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A novel approach for distribution system state estimation with renewable energy sources based distributed generations

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ABSTRACT

State estimation in electrical distribution systems (EDSs) is an analyzing tool for estimating the state of it for close monitoring and controlling by distribution management system (DMS). In this paper, RESs integrated EDS's state is estimated using the distribution system state estimation (DSSE) model. It is a minimization problem with equality and inequality constraints which describe the practical considerations of real time EDS. The objective of DSSE modeling and its minimization is to compute state variables. For minimizing the objective function of DSSE model Artificial Bee Colony (ABC) algorithm is used to estimate load and Renewable Energy Sources (RESs) output. The performance of the proposed work is evaluated on IEEE 33 bus test system using MATLAB working platform and compared with other evolutionary optimization algorithms.

Introduction

Although fossil fuels are expected to continue supplying much of the energy used worldwide, renewable energy source (RES) is the world's fastest growing energy market due to the reasons of green house effect and reproducible [1]. The technological innovations, changing economic and regulatory environment has resulted in a penetration of RESs as distribution generators (DGs) in electrical distribution grid [2]. However, systems based on RESs like wind, small hydro, solar and biomass [3] have a major drawback due to variable in supply intensity and considerably unpredictable [4]. Thus resulted in grid disturbances such as power fluctuations, voltage rise and high losses if uncontrolled [5]. Hence, it is necessary to monitor and control output levels and scheduling for secure and efficient operation of RESs integrated electrical distribution systems [6]. To meet such a requirement, estimation of present state of the distribution network is needed i.e., distribution system state estimation (DSSE) is the primary tool used for regular monitor and control of distribution management system (DMS) [7].

In DMS, DSSE is defined as the process of assigning a value to state variables such as voltage magnitudes and relative phase angles etc. based on measurements from the system by minimizing the least square error between the estimated and measured values [8-9].

The estimation of state variables in the DSSE with the presence of RESs is an optimization problem for EDSs. By utilizing the available measurements in EDS, the objective of the DSSE had been minimized by meta-heuristic approaches such as GA, PSO, etc. These approaches have issues like complex operations: selection, crossover, mutation and more parameter to be set. This leads to slow convergence and may trap the solution to local minima which causes worst solution. In this paper, the proposed ABC algorithm has the ability to get out of the local minima and can be efficiently used for Multivariable, function optimization problems like DSSEs. The rest of the paper is organized as: in section 2, recent research works carried on the DSSE model are presented, in section 3, DSSE is modeled and proposed algorithm to estimate the state variables of the EDS are illustrated with mathematical represented, in section 4, proposed work implementation results and discussion are shown, at the paper is concluded.

Numerous related works have been done as an advance to formulate and solve the DSE problem [10–32]. Some of them reviewed here. Naka et al. have proposed a hybrid particle swarm optimization (PSO) for DSE including Distributed Generators (DGs) [10]. The nonlinear characteristics of the practical equipment and actual limited measurements in distribution systems have been considered in the proposed method. Niknam has presented an approach based on HBMO for DSE including DGs [11]. In [12], Lu et al. have presented an algorithm for harmonic estimation. The algorithm utilizes the particle swarm optimizer with passive congregation (PSOPC) to estimate the phases of the harmonics and a least-square (LS) method that is used to estimate the amplitudes.

Niknam et al. have presented an approach based on ant colony optimization for DSE including DGs [13]. In that approach, the values of loads and DGs are considered as state variables. J. S. Thorp et al. have presented a regression based prediction approach to address the load estimation problem in [14]. A general framework for self-adapting dynamic estimator has been proposed to improve the forecasting and filtering models for power system dynamic state estimation in [15]. Sun et al. have proposed a mathematical-based of state estimation method for power systems according to information theory [16]. In [17] and [18] the authors have presented a branch current based three-phase state estimation algorithm for distribution systems whose state variables are chosen the magnitude and phase angle of the branch current. In [19], a methodology for estimating load curves at low-voltage substations has been described. The system is constructed by the aggregation of a fuzzy inference system of the Takagi–Sugeno type. Load

