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A MODIFIED DYNAMIC BACTERIAL FORAGING ALGORITHM FOR AN ENHANCED POWER SYSTEM STATE ESTIMATION

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ABSTRACT

Power systems are getting more complex with the ongoing growing of the ever changing energy demand. This dynamic situation of the electric power networks makes the control and monitoring of the system a crucial issue. In order to have an accurate real time monitoring and representative models, state estimation practices are essential. This requirement becomes more significant for nonlinear systems such as the electric power networks. The objective of the state estimation problem is to apply a variety of statistical and optimization methods in order to determine the best estimate of the power system variables. The variables of the power system are conventionally measured using various common metering devices in spite of the complexity and gradual expansion of the networks. However, these measuring meters are associated with errors and inaccurate output readings due to several operational, communicational and device-linked causes. Consequently, determining an improved and optimized estimation of the system state is significant and essentially needed, and hence this topic is getting more attraction among the researchers. The most typically applied approach to deal with the state estimation problem is the Weighted Least-squares (WLS) method. In this paper a hybrid algorithm is introduced utilizing a WLS-based dynamic bacterial foraging algorithm (DBFA). The proposed algorithm was applied and validated using the well-known IEEE 14-bus system. The results demonstrated the effectiveness and superiority of the algorithm when compared to some of other techniques used to tackle the state estimation issue.

Keywords
Bacterial foraging algorithm.
Power system state estimation.
Weighted least-squares method.

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1 INTRODUCTION

State estimation is a significantly essential function for monitoring and security of power system networks. Power system operation and control problems such as optimal power flow, economic load dispatch and contingency analysis are solved based on the system state estimation outcomes. State estimation is

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conventionally performed based on the data measured by the various measuring devices located in different parts of the network. These measurements are then sent to the SCADA system and employed for various power system operation and control problems. Inaccuracy of measurements is a crucial issue that has an impact on determining the realistic state of the system variables such as the voltage profile as well as active and reactive powers of the grid. The inaccurate measurement could generally be caused by device deficiency and data transfer-linked issues. The state estimation approach is to employ existing measured data for statistically computing the most optimal state of the power system [1]. Traditionally, the most used methods for determining the optimal power system state estimation are the Weighted Least-squares (WLS) and the Maximum Likelihood Methods [2]. The WLS technique is based on the criterion of minimizing the measurement errors so that optimal estimated values of system variables (states) are reached. Mathematically, this is usually carried out by minimizing the Jacobian matrix whose elements are the received measurements of the system. Due to the network topology and grid structure and because of the fact that not all the busses are directly coupled, the Jacobian matrix is usually a sparse matrix. As a consequence of the matrix sparsity, the resultant estimation could be considerably inaccurate. This dilemma is the main drawback associated with the WLS method [3-5]. In order to tackle this downside of the typical WLS method, and to accomplish the most accurate estimated state of the monitored system, various optimization techniques are implemented. The Newton-Raphson method is one of the widely used optimization methods by which the first order optimality condition is satisfied. However this cannot be successfully applied to nonsmooth and nonconvex problems. In addition to that, when the Hessian is inverted, ill conditioned matrix is resulted. This situation can lead to an inaccurate estimation which needs to be improved by applying some effective rules [1]. A great number of various optimization methods have been reported in the literature and applied to solve power system problems [6, 7]. Traditionally, most of these methods are deterministic calculus-based while the most recently introduced are the heuristic and artificial optimization methods. Non-calculus-based optimization techniques have demonstrated good convergence characteristics in solving nonconvex large scale optimization problems with high nonlinearities [8, 9]. Genetic algorithms have been applied to determine the optimal placement of phasor measurements units for an accurate state estimation [10]. Particles Swarm Optimization (PSO) method is utilized to investigate the state estimation problem in [11]. Bacterial foraging algorithm (BFA) is another non-deterministic method that has been used to solve many power system optimization problems. This evolutionary heuristic method was originally inspired by the foraging behaviour of the *E coli* bacteria [12]. The basic BFA is associated with critical and poor convergence properties when used with large-scaled high-dimensioned constrained nonlinear and nonconvex functions. To overcome these weaknesses, the BFA was modified, improved and implemented to find the optimal or near optimal solution for the economic dispatch [13] and hydrothermal scheduling problem [14-18]. In this paper a WLS-based dynamic bacterial foraging algorithm (WLS-DBFA) is presented and implemented to compute the optimally accurate estimation of the system state. The reminder of the paper is organized as follows: Section 2 provides the formulation of the problem using WLS. In Section 3, the DBFA is described. Simulation results are demonstrated in Section 4. The conclusion is drawn in Section 5.

