac{\mathrm{d}E'_d}{\mathrm{d}t} &= \frac{-E'_d+(x_q-x'_q)i_q}{T'_{q0}}\,,
\end{aligned} \tag{1}$$

where $\delta$ (rad/s) is the rotor angular position; $\omega$ (pu) is the rotor angular velocity; $E'_d$ (pu) and $E'_q$ (pu) are $d$-axis and $q$-axis transient voltages. $\Omega_b = 2\pi f_0$ ($\Omega_b =$ 314 for a 50 Hz system and 377 for a 60 Hz system); $P_m$ and $P_e$ are the mechanical input power and electrical active output power, respectively. $x_d$ (pu), $x_q$ (pu), $x'_d$ (pu) and $x'_q$ (pu) are the $d$-axis and $q$-axis steady state and

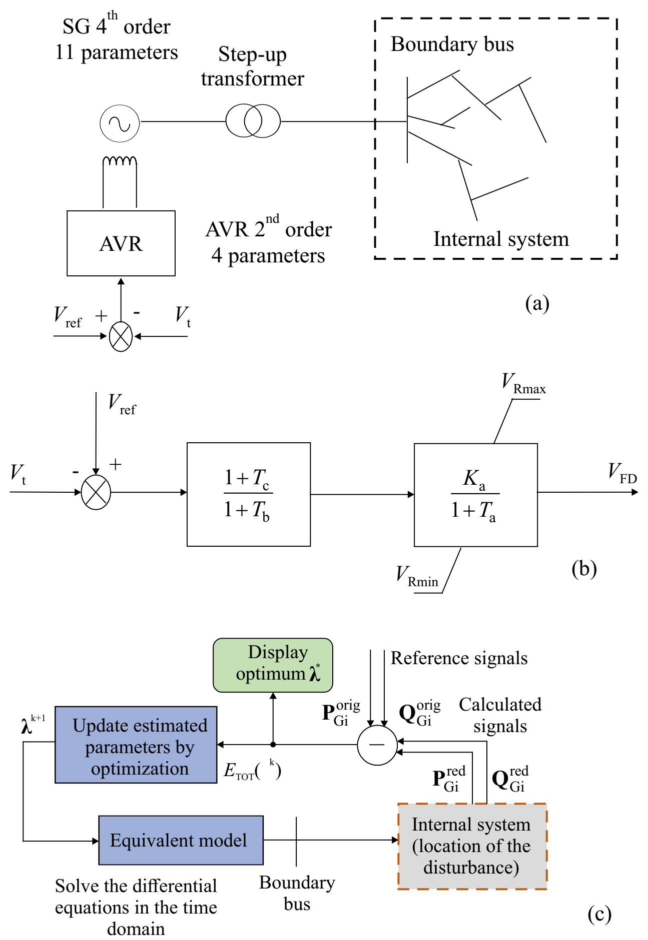


**Fig. 1.** The equivalent schematic diagram of external systems: (a) – structure diagram of the equivalent system components, (b) – block diagram of the equivalent excitation regulator, (c) – structure diagram based on parameters identification

transient reactances, respectively. $T'_{d0}$ (s)and $T'_{q0}$ (s) are the $d$-axis and $q$-axis open circuit time constant; $r_a$ (pu) is the armature resistance; $H(s)$ is the inertia constant; $D$ (pu) is the damping coefficient and $f_s$ is the magnetic saturation function. $i_d$ and $i_q$ are direct and quadrature currents, respectively.

The constraint of using this model is that $x'_d = x'_q$ . This is due to the way in which the transient reactance is used in PST's network interface. PST checks that the direct and quadrature transient reactances are equal, if they are unequal it makes them equal. Therefore, only $x'_d$ is estimated, which reduced the number of parameters to be determined for the generator to 8 parameters. The equivalent generator is equipped with a simplified excitation system whose block diagram is shown in Fig. 1, where $K_a$ (pu) and $T_a$ (s) are the voltage regulator gain and time constant, respectively; $T_b$ (s) and $T_c$ (s) are the transient gain reduction time constants; $V_{R\max}$ (pu) and $V_{R\min}$ (pu) are the maximum and minimum voltage regulator outputs, respectively. Moreover, the generator cannot be connected directly to the system without any transformer. Therefore, an additional bus is added to connect the equivalent generator to the boundary bus through a step-up transformer with a very small reactance of 0.00001 per unit. The overall decision variable vector $\boldsymbol{\lambda}$ has 12 parameters per each equivalent generator: $\boldsymbol{\lambda} = \{r_a, x_d, x_q, x'_d, T'_{d0}, T'_{q0}, H, D, K_a, T_a, T_b, T_c\}$. These parameters are to be identified by an optimal approach.

### *2.2 Problem formulation based on measurements*

Dynamic equivalent of power systems is a computational process that aims to minimize the overall error between the whole system including the detailed representation and an equivalent system with fewer machines and lower dynamic order. The goal is to preserve the main signals in the internal area (area of interest) while replacing the external parts of the system by an equivalent [24].

