Intelligent Meter Placement Approach for Power Distribution System

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Abstract— *Distribution System monitoring become a very important function in today's deregulated power markets and thus, state estimators have become the essential tools of choice for the implementation of this function. Determination of the best possible combination of meters for monitoring a given Distribution System is referred to as the optimal meter placement. Whether a new state estimator is put into service or an existing one is being upgraded, placing new meters for improving or maintaining reliability and the observability of the measurement system, is of great concern. This paper proposes an PSO optimization algorithm suitable to choose the optimal number and position of the measurement devices needed to operate management and control issues, such as energy dispatching and protection coordination, in modern electric distribution networks.*

Key words: *Distribution system***,** *Distributed Generation***,** *Loss Minimization***,** *Optimization*

1. Introduction

Distribution state estimation (SE) [1] [2] [3] [4] [5], is used to facilitate data collection. It is performed by processing a set of measurement data consisting of power line flows and bus voltage measurements. These measurements are collected by RTU's and transmitted to the control center through telemeter lines. The success of state estimation depends on the number, type and location of established meters and RTUs in the system. This paper presents a new measurement placement method that allows determining, in a straightforward manner, where to install meters and RTUs in a distribution system in order to obtain a measurement placement plan that satisfies the reliability criteria.

Electric power system SE [6] was first introduced by Fred Schweppes of MIT in 1969. Power system meter placements have been addressed by various researchers in the past. Koglin [7] adopted a criterion for estimation accuracy with respect to quantities of interest. He proposed the Koglin algorithm on the basis of measurement elimination procedure with measurement sensitivity as the performance criterion. Baran et al. [8] developed rule based meter placement scheme which identifies the data requirements for real-time monitoring and control of distribution systems. J.C.S.Souza et al. [9] presented an optimal meter placement methodology for real-time power distribution system monitoring where Genetic Algorithms technique is employed to achieve a trade-off between investment costs and real-time monitoring capability. J.Wan et al. [10] proposed heuristic incremental meter placement zonal method which addressed the meter placement problem with respect to load estimation in radial power distribution systems. H.Wang et al. [11] developed a revised branch-current-based three-phase distribution system SE algorithm for studying impact of meter placement on the proposed estimator. A.Shafiu et al. [12] developed a heuristic approach to identify the best locations for placing voltage measurements for distribution SE with distributed generation. The method identifies busbars on which a given number of voltage measurements are to be placed, so as to reduce the standard deviation of the voltages at those busbars in the network which do not have a measurement. C.Muscas et al. [13] proposed an optimization algorithm for choosing the optimal number and position of the measurement devices needed for energy dispatching and protection coordination in modern electric distribution networks. The goal of the proposed dynamic programming procedure is to guarantee the minimum cost and the accuracy required to the measured data. V.Cecchi et al. [14] designed a unique and flexible Instrumentation and Measurement system consisting of software and hardware instruments to perform network reconfiguration and meter placement studies; it can adapt to power system planning and operating scenarios. C.Muscas et al. [15] also proposed an optimization algorithm, based on dynamic programming technique, suitable for choosing the optimal number and position of measurement devices in modern distribution networks. A.Moradi et al. [16] discussed how to determine the optimum number and location of two types of switches in distribution systems. A novel multistage version of a discrete PSO algorithm is presented in this paper to determine the optimum number and locations of CBs and sectionalizes in a distribution system. The convergence rate and the ability of the proposed algorithm for finding near global minimum are tested on the RBTS BUS 4 and the IEEE 123-node feeder standard test system

In their previous paper [17] [18], the authors addressed on intelligent meter placement algorithm in power system SE. This method allows the cost optimal selection of meters so that the system remains observable under any single or multiple measurement losses, branch outages, bus splitting and any other pre-defined contingency. The proposed qualitative method and Genetic Algorithm is tested with IEEE 6 and IEEE 14 Bus system. This paper proposes a PSO algorithm for optimal meter and RTU placement in a distribution network. The algorithm identifies the minimum number of meters required by considering the meter cost to make the system observable. The algorithm is tested with IEEE and Indian distribution system. The superiority of PSO is validated by comparing the tested result with branch and bound technique.

2. Problem Definition

2.1 Meter Placement Strategy

In distribution system planning [19][20], optimal metering is formulated as optimization problem. The investment costs should be minimized subject to some constraints in order to guarantee a good performance of SE. The formulated problem is expressed as Equation (1) given below:

$$Min \sum_{i}^{n} w_i * x_i \qquad (1)$$

$$subject\ to: \ f(x) \geq \hat{1}$$

Where,

W_i = the cost of meter including RTU

$\hat{1}$ = a vector whose entries are all ones.

