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Hybrid PSO-Complex Algorithm Based Parameter Identification for a Composite Load Model

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Abstract – This paper proposes a hybrid searching algorithm based on parameter identification for power system load models. Hybrid searching was performed by the combination of particle swarm optimization (PSO) and a complex method, which enhances the convergence of solutions closer to minima and takes advantage of global searching with PSO. In this paper, the load model of interest is composed of a ZIP model and a third-order model for induction motors for stability analysis, and parameter sets are obtained that best-fit the output measurement data using the hybrid search. The origin of the hybrid method is to further apply the complex method as a local search for finding better solutions using the selected particles from the performed PSO procedure.

Keywords: Composite load model, Complex method, Hybrid search, Parameter identification, Particle swarm optimization

1. Introduction

The modeling of system components critically affects the accuracy of stability analysis in power system operation and planning [1]. Thus, system identification is considered as important as those approaches to stability analysis [2]. In power systems, there are diverse components that need to be modeled; among them, loads are said to be difficult to model owing to the fact that they are composed of several parts and have different topological features. In addition, the load parameters need to be precisely determined for adequate stability analysis because power balances should continuously operate within the acceptable range even during disturbances. This paper primarily discusses the identification of load model parameters for stability studies.

Power system load models can be classified into static and dynamic models. For static load representation, ZIP and exponent-based models are adopted for analysis, and their parameters express the voltage and frequency dependencies for power consumption [1, 3-4]. For dynamic load representation, there are several models that have been proposed in the literature, but two types of models are typically used. The first model represents the load recovery characteristics during disturbances with first-order dynamics for the active and reactive powers [5-6]. The other model employs induction motor models for the dynamic behavior of loads with a static model such as the ZIP model [7-11]. The inclusion of induction motors is required to analyze short-term voltage stability of the system because of their fast reactive power consumption during disturbances, with a comparatively low voltage level.

In the literature, there are several identification methods that have been employed for load model parameters. In [12-13], linear and nonlinear least square methods were adopted for a model with first-order load recovery dynamics from the measurement data. In [7], a conjugate-gradient-type stochastic approximation algorithm was adopted to estimate the parameters in a linearized induction motor model. In [10], a combined learning algorithm with a genetic algorithm (GA) and Levenberg-Marquardt (LM) method was applied to a composite load model to search the parameter space more efficiently. In [11], reducing the number of parameters for the composite model was discussed using the concept of trajectory sensitivity.

This paper presents a parameter estimation method for a composite load model that applies hybrid optimization with particle swarm optimization (PSO) [14-16] and a complex method [17]. PSO algorithms have the advantages of simplicity in implementation and quick convergence to a reasonably good solution [18]. In [19-20], PSO had been proposed in combination with the Nelder-Mead (NM) simplex method to benefit from the highly accurate local search ability of NM simplex and powerful global search ability of PSO. This paper adopts the complex method to further improve this hybrid by replacing the local search method. The complex method is an improved version of simplex that increases the possibility of finding local optima.

In this paper, a method using Runge-Kutta 4^{th}-order numerical integration is employed to view the change in the time trajectories with respect to several parameter attempts from the hybrid-simulation-based optimization. To avoid integration divergence and unfeasible conditions,

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two penalty terms are added to form the extended objective function with which the PSO-complex hybrid method searches the parameter space for the composite load model. Similar to other simulation-based search methods, PSO has difficulty in capturing the exact local minima, and there is a chance to simply pass better solutions in early iterations. To overcome these problems, the complex method is applied to the selected particles in a PSO iteration to replace a particle's location after the objective function reaches a certain threshold value. This paper describes the numerical experiences when applying PSO-based methods for parameter identification to a composite load model. In addition, this paper includes a comparison between the results for the PSO-complex hybrid, PSO, and PSO-simplex hybrid methods for minimizing the output error using the estimated parameters.

2. Load Model Structure

The load model considered has two components, the ZIP model for the static component and an induction motor for the dynamic component, as shown in Fig. 1.

