Computers and Electrical Engineering 81 (2020) 106547

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Improved football game optimization for state estimation and power quality enhancement☆

Shanmugapriya Subramaniyan*, Jegatheesan Ramiah

Department of Electrical and Electronics Engineering, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, Tamil Nadu, India

ARTICLE INFO

Article history:
Received 4 October 2019
Revised 27 December 2019
Accepted 27 December 2019
Available online 6 January 2020

Keywords:
Football game optimization
State estimation
Power quality
Hybrid active power filter
Harmonic distortion

ABSTRACT

Football game optimization (FGO) is a swarm-intelligence-based optimization technique, inspired from the behaviour of football players in finding the best positions with a view of scoring a goal while playing the game. FGO considers only the good players, without accounting the behaviour of offensive players who may cause injuries to other players. This paper presents an improved FGO (IFGO) for enhancing the robustness of the FGO by considering the influence of offensive players and studies the performance of IFGO on two diversified problems. The former one is the static state estimation problem of processing the real-time measurements and providing required database for security control and management of power systems, while the latter one is the optimal design of hybrid active power filter for enhancing the power quality of the system supplying harmonic load. The simulation results on standard test problems exhibit the superiority of the developed IFGO.

1. Introduction

Classical optimization algorithms are in use for solving engineering optimization problems, but they require the problem to be reconstructed to a specific format of objective and constraint functions, which is difficult in many cases. Besides, they find difficulty in handling discontinuous and non-differentiable objective and constraint functions, and suffer from poor convergence on ill-conditioned systems.

Recently, evolutionary algorithms, such as simulated annealing, genetic algorithm, particle swarm optimization (PSO), artificial bee colony (ABC), ant colony, bacterial foraging, gravitational search, biogeography, teaching-learning, shuffled frog leaping, black-hole, grenade explosion, flower pollination, stud krill, dragonfly, glow worm, grey-wolf, bat, moth swarm and imperialist competitive algorithm, have been widely employed in solving different kinds of optimization problems in order to overcome the drawbacks of classical approaches in all engineering fields. These approaches require only the evaluation of the cost function to explore the problem space in finding the optimal solution, unlike the traditional algorithms that require the derivative information. They are well known to be highly inefficient taking large computations, thereby making them unsuitable for real-time applications. However, in recent years, the exponentially increasing speed of computers and the advent of parallel processing create an avenue for overcoming the computational inefficiency of the evolutionary algorithms.

☆ This paper is for regular issues of CAEE. Reviews processed and recommended for publication to the Editor-in-Chief by Associate Editor Dr. S. Smys.

* Corresponding author.
E-mail address: shanmugs4@srmist.edu.in (S. Subramaniyan).

https://doi.org/10.1016/j.compeleceng.2019.106547
0045-7906/© 2019 Published by Elsevier Ltd.

The prime requirement of any optimization algorithm is to obtain the global best solution with minimum computational efforts even for larger, nonlinear and complex problems [1].

More recently, Fadakar and Ebrahimi proposed a football game optimization (FGO), belonging to the family of evolutionary algorithms, for solving real-world problems and portrayed the algorithm to be superior to existing evolutionary algorithms such as PSO, ABC, and so on in [2]. The superior performances of FGO on various test functions have motivated the authors to choose this algorithm for further improvisation and application in power system problems.

FGO is inspired from the behaviour of football players in finding the best positions with a view of scoring a goal while playing the game under the guidance of a team coach. This algorithm considers only the good players without accounting the influence of offensive players who may cause injuries to other players. In this paper, an improved FGO (IFGO) has been proposed by considering the behaviour of offensive players for enhancing the robustness of FGO, and studied on two diversified optimization problems in the area of power systems with a view of exhibiting its numerical stability and robustness. The first problem is the static state estimation (SE) problem and the second one is the optimal design of hybrid active power filter (HAPF) for power quality (PQ) enhancement.

The paper is divided into eight sections. Section 2 presents the static SE; Section 3 briefs HAPF; Section 4 proposes IFGO; Section 5 explains IFGO based SE; Section 6 describes IFGO based optimal design of HAPF; Section 7 discusses the simulation results; and Section 8 concludes.

2. Static state estimation

SE is an important tool for processing real-time noisy measurements such as real and reactive loads and generations at various buses, line flows, voltage magnitudes, and status of circuit breakers, and providing a reliable, coherent and complete database at frequent intervals to energy management systems for effective monitoring and control. The weighted least square (WLS) approaches have been widely used for SE but found to be numerically unstable and not robust. Weighted least absolute value (WLAV) approaches have been developed and solved as a linear programming (LP) problem to circumvent the drawbacks of WLS approaches but known to be computationally inefficient, thereby making them unsuitable for real-time applications [3]. The decoupling concept has been applied to both WLS and WLAV approaches to improve the computational speed [4]. Still the convergence of decoupled versions has been influenced by the branch reactance to resistance ratio and system loading levels and may become oscillatory, thereby failing to perform estimation [5].

Jabr [6] presented an iteratively reweighted least square scheme with a view of avoiding LP iterations in WLAV procedure. Aravindhababu et al. [5] suggested a reliable and fast decoupled SE considering only the line flows and bus voltage magnitudes as measurements without involving any key assumptions. Jabr and Pal [7] explained a least absolute value state estimator involving modified equations comprising first- and second-order derivatives and scaling techniques. Overbye et al. [8] suggested a method that matches the load flow solution with the available PMU data. Dhadbanjan and Vanjari [9] proposed an iteratively reweighted least square procedure involving LP for SE. Zima-Bockjova et al. [10] suggested a scheme involving modified measurement set with an objective of lowering the weighted integrals under specified time duration.

Zhang et al. [11] developed a Kalman-filter based method for performing static SE besides estimating dynamic states of the rotor angles and speeds of the generators. Muscas et al. [12] studied the significance of correlation between actual and pseudo measurements on WLS approach in distribution systems. Gu and Jirutitijaroen [13] proposed a power system dynamic SE problem involving extended Kalman filter integrated with load forecasting with a view of enhancing the estimation accuracy. Risso et al. [14] presented a SE strategy that integrates the ‘unscented’ Kalman filter and the WLS. Zhao et al. [15] proposed a PMU-based SE scheme, wherein the weights are adjusted based on the distance of the largest disturbance from the PMU, and studied under dissimilar operating conditions. Sivan et al. [16] introduced a maximum likelihood method for blind estimation of states and topology in power systems, by formulating the problem as a graph blind source separation with a Laplacian mixing matrix, and illustrated that the suggested strategy succeeds in reconstructing the topology and estimating the states. The IEEE task force on power system dynamic state and parameter estimation presented the similarities and differences between dynamic SE and other existing estimation methods such as forecasting aided SE, tracking SE and static SE, and discussed the potential applications on enhanced monitoring, protection and control [17].