The main procedure is to search for the best or satisfied parameter vector $\boldsymbol{\lambda}$ that minimizes the objective function

$$\min E \min \|\mathbf{Y}_m - \mathbf{Y}_s(\boldsymbol{\lambda})\|^2 \tag{2}$$

Subjected to:

$$\boldsymbol{\lambda}_{\min} \le \boldsymbol{\lambda} \le \boldsymbol{\lambda}_{\max} \tag{3}$$

with:

$$\mathbf{Y}_m = \begin{bmatrix} P_{\mathrm{G1}}^{\mathrm{orig}}(t_0) & P_{\mathrm{G2}}^{\mathrm{orig}}(t_0) & \dots & P_{\mathrm{G}n}^{\mathrm{orig}}(t_0) \\ P_{\mathrm{G1}}^{\mathrm{orig}}(t_1) & P_{\mathrm{G2}}^{\mathrm{orig}}(t_1) & \dots & P_{\mathrm{G}n}^{\mathrm{orig}}(t_1) \\ \vdots & \vdots & \ddots & \vdots \\ P_{\mathrm{G1}}^{\mathrm{orig}}(t_f) & P_{\mathrm{G2}}^{\mathrm{orig}}(t_f) & \dots & P_{\mathrm{G}n}^{\mathrm{orig}}(t_f) \end{bmatrix} \tag{4}$$

$$\mathbf{Y}_s = \begin{bmatrix} P_{\mathrm{G1}}^{\mathrm{red}}(t_0) & P_{\mathrm{G2}}^{\mathrm{red}}(t_0) & \dots & P_{\mathrm{G}n}^{\mathrm{red}}(t_0) \\ P_{\mathrm{G1}}^{\mathrm{red}}(t_1) & P_{\mathrm{G2}}^{\mathrm{red}}(t_1) & \dots & P_{\mathrm{G}n}^{\mathrm{red}}(t_1) \\ \vdots & \vdots & \ddots & \vdots \\ P_{\mathrm{G1}}^{\mathrm{red}}(t_f) & P_{\mathrm{G2}}^{\mathrm{red}}(t_f) & \dots & P_{\mathrm{G}n}^{\mathrm{red}}(t_f) \end{bmatrix} \tag{5}$$

where $\mathbf{Y}_m$ and $\mathbf{Y}_s$ are the measured and simulated outputs, respectively. Further, $\boldsymbol{\lambda}$ is the vector of estimated parameters that lies in the interval of $[\boldsymbol{\lambda}_{\min}, \boldsymbol{\lambda}_{\max}]$, $\mathbf{P}_{\mathrm{G}}^{\mathrm{orig}}$ is the active power behavior of those generators within the retained area in the original system, $\mathbf{P}_G^{\mathrm{red}}$ is the active power behavior of the same generators in the reduced system. Notice that, after the disturbance takes place in the internal system, both signals are measured/simulated in a closed interval of $[t_0, t_f]$.

Generally, a single case is not adequate to completely solve the estimation problem. In most situations, the equivalent is identified based on a specific disturbance and may not be valid for those disturbances with a different impact on the system [37]. Thus, to avoid the identification of the equivalent based on a specific disturbance, a set of events can be registered. In this case, the total objective function will be

$$E_{\mathrm{TOT}}(\boldsymbol{\lambda}) = \sum_{np=1}^{P} \omega_{np} E_{np}(\boldsymbol{\lambda}) \tag{6}$$

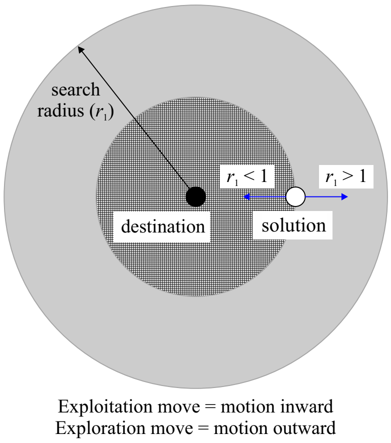


**Fig. 2.** Effects of sine and cosine on the next position

where $P$ is defined as the number of available disturbances and $\omega_{np}$ as the weight factor of the $np^{\text{th}}$ disturbance.

### 2.3 Hybrid sine cosine algorithm pattern search (h-SCAPS)

#### 2.3.1 Sine cosine algorithm (SCA)

Sine cosine algorithm (SCA) is a novel population-based optimization algorithm introduced in [38]. The algorithm exploits the mathematical sine and cosine functions to perform local and global searches (hence the name sine-cosine). Like other optimization techniques, the search starts by creating a random set of solutions. Afterward, these solutions are repeatedly evaluated over the course of iterations to improve a cost function.

Mathematically, the population's positions are updated based on the following equation

$$\mathbf{X}_i^{t+1} = \begin{cases} \mathbf{X}_i^t + r_1 \sin(r_2)|r_3 \mathbf{Pos}_i^t - \mathbf{X}_i^t|, & r_4 < 0.5\,, \\ \mathbf{X}_i^t + r_1 \cos(r_2)|r_3 \mathbf{Pos}_i^t - \mathbf{X}_i^t|, & \text{otherwise} \end{cases} \tag{7}$$

where $\mathbf{X}_i^t$ is the position of the current solution in the $i^{\text{th}}$ dimension of the $t^{\text{th}}$ iteration; $\mathbf{Pos}_i^t$ is the position of the best solution so far in the $i^{\text{th}}$ dimension, referred to as the destination position; $r_1$, $r_2$, $r_3$ and $r_4$ are random numbers, and $|\cdot|$ donates the absolute value.