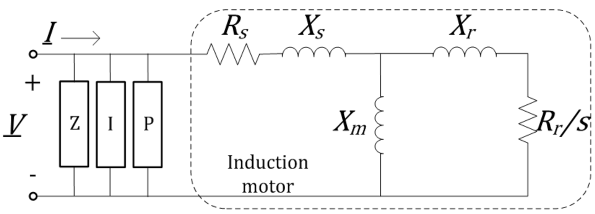

Fig. 1. Load model structure of interest

The active and reactive powers of the ZIP load, P_{ZIP} and Q_{ZIP}, can be expressed as

$$P_{ZIP} = P_{ZIPo}\left[a_p\left(V/V_o\right)^2 + b_p\left(V/V_o\right) + c_p\right] \tag{1}$$

$$Q_{ZIP} = Q_{ZIPo}\left[a_q\left(V/V_o\right)^2 + b_q\left(V/V_o\right) + c_q\right] \tag{2}$$

where P_{ZIPo} and Q_{ZIPo} are the active and the reactive load demands when the magnitude of the voltage of the load bus is V_o as the reference. In (1) and (2), a_p, b_p, and c_p are the coefficients for the ratio of constant impedance, constant current, and constant power portion to the active load, respectively, considering $a_p + b_p + c_p = 1$; a_q, b_q, and c_q are similarly defined for the reactive load, and these coefficients also sum to 1.

For the dynamic load response, a 3rd-order induction motor model is employed. R_s and X_s are the stator resistance and reactance, respectively. X_m is the magnetization reactance, and R_r and X_r are the rotator resistance and reactance, respectively. V and I are the vectors for the motor terminal voltage and current, respectively, and s is the slip of the motor, which can be expressed as $(\omega_o\text{-}\omega_m)/\omega_o$. ω_m and ω_o are the rotor angular velocity and its synchronous velocity, respectively. The 3rd-order induction motor model equations are

$$\dot{E}_d' = -\frac{1}{T_o'}\left[E_d' + \left(X - X'\right)I_q\right] + \omega_o s E_q' \tag{3}$$

$$\dot{E}_q' = -\frac{1}{T_o'}\left[E_q' - \left(X - X'\right)I_d\right] - \omega_o s E_d' \tag{4}$$

$$\dot{s} = \frac{1}{2H}\left(T_m - T_e\right) \tag{5}$$

$$I_d = \frac{1}{R_s^2 + X'^2}\left[R_s(V_d - E_d') + X'(V_q - E_q')\right] \tag{6}$$

$$I_q = \frac{1}{R_s^2 + X'^2}\left[R_s(V_q - E_q') - X'(V_d - E_d')\right] \tag{7}$$

where E_d' and E_q' denote the direct and quadrature-axis components of the internal voltage, respectively; X' is the short-circuit reactance inside the transient rotor from the terminal; X is the rotor open-circuit reactance; T_o' is the transient open-circuit time constant; H is the inertia constant; T_m and T_e are the mechanical and electrical torque, respectively; I_d and I_q are the direct and quadrature-axis components of the injected motor current, respectively; and V_d and V_q are the direct and quadrature-axis components of the terminal voltage, respectively. In the above model, X, X', and T_o' are functions of R_s, X_s, R_r, X_r, and X_m.

In the composite model, ten parameters are included, namely, a_p, b_p, a_q, and b_q for the ZIP load model; and R_s, X_s, R_r, X_r, X_m, and H for the induction motor model. As mentioned in [11], parameters X_s, X_m, and H can be regarded as constant to reduce the number of parameters because they have low sensitivities to the change in the time trajectories. Thus, they can be fixed to their respective values from the IEEE type-6 motor values: 0.094 [pu], 2.8 [pu], and 0.93 [MW·s/MVA], respectively, and then the dimension of the solution space is reduced to seven. We note that these values are determined with the consideration of the chosen base value with the machine rating.

3. Hybrid PSO-Complex-Based Load Model Parameter Identification

3.1 Parameter identification problem for the load model

When taking the prediction-error approach for parameter identification [2], the fitness function is the summation of the squared error between the measured outputs $\{P, Q\}$ of the load and the simulated outputs, with parameters derived from the optimization, $\{P^*, Q^*\}$. The fitness function can be expressed mathematically as follows:

$$f = \sum_{i=1}^{Ns} \frac{1}{2Ns}\left[(P_i - P_i^*)^2 + (Q_i - Q_i^*)^2\right] \quad (8)$$

where N_S is the number of samples. In [6], the simulated active and reactive powers can be obtained by adding together the ZIP and induction motor active powers as well as the reactive power. We note that when the objective function is smaller, better sets of parameters are found.