2.1. Problem formulation

The prime objective of SE is to estimate the system state by processing a set of measurements,z, whose error components are represented by an error vector,e. The set of nonlinear equation $g(x)$ that relate the measurements with the true state vector x as:

$$z = g(x) + e \tag{1}$$

The goal of SE can be realized by employing WLS or WLAV criterions [3]. Both the solution approaches require formation of Jacobian matrix comprising derivative information. The following sub-sections outline the WLS and WLAV criterions.

2.1.1. WLS criterion

In the WLS criterion, the objective function is formed by minimizing the sum of squares of weighted deviations of estimated measurements from actual measurements as

$$\text{Minimize} \quad J = [z - g(x)]^T W \, [z - g(x)] \tag{2}$$

where W represents diagonal matrix containing weight values of measurements.

Differentiating J partially with respect to x and equating the resulting equation to zero gives

$$\frac{\partial J}{\partial x} = G^T W \, \Delta z = 0 \tag{3}$$

where $G = \frac{\partial g(x)}{\partial x}$ and $\Delta z = z - g(x)$.

Employing Taylor series expansion of Eq. (3) and ignoring the higher-order derivative terms yield

$$(G^T W \, G) \Delta x = G^T W \, \Delta z \tag{4}$$

Eq. (4) is solved for the state correction vector Δx and the state vector x is updated by $(x = x + \Delta x)$ iteratively, until Δx is less than a small tolerance value. The inverse or factorization of the gain matrix $(G^T W G)$ involving large computations and the assignment of very large weight values for good measurements and very small weight values for unreliable measurements may cause convergence problems. Besides, if any one of the good measurements becomes bad, the approach may not yield reliable estimate as the objective function also attempts to minimize square of deviation of the bad measurement from its estimated component, thereby requiring some kind of bad data detection and identification procedures. Because of these problems, the WLS is not considered as a stable and robust algorithm.

2.1.2. WLAV criterion

In the WLAV criterion, the objective function is formed by minimizing the sum of absolute values of weighted deviations of estimated measurements from actual measurements as

$$\text{Minimize} \quad J = [diag(W)]^T |z - g(x)| \tag{5}$$

Eq. (5) can be combined with Eq. (1) and tailored as LP problem as

$$\text{Minimize} \quad J = [diag(W)]^T \left[e' + e''\right] \tag{6}$$

subject to

$$G \, \Delta x + e' - e'' = \Delta z \tag{7}$$

$$e', \; e'' \; \geq \; 0 \tag{8}$$

where e' and e'' are slack variables and relates e by $(e = e' - e'')$.

The above problem can be solved for Δx by employing LP technique, and the state vector x is updated by $(x = x + \Delta x)$ iteratively, until Δx is less than a small tolerance value. The LP selects a set of good measurements, whose size equals the number of state variables, from the available measurements and offers the estimate that exactly satisfies the chosen measurements. If any of the good measurements becomes bad all of a sudden, the LP attempts to consider that measurement at the beginning of the iterations and rejects it automatically in the subsequent iterations. Besides, it admits assignment of wide range of weight values for measurements. Because of these features, the algorithm is said to be robust and stable. But the LP process requires large computation time, thereby making it unsuitable for real-time applications.

3. Hybrid active power filter

The PQ issues may be caused by the power-electronic loads and/or by the power system itself [18]. Extensive research has been carried out, and several strategies to reduce current harmonics have been suggested, developed and commercialized in recent decades. A few of them increase the tolerance of existing electric devices to withstand harmonic currents such as K-rated transformers, and increased cross-section of neutral conductors [19], which are designed to operate normally even in the presence of significant harmonic distortions in the source voltage. The others counteract or suppress the harmonic disturbances through power electronics-based converters such as multi-pulse rectifiers, active front-end converters and power filters. Among them, the power filters are very popular and classified into passive power filters (PPF), shunt active power filters (SAPF) and HAPFs.

The PPF eliminates selective harmonic components, while the SAPF attempts to generally minimize the total harmonic distortion (THD) and may not eliminate selective harmonic components. The HAPF eliminates the selective harmonics besides minimizing the overall THD. Turunen et al. [20] extensively overviewed the various topological structures of HAPFs. Sahithullah et al. [21] outlined the classical design procedure of SAPF, formulated the design procedure

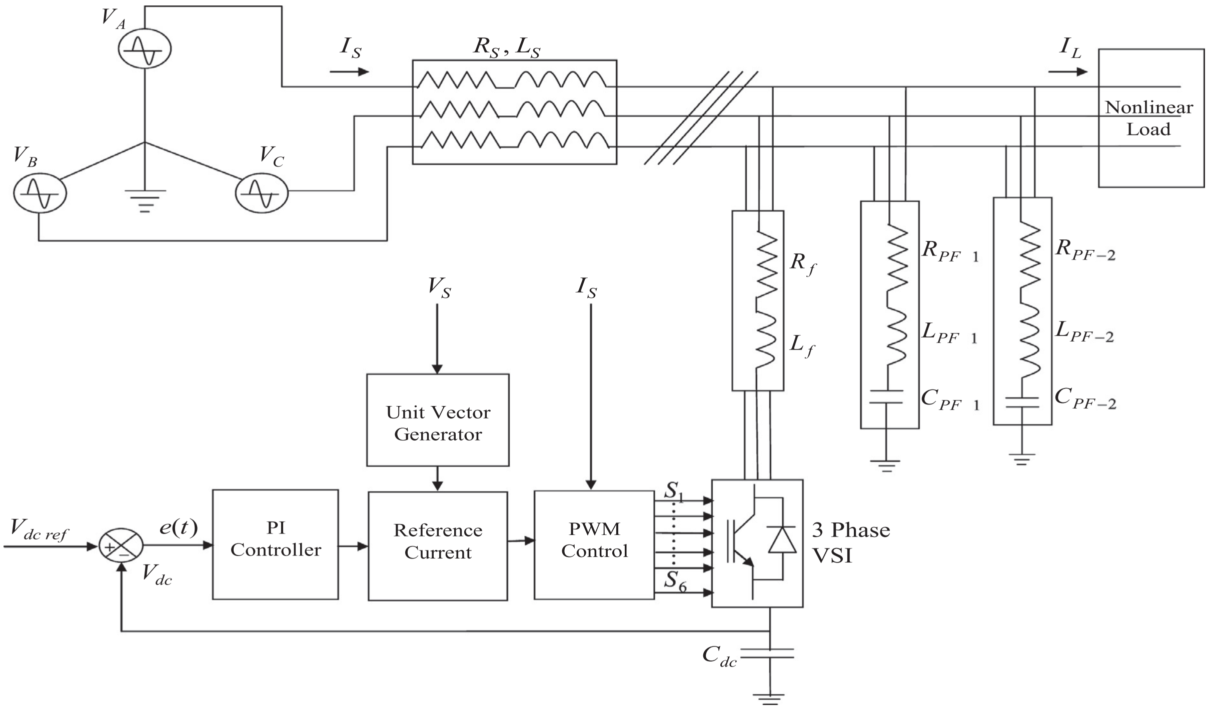

Fig. 1. Schematic of hybrid active power filter.

as an optimization problem with an objective of minimizing the THD and solved it using enhanced firefly optimization. Shixi et al. [22] proposed an indirect adaptive fuzzy global sliding mode control method for single-phase SAPF with a view of providing good robustness against unknown disturbances and parameter perturbations. Hua et al. [23] suggested a fast repetitive control scheme with cumulative error cancellation and harmonic correction loops for the SAPF in balanced three-phase three-wire system with a view of improving the performance in weak grid situation. Bachar et al. [24] proposed the use of the predictive strategy concept to improve the active power filter performance by compensation of the reactive power and elimination of the harmonic currents generated by non-linear loads, and exhibited that the proposed method reduced the number of sensors, system size and cost. The schematic of HAPF is shown in Fig. 1.