2 WLS-BASED STATE ESTIMATION

Computing unknown variables in a power system using measurements (samples) is a statistical estimation procedure. In this process the available inexact measurements are employed to formulate the optimal estimate of the unknown variables [2]. It is obvious that the measured values are obtained from a number of measuring devices with some unidentified errors. These errors can mathematically be modelled as follows:

$$\eta_i = z - h_i(x) \tag{1}$$

where: $i = 1,2,3\ldots .m$, m is number of measurements.

η_i is the i^{th} random measurement error.

z_i is the i^{th} measurement value.

h_i is the i^{th} nonlinear function that relates the estimated value with its measurements.

x is a state vector that represents the estimated variables.

2.1 Formulation of the state estimation problem

The state estimation problem is formulated as an optimization problem in which the objective function to be minimized is the sum of the residual errors. If the number of available measurements is *m* and the number of unknown variables is *n*, then this minimization problem is formulated as follows [2]:

$$\min_{x_1,x_2,\dots,x_n} J(x_1,x_2,\dots,x_n)=\sum_{i=1}^{m}\frac{[z_i-\mathrm{h}_i(x_1,x_2,\dots,x_n)]^2}{\sigma_i^2} \tag{2}$$

where σ_i^2 = variance for the ith measurement, and $J(x)$ = measurement residual

The expression given in Equation (2) is known as the weighted least-squares estimator which is the maximum likelihood estimator when the errors are modelled as random numbers with normal distribution characteristics. The above minimization function can be expressed in a vector form as follows:

$$\mathrm{h}_i(x_1,x_2,\dots,x_n)=\mathrm{h}_i(\mathbf{x})=h_{i1}x_1+h_{i2}x_2+\cdots+h_{in}x_n \tag{3}$$

$$\text{and}\quad h(\mathbf{x})=\begin{bmatrix}\mathrm{h}_1(\mathbf{x})\\ \mathrm{h}_2(\mathbf{x})\\ \vdots\\ \mathrm{h}_n(\mathbf{x})\end{bmatrix}=[H]\mathbf{x} \tag{4}$$

where [H]*x* is an *m* by *n* matrix and its elements are the coefficients of the linear function $h_i(x)$.

The measurements are expressed in a column vector as:

$$\mathbf{z}=\begin{bmatrix}z_1\\ z_2\\ \vdots\\ z_n\end{bmatrix} \tag{5}$$

Then Equation (2) can be expressed in a compact matrix notation as:

$$\min_{\mathbf{x}} J(\mathbf{x})=[\mathbf{z}-h(\mathbf{x})]^T[R^{-1}][\mathbf{z}-h(\mathbf{x})] \tag{6}$$

Where [R] is known as the covariance matrix of measurement errors and defined as follows:

$$[R] = \begin{bmatrix} \sigma_1^2 & & & \\ & \sigma_2^2 & & \\ & & \ddots & \\ & & & \sigma_{N_m}^2 \end{bmatrix} \tag{7}$$

The formulation in Equation (6) can be expanded to obtain a general minimization form expressed in the following equation [2]:

$$\begin{aligned} \min_{\mathbf{x}} J(\mathbf{x}) = \{ & \mathbf{z}^T [R^{-1}] \mathbf{z} - \mathbf{x}^T [H]^T [R^{-1}] \mathbf{z} \\ & - \mathbf{z}^T [R^{-1}][H] \mathbf{x} + \mathbf{x}^T [H]^T [R^{-1}][H] \mathbf{x} \} \end{aligned} \tag{8}$$

2.2 Constraints

The objective function formulated above is subject to a number of equality and inequality constraints that must be satisfied. The upper and lower boundaries of the problem are specified as [1]:

$$\begin{aligned} V_i^{\min} < V_i < V_i^{\max} \\ \theta_i^{\min} < \theta_i < \theta_i^{\max} \end{aligned} \tag{9}$$

$$\begin{aligned} P(x) = \lambda \Bigg\{ & \sum_{i=1}^{N} \{\max(0, x_i - x_i^{\max})\}^2 \\ & + \sum_{i=1}^{N} \{\max(0, x_i^{\max} - x_i)\}^2 \Bigg\} \end{aligned} \tag{10}$$

where λ is the penalty factor and N is the number of variables..