X = a binary decision variable vector, whose entries are defined in Equation (2):

$$x_i = \begin{cases} 1 \rightarrow if\ \ a\,meter\,is\,installed\ at\,bus\,i \\ 0 \rightarrow otherwise \end{cases} \qquad (2)$$

f(x) = a vector function whose entries are non-zero if the corresponding bus voltage is solvable using the given measurement set and zero otherwise.

The product of the binary decision variable vector and the cost vector represents the total installation cost of the selected meters. Constraint functions ensure full network observability while minimizing the total installation cost of the meters. The procedure for building the constraint equations is described in this paper by considering a system with no conventional measurements or zero injections. In this case, the flow measurement and the zero injection are ignored. In order to form the Constraint set, the binary connectivity matrix A is first formed as:

$$A_{k,m} = \begin{cases} 1 \rightarrow if\ k = m\ or\ k\ \&\ m\,connected \\ 0 \rightarrow otherwise \end{cases} \qquad (3)$$

For demonstration, the authors consider the 8-bus example system shown in Fig.1.,where M represents RTU location and X represents meter location with respect to RTU.

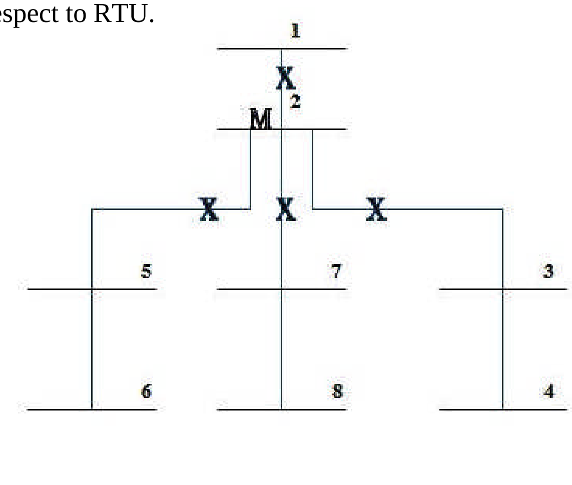

Fig. 1 Network diagram for the 8-bus system with RTU and meter location

Assumptions are made that a given RTU provides measurement for the branch current with respect to connected neighbour buses. Once a bus is assigned a RTU, voltages at all to of its neighbours are assumed to be known. An easy way of determining all such known buses are to use the binary connectivity Matrix A as defined in Equation (2)

This yields the following matrix in Equation (4) for the 8-bus system of Fig. 1:

$$A = \begin{matrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{matrix} \quad (4)$$

The product of this matrix and the binary decision vector X provides the desired vector function. Elements of this vector function will be at least equal to one, if at least one neighbor of the corresponding bus is assigned a RTU. Hence, the constraint equations for the above example for this case are as given by Equations (5) and (6):

$$f(X) = A.X$$

$$f1 = x1 + x2 \quad >= 1 \quad (5)$$

$$f(X) = \begin{matrix} f2 = x1+x2+x3+x5+x7 & >=1 \\ f3 = x2+x3+x4 & >=1 \\ f4 = x3+x4 & >=1 \\ f5 = x2+x5+x6 & >=1 \\ f6 = x5+x6 & >=1 \\ f7 = x2+x7+x8 & >=1 \\ f8 = x7+x8 & >=1 \end{matrix} \quad (6)$$

The operator "+" implies logical "OR" and the use of 1 in the right hand side of the inequality ensures that at least one of the variables appearing in the sum will be non-zero. For example, the constraints associated with bus 1 and bus 2 are as given by Equations (7) and (8):

$$f1 = x1 + x2 \quad >= 1 \quad (7)$$

$$f2 = x1+x2+x3+x5+x7 \quad >=1 \quad (8)$$

The first constraint $f1 \geq 1$ implies that at least one RTU must be placed at either one of or both bus 1 and bus 2 to make bus 1 observable. Similarly, the second constraint $f2 \geq 1$ indicates that at least one RTU should be installed at any one of the buses 1, 2, 3, 5, or 7 in order to make bus 2 observable.

Matrix A can be directly obtained from the bus admittance matrix by transforming its entries into binary form. Matrix A is solved for obtaining possible combination of optimal placement of meter and then solved for considering cost minimization.