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estimation problem in unbalanced, radial power distribution networks has been modelled as a weighted HN estimation problem with equality and inequality constraints in [19]. D. Karaboga et al. have presented a branch-based state estimation method which is an estimation technique for radial distribution systems that can support most kinds of real-time measurements [20]. In [21], the authors have presented an approach to DSE using a probabilistic extension of the radial load flow algorithm. A method considering uncertainty of network data, load distribution information and telemetric data for voltage measurement has been proposed in [22]. In the presented method, data involved in the calculation are calculated by using fuzzy numbers. In [23], a three-phase power flow model and state estimation for distribution systems have been formulated. A method for state distribution of electric power distribution in quasi real-time conditions has been presented in [24]. A three-phase state estimation method has been developed to increase the accuracy of load data in [25]. In [26], an artificial neural networks (ANNs) approach to pseudo measurement modeling in DSE which could produce acceptable estimation accuracy with a limited number of real measurements was presented. Although these methods above obtained good results, the estimation errors and precisions can be further enhanced.

Dsse Model Of Eds With Ress

RESs should be modeled properly as DGs in the EDS to estimate the state. Based on the problem of interest, the DGs are modeled as constant power factor model, constant voltage model and variable reactive power model [27]. The RESs are possibly modeled as PQ-model and PV-model. PQ-model means, it generates the active power to the connected EDS and PV-model means it provides the reactive power to support the voltage magnitude at the point of connection. In the paper, we use the PQ-model of RESs to integrate in the EDS network i.e., if the RESs is installed at i^{th} bus then it injects/provides active power to the bus. Here, we want to estimate the active power support provided by the RESs at selected buses and load variations at that nodes using the DSSE model. So, the selected state variables to be estimate are given as

$$X = [P_{R1}, P_{R2}, \ldots\ldots, P_{Rg}, P_{L1}, P_{L2}, \ldots\ldots, P_{Lh}]_{1xn} \qquad (1)$$

Where, X represents the state variables vector. The terms from P_{R1} to P_{Rg} are 'g' number of renewable outputs and from P_{L1} to P_{Lh} are 'h' number of load outputs i.e., number of state variables are, n=(g+h).

The objective function to be minimized is the difference of measured value and state equation of the measured value [35]. The objective function and constraints involved for DSSE model are given as

Objective function:

$$\min_X E(X) = \sum_{i=1}^{m} [M_i - S_i(X)]^4 \qquad (2)$$

Where, X, M, $S(\bullet)$ and m are state vector, measured value, state equation of the measured value and no. of measurements respectively. Here, the residue of measured and state equations is powered by 4 to make the estimation of state variables more significant for possible small errors induced by used meters.

Constraints:

Constraints involved in the DSSE model are similar to that of other optimization problems of EDSs such as optimal active and reactive power flow, load dispatching, load shedding, and optimal placement of DGs etc. The constraints should be satisfied for the stable, secure, reliable and economic operation of the EDSs. The constraints involved in DSSE model are given as,

Bus voltage magnitude constraints

$$V_{i-\min} \le V_i \le V_{i-\max} \qquad (3)$$

Here, V_i represents the voltage magnitude at i^{th} bus of total Nbus. $V_{i-\min}$ and $V_{i-\max}$ are the lower and upper limits of the ith bus voltage. This constraint determines whether the bus voltage is in tolerance range or violated the bus profile.

Distribution line constraints

$$|P_l| < P_{l-\max} \qquad (4)$$

Here, P_l and $P_{l-\max}$ are the absolute power flow through the line l of total N_l distribution lines and its maximum power transfer capability respectively. This constraint represents the overflow present in any distribution line and facilitates to the contingency operation or load sharing.

Reactive power of capacitors constraint

$$0 \le Q_{ci} \le Q_{ci-\max} \qquad (5)$$

Here, the Q_{ci} is the capacitor installed at ith bus and its maximum is $Q_{ci-\max}$. It is used to improve the power factor which lowers the line current for reducing power losses. These capacitors are connected at optimal locations for lowering the total power losses.

Active power constraints of RESs

$$P_{Ri-\min} \le P_{Ri} \le P_{Ri-\max} \qquad (6)$$

Here, P_{Ri} represent the active power generation by RES connected at i^{th} bus of total g buses and its lower & upper limits of generation are $P_{Ri-\min}$ & $P_{Ri-\max}$. The power generation by the connected RES should be in the specified range. The violation in any of the limits will result in the operational costs or production costs and sometimes not good for the connected EDS.