Various optimization methods had been adopted throughout the years for finding the best solutions for the nonlinear parameter estimation of dynamic systems. Many researchers applied global optimization methods because of the non-convexities of the problems, leading to the issue of multiple local solutions. In addition, the recent trend to improve the reliability of optimization methods for searching is to make hybrids or combinations of search methods in order to obtain synergistic results and minimize the disadvantages of their standard forms.

For parameter identification of the composite load model in [21], PSO was chosen to search the parameter space. The results of that paper showed that the overall optimization process had derived the parameters, and the model there follows the response of the active and reactive powers during a fault when compared with the actual data. However, in the authors' experience, PSO itself cannot capture the exact local optima; therefore, it was expected to further reduce the fitness function by taking another solution procedure from the particles obtained in advance.

When applying PSO or its variants as one of many simulation-based methods, a better approach would be to convert the inequality constraints for the physical limits of the model parameters or for the model's properties into the objective function as the penalty terms. We adopt an extension of the fitness function, in order to avoid divergence in the numerical integration due to the inadequately selected induction parameters outside the feasible solution space. The extended fitness function is

$$\tilde{f} = f + K_1 b_{div} + K_1 b_{\inf} \quad (9)$$

where b_{div} and b_{inf} are the binary variables for the numerical divergence and infeasibility, respectively, and can be either 0 or 1. K_1 and K_2 are the penalty constants for the divergent and infeasible cases, respectively, and they are set for very large values. During the searching procedure, b_{div} is set to 1 for those cases where the trajectories obtained by the numerical integration of the motor dynamics with (3)-(7) diverge. In this paper, a Runge-Kutta 4th-order method is carried out for numerical integration. b_{inf} is set to 1 for those cases where the sum of a_p and b_p or a_q and b_q is greater than 1. In earlier iterations, the initial positions of some particles might be incorrectly selected, and then, the penalty terms can be activated. Using the extended objective function in (9) results in the division of the parameter space into several compartments with boundaries, and this fact may necessitate global optimization methods.

3.2 Application of PSO-complex hybrid

Our purpose is to propose a better searching method for parameter identification of the composite load model. There are possibly two ways to combine PSO and one of local search methods. The first combination simply adds the selected local search procedure after PSO ends. In [22], the NM-simplex method was chosen to further search for the local optimum from the selected particles at the final PSO iteration. The other combination combines local search into the PSO iteration. We take the latter combination as the hybridization scheme with a complex method, which is an advanced form of the simplex method.

PSO is population-based and evolutionary in nature. PSO has memory in terms of the inertia weight, and the social exchange information simulates a commonly observed social behavior, where members of a group tend to follow the lead of the best of the group. Because PSO is simple in concept and economic in computational costs, it has a definite advantage over other evolutionary optimization techniques. Below are the particle position and velocity update equations involved in the PSO process with linearly decreasing inertia weight:

$$V_i^{k+1} = w.V_i^k + C_1.r_1(p^k{}_{pbest} - X_i^k) + C_2.r_2(p_{gbest} - X_i^k) \quad (10)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (11)$$

$$w = w_2 + (w_2 - w_1).(k_{\max} - k)/(k_{\max}) \quad (12)$$

where X_i^{k+1} and X_i^{k+1} are the present and previous particle's positions, respectively. V_i^{k+1} and V_i^k are the present and previous particle's velocities, respectively. C_1 and C_2 are the cognitive and social parameter coefficients, respectively, whereas r_1 and r_2 are random numbers ranging from 0 to 1. $p^k{}_{pbest}$ is the personal-best position of the particle, and p_{gbest} is the global-best position of the group. w_1 and w_2 are the initial and final values of the inertia weight, respectively. $k_{\max}$ is the maximum number of iterations, and k is the present iteration number.

The complex method is another efficient optimization algorithm searching from the initial simplexes for the optimization of either physical processes or mathematical functions [17]. Even though the complex method is a direct method, it does not require the gradients of the objective function for searching. Instead, the complex method operates with the information about the relative response rank associated with control levels. Like the NM-simplex method, the complex method solves the optimization problem by rescaling the original "n"-dimension by creating "n+1" vertex points at each iteration using four basic operations: reflection, expansion, contraction, and shrinkage, with the aim of moving away from the point of worst performance. The flow of these four operations is discussed in detail in [28,29,30].

The need to improve the simplex method and become the complex method is presented in [17]. With the concavity of nonlinear functions, the simplex method may be directed to a less feasible solution space during the reflection and expansion operations. To avoid this dilemma, the complex method was modified by adding condition checking before replacing the worst vertex during the reflection and expansion operations. The new conditions of the complex method compared with the simplex method as applied to a minimization problem are listed in Table 1.