3 THE DYNAMIC MODIFIED BACTERIAL FORAGING ALGORITHM

In this section, the basic BFA is introduced first. Afterwards, the DBFA which is applied to solve the minimization state estimation problem is demonstrated.

3.1 The basic bacterial foraging algorithm (BFA)

The BFA is a heuristic optimization technique which is motivated by the foraging behavior of the *E coli*. bacteria [12]. BFA was introduced in order to find the optimal solution vector for non-differentiable and non-gradient complex objective functions. The hyperspace search is performed using three main operations; chemotaxis, reproduction and elimination dispersal activities [12]. The chemotaxis process is carried out by swimming and tumbling. The bacterium spends its life alternating between these two modes of motion. In the BFA, a tumble is represented by a unit length in a random direction, which specifies the direction of movement after a tumble. The size of the step taken in the random direction is represented by the constant run-length unit, *C (i)*. For a population of bacteria, the location of the i^{th} bacterium at the j^{th} chemotactic step, kth reproduction step and lth elimination/dispersal event is represented by. At this location the cost function is denoted by, which is also known as the nutrient function. After a tumble, the location of the i^{th} bacterium is represented by [12]:

$$\theta^i(j+1,k,l)=\theta^i(j,k,l)+C(i,j)\phi(j) \tag{11}$$

When at the cost function is lower then, another step of size *C(i,j)* in the same direction is taken. This operation is repeated as long as a lower cost is obtained until a maximum number of steps, N_s, is reached. The cost function of each bacterium is affected by a kind of swarming that is performed by the cell-to-cell signalling released by the bacteria groups to form swarm patterns. This swarming is expressed as follows [12]:

$$\begin{aligned} J_{cc}\left(\theta,P(j,k,l)\right) &= \sum_{i=1}^{S} J_{cc}^{i}\left(\theta,\theta^i(j,k,l)\right) \\ &= \sum_{i=1}^{S}\left[-d_{attract}\exp\left(-\omega_{attract}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right] \\ &+\sum_{i=1}^{S}\left[h_{repellant}\exp\left(-\omega_{repellant}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right] \end{aligned} \tag{12}$$

where $d_{attract}$, $\omega_{attract}$, $h_{repellant}$ and $\omega_{repellant}$ are coefficients represent the characteristics of the attractant and repellent signals released by the cell and is the m^{th} component of i^{th} bacterium position θ^i. $P(j,k,l)$ is the position of each member of the population of the *S* bacteria and defined as [12]:

$$P(j,k,l)=\left\{\theta^i(j,k,l)\,|\,i=1,2,...,S\right\} \tag{13}$$

where *S* is the size of the bacteria population. The function which represents the cell-to-cell signalling effect is added to the cost function [12]:

$$J(i,j,k,l)+J_{cc}(\theta,P) \tag{14}$$

A reproduction process is performed after taking a maximum number of chemotactic steps, N_c. The population is halved so that the least healthy half dies and each bacterium in the other healthiest one splits into two bacteria which takes the same position [12]:

$$S_r = \frac{S}{2} \tag{15}$$

After N_{re} reproduction steps an elimination/dispersal event takes place for N_{ed} number of excisions. In this operation each bacterium could be moved to explore another parts of the search space. The probability for each bacterium to experience the elimination/dispersal event is determined by a predefined fraction p_{ed}.

3.2 Dynamic Modified bacterial foraging algorithm

In the basic BFA, the length unit step is fixed. This could be satisfying for small linear minimization or maximization problems. However, it may not be guaranteed that good convergence properties can be obtained if it is applied to solve large-scaled nonlinear optimization problems. Search spaces that involve high dimensionality require more dynamic characteristics to converge to global minima. In order to achieve the desired results using this algorithm, the run-length parameter is adjusted so that it could be dynamically adaptive. In fact, it is the main factor that controls the local and global search capabilities of the BFA. Accordingly, balancing the exploration and exploitation of the search could be accomplished by modifying the run-length unit. A decreasing nonlinear dynamic function is augmented to execute the swim walk as an alternative of the constant length unit step. This function is formulated as [19]:

$$C(i, j+1) = \left(\frac{C(i, j) - C(N_C)}{N_C + C(N_C)}\right)\left(N_C - j\right) \tag{16}$$

where j is the chemotactic step index and N_c is the maximum number of chemotactic steps while $C(N_c)$ is the initial predefined parameters.