Many of the traditional design approaches of HAPF do not use optimization algorithms and do not offer global best design parameters. The effective functioning of HAPF depends on the extraction procedure of reference signals from source and load currents and voltages, and the dynamic behaviour of chosen controllers, which require perfect mathematical models. The changes in parameters, transient disturbances at load side, nonlinear behaviour, and so on will also deteriorate the performance of the HAPF. The controller parameters of HAPF are most commonly adjusted by a trial and error approach, which may not offer the best possible performances.

4. Proposed meta-heuristic optimization algorithm

4.1. Football game optimization

FGO is a population-based algorithm, inspired from the behaviour of football players, for solving optimization problems. It initially requires random formation of a team, wherein the position of each player represents a solution point and its goodness is assessed by a cost function. The players randomly move besides following the guidance given by the team coach in taking the ball and scoring a goal. The movements of the players are performed in two phases.

4.1.1. Phase-1: Random walk

Each player performs random walk (searching) in finding a better position and also moves towards the ball in the football pitch (solution space) with a view of receiving the ball and attempting to score a goal (finding the global best solution). The players at good positions have a better chance of taking the ball. The player possessing the ball randomly passes it to players with better positions (lower cost function values). The usual movement of the i th player towards the ball without the guidance of the coach is performed by

$$P_i^t = P_i^{t-1} + \alpha_i \, \beta + \gamma \, \left(P_{Ball}^t - P_i^{t-1}\right) \tag{9}$$

where

P_i^t represents the position of i th player, who has the ball at time t.
β and γ are uniformly distributed random numbers in the range of [−1,1] and [0,1], respectively.
α_i is the step size, which is gradually decreased during iteration by $\alpha_i = \alpha_o\theta$, as the team is progressing towards scoring a goal.
θ is a reduction constant in the range of [0,1]
P_{Ball}^t represents the position of the player who has the ball at time t.

4.1.2. Phase-2: coaching

The team coach studies the movement of the players and memorizes the best positions along with their cost function value (CFV) in his memory, whose size will be smaller than the team size. He applies two strategies, attacking and substitution strategies, for improving the chance of obtaining a goal through local search.

In attacking strategy, the team coach uses the best positions stored in his memory in guiding and encouraging the defenders and midfielders to move forward, and raises the pressure of the opponent team. In this regard, the hyper distance (HD) between the positions of i th player, P_i^{t-1}, and the best players, P_{best}^{t-1}, is calculated by the following equation.

$$HD_i = \left\| P_i^{t-1} - P_{best}^{t-1} \right\| \tag{10}$$

A larger HD represents an inferior position far away from the best position and vice-versa. A HD limit ($\Re$) is chosen to find the inferior positions of the players. The players possessing larger HD values than $\Re$ are pushed towards the nearest best positions, $P_{nearest-best}^{t-1}$, by the following equation:

$$P_i^t = P_{nearest-best}^{t-1} + \alpha_i \, \beta \tag{11}$$

$\Re$ is gradually reduced towards its chosen lowest value ($\Re_{\min}$) during iterations by the following equation.

$$\Re^t = \Re_{\min} + \eta(\Re^{t-1} - \Re_{\min}) \tag{12}$$

where η is a reduction constant in the range of (0, 1).

In substitution strategy, the coach replaces weaker players by better strikers with a view of improving the probability of scoring a goal. Each player in the team possessing larger CFV than cost limitation value ($\Im$) are replaced by a neighbouring best solution according to coach memory (CM) using Eq. (11). $\Im$ is gradually decreased as the iteration proceeds by the following equation.

$$\Im^t = \Im_{\min} + \lambda(\Im^{t-1} - \Im_{\min}) \tag{13}$$

where λ is an accession constant similar to η.

If the resulting position of player is located outside of the football pitch, the player is relocated closer to the nearest best position by Eq. (11). These strategies are repeatedly applied till the team scores a goal. The pseudo-code of this algorithm is available in [2].

4.2. Improved FGO (IFGO)

Although FGO is a robust algorithm, it may land at sub-optimal solutions and converge slowly. The FGO requires improvisation to avoid the suboptimal solutions and enhance the convergence. This sub-section proposes an improvisation mechanism, inspired from the behaviour of players in avoiding the nearest offensive player, who may cause injury to other players while playing. The physical hit of the offensive player on other players may throw them on ground and the resulting injuries can lower the performance of the players. The proposed mechanism attempts to increase the HD between the players and the nearest offensive player by the following equation.

$$P_i^t = P_i^{t-1} + \sigma \; e^{\psi} \tag{14}$$

where ψ represents HD between the i th player and the nearest offensive player, and σ is an offensive factor in the range of (0,1).

The above technique aids the players to get away from the offensive players in the football pitch, thereby improving the exploration and helps the team to score a goal quickly.

5. Proposed IFGO based SE

5.1. Estimation

The SE employing IFGO involves representation of players in terms of problem variables and formation of a cost function. In this approach, the state correction vector (Δx) is considered as problem variables. The position of each player is therefore considered to represent the state correction vector of the SE problem as

$$\begin{aligned} P_i &= [P_{i,1},\ P_{i,2},\ \cdots,\cdots,\cdots,\cdots,\cdots,\cdots,\cdots\ \ ,P_{i,ns}] \\ &= [\Delta\delta_2,\ \Delta\delta_3,\ \cdots\ ,\ \Delta\delta_{nb},\ \Delta V_1,\ \Delta V_2,\ \cdots\ ,\ \Delta V_{nb}] \end{aligned} \tag{15}$$

The lower and upper bounds of the players' position is limited by the following constraints.

$$-\Delta\delta^{limit} \leq \Delta\delta \leq \Delta\delta^{limit} \tag{16}$$

$$-\Delta V^{limit} \leq \Delta V \leq \Delta V^{limit} \tag{17}$$

Treating state correction vector (Δx) as the problem variable, the cost functions can be written in terms of player's position from Eqs. (2) and (5) as follows:

$$\text{Minimize} \quad J = [z - g(x_o + \Delta x)]^T W\ [z - g(x_o + \Delta x)] \tag{18}$$

$$\text{Minimize} \quad J = [diag(W)]^T |z - g(x_o + \Delta x)| \tag{19}$$

where x_o is vector of previously estimated system state.