Active power constraints of loads

$$P_{Li-\min} \le P_{Li} \le P_{Li-\max} \qquad (7)$$

Here, P_{Li}, $P_{Li-\min}$ and $P_{Li-\max}$ are the load value, lower and upper value of i^{th} bus respectively. If the violation appeared in any nodes, it drops the voltage at that node and may leads to the blackout for the worst case.

Unbalanced 3-phase power flow equations

These illustrate the behavior of EDSs. In EDSs, the load supported by one phase may vary from other phase and it differs from place to place.

Now, the equations (2-7) represent the objective function and its constraints involved for the minimization in the DSSE model. Here, the state variables to be optimized for minimization are presented in equation (1). The constraints presented in the DSSE model represent the practical considerations of real time EDSs for state estimation.

Proposed Methodology for DSSE Model

The objective function minimization of the DSSE model is presented in this subsection. For this purpose ABC algorithm is proposed. ABC algorithm is the nature inspired-swarm intelligence based algorithm, introduced in 2005 by Karaboga, from the motivation of the foraging behavior of natural honey bees [28]. Initially, it was proposed for unconstrained optimization problems. Then, an extended version of ABC algorithm was offered to handle constrained optimization problems [29]. The colony of artificial bees consists of three groups of bees: employed, onlookers, and scout bees. One half of the colony size of the ABC algorithm represents the number of employed bees, and the second half stands for the number of onlooker bees. For every food-source's position, only one employed bee is assigned. In other words, the number of food-source positions (possible solutions) surrounding the hive is equal to the number of employed bees. The scout initiates its search cycle once the employed bee has exhausted its food-source position (solution.) The number of trials for the food source to be called "exhausted" is controlled by the limit value of the ABC algorithm's parameter. Each cycle of the ABC algorithm comprises three steps: first, sending the employed bee to the possible food-source positions (solutions) and measuring their nectar amounts (fitness values); second, onlookers selecting a food source after sharing the information from the employed bees in the previous step; third, determining the scout bees and then sending them into entirely new food-source positions [30].

The ABC algorithm creates a randomly distributed initial population of solutions (i=1, 2, 3,….., N) , where i signifies the size of population and N is the number of employed bees. Each solution is a D-dimensional vector, where D is the number of parameters to be optimized. The position of a food-source, in the ABC algorithm, represents a possible solution to the optimization problem, and the nectar amount of a food source corresponds to the quality (fitness value) of the associated solution. After initialization, the population of the positions (solutions) is subjected to repeated cycles, (cycle= 1, 2, 3,….., MCN), of the search processes for the employed, onlooker, and scout bees cycle , where MCN is the maximum cycle number of the search process. Then, an employed bee modifies the position (solution) in her memory depending on the local information (visual information) and tests the nectar amount (fitness value) of the new position (modified solution.) If the nectar amount of the new one is higher than that of the previous one, the bee memorizes the new position and forgets the old one[a]. Otherwise she keeps the position of the previous one. After all employed bees complete the search process, they share the nectar information of the food sources (solutions) and their position information with the onlooker bees on the dance area. An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with a probability related to its nectar amount. As in the case of the employed bee, she produces a modification on the position (solution) in her memory and checks the nectar amount of the candidate source (solution). Providing that its nectar is higher than that of the previous one, the bee memorizes the new position and forgets the old one.

An onlooker bee chooses a food source depending on the probability value associated with that food source, Pi, calculated by the following expression

$$P_i = \frac{F_i}{\sum_{i=1}^{N} F_i} \qquad (8)$$

Where, F_i is the fitness value of the solution i evaluated by its employed bee, which is proportional to the nectar amount of the food source in the position i and N is the number of food sources which is equal to the number of employed bees (EB). In this way, the employed bees exchange their information with the onlookers.

Clearly, resulting from using (8), a good food source (solution) will attract more onlooker bees than a bad one. Subsequent to onlookers selecting their preferred food-source, they produce a neighbour food-source position i + 1 to the selected one i, and compare the nectar amount (fitness value) of that neighbour i + 1 position with the old i position. The same selection criterion used by the employed bees is applied to onlooker bees as well. This sequence is repeated until all onlookers are distributed. Furthermore, if a solution does not improve for a specified number of times (limit), the employed bee associated with this solution abandons it, and she becomes a scout and searches for a new random food-source position. Once the new position is determined, another ABC algorithm cycle (MCN) starts. The same procedures are repeated until the stopping criteria are met.