As can be seen from (7), SCA is controlled by four random parameters $r_1$, $r_2$, $r_3$ and $r_4$ defined as follows:

- The parameter $r_1$ uniformly distributed from $[0,2]$: controls the movement direction (the next position region), it is either the region between the destination and candidate solution or the region outside, see Fig. 2.
- The parameter $r_2$ uniformly distributed from $[0,2\pi]$: defines whether the movement should be towards or outwards the destination.
- The parameter $r_3$ uniformly distributed from $[0,2]$: introduces a random weight to the destination in order to stochastically affect displacement from the current position.
- The parameter $r_4$ uniformly distributed from $[0,1]$: ensures an equal probability to choose at random sine or cosine function.

To balance between exploration (global search) and exploitation (local search) in the SCA, and ultimately converge toward the global optimum, the parameter $r_1$ is adjusted adaptively over the course of iterations in order to change the ranges of the sine and cosine functions to emphasize exploitation of the search space as the iteration counter increases [38].

$$r_1 = A\left(1 - \frac{t}{T}\right) \tag{8}$$

**Initialize** randomly the locations of the search agents in the permissible search bounds
  **While** (Stop criteria are not satisfied)
    **Evaluate** the fitness of the search agents using the objective function (6)
    **Update** the best solution found so far (destination) ($Pos = X^*$)
    **Update** the parameters $r_1, r_2, r_3$ and $r_4$
    **Update** the position of the search agents using (7)
  **End**
**Save** the best solution found so far as the global optimum

**Fig. 3.** SCA pseudo code

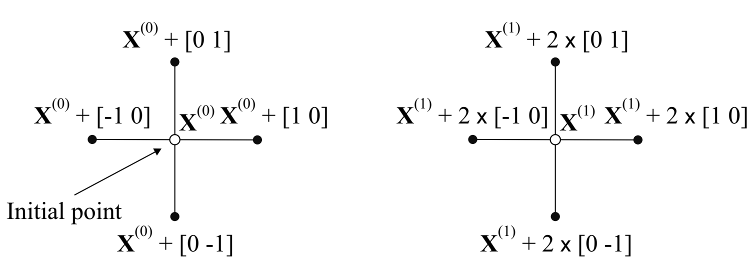


**Fig. 4.** (a) – PS initial point and mesh points, (b) – iteration 2 after a successful poll

**Construct** pattern vectors and create mesh points in the permissible search bounds
  **While** (Stop criteria are not satisfied)
    **Evaluate** the mesh points
    **Double** mesh size if the value at one of the mesh points minimizes the objective function
    **Reduce** mesh size to half if none the mesh points minimize the objective function
  **End**
**Save** the best solution found so far as the global optimum

**Fig. 5.** PS pseudo code

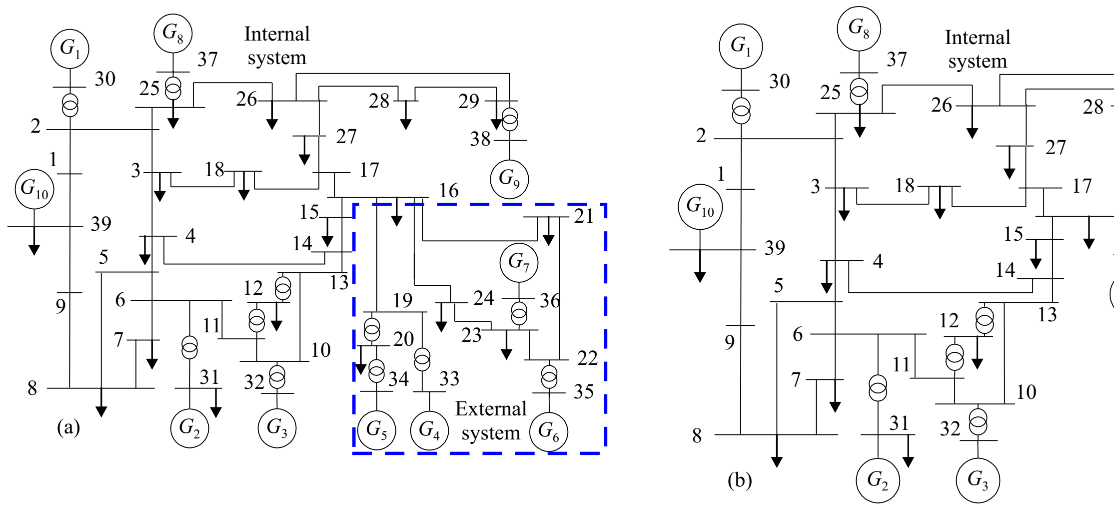


**Fig. 6.** (a) – New England (NE) original system, (b) – reduced New England (RNE) system

where $A$ is a constant equal to 2 in this case, $t$ and $T$ are the current iteration and the maximum number of iterations, respectively. The general steps of the SCA algorithm are presented in Fig. 3.