Table 1. Improvement of the simplex method to the complex method

Simplex Method	Complex Method
Reflection	
$f_{re\text{리}} < \Phi[f_{secworst}]$	$f_{refl} < min\ \{\Phi[f_{secworst}], \Phi[f_{secworst}][1\text{-}sign(f_{secworst})\varepsilon]\}$
Expansion	
$f_{exp} < f_{best}$	$f_{exp} < f_{refl} < f_{best}$

In Table 1, f_{refl}, f_{exp}, f_{best}, $f_{secworst}$, and f_{worst} are the objective functions of the reflection, expansion, best, second-worst, and worst points, respectively. For reflection in the complex method, ε represents the tolerance level and was set to 0.001 for the problems presented here. The added condition in the complex method assures that the solution search is directed to a more feasible region within the solution space before accepting the reflection and expansion points.

With the global searching power of PSO and more advanced local search of the complex method, the PSO-complex hybrid method is proposed by incorporating the complex method within the PSO procedure. Specifically, this method is outlined as follows and shown in Fig. 2:

Step 1: Start with the PSO global search. As the group of initial particles is created (40 particles), the position and velocity of each particle are determined and correspondingly updated on the basis of the evaluation of the fitness function. Note that during the first few iterations of PSO, the group-best value is very high owing to the random selection of the initial points.

Step 2: As the iteration progresses, PSO will be able to find a better group-best objective function value. Once it reaches a specified threshold value, the complex local search will be implemented for the top-five particles. During this search, the complex method can maximize its local search power because it started on a more feasible search space initially found by PSO.

Step 3: The complex method will undergo its four basic operations: reflection, expansion, contraction, and shrinkage using n+1 particles, where n is the dimension of the parameter space. Via the complex method, the current location of the particles will be improved by moving away from the point of worst performance.

Step 4: As the complex method improves the group-best value, the (n+1)th particle will be replaced by an improved location. This continues until the complex method reaches its maximum iteration and then proceeds with the next iteration of PSO.

Step 5: The next iteration of PSO will continue its global search and will be coupled with the local search ability of the complex method until the stopping criteria are satisfied for the entire run of the PSO-complex hybrid method.

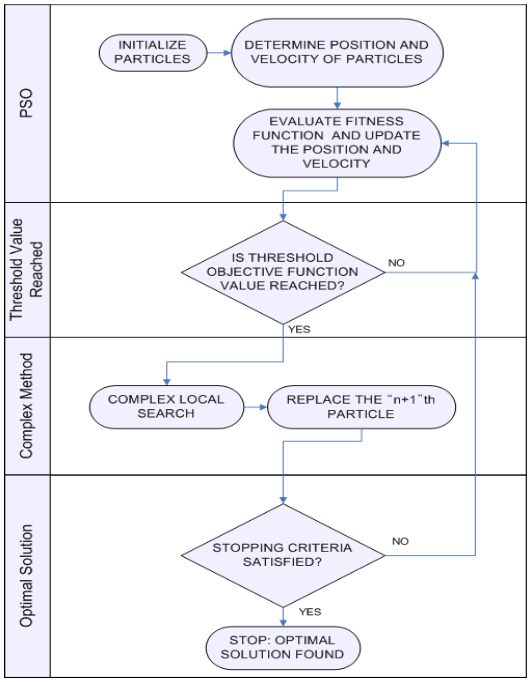

Fig. 2. Flow chart of the PSO-complex hybrid method

The proposed PSO-complex hybrid method aims to produce more satisfactory results. PSO focuses more on the global exploration of the best solution, whereas the complex method uses local exploitation, similar to the simplex method. Therefore, the hybrid method results in a mutual benefit of the two optimization methods; hence, there is a good chance of deriving more precise load model parameters to represent the actual measured active and reactive power responses to a fault.

Unlike the previous optimization hybrids made with PSO, the complex method is integrated within the PSO process before each iteration ends. With this, the hybrid assures that a local optimum search is contributed by the complex method within the location of the best solution found by PSO. This new algorithm yields a better synergistic combination of PSO and the complex method. The global searching power of PSO and better local exploitation ability of the complex method are very well utilized in the algorithm.