In order to determine a neighbouring food-source position (solution) to the old one in memory, the ABC algorithm alters one randomly chosen parameter and keeps the remaining parameters unchanged. In other words, by adding to the current chosen parameter value the product of the uniform variant and the difference between the chosen parameter value and other "random" solution parameter value, the neighbour food-source position is created. The following expression verifies that:

$$NS_i^j = CS_i^j + \varphi_i^j (\mathrm{CS}_i^j - RS_i^j) \qquad (9)$$

The multiplier φ is a random number between [-1, 1]. In other words, NS_i^j is the j[th] parameter of a solution NS that was selected to be modified. When the food-source position has been abandoned, the employed bee associated with it becomes a scout. The scout produces a completely new food-source position as follows:

$$X_{i,j} = X_{min,j} + rand(0,1)(X_{max,j} - X_{min,j}) \qquad (10)$$

If a parameter value produced using (9) and/or (10) exceeds its predetermined limit, the parameter can be set to an acceptable value. In this paper, the value of the parameter exceeding its limit is forced to the nearest (discrete) boundary limit value associated with it.

Thus, the ABC algorithm has the following control parameters:

1) the colony size CZ, that consists of employed bees EB plus onlooker bees OB; 2) the limit value, which is the number of trials for a food-source position (solution) to be abandoned; and 3) the maximum cycle number MCN.

Proposed Algorithm for State Estimation The flowchart of the ABC algorithm is illustrated in Fig. 2. The solution steps of the proposed ABC algorithm for DSSE are described as follows.

Initialization phase:

Step 1: Initialize the random solutions (X) of population size N with equation (10). Provide limit (L) and maximum cycle number (MCN) values.

Employed bee phase:

Step 2: Each employ bee (EB) goes for a single solution and search for a neighbour solution (NS) with equation (9)

Step 3: If the NS has no minimum objective value than the current solution (CS), ignore it. Otherwise, replace the CS with NS. Each EB remembers the best solution and returns to hive to share the information with onlooker bees (OB).

Onlooker bee phase:

Step 4: Probability (P) of fitness of each solution is computed based on the equation (8).

Step 5: In the order of best P valued solutions are chosen by OBs and each goes for one solution.
Step 6: Each OB searches its neighbour as similar in EB phase using equation (9) and gets replaced if the NS has better objective value and remembers it.
Scout bee phase:
Step 7: if the objective value of any solution is not updated for limited number of cycles, then it is abandoned and a new solution is randomly generated using equation (10).
Termination phase:
Step 8: Checks for termination condition (TC), if it is reached, the best solution obtained so far is provided as optimal solution. If not, the steps from EB phase to TC are repeated.

Results and Discussion

In the paper, IEEE 33 bus radial distribution system is used to test the estimation capability of the proposed work. The single line diagram of the test system is illustrated in figure 1.