4 RESULTS AND DISCUSSION

The WLS-based DMBFA was implemented to determine the optimal and “best” accurate state estimation of the well-known IEEE 14-bus standard power system as shown in figure 1 [20]. The algorithm was implemented and coded in MATLAB and executed on an Intel Core i7-8750H 2.20GHz personal computer with 8 GB RAM. In order to check for consistency, 50 independent runs were conducted with different random initial solution for each run. The line and bus data can be found in [20] and are tabulated as shown in tables 1, 2 respectively. The available measurements are given in [21].

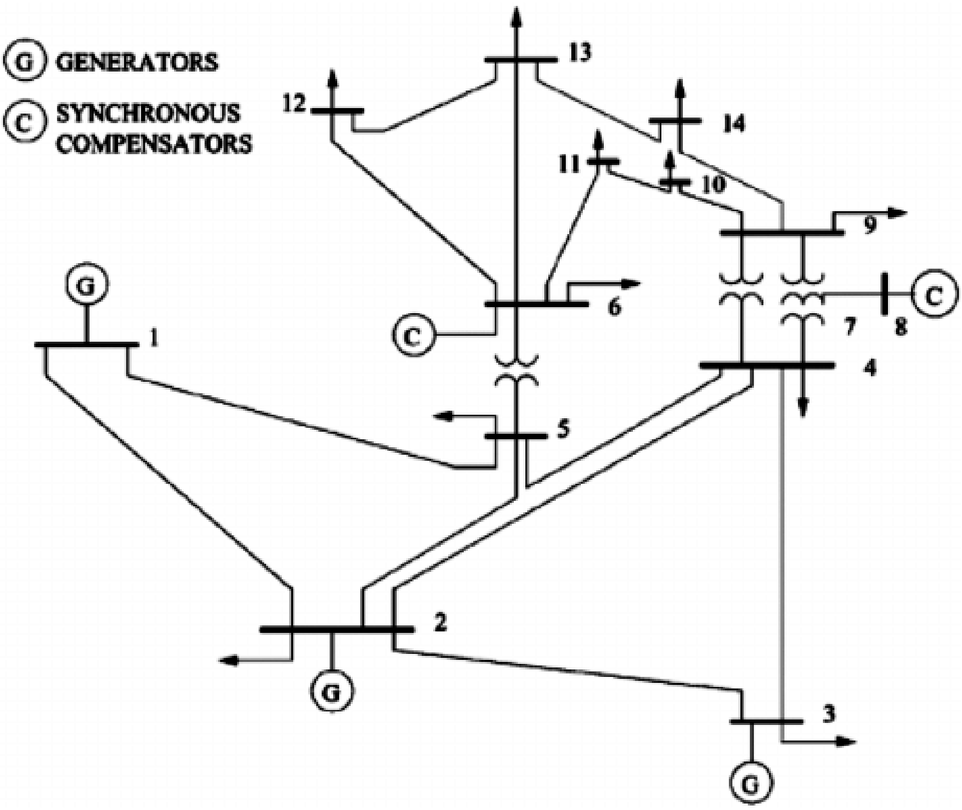

Figure 1. IEE 14-bus system.

Table 1. Line Data.

From Bus	To Bus	R (pu)	X (pu)	B/2 (pu)	Tap (*a*)
1	2	0.0194	0.0592	0.0264	1.0000
1	5	0.0540	0.2230	0.0219	1.0000
2	3	0.0470	0.1980	0.0187	1.0000
2	4	0.0581	0.1763	0.0246	1.0000
2	5	0.0570	0.1739	0.0170	1.0000
3	4	0.0670	0.1710	0.0173	1.0000
4	5	0.0134	0.0421	0.0064	1.0000
4	7	0.0000	0.2091	0.0000	0.9780
4	9	0.0000	0.5562	0.0000	0.9690
5	6	0.0000	0.2520	0.0000	0.9320
6	11	0.0950	0.1989	0.0000	1.0000
6	12	0.1229	0.2558	0.0000	1.0000
6	13	0.0662	0.1303	0.0000	1.0000

7	8	0.0000	0.1762	0.0000	1.0000
7	9	0.0000	0.1100	0.0000	1.0000
9	10	0.0318	0.0845	0.0000	1.0000
9	14	0.1271	0.2704	0.0000	1.0000
10	11	0.0820	0.1921	0.0000	1.0000
12	13	0.2209	0.1999	0.0000	1.0000
13	14	0.1709	0.348o	0.0000	1.0000

Table 2. Bus Data.