Moreover, their disadvantages are also minimized. For PSO, an extended fitness function is provided to avoid searching outside the feasible region. For the complex method, a good starting location for its local search was provided by PSO. The hybrid also promises simpler load model parameter searching by adopting the reduction of load model parameters by omitting the load model parameters with low sensitivity. With this, a more consistent set of parameters are found that can better satisfy the objective function. Therefore, the proposed PSO-complex hybrid method is very helpful for providing more precise load model parameters to represent the load system behavior for power system studies.

4. Numerical Example

In Fig. 3, a trajectory of voltage magnitude samples measured at a substation during a 3-phase short-circuit fault is illustrated, and this sample data is used in this paper to describe the advanced features of the proposed hybrid method. The sampling period was a half of a millisecond.

Fig. 4 and Fig. 5 show the active and reactive powers, respectively, obtained by numerical integration of the original parameter set. Table 2 shows the range of values that limit the search space for the random initial points for the optimization methods. The three parameter estimation methods were applied to find the best set within the range. However, X_s, X_m, and H are fixed to the standard values, as described in Section 2, for the proposed PSO-complex hybrid method. This is done to reduce the number of load model parameters to be searched and to simplify the search process.

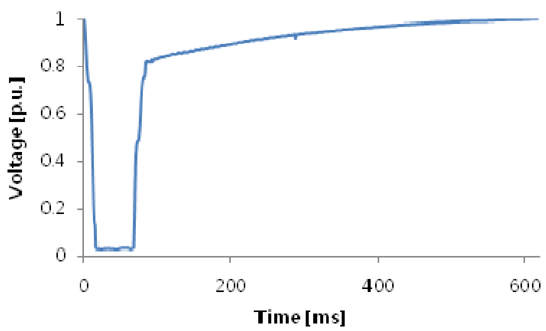

Fig. 3. Trajectory of the voltage magnitude samples

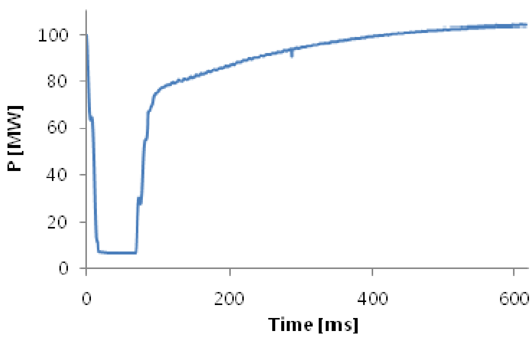

Fig. 4. Trajectory of the active power load

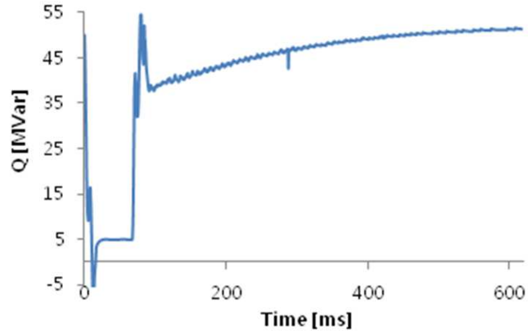

Fig. 5. Trajectory of the reactive power load

Table 2. Range of values for the estimated parameters

Parameters	Range of Values
R_s	0.001 - 0.5
X_s	0.001 - 1.0
X_m	0.001 - 5.0
R_r	0.001 - 0.5
X_r	0.001 - 1.0
a_p	0 - 1.0
H	1 - 5.0
b_p	0 - 1.0
a_q	0 - 1.0
b_q	0 - 1.0

Table 3 lists the parameters used when applying the specified optimization method. The PSO parameters are based on the more generally used values, as in [18-20]. The simplex and complex control parameters are based on [20-23] for the best local searching ability. The estimated parameters resulting from the optimization methods and objective function values obtained by each method are tabulated in Table 4. We note that the parameter sets were chosen on the basis of the best objective function value within 50 runs of each optimization method.

As shown in Table 5, the objective function value was evaluated using the three optimization methods within 50 runs. Because the PSO-complex hybrid method yielded the lowest objective function value (0.0206), it yields the best set of parameters as compared with the other two methods. Further, we find that the average objective function values of the two hybrid methods, PSO-simplex and PSO-complex, are higher than the values for PSO.