In [38], the algorithm demonstrates its efficiency to handle unimodal, multi-modal, and composite functions along with real problems like airfoil design. SCA is viewed as simple in concept and easy to tune only by varying the number of search agents and the total number of iterations, which justified the selection of SCA to solve the dynamic equivalence problem.

### *2.3.2 Fine tuning by pattern search (PS)*

Pattern Search (PS) is a derivative-free optimization method, suitable to solve a variety of optimization problems such as complex engineering problems that lie outside the scope of the standard optimization methods. It has been introduced by Hooke and Jeeves in [39]. PS has a flexible and well-balanced operator to enhance the global search and to fine-tune the local explore capability [40]. Therefore, it is considered as simple in concept, easy to implement with strong computational efficiency.

Pattern search starts at the initial point $\mathbf{X}^0$ provided by SCA. Then, it creates a set of points called mesh by adding the initial point to a scalar multiple of a set of vectors called a pattern, see Fig. 4(a). At the first iteration, the mesh size is 1 and the algorithm computes the following mesh points: $\mathbf{X}^0 + [1\ 0]$, $\mathbf{X}^0 + [0\ 1]$, $\mathbf{X}^0 + [-1\ 0]$ and $\mathbf{X}^0 + [0\ -1]$. The algorithm polls the mesh points by evaluating their objective. If the objective function value decreases at some mesh point, the poll is said to be successful and the algorithm sets this point as a starting point for the next iteration. After a successful poll, the current mesh size is multiplied by 2, see Fig. 4(b). Otherwise, if none of the mesh points decreases the objective function value, the poll is said to be unsuccessful. The initial/current point is then kept as a starting point for the next iteration and the mesh size is reduced to half [39]. This process is repeated until stopping criteria are met. Pseudo code of the PS algorithm is presented in Fig. 5.

## 3 Case study

Dynamic systems (DE) is an important process of multi-area interconnected power systems. It allows performing stability assessment of a specific region (area of interest) at minimum cost. This study is intended to investigate the dynamic equivalent of two relatively large power systems: the New England (NE) system and the Northeast Power Coordinating Council (NPCC) system shown in Fig. 6(a) and 7(a), respectively. The optimization of the equivalent model is coordinated in such a way as to minimize the overall error between the original system dynamic responses following some disturbances and the equivalent system dynamic responses after subjected to the same disturbances. The single line diagram of the Reduced New England (RNE) system is shown in

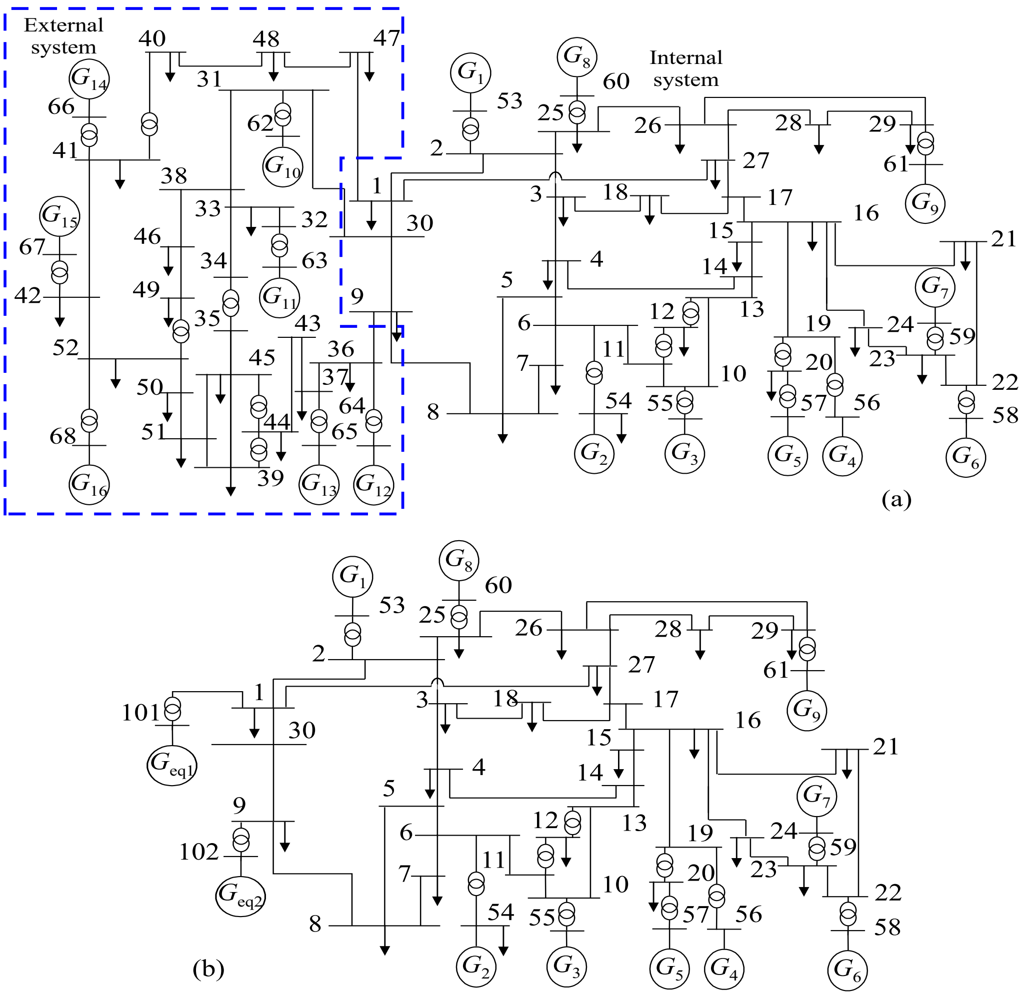


**Fig. 7.** (a) – Northeast power coordinating council (NPCC), (b) – reduced Northeast power coordinating council (RNPCC)