The goodness of the position of the players can be assessed by their CFVs. In this problem, the objective function of Eq. (18) or Eq. (19) is considered as the cost function depending on the chosen WLS or WLAV criterion. The CFV is calculated for each player by substituting player's position in the cost function.

5.2. Detection and identification of bad measurements

The presence of bad measurements can be detected and identified by the following procedure:

1. The maximum tolerable error of each measuring unit is fixed and the maximum objective function value for these errors can be calculated by

$$J^{max} = [E]^T W\ [E] \qquad \text{for WLS objective function} \tag{20}$$

$$J^{max} = [diag(W)]^T |E\ | \quad \text{for WLAV objective function} \tag{21}$$

   where E is the vector of maximum tolerable errors. J^{max} should be calculated only once for a given power system with a set of measurements.
2. The presence of bad measurements is detected first by evaluating the objective function value (J) by substituting the estimated system state in Eq. (2) or Eq. (5) and comparing with J^{max}. If J is less thanJ^{max}, there is no presence of bad measurements and the estimated system state is considered as the actual system state; else, the presence of one or more bad measurements is detected.
3. Once the presence of bad measurement is detected, the bad measurement must be identified by computing the weighted error component (WEC) of $\{\ W_i\ [z_i\ -\ g_i(x_o\ +\ \Delta x)]^2\}$ or $\{\ W_i\ |z_i\ -\ g_i(x_o\ +\ \Delta x)|\}$ for all the measurements, and the measurement with largest WEC is identified as the bad measurement. The identified bad measurement is discarded and J^{max} is recalculated accordingly. The SE is again performed, and steps (2) and (3) are repeated till $J < J^{max}$.

5.3. Solution process

An initial team of players is generated by producing random values within their respective limits of Eqs. (16) and (17). The CFVs of all the players are computed either by Eq. (18) or by Eq. (19) and the players are ranked based on the CFVs. A set of best players' positions are saved in the CM. The HDs of all the players with the best player are then evaluated. Comparing the CFVs and HDs with their respective limits, all the players in the team are moved by either Eq. (9) or Eq. (11), or replaced by neighbouring best positions. The players are then probabilistically moved away from the nearest offensive players by Eq. (14). This process represents an iteration, which is continued for a specified number of iterations and the best player's position at the end of convergence is taken as the optimal state correction vector. The state vector can be obtained by updating the state vector by($x = x_o + \Delta x$). Then the procedure, explained in Section 5.2, for detection and identification of bad measurements is performed and SE process is repeated after removal of bad measurements if the presence of bad measurements is detected. The flow of the proposed SE method (PSEM) is shown in Fig. 2.

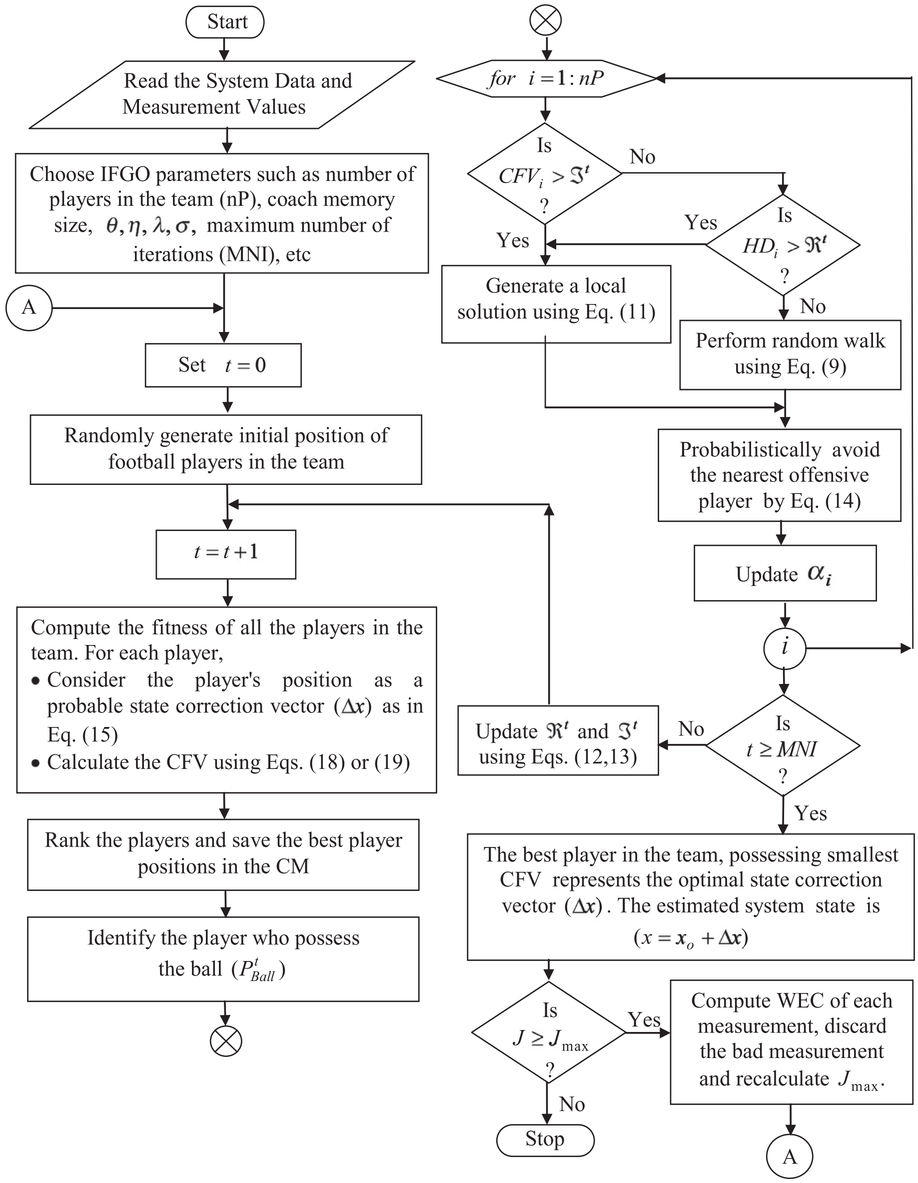

Fig. 2. Flow chart of the proposed state estimation method.

6. Proposed IFGO-based design of HAPF

The problem of designing HAPF can be tailored as an optimization problem with a goal of maximizing the PQ by choosing appropriate design parameters. The IFGO-based design procedure requires definition of problem variables as position of players and development of a procedure for evaluating CFV. The design parameters of the HAPF are identified as $V_{dc,ref}$, K_p, K_i, R_f, R_{PF-1}, R_{PF-2}, L_f, L_{PF-1}, L_{PF-2}, C_{dc}, C_{PF-1} and C_{PF-2}. The position of each player is therefore considered to represent the design parameters as

$$P_i = \left[V_{dc,ref},\ K_p,\ K_i,\ R_f,\ R_{PF-1},\ R_{PF-2},\ L_f,\ L_{PF-1},\ L_{PF-2},\ C_{dc},\ C_{PF-1},\ C_{PF-2}\right] \tag{22}$$

The goodness of each player in the team is obtained by setting the player's position as design parameters of HAPF and the simulation is performed with nonlinear load, and the resulting THD is computed and considered as CFV in the proposed approach.