Table 3. Parameters for PSO, simplex, and complex

Parameters	Estimated Values
PSO	
W_1 *(Initial Inertia Weight)*	0.9
W_2 *(Final Inertia Weight)*	0.4
c_1 *(Cognitive Parameter)*	2
c_2 *(Social Parameter)*	2
Simplex and Complex	
ρ *(reflection coefficient)*	1
Ψ *(expansion coefficient)*	2
γ *(contraction coefficient)*	0.5
σ *(shrinkage coefficient)*	0.5

Table 4. Load model parameters using the three methods

Param.	PSO-complex	PSO-simplex	PSO
R_s	0.1888	0.3149	0.2447
X_s	0.0841	0.2074	0.1945
X_m	2.5044	2.3960	2.0282
R_r	0.2353	0.2001	0.1450
X_r	0.3275	0.2074	0.1945
H	1.0398	1.3201	1.3135
a_p	0.5821	0.6454	0.4362
b_p	0.3019	0.1691	0.4904
c_p	0.1160	0.1855	0.0733
a_q	0.3173	0.1380	0.0698
b_q	0.0758	0.2898	0.4624
c_q	0.5723	0.5723	0.5723

The main advantage of the two hybrid methods is the addition of local optimum search. More importantly, the PSO-complex hybrid method yields the lowest average objective function (0.0483) within fifty independent runs. Moreover, we find that more consistent values for each parameter are obtained in each run of the PSO-complex hybrid method compared to the values for the other two optimization methods.

Table 5. Objective function values for 50 runs by the three methods

	Standard Deviation	Average Obj. Function
PSO	0.0341	0.0584
PSO-Simplex	0.0329	0.0523
PSO-Complex	0.0206	0.0483

These results show better performance for the proposed PSO-complex hybrid method as compared to the other two optimization methods. This is attributed to the better local search ability of the complex method that was incorporated within the powerful global-search power of PSO, improved algorithm of the hybrid, and reduction in the number of parameters for our dynamic load model.

To further show the effectiveness of the PSO-complex hybrid method, time series for the active and reactive powers obtained with the best load model parameters were compared with those of the sample data, as shown in Fig. 6 and Fig. 7.

The time-series waveform of the response of active and reactive powers using the PSO-complex hybrid method derived parameters matches the waveform of the measured sample data showing the load response during a disturbance. This simply implies that the PSO-complex hybrid method successfully determined the load model parameters to represent the behavior of the load in terms of the responses to the fault. Hence, the proposed hybrid method can be a very useful tool for determining the load model parameters for power systems stability studies.

PSO has shown itself to be a very powerful optimization tool, and the objective function was improved and yielded a better chance of finding the best set of parameters for the load model with the hybridization of PSO with simplex in [18, 21-22]. With the previous studies cited to affirm the effectiveness of PSO and the improved conditions afforded by the complex method compared to the simplex method, the PSO-complex hybrid method justifiably shows the best performance for load model parameter searching among the two methods.

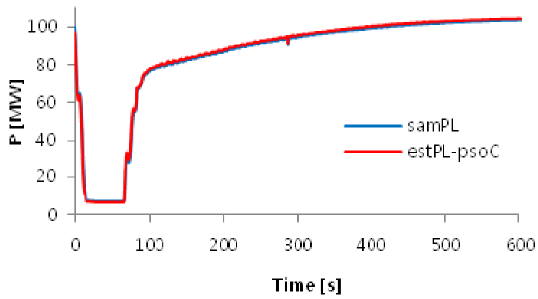

Fig. 6. Active power sample data vs. estimated active power (using PSO-complex derived parameters)

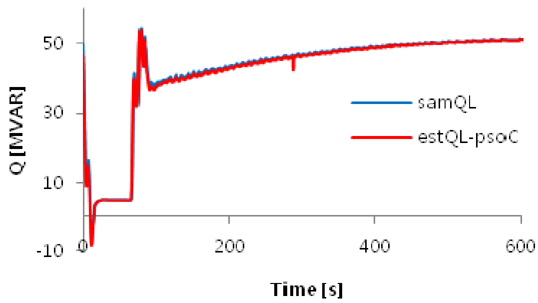

Fig. 7. Reactive power sample data vs. estimated reactive power (using PSO-Complex derived parameters)

5. Conclusion

This paper presents the application of a hybrid PSO-complex method for determining the parameters of a composite load model. The method explores the parameter space using the standard PSO initially, but after the objective function reaches a threshold value, the complex method is employed to replace the worst selected particle to aggressively search around the particle. Through a comparison with two other simulation-based methods, the proposed algorithm successfully and effectively determined the load model parameters and adequately depicted the behavior of load change during disturbances.

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