Fig. 6(b); whereas the Reduced Northeast Power Coordinating Council (RNPCC) system single line diagram is shown in Fig. 7(b). Brief descriptions of the power systems utilized in this paper are granted in Tab. 1.

In order to conduct the optimization of dynamic equivalents, the non-linear model of power systems is used to formulate the required objective function in (6). After that, with the help of time-domain analysis, optimized parameters of equivalent models are taken out to verify their capability of reducing the cost function in (6). The comprehensive non-linear modeling of a multimachine power system requires the proper and accurate mathematical representation, which is very tedious and complicated to handle. Therefore, the Power System Toolbox (PST) has been adopted in this study to simplify the overall modeling burden, and the focus is conveyed to the design of dynamic equivalents. This toolbox is a MATLAB based package and it is considered as one of the popular toolbox commonly used for the study of power system electromechanical dynamics. Models in PST were developed based on IEEE standards of power system components, along with a large variety of power system benchmarks including the two systems used in this study [41, 42].

## 4 Simulation results

The following experiments were carried out on Lenovo ThinkPad T470 personal computer, running on Intel® Core$^{TM}$ i7-7500U CPU, 2.70 GHz processing speed, and physique memory of 8GB DDR4. In the flow chart shown in Fig. 8, the optimization method will generate candidate parameters to the equivalent model. According to these last, transient stability analysis are carried out for all cases using PST to evaluate the fitness of each solution. The applicability of the proposed approach has been verified using two large-scale power systems mentioned in the previous section. For each system, the identification is carried out using two scenarios by performing time-domain simulations with the original-size and the reduced-size, respectively. The system responses are then observed in a closed interval of 3 seconds. To take account for each scenario into the total objective function (6), equal weight factors have been utilized (*ie* $\omega_{np} = 1/P$).

### Case study 1

*scenario* 1: At time $t = 0$ s, a three-phase fault is applied at bus 27 on line 27-17. At 80 ms the line is disconnected