An initial team of players is randomly generated and their CFVs are calculated by performing simulations of the HAPF with nonlinear load. Comparing the CFVs and HDs with their respective limits, all the players in the team are moved or replaced by neighbouring best positions. This process is continued for a specified number of iterations and the best player's

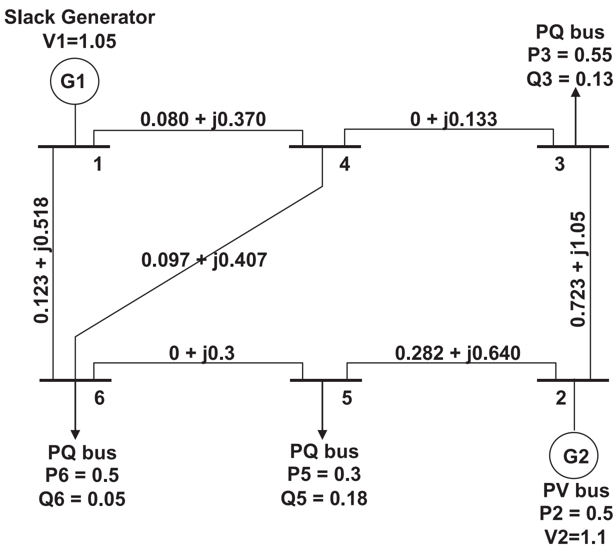

Fig. 3. IEEE six-bus test system.

position at the end of convergence is taken as the optimal design parameter of HAPF. The pseudo code of the suggested scheme for optimal design of HAPF is furnished below:

Obtain the HAPF data such as load values, resistance and reactance of the line, source voltage detail, etc.
Select IFGO parameters such as number of players in the team (nP), coach memory size, θ, η, λ, σ, maximum number of iterations (MNI), etc
Generate initial population comprising of nP-players
For each player in the team,
- *Consider the player's position as design parameters of HAPF*
- *Run the Simulink model with the design parameters*
- *Calculate the THD, and set the THD as CFV*

Rank the players based on CFVs and save the best player positions in the CM
Find the player who has the ball (P^t_{Ball})
➢ *While not converged, Repeat*
- *For each player,*
  - *Consider the player's position as design parameters of HAPF.*
  - *Run the Simulink model with the design parameters.*
  - *Calculate the THD, and set the THD as CFV.*
- *Perform an iteration by performing the following for all the players in the team.*
  - *if ($CFV_i > \Im^t$ or $HD_i > \Re^t$), generate a local solution using Eq. (11), else perform random walk using Eq. (9).*
  - *Probabilistically avoid the nearest offensive player by Eq. (14).*
  - *Update α_i*
  - *Update $\Re^t$ and $\Im^t$ using Eqs. (12) and (13).*

➢ *end*
The best player in the team, possessing smallest CFV represents the optimal design parameters of HAPF.

7. Simulation results

7.1. State estimation (SE)

The PSEM has been studied on IEEE 6-, 14-, 30- and 57-bus test systems, whose data have been taken from [25]. The one-line diagram of six-bus system with load data is shown in Fig. 3. The real and reactive line flows, and real and reactive bus powers and voltage magnitudes are calculated at the end of power flow analysis, and measurement values are obtained by adding low noise to these calculated values. A few of them are so selected to ensure that the system is observable and used as a measurement set. The type of measurements, the metre locations and their measurement values for six-bus system are furnished in Table 1. The first column of the table indicates the type of measurement, the second one represents the metre locations and the last column contains the metre readings representing the measurement set. The PSEM is then performed with this measurement set, by considering either WLS or WLAV objective, one at a time. The previously estimated system state has been assumed to be 1.0 per unit for voltage magnitudes and 0 radians for voltage angles. The results are compared with true system state for validation. Besides the results are also obtained by the WLS, WLAV, PSO and ABC approaches for portraying the superiority of the developed method. The cost function, given by Eq. (18), is employed in both PSO and ABC approaches.

Table 1
Measurement set for six-bus system.

Type of measurement	Location	Measurement values (p.u)
Real bus-power	Bus-1	0.961
	Bus-2	0.495
	Bus-3	−0.558
	Bus-4	−0.000
	Bus-5	−0.301
	Bus-6	−0.495
Real line flow	Line 2	0.437
	Line-4	0.312
	Line-6	0.100
Reactive bus-power	Bus-1	0.314
	Bus-2	0.200
	Bus-3	−0.129
	Bus-4	0.000
	Bus-5	−0.181
	Bus-6	−0.049
Reactive line flow	Line-2	0.138
	Line-4	0.163
	Line-6	−0.055
Voltage magnitude	Bus-1	1.073
	Bus-3	0.957
	Bus-5	0.935

The estimated system state, obtained by all the methods, along with true system state for six-bus system without bad measurements is presented in Table 2. The results of the PSEM are very similar to the classical WLS and WLAV methods. It is very clear that the difference between the respective estimated and true values are very small, thereby inferring that the developed method is accurate enough to perform SE. But the PSO and ABC approaches offer inferior results while comparing with the true system state. Visual comparison of two sets of values may not yield quantitative results. In order to quantitatively measure the accuracy of the developed method, the following performance indices for voltage magnitudes and angles are calculated and furnished in Table 3.

$$\Delta V_{rms} = \sqrt{\frac{1}{nb}\sum_{i}^{nb}\left(V_i^t - V_i\right)^2} \tag{25}$$

$$\Delta \delta_{rms} = \sqrt{\frac{1}{nb}\sum_{i}^{nb}\left(\delta_i^t - \delta_i\right)^2} \tag{26}$$

The detailed results for 14-, 30- and 57-bus systems are not included in this article but the performance indices ΔV_{rms} and $\Delta\delta_{rms}$ are calculated for all the methods and included in Table 3. It is very clear that the r.m.s. error components of the PSEM are lower than those of the existing approaches for all test systems. It can be inferred that the PSO and ABC approaches offer inferior results.

To study the performance of the developed algorithms with bad measurements, three measurements are randomly chosen and altered as bad measurements by setting them as zero for 57-bus test system. The developed algorithms are then applied on the measurement set with bad measurements and the performance indices ΔV_{rms} and $\Delta\delta_{rms}$ are calculated from the estimated system state. The calculated performance indices are graphically displayed in Figs. 4 and 5, which clearly indicate that ΔV_{rms} and $\Delta\delta_{rms}$ of the PSEM with WLS and WLAV objectives are comparatively lower than the existing methods. For example, ΔV_{rms} of the PSEM with WLS and WLAV objectives is 0.000199 and 0.0001 respectively for a set of measurements without bad ones. The inclusion of bad measurements degrades the estimate of the PSEM by increasing ΔV_{rms} to 0.000427 and 0.000419 respectively for WLS and WLAV objectives. The rise in the ΔV_{rms} values after inclusion of bad measurements is so small and comparatively lower than those of WLS, WLAV, PSO and ABC methods. This study clearly exhibits that the PSEM method is able to effectively estimate the system state by rejecting the bad measurements, thereby portraying it as a robust algorithm.