Bus No.	Type	|V|	θ	P_{Gi}	Q_{Gi}	P_{Li}	Q_{Li}
1	1	1.06	0	0	0.00	0.00	0.00
2	2	1.05	0	40	42.20	21.70	12.70
3	2	1.01	0	0	23.40	94.20	19.00
4	3	1.00	0	0	0.00	47.80	-3.90
5	3	1.00	0	0	0.00	7.60	1.60
6	2	1.00	0	0	12.20	11.20	7.50
7	3	1.00	0	0	0.00	0.00	0.00
8	2	1.00	0	0	17.40	0.00	0.00
9	3	1.00	0	0	0.00	29.50	16.60
10	3	1.00	0	0	0.00	9.00	5.80
11	3	1.00	0	0	0.00	3.50	1.80
12	3	1.00	0	0	0.00	6.10	1.60
13	3	1.00	0	0	0.00	13.50	5.80
14	3	1.00	0	0	0.00	5.00	5.00

In order to validate the proposed algorithm, a small power system with only three buses was utilized before applying it to the IEEE 14-bus system. The WLS-DBFA was executed for the test system. Upper and lower limits for the system variables were set appropriately and so as for the DBFA parameters and its stopping criteria. The results were compared to those determined by applying the WLS-Newton-Raphson, WLS and the Particle Swarm Optimization PSO-WLS [21]. The obtained results as well as the comparison with the mentioned methods are shown in table 3.

Table 3. State estimation for the voltage profile of the IEEE 14-bus system

Bus No.	N-R PF		WLS		PSO-WLS [21]		WLS-DBFA	
	|V|	Θ	|V|	θ	|V|	θ	|V|	θ
1	1.060	0.000	1.0743	0.0000	1.0485	0.0000	1.0878	0.00000
2	1.045	-4.980	1.0639	-4.4835	1.0374	-4.7034	1.0643	-4.88638
3	1.060	-12.353	1.0342	-11.3084	1.0067	-11.9105	1.0790	-11.97230
4	1.069	-9.854	1.0387	-9.2738	1.0121	-9.7701	1.0645	-9.66553
5	1.063	-8.516	1.0405	-7.9021	1.0139	-8.3243	1.0581	-8.43676
6	1.120	-13.362	1.0713	-12.9168	1.0573	-13.5342	1.0988	-13.13645
7	1.108	-12.633	1.0572	-11.9925	1.0313	-12.6559	1.0923	-13.00631
8	1.090	-12.633	1.0000	-11.9925	0.8718	-12.6607	1.0776	-13.00340
9	1.127	-14.051	1.0476	-13.4945	1.0291	-14.1704	1.0937	-14.27654
10	1.133	-14.183	1.0523	-13.8106	1.0399	-14.6182	1.1002	-14.48653
11	1.130	-13.898	1.0588	-13.4274	1.0464	-14.1323	1.1008	-14.08876
12	1.133	-14.126	1.0554	-13.8265	1.0432	-14.4774	1.1057	-14.00743
13	1.137	-14.199	1.0419	-13.4905	1.032	-14.2571	1.1076	-13.91435
14	1.147	-14.957	1.0291	-14.3267	1.0151	-14.9733	1.1154	-15.11107

The absolute percent error was computed for the bus voltage magnitude and angle. Figure 2 illustrates this error percentage.