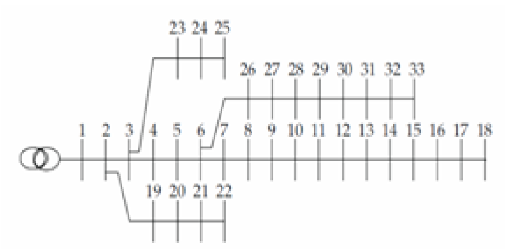

Fig 1: The single line diagram of IEEE 33 bus system

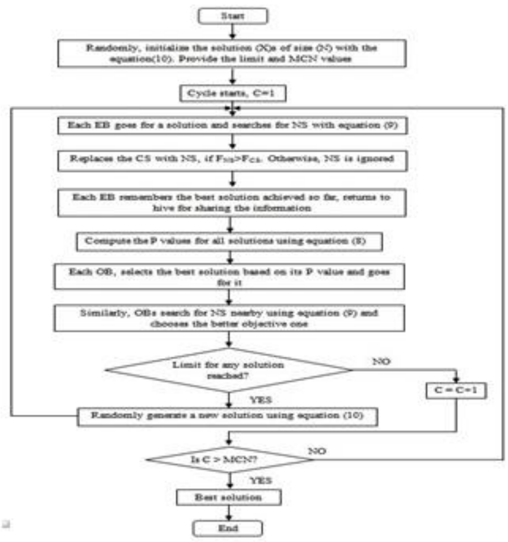

Fig. 2: The flow chart of the proposed algorithm for DSSE model

The average of active power outputs of RESs with unity power factor and type of connected RESs at nodes 4, 8, 12, 15, 21, 23, 28 & 31 and their corresponding load values is shown in Table 1. Because of the RESs integration, the node voltages and power values will change. For validating the performance of the proposed work, the load values at these nodes are varied and checked for the proposed work estimation performance. The variation in the load values of RESs connected nodes are tabulated in table 2.
Here, P_L stands for load active power and Q_L stands for load reactive power at respective buses. Third column shows the P_L & Q_L value after the integration of RESs in the test system i.e., now, the total P_L at that node equal to sum of the normal value and RES average of active power value. Here, P+ and Q+ are the added load active and reactive power in the respective nodes. This variation is user determined based on demand or problem of interest. Fifth column shows the P_L & Q_L values at each node due to the load variation. Table 3 and 4 show the simulation results of the proposed algorithm for estimation of loads and RESs output values. Fig. 3 shows the comparison of Estimated and actual values of Load and RESs output.

Now, the performance of the proposed algorithm is compared with other evolutionary optimization algorithms such as PSO [10], Honey Bee mating Optimization (HMBO) [11], Neural Networks (NN) [13], Ant Colony Optimization (ACO) [13], Genetic Algorithm (GA) [13], Quantam-Inspired Evolutionary Algorithm (QIEA) [32] and Greedy randomized Adaptive Search Procedures (GRASP) [33] to check its effectiveness.

The comparison is developed based on the error handling capabilities of estimation by different algorithms. The error handling capability is measured in terms of Maximum Individual relative error (MIRE) and Maximum Individual Absolute Error (MIAE) of the state variable estimated by the mentioned works. Table 5 shows the simulation results for the following errors:

Maximum Individual Relative Error

$$MIRE(\%)=Max((|Actual-Estimation|)/Actual)\times 100 \quad (11)$$

Maximum Individual Absolute Error

$$MIAE=Max(|Actual-Estimation|) \quad (12)$$

Where, Actual value indicates the actual value of the state variable which is either load powers or RESs output power.

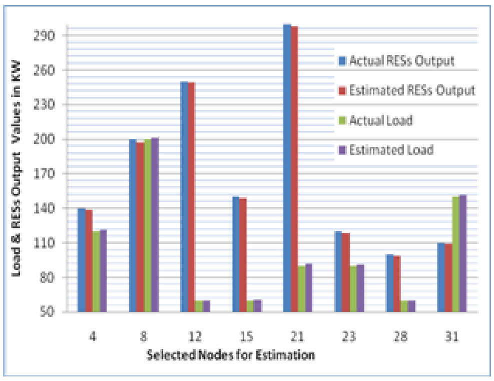

Fig.3. Comparison between Actual and Estimated Values of Load and RESs Output

Conclusion

In this paper, ABC algorithm is proposed for estimating the state of RESs integrated EDS. The considered state variables are RESs output powers and load power values. The practical considerations of the EDS are presented to represent the real time network performance. The proposed ABC algorithm was tested on an IEEE 33-bus radial distribution test feeders. The algorithm is successful to reach the global optimum over all runs. Considering errors for estimated values, ABC shows very competitive performance to PSO, HBMO, NNs, ACO, GA, QIEA, and GRASP.

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TABLE I: CHARACTERISTIC OF RESS AND LOAD VALUES AT SELECTED NODES

Node	RESs			Variable Loads	
	Average of active power output, P_R (in KW)	Power factor	Type of RES	Active power, P_L (in KW)	Reactive power, Q_L (in KVAR)
4	140	1	PV	120	0
8	200	1	Wind	200	60
12	250	1	Fuel cell	60	40
15	150	1	Hydro	60	80
21	300	1	Wind	90	30
23	120	1	PV	90	20
28	100	1	Wind	60	100
31	110	1	Fuel cell	150	100

Table 2: The power variations at selected nodes

Node	Normal		After RESs added		Adding Load		After load Added	
	P_L	Q_L	P_L	Q_L	P+	Q+	P_L	Q_L
4	120	80	260	80	140	0	400	80
8	200	100	400	100	200	0	600	100
12	60	35	310	35	250	0	560	35
15	60	10	210	10	150	0	360	10
21	90	40	390	40	300	0	690	40
23	90	50	210	50	120	0	330	50
28	60	20	160	20	100	0	260	20
31	150	70	260	70	110	0	370	70