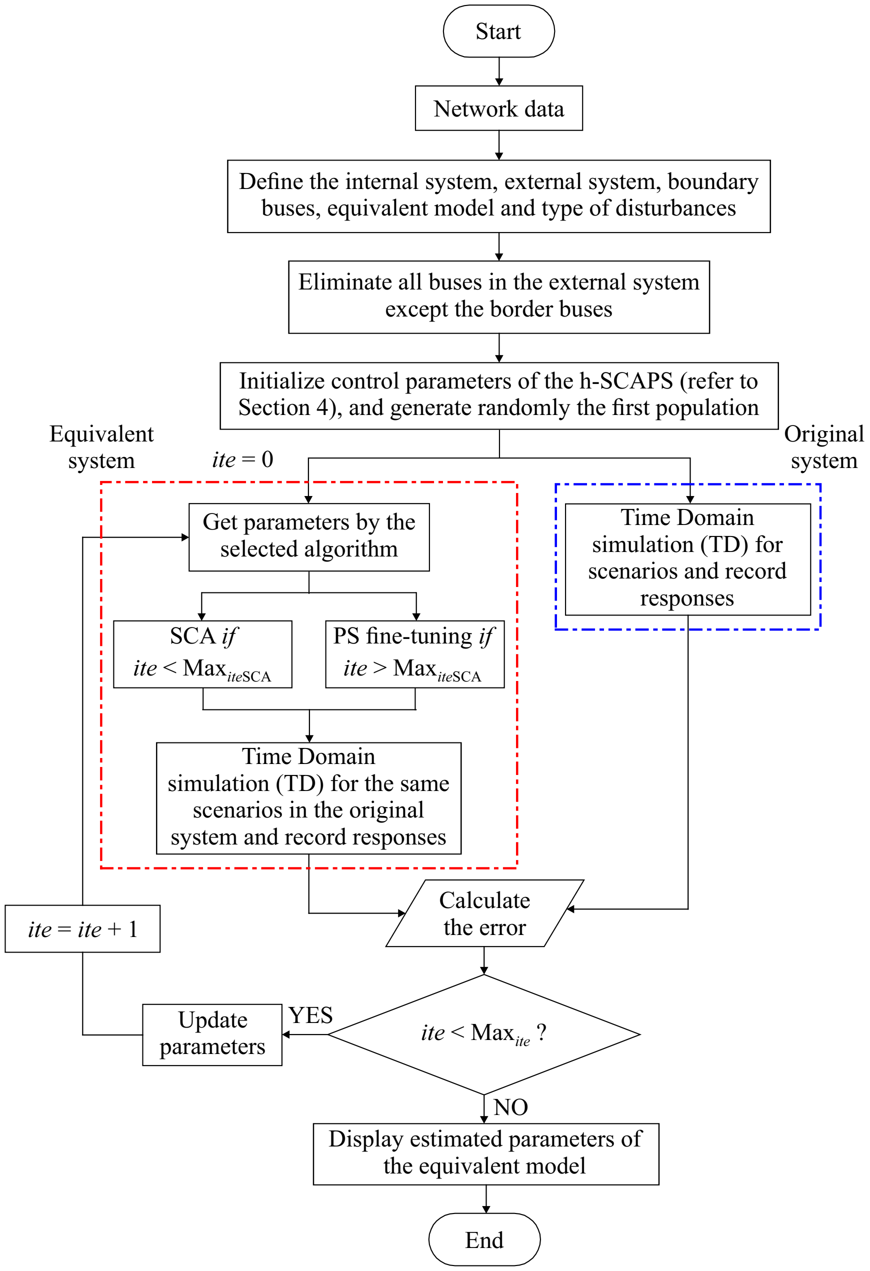


**Fig. 8.** Flow chart of networks reduction based on h-SCAPS

**Table 1.** Comparison between the original and equivalent systems

| System representation | Case Study 1 (NE) system | | Case Study 2 (NPCC) system | |
|---|---|---|---|---|
| No of | Original | Reduced | Original | Reduced |
| machines | 10 | 7 | 16 | 9 |
| buses | 39 | 30 | 68 | 40 |
| branches | 46 | 36 | 86 | 47 |
| transformers | 12 | 8 | 20 | 14 |
| order | 67 | 45 | 148 | 100 |

at bus 27. The fault persists until 100 ms when the line is disconnected from bus 17.

*scenario* 2: At time $t = 0$ s, a three-phase fault is applied at bus 7 on line 7-8. At 80 ms the fault is cleared at bus 7. However, the fault persists until 100 ms when the line is disconnected from bus 8.

### Case study 2

*scenario* 1: At time $t = 0$ s, a three-phase fault is applied at bus 28 on the transmission line between buses 28 and 26. At 90 ms the line is opened at bus 28 to clear the fault. The fault persists until 100 ms when the line is opened at bus 26.

*scenario* 2: At time $t = 0$ s, a three-phase fault is applied at bus 14 on the transmission line between buses 14 and 4. At 90 ms the line is disconnected at the first end to clear the fault. However, the fault persists until 100 ms when the line is cleared at the second end.