7.2. Optimal design of HAPF

The proposed design method (PDM) involving IFGO has been studied in designing a HAPF for a 3Φ, 415 Vs AC system-feeding rectifier with RL load in MATLAB environment. The same HAPF has also been designed using PSO and ABC besides employing PDM for studying the performance in terms of improvement in PQ, and the obtained design parameters have been compared in Table 4. The source voltage, load current, active filter current and the source current waveforms of the chosen system are shown in Fig. 6. It is seen from the figure that the source voltage (Fig. 6(a)) is purely sinusoidal but the load current (Fig. 6(b)) is non-sinusoidal due to nonlinear nature of rectifier load. If no active filter is connected, the source

Table 2
Comparison of results for six-bus system without bad measurements.

Bus-no.	PSEM with WLS objective		Classical WLS method		PSEM with WLAV objective		Classical WLAV method		PSO method		ABC method		True system state	
	VM	VA	VM	VA	VM	VA	VM	VA	VM	VA	VM	VA	VM	VA
1	1.048	0.000	1.040	0.000	1.050	0.000	1.039	0.000	1.076	0.000	1.052	0.000	1.050	0.000
2	1.087	−0.062	1.080	−0.053	1.086	−0.062	1.080	−0.058	1.105	−0.047	1.091	−0.063	1.086	−0.063
3	0.941	−0.227	0.933	−0.225	0.941	−0.228	0.931	−0.225	0.970	−0.210	0.944	−0.234	0.942	−0.229
4	0.960	−0.171	0.953	−0.170	0.961	−0.171	0.951	−0.170	0.989	−0.159	0.963	−0.176	0.961	−0.172
5	0.920	−0.219	0.911	−0.218	0.918	−0.218	0.910	−0.218	0.937	−0.204	0.919	−0.221	0.918	−0.219
6	0.946	−0.214	0.937	−0.213	0.945	−0.213	0.936	−0.215	0.970	−0.203	0.946	−0.218	0.945	−0.214

Table 3
Comparison of performance indices without bad measurements.

Test system	Index	PSEM with WLS objective	Classical WLS method	PSEM with WLAV objective	Classical WLAV method	PSO method	ABC method
6 bus	ΔV_{rms}	0.000828	0.004350	0.000669	0.002550	0.013456	0.003314
	$\Delta \delta_{rms}$	0.001185	0.008176	0.000339	0.009094	0.024619	0.002657
14 bus	ΔV_{rms}	0.000358	0.000680	0.000453	0.002277	0.001212	0.000671
	$\Delta \delta_{rms}$	0.000566	0.001679	0.000801	0.000699	0.002781	0.001603
30 bus	ΔV_{rms}	0.000258	0.000540	0.000374	0.000665	0.001742	0.000490
	$\Delta \delta_{rms}$	0.001475	0.001378	0.001434	0.001124	0.008463	0.001282
57 bus	ΔV_{rms}	0.000199	0.001888	0.000100	0.001658	0.009077	0.001863
	$\Delta \delta_{rms}$	0.000873	0.000980	0.000726	0.001545	0.008191	0.000967

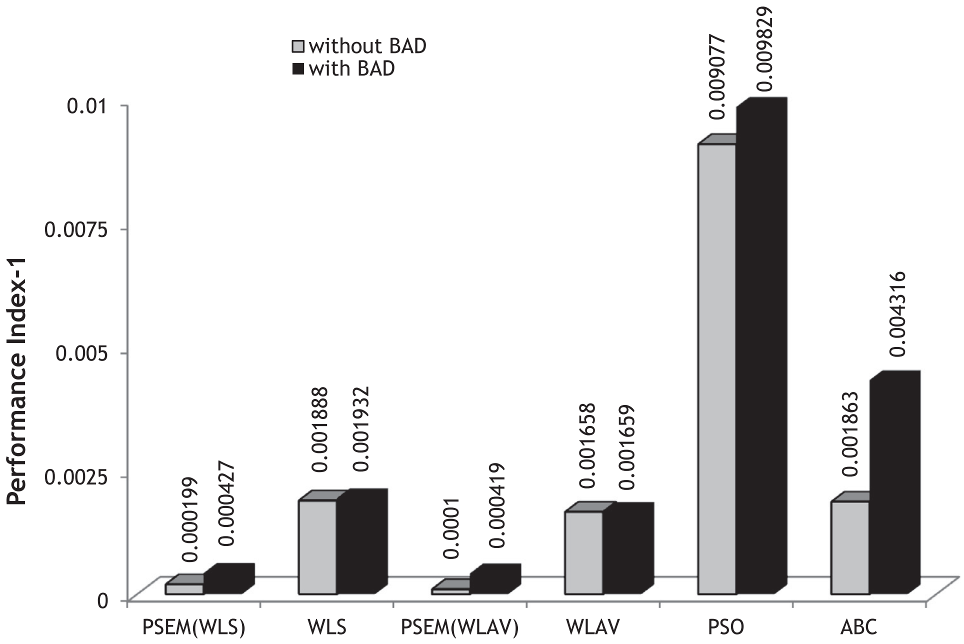

Fig. 4. ΔV_{rms} of different methods for 57-bus system with and without bad measurements.

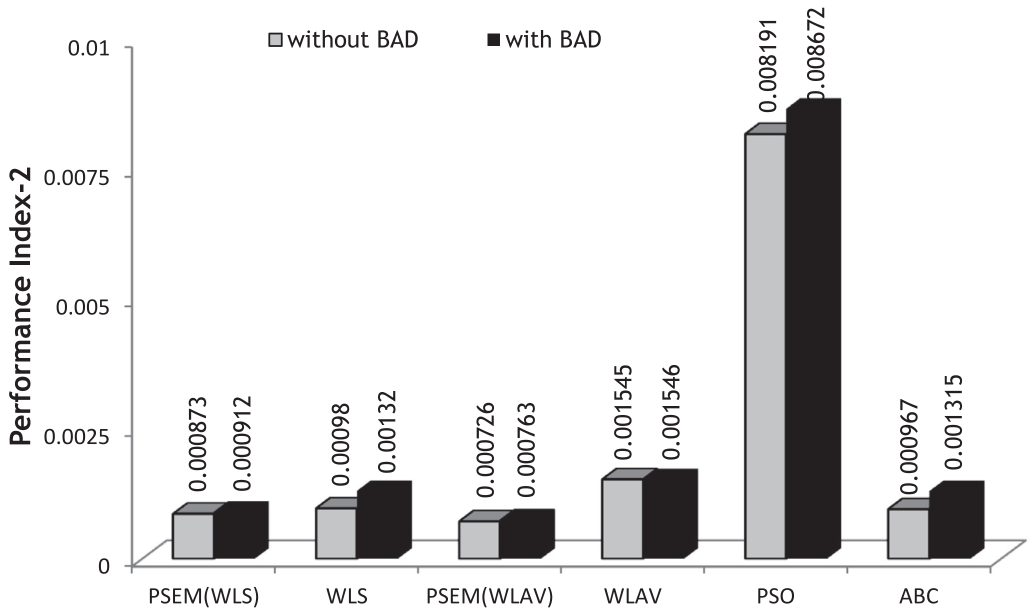

Fig. 5. $\Delta\delta_{rms}$ of different methods for 57-bus system with and without bad measurements.