Table 3: simulation results of ABC for the actual and estimated values of loads

Node	Actual P_L (in KW)	Actual Q_L (in KVAr)	Estimated P_L (in KW) by ABC algorithm	Estimated Q_L (in KVAr) by ABC algorithm
4	120	80	121.1639	081.3330
8	200	100	201.6233	101.0903
12	60	35	059.6921	035.8166
15	60	10	060.5869	009.9052
21	90	40	091.567	039.8708
23	90	50	091.2000	049.3149
28	60	20	059.5265	020.9422
31	150	70	151.1522	069.7494

Table 4: Simulation results of ABC for the actual and estimated values of ress

Node	Actual P_R (in KW)	Estimated P_R (in KW) by ABC algorithm
4	140	138.297
8	200	197.40
12	250	249.737
15	150	148.525
21	300	298.131
23	120	118.556
28	100	98.690
31	110	108.909

Table 5: comparison of errors for estimated load values and RESs output for eight algorithms

Algorithm		Estimated Loads		Estimated RESs Output	
		MIRE (%)	MIAE	MIRE (%)	MIAE
ABC	Value	1.75	1.623	1.31	2.6
	Location	8	21	28	8
PSO	Value	3.934	7.638	3.736	6.834
	Location	4	64	8	35
HMBO	Value	2.36	4.673	2.637	4.667
	Location	21	14	41	14
NN	Value	5.67	8.923	6.379	10.966
	Location	42	64	21	62
ACO	Value	2.713	5.6348	2.834	4.869
	Location	26	34	8	29
GA	Value	4.653	7.831	4.973	7.937
	Location	26	64	35	58
QIEA	Value	1.77	2.13	1.369	2.940
	Location	4	34	62	58
GRASP	Value	1.96	1.67	1.750	3.812
	Location	21	64	62	14