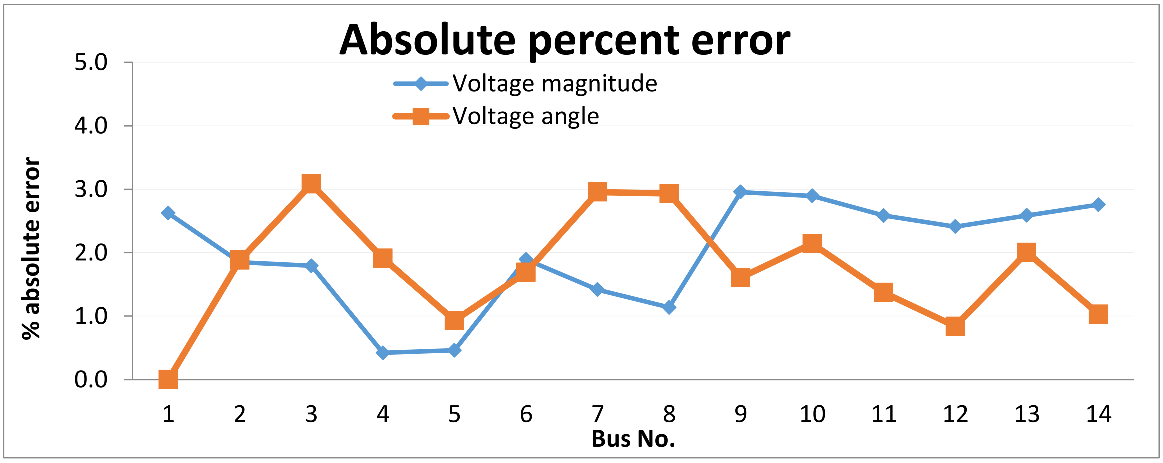

Figure 2. The absolute percent error of the estimated voltage magnitude and angle.

5 CONCLUSIONS

In this paper a WLS-based dynamic bacterial foraging algorithm was presented and implemented to compute the optimal and “best” accurate state estimation of a selected power system. The IEEE 14-bus system was utilized to test and validate the proposed algorithm. The statistical weighted least squares method augmented by the dynamic bacterial algorithm was formulated, implemented and executed for the power system state estimation function. The WLS-based DBFA was successfully proved to be effective and superior when compared to other approaches. The absolute percent error was determined for the estimated voltage profile and found to be within the accepted tolerance margins.

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خوارزمية البحث البكتيري الديناميكية المعدلة لإيجاد الحالة التقديرية لمنظومات القدرة

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الملخص

تزداد أنظمة الطاقة تعقيدًا مع النمو المضطرد للطلب المتغير باستمرار على الطاقة. هذا الوضع الديناميكي لشبكات الطاقة الكهربائية يجعل التحكم في النظام ومراقبته مسألة حاسمة. من أجل الحصول على مراقبة دقيقة في الوقت الحقيقي وباستعمال نماذج تمثيلية تحاكي الوضع الحقيقي، فإن ممارسات تقدير الحالة ضرورية. يصبح هذا المطلب أكثر أهمية للأنظمة غير الخطية مثل ما هو الحال بالنسبة لشبكات الطاقة الكهربائية. الهدف وراء دراسة مسألة تقدير الحالة هو تطبيق مجموعة متنوعة من الأساليب الإحصائية وطرق التحسين من أجل تحديد أفضل تقدير لمتغيرات نظام الطاقة. يتم قياس متغيرات نظام الطاقة بشكل تقليدي باستخدام العديد من أجهزة القياس الشائعة على الرغم من التعقيد والتوسع التدريجي للشبكات. ومع ذلك ، ترتبط عدادات القياس هذه بالأخطاء وقراءات الإخراج غير الدقيقة بسبب العديد من الأسباب التشغيلية والتواصلية بالإضافة إلى تلك المتعلقة بالجهاز نفسه. وبالتالي ، فإن تحديد تقدير محسّن وأكثر دقة لحالة النظام أمر مهم ومطلوب بشكل أساسي، وبالتالي فإن هذا الموضوع يكتسب المزيد من الجاذبية في أوساط الباحثين. الطريقة الأكثر تطبيقاً للتعامل مع مشكلة تقدير الحالة هي طريقة المربعات الصغرى الموزونة (WLS). في هذا البحث تم تقديم خوارزمية هجينة باستخدام خوارزمية البحث البكتيرية الديناميكية القائمة على طريقة المربعات الصغرى الموزونة. تم تطبيق الخوارزمية المقترحة والتحقق من صحتها باستخدام نظام IEEE 14-bus المعروف. أظهرت النتائج فعالية وتفوق الخوارزمية عند مقارنتها ببعض التقنيات الأخرى المستخدمة لمعالجة مسألة تقدير الحالة.

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خوارزمية البحث البكتيري.
الحالة التقديرية لمنظومات القدرة.
طريقة المربعات الصغرى الموزونة.