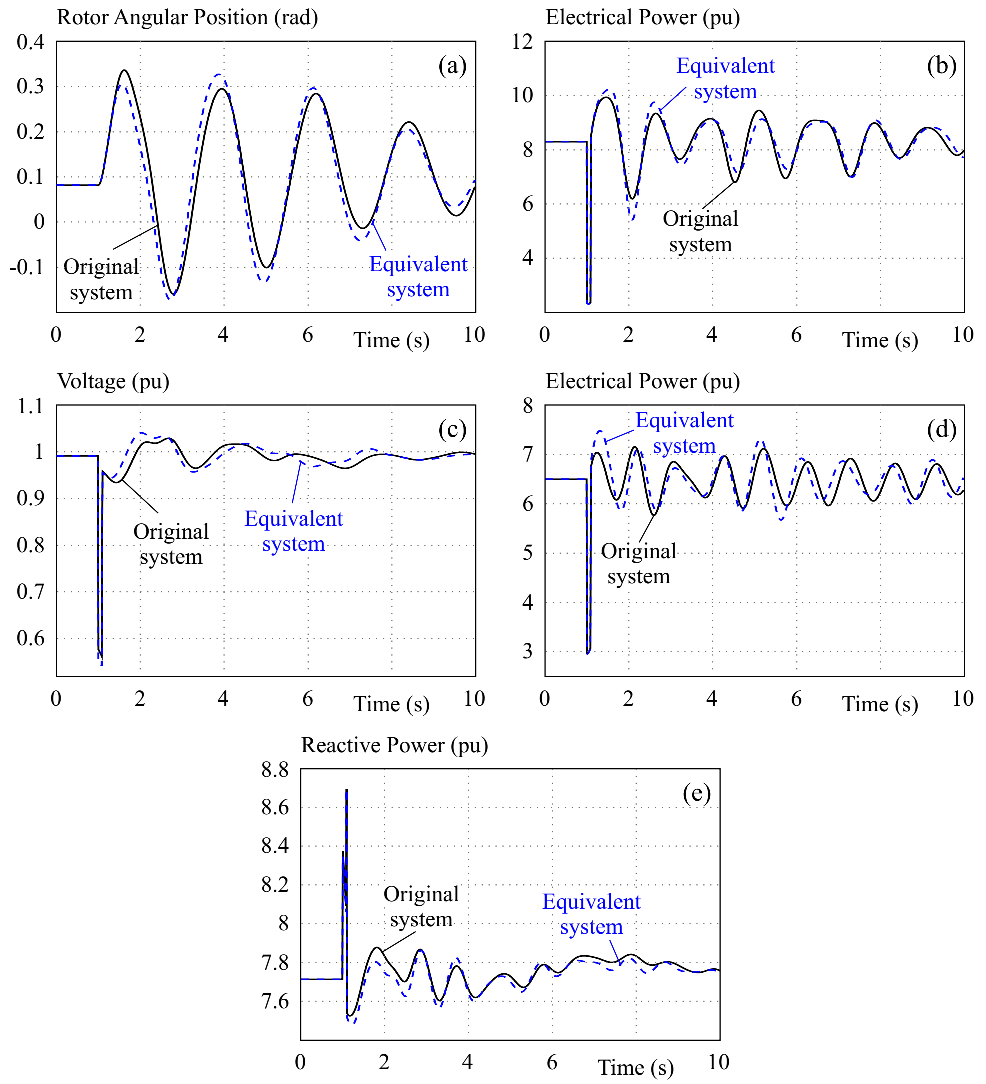


**Fig. 9.** (a) – angular position of $G_1$ after a three-phase fault at bus 9, ($MSE = 1 \times 10^{-3}$), (b) – electrical power of $G_9$ after a three-phase fault at bus 27, ($MSE = 6.41 \times 10^{-2}$), (c) – voltage magnitude of bus 12 after a three-phase fault at bus 3, ($MSE = 1.84 \times 10^{-4}$), (d) – electrical power of $G_3$ after a single-phase fault at bus 15, ($MSE = 1.99 \times 10^{-2}$), (e) – reactive power of G2 after a double-phase fault at bus 10, ($MSE = 1.03 \times 10^{-3}$)

Although h-SCAPS like other meta-heuristic algorithms is a high-level problem-independent technique, it is nonetheless necessary to do some fine-tuning of its control parameters in order to adapt the algorithm to the studied problem. In this paper and after several attempts, h-SCAPS control parameters were set as follows: SearchAgents=30; MaxIteSCA=100; MaxItePS=50. The estimated parameters of the equivalent models are granted in Tab. 2 and 3, respectively. Reference [43] provides standard parameters of synchronous machines, based on which the maximum and minimum values of the estimated parameters were selected.

To confirm the ability of the optimized model to preserve the main dynamic properties of the original system, various scenarios (ie single, double and three-phase faults), different from those used in the estimation phase were applied in the internal system. Each scenario is triggered at the first second and lasts 6 cycles before the protection eliminates the fault by opening the corresponding transmission line at both ends. Then, responses from the original and equivalent systems are observed for 10 seconds.

The Mean Square Error (MSE) in (9), is a popular statistical method employed to compare the main signals. The MSE is computed as

$$MSE = 1/N \sum_{(i=1)}^{N} (\mathbf{S}_i^{\text{orig}} - \mathbf{S}_i^{\text{red}})^2 \qquad (9)$$

where, $\mathbf{S}$ is a vector of the measured signal, $N$ is the length of the signal. $\mathbf{S}$ could be any signal. In this work, the rotor angular position, rotor angular velocity and power outputs of the generators were chosen as representative signals. A small error will indicate that a close fitting of the dynamic behaviors is attained between signals with the original and equivalent model.