Table 4
Optimal design parameters.

	$V_{dc,ref}$ (V)	K_p	K_i	R_f (Ω)	R_{PF-1} (Ω)	R_{PF-2} (Ω)	L_{PF-1} (mH)	L_f (mH)	L_{PF-2} (mH)	C_{dc} (μF)	C_{PF-1} (μF)	C_{PF-2} (μF)
PDM	855.16	2.2981	8.3963	0.1817	0.9325	0.0003	4.7836	0.017	2.779	5100	48	24
PSO	826.66	2.1830	10.2371	0.1902	0.8127	0.0046	4.9823	0.028	2.299	3450	59	28
ABC	862.11	3.7275	44.8793	0.1816	0.9269	0.0003	6.6397	0.148	2.682	4300	51	26

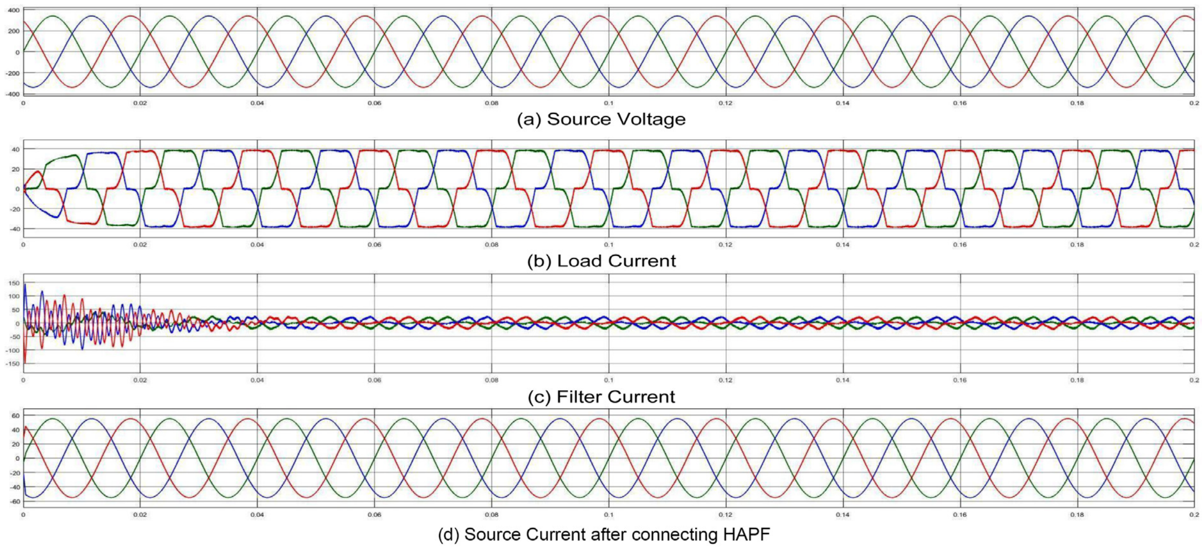

Fig. 6. Waveforms of the optimally designed hybrid active power filter.

Table 5
Comparison of performances.

Method	%THD (CFV)	Power Factor		
		a	b	c
Without HAPF	11.443	0.9646	0.9646	0.9646
PDM	1.7685	0.9999	0.9999	0.9999
PSO	1.9932	0.9998	0.9999	0.9998
ABC	1.7696	0.9999	0.9999	0.9999

supplies the non-sinusoidal load current and deteriorates the performances of the grid and other connected equipments. The inclusion of the designed HAPF injects appropriate filter current (Fig. 6(c)) that adds with the load current with a view of making the source current (Fig. 6(d)) pure sinusoidal. In fact, the filter supplies the difference between the load current and the expected sinusoidal current, thereby making the source current sinusoidal.

The power factor at the grid side before and after connecting HAPF is calculated by the following expression:

$$\text{power factor} = \frac{1}{\sqrt{1+THD^2}} \times \cos\varphi \tag{27}$$

where ϕ is the measured phase angle between the grid current and voltage waveforms, and $(\frac{1}{\sqrt{1+THD^2}})$ indicates the displacement factor.

The THD values at the point of common coupling are compared prior to and after connecting the designed HAPF in Table 5, which also includes the power factors at source side with and without HAPF. It can be observed that the PDM is able to lower the THD from the initial value of 11.443% to 1.7685%, which is much lower than those of its counterparts. All the methods correct the power factor to be almost unity and make the supply current to be perfectly sinusoidal.

The above discussions clearly portray that the PDM is able to enhance the PQ by lowering the THD to be within 5% limit, specified by IEEE 519-2014 standard, thereby making the supply current sinusoidal.

7.3. Performances of the developed methods

It is well known that the WLS method is not categorized as a stable method, as it involves multiplication of three matrices ($G^T W G$), as in Eq. (4) and inversion of the resulting gain matrix, which results in numerical round-off errors. Besides, the assignment of wide range of weight parameters may make the resulting gain matrix singular and the problem cannot be solved. But the PSEM requires only the evaluation of a cost function and avoids repeated matrix multiplications and matrix inversion, thereby making it as a stable method. Besides, it avoids complex matrix multiplication and inversion, and requires lower computations than its counterparts, thereby making it more computationally efficient.

The CFVs of PSEM have not been presented but analysed for the design of HAPF. With a view of studying the robustness of the developed methods, the minimum, maximum and average CFVs of the PDM over 100 runs have been presented in Table 6. It also includes the success rate. It can be revealed from the table that the average CFV of the PDM is very closer

Table 6
Statistical study.

Methods	CFV (%THD)			Success Rate (%)
	Maximum	Minimum	Average	
PDM	2.1162	1.7685	1.7712	97
PSO	3.8923	1.9932	2.3158	89
ABC	3.6216	1.7696	2.2417	91

to the lowest CFV than those of other methods. Besides, the success rate over 100 trials is greater than other strategies. The greater success rate and smaller CFV project the robustness of the PDM.

8. Conclusions

Football game optimization, a population-based algorithm, randomly moves a team of players in occupying better positions to receive the ball and score a goal while solving real-world problems. The convergence, stability and robustness of this algorithm have been improved by considering the behaviour of offensive players. The improved algorithm has been applied on static state estimation and optimal design of hybrid active power filter with a view of studying its performances. The proposed state estimation method has been tailored to choose either the weighted least square or weighted least absolute value objective without any major change in the flow of the algorithm. The calculated performance indices indicate that the estimated system state of the proposed method closely agrees with the true system state for all test systems. The effect of bad measurements has also been studied on 57 bus-system and illustrated that the proposed method is able to reject the bad measurements. It can be inferred that the proposed method is robust, stable and efficient.