References

1. Abdulkerim Karabiber, Cemal Keles, Asim Kaygusuz and B Baykant Alagoz, "An approach for the integration of renewable distributed generation in hybrid DC/AC micro grids", Renewable Energy, Vol.52, pp.251-259, 2013.
2. T J Hammons, "Integrating renewable energy sources into European grids," Electrical Power and Energy Systems, Vol.30, pp.462-475, 2008.
3. Carmen Lucia Tancredo Borges, "An overview of reliability models and methods for distribution systems with renewable energy distributed generation," Renewable and Sustainable Energy Reviews, Vol.16, pp.4008-4015, 2012.
4. J E Paiva and A S Carvalho, "Controllable hybrid power system based on renewable energy sources for modern electrical grids," Renewable Energy, Vol.53, pp.271-279, 2013.
5. Duong Quoc Hung, N Mithulananthan and Kwang Y Lee, "Optimal placement of dispatchable and nondispatchable renewable DG units in distribution networks for minimizing energy loss," Electrical Power and Energy Systems, Vol.55, 179-186, 2014.
6. G A Taylor, M R Irving, P R Hobson, C Huang, P Kyberd and R J Taylor, "Distributed Monitoring and Control of Future Power Systems via Grid Computing," Power Engineering Society General Meeting, pp.1-5, 2006.
7. Pierre Janssen, Tevfik Sezi and Jean-Claude Maun, "Distribution System State Estimation Using Unsynchronized Phasor Measurements," 3rd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe), pp.1-6, 2012.
8. S Gayathri and R Meenakumari, "Hybrid State Estimation Approach for the Optimal Placement of Phasor Measurement Units," International Journal of Soft Computing and Engineering, Vol.3, No.2, 2013.
9. Efthymios Manitsas, Ravindra Singh, Bikash C Pal and Goran Strbac, "Distribution System State Estimation Using an Artificial Neural Network Approach for Pseudo Measurement Modeling," IEEE Transactions On Power Systems, Vol.27, No.4, pp.1888-1896, 2012.
10. Naka S, Genji T, Yura T, Fukuyama Y, "A hybrid particle swarm optimization for distribution state estimation," IEEE Transactions on Power Systems 2003;18 (1):60–8.
11. Niknam T, "Application of honey bee mating optimization on distribution state estimation including distributed generators", Journal of Zhejiang University Science A 2008 9(12): 1753-1764.
12. Lu Z, Ji TY, Tang WH, Wu QH, "Optimal harmonic estimation using a particle swarm optimizer," IEEE Transactions on Power Delivery 2008; 23(2):1166–74.
13. Niknam T, Ranjbar AM, Shirani AR, "A new approach for distribution state nestimation based on ant colony algorithm with regard to distributed generation," Journal of Intelligent & Fuzzy Systems 2005;16(2):119–31.
14. Peidong Z, Yanli Y, Jin S, Yonghong Z, Lisheng W, Xinrong L, "Opportunities and challenges for renewable energy policy in China," Renewable and Sustainable Energy Reviews, Volume 13, Issue 2, February 2009, Pages 439–449.
15. Baran ME, Freeman LAA, Hanson F, Ayers V, "Load estimation for load monitoring at distribution substations," IEEE Transactions on Power Systems 2005;20:164–70.
16. Sun H, Gao F, Zhang B, "Minimum information loss based state estimation for power systems," IEEE Power Engineering Society General Meeting 2006:1–10.
17. Wangand H, Schulz NN, "A revised branch current-based distribution system state estimation algorithm and meter placement impact," IEEE Transactions on Power Systems 2004;19:207–13.
18. Meliopoulos APS, Zhang F, "Multiphase power flowa nd state estimation for power distribution systems," IEEE Transactions on Power Systems 1996; 11: 939–46.
19. Konjic T, Miranda V, Kapetanovic I, "Fuzzy inference systems applied to LV substation load estimation," IEEE Transactions on Power Systems 2005; 20(2):742–9.
20. Wan J, Miu KN, "A zonal load estimation studies in radial power distribution networks," IEEE Transactions on Power Delivery 2002; 17(4):1106–12.
21. Ghosh AK, Lubkeman DL, Downey MJ, Jones RH, "Distribution circuit state estimation using a probabilistic approach", IEEE Transactions on Power Systems 1997; 12:45–51.
22. Leou RC, Lu CN, "Improving feeder voltage calculation results with telemeter data," IEEE Transactions on Power Delivery 1996; 11:1914–20.
23. Deng Y, He Y, Zhang B, "Branch-estimation-based state estimation for radial distribution systems," IEEE Power Engineering Society Winter Meeting 2000; 4:2351–6.
24. Roytelman I, Shahidehpour SM, "State estimation for electric power distribution systems in quasi real-time conditions," IEEE Transactions on Power Delivery 1993; 8:2009–2015.
25. Baran ME, Kelley AW, "State estimation for real-time monitoring of distribution Systems," IEEE Transactions on Power Systems 1994; 9:1601–9.
26. E. Manitsas, R. Singh, B. C. Pal, and G. Strbac, "Distribution system state estimation using an artificial neural network approach for pseudo measurement modeling," IEEE Trans. Power Systems 2012; 27: 1888–1896.
27. Jen-Hao Teng, "Integration of Distributed Generators into Distribution Three-Phase Load Flow Analysis," IEEE Russia Power Tech, pp.1-6, 2005.
28. Dervis Karaboga and Bahriye Akay, "A comparative study of Artificial Bee Colony algorithm," Applied Mathematics and Computation, Vol.214, pp.108-132, 2009.
29. Basturk and D. Karaboga, "An artificial bee colony (ABC) algorithm for numeric function optimization," in Proc. IEEE Swarm Intell. Symp., Indianapolis, IN, May 12–14, 2006.
30. Fahad S. Abu-Mouti and M. E. El-Hawary, "Optimal Distributed Generation Allocation and Sizing in Distribution Systems via Artificial Bee Colony Algorithm," IEEE Transactions on Power Delivery 2011; 26: 2090-2101.
31. E Afzalan, M A Taghikhani and M Sedighizadeh, "Optimal placement and Sizing of DG in Radial Distribution Networks Using SFLA", International Journal of Energy Engineering, Vol.2, No.3, pp.73-77, 2012.
32. K. H. Han and J. H. Kim, "Quantum-inspired evolutionary algorithm for a class of combination optimization," IEEE Trans. Evol. Computer 2002; 6: 580–593.
33. A. F. Thomas and G. C. R. Mauricio, "Greedy randomized adaptive search procedures," J. Global Optim. 6, 109–133 (1995).