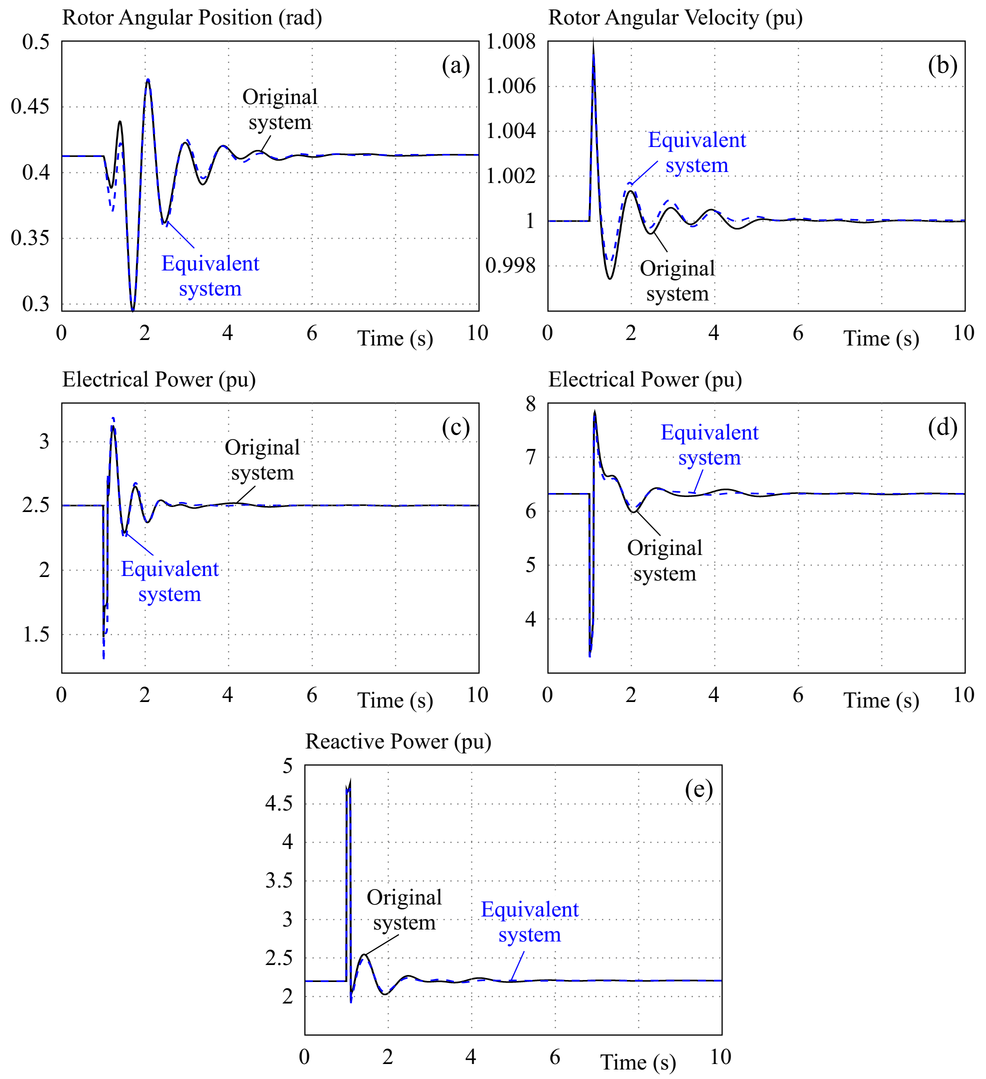


**Fig. 10.** (a) – angular position of $G_2$ after a three-phase fault at bus 4, ($MSE = 1 \times 10^{-5}$), (b) – angular velocity of G9 after a three-phase fault at bus 26, ($MSE = 4,\ 75 \times 10^{-8}$), (c) – electrical power of G1 after a three-phase fault at bus 24, ($MSE = 6.14 \times 10^{-4}$), (d) – electrical power of $G_4$ after a single-phase fault at bus 3, ($MSE = 1.53 \times 10^{-3}$), (e) – reactive power of $G_6$ after a double-phase fault at bus 7, ($MSE = 2.82 \times 10^{-4}$)

### New England system (NE)

Figure 9 reports time-domain responses of the dynamic equivalent and the original system for some representative signals under a single, double and three-phase faults.

### Northeast power coordinating council (NPCC)

Figure 10 reports the time-domain responses of the dynamic equivalent and the original system for some representative signals under a single, double and three-phase faults.

As can be seen from the above figures, the obtained results are satisfying in all analyzed scenarios. Even if the equivalent model cannot fit the original system responses point by point which is not the objective, it reflects the general behaviors both in terms of disturbance amplitude and in extinction time. This proves that the whole tendency is preserved. Moreover, the equivalent model is clearly able to maintain the original system dynamics; the interval granted by the MSE's in the order of $10^{(}-2)$ and less in some signals.

## 5 Conclusion

Dynamic equivalent model identification is a difficult task including reduction of the model complexity by replacing less important areas by appropriate equivalents. This paper presented a new approach to obtain a dynamic equivalent model that can be embedded easily in transient stability simulation packages. Using only measurements available within the internal system, the identification was carried out without the need for the external system topology and parameters. The fourth-order model of synchronous generators with a simplified exciter was used to replace the external system. Estimation of the model's parameters was carried out in two stages by incorporat-

**Table 2.** Optimized parameters for the Reduced New England (RNE) system

| | | | |
|---|---|---|---|
| $r_a$ (pu) | 0.0034 | $H(s)$ | 13.7339 |
| $x_d$ (pu) | 1.6464 | $D(pu)$ | 0 |
| $x'_d$ (pu | 0.4 | $K_a(pu)$ | 33.3357 |
| $x_q$ (pu) | 2.3 | $T_a(s)$ | 0.3063 |
| $T'_{d0}$ (s) | 5.2342 | $T_b(s)$ | 0.4814 |
| $T'_{q0}$ (s) | 1.9649 | $T_c(s)$ | 0 |

**Table 3.** Optimized parameters for the Reduced Northeast Power Coordinating Council (RNPCC) system

| | $G_{eq1}$ | $G_{eq2}$ |
|---|---|---|
| $r_a$ (pu) | 0.0015 | 0.0042 |
| $x_d$ (pu) | 2.3 | 1.6349 |
| $x'_d$ (pu) | 0.15 | 0.15 |
| $x_q$ (pu) | 1 | 1.3501 |
| $T'_{d0}$ (s) | 9.9526 | 8 |
| $T'_{q0}$ (s) | 2 | 2 |
| $H$ (s) | 122.3470 | 86.2512 |
| $D$ (pu) | 4.8750 | 0 |
| $K_a$ (pu) | 28.7052 | 182.6938 |
| $T_a$ (s) | 0 | 0.319 |
| $T_b$ (s) | 0.0572 | 20 |
| $T_c$ (s) | 1 | 6 |

ing two optimization algorithms: Sine Cosine Algorithm (SCA) and Pattern Search (PS) in cascade. In addition, two scenarios were used to avoid the dependence of the model's parameters on a specific event. Simulation results on the 10 machines "New England" and the 16 machines "Northeast Power Coordinating Council" demonstrated the ability of the proposed methodology. The validity of the optimized parameters was confirmed using transient stability analysis of several scenarios in different locations in the internal system, where the main dynamic properties of the original system were preserved with accuracy.

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