The application of improved football algorithm in designing hybrid active power filter exhibits the superiority of the algorithm in providing the global best design through minimizing the total harmonic distortion to the lowest possible value besides enhancing the power factor.

The convergence of the improved football algorithm can be further studied by employing adaptive or self-adaptive techniques for tuning its parameters and studied on diversified optimization problems such as dynamic state estimation, image processing and unit commitment as future work.

Funding

This research received no external funding.

Declaration of Competing Interest

The authors declare no conflict of interest.

CRediT authorship contribution statement

Shanmugapriya Subramaniyan: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Investigation. **Jegatheesan Ramiah:** Supervision, Validation, Writing - review & editing.

Acknowledgments

The authors gratefully acknowledge the authorities of SRM Institute of Science and Technology, Kattankulathur Campus, for the facilities provided in performing the research work.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compeleceng.2019.106547.

References

[1] Yang Xin-She. Nature-inspired metaheuristic algorithms. 2nd Ed. Luniver Press; 2016.
[2] Fadakar E, Ebrahimi M. A new metaheuristic football game inspired algorithm. In: Proceedings of the first IEEE conference on swarm intelligence and evolutionary computation (CSIEC); 2016. p. 6–11.
[3] Kotiuga WW, Vidyasagar M. Bad data rejection properties of weighted least absolute techniques applied to static state estimation. IEEE Trans Power Appar Syst 1982:844–53 PAS-101.
[4] Lin WM, Teng JH. A new transmission fast-decoupled state estimation with equality constraints. Int J Elect Power Energy Syst 1998;20:489–93.
[5] Aravindhababu P, Neela R. A reliable and fast decoupled WLS state estimation for power systems. Electr Power Comp Syst 2008;36:1200–7.

[6] Jabr RA. Power system state estimation using an iteratively reweighted least squares method for sequential L1-regression. Int J Elect Power Energy Syst 2006;28:86–92.
[7] Jabr R, Pal B. AC network state estimation using linear measurement functions. IET Gen Trans Dist 2008;2:1–6.
[8] Overbye T, Sauer P, DeMarco C, Lesieutre B, Venkatasubramanian M. Using PMU data to increase situational awareness. Power System Engineering Research Center (PSERC) Publication; 2010. p. 10–16.
[9] Dhadbanjan T, Vanjari SSK. Linear programming approach for power system state estimation using upper bound optimization techniques. Int J Emerg Electr Power Syst 2010;11(3). doi:10.2202/1553-779X.2464.
[10] Zima-Bockarjova M, Zima M, Andersson G. Analysis of state estimation performance in transient conditions. IEEE Trans Power Syst 2011;26(4):1866–74.
[11] Zhang J, Welch G, Bishop G, Huang Z. A two-stage Kalman filter approach for robust and real-time power system state estimation. IEEE Trans Sustain Energy 2014;5:629–36.
[12] Muscas C, Pau M, Pegoraro P, Sulis S. Effects of measurements and pseudomeasurements correlation in distribution system state estimation. IEEE Trans Instrum Meas 2014;63:2813–23.
[13] Gu C, Jirutitijaroen P. Dynamic state estimation under communication failure using Kriging based bus-load forecasting. IEEE Trans Power Syst 2015;30:2831–40.
[14] Risso M, Rubiales AJ, Lotito PA. Hybrid method for power system state estimation. IET Gen Trans Dist 2015;9:636–43.
[15] Zhao J, Zhang G, Das K, Korres GN, Manousakis NM, Sinha AK. Power system real-time monitoring by using PMU-based robust state estimation method. IEEE Trans Smart Grid 2016;7:300–9.
[16] Sivan G, Yair Y, Idan G, Tirza R. Power systems topology and state estimation by graph blind source separation. IEEE Trans Signal Process 2019;67(8):2036–51.
[17] Junbo Z, Antonio G, Marcos N, Lamine M, Ali A, Vladimir T, Innocent K, Bikash P, Abhinav KS, Qi Junjian, Zhenyu H, Sakis Meliopoulos AP. Power system dynamic state estimation: motivations, definitions, methodologies and future work. IEEE Trans Power Syst 2019. doi:10.1109/TPWRS.2019.2894769.
[18] Suresh M, Panda AK. Real-time implementation of PI and fuzzy logic controllers based shunt active filter control strategies for power quality improvement. Int J Electr Power Energy Syst 2012;43:1114–26.
[19] Deniz D, Fuch EF. Measured transformer derating and comparison with harmonic loss factor (FHL) approach. IEEE Trans Power Deliv 2000;15:186–91.
[20] Turunen J, Salo M, Tuusa H. Comparison of three series hybrid active power filter topologies". In: Proceedings of the 11th international conference on harmonics and quality of power; 2004. p. 324–9. Sept. doi:10.1109/ICHQP.2004.1409375.
[21] Sahithullah M, Senthil Kumar A, Sasikala J. Optimal design of shunt active power filter for power quality enhancement using predator-prey based firefly optimization. Swarm Evolut Comput 2019;44:522–33. doi:10.1016/j.swevo.2018.06.008.
[22] Shixi H, Juntao F, Yundi C;, Chen C. Experimental investigation of adaptive fuzzy global sliding mode control of single-phase shunt active power filters. IEEE Access 2019;7:64442–9. doi:10.1109/ACCESS.2019.2917020.
[23] Hua G, Zedong Z, Tianming Z, Bing C, Ambrish C. Fast repetitive control with harmonic correction loops for shunt active power filter applied in weak grid. IEEE Trans Ind Appl 2019;55(3):3198–206. doi:10.1109/TIA.2019.2895570.
[24] Bachar R, Golea A, Benchouia MT, Chebaani M. High-performance active power filter implementation based on predictive current control. Int J Power Electron Drive Syst 2019;10(1):277–87. doi:10.11591/ijpeds.v10.i1.
[25] Test Systems Archive, Available online: http://www.ee.washington.edu/research/pstca/ (Accessed 20 April 2019).

Shanmugapriya Subramaniyan received the B.E. (Electrical and Electronics) and M.E. (Power Systems) from Annamalai University in 2003 and 2005 respectively. She is serving as an Assistant Professor in Electrical and Electronics Engineering, SRM Institute of Science and Technology, India, and working towards her Ph.D. Degree. She is specialized in the area of state estimation, evolutionary algorithms and power system analysis.

Jegatheesan Ramiah is currently working as a Professor of Electrical and Electronics Engineering, SRM Institute of Science and Technology, India. He has over 55 years of experience at various levels as faculty member, Director, Registrar and Principal at institutions like Anna University and Universiti Teknologi Petronas, Malaysia. He is specialized in the area of power system problems and state estimation.