2.2 Meter Cost

The aim of the RTU is to perform Wide Area Monitoring (WAM) protection and control for electric power distribution system. Here the power system is managed by Supervisory Control and Data Acquisition/Energy Management System (SCADA/EMS) including a RTU. The RTU is likelyto be located at the substation of the power distribution system and at the nodes of the system where the RTU comprises first level of data acquisition. This means acquiring measurement data which is to be evaluated by the SCADA/EMS system.The formulated problem for cost of meter to be installed is in (9):

$$W_i = \quad Min\ (Crtu + Cm) \quad (9)$$

subject to performance requirements
where:
Cm = cost of meters that will be installed
Crtu = cost of RTUs

The meters are placed to collect data at branches 1-2, 2-3, 2-7 and 2-5, but the RTU is placed at node 2 in the figure 1. To calculate the cost of metering this system, the following method is adopted. The cost of RTU would be Crtu=1 unit. One unit equals to 100 *US $*. The cost of meter at each node is 0.2 units, so the cost of placing the meters at all the 4 nodes is: Cm=0.2 x 4=0.8 units. Therefore the total cost of metering the system would be: C=Cm+Cr=1.8 units. The same procedure is adapted to all the systems to calculate the cost function.

3 PSO Methodology

PSO was formulated by Edward and Kennedy in 1995. The algorithm was inspired by the social behavior of animals, such as bird flocking or fish schooling. PSO is similar to the continuous GA in that it begins with a random population matrix. Unlike the GA, PSO has no evolution operators such as crossover and mutation. The rows in the matrix are called particles (same as the GA chromosome). They contain the variable values and are not binary encoded. Each particle moves about the cost surface with a velocity. The particles update their velocities and positions based on the local and global best solutions:

$$V_{m,n}^{new} = V_{m,n}^{old} + \Gamma_1 * r_1 * (P_{m,n}^{localbest} - P_{m,n}^{old}) + \Gamma_2 * r_2 * (P_{m,n}^{globalbest} - P_{m,n}^{old})$$

Where

$V_{m,n}$ = particle velocity, $P_{m,n}$ = particle variables

r_1, r_2 = independent uniform random numbers

Γ_1, Γ_2 = learning factors = 2

The PSO algorithm [21] [22] [23] [24] updates the velocity vector for each particle then adds that velocity to the particle position or values. Velocity updates are influenced by both the best global solution associated with the lowest cost ever found by a particle and the best local solution associated with the lowestcost in the present population. If the best local solution has a cost less than the cost of the current global solution, then the best local solution replaces the best global solution. The particle velocity is reminiscent of local minimizes that use derivative information, because velocity is the derivative of position. The constant Γ_1 is called the cognitive parameter. The constant Γ_2 is called the social parameter. The advantages of PSO are that it is easy to implement and there are few parameters to adjust. The PSO is able to tackle tough cost functions with many local minima. The initial random swarm set loose on the cost surface. The particle swarming becomes evident as the generations pass. The largest group of particles ends up in the vicinity of the global minimum and the next largest group is near the next lowest minimum. A few other particles are roaming the cost surface at some distance away from the two groups. Figure 3.1 shows plots of $P_{m,n}$ local best and $P_{m,n}$ global best as well as the population average as a function of generation. The particle $P_{m,n}$ global best serves the same function as elite chromosome in the GA.

3.1Binary PSO

The initial development of PSO is on continuous-valued search spaces. The first discrete PSO to operate on binary search spaces was developed by Kennedy and Eberhart [25].The binary PSO can be applied to real value optimization problem after real-binary transformation using gray coding. Each element of a particle's position vector can take on the binary value 0 or 1.By proper mutation of bits, position of particles will change. A particle may then be seen to move to near and far corners of the hypercube by flipping bits. One of the first problems to be addressed in the development of the binary PSO is how to interpret the velocity of a binary vector.

3.2 PSO Meter Placement Problem

Binary PSO algorithm is used for solving the meter placement problem. In this context, the algorithm stated above is not used because of the level of randomness is present in the above stated algorithm. Due to this randomness it becomes difficult to satisfy the constraint equations when the program is run. To deal with the difficulty that occurred, the original PSO algorithm is used for solving the continuous optimization problems, but a few changes are made to the algorithm. First of all, the range of the particles is restricted to [0, 1]. Then the velocity is calculated in the normal procedure; but while updating the position of the particles it is rounded off to either 0 or 1.The flowchart for binary PSO is shown in Fig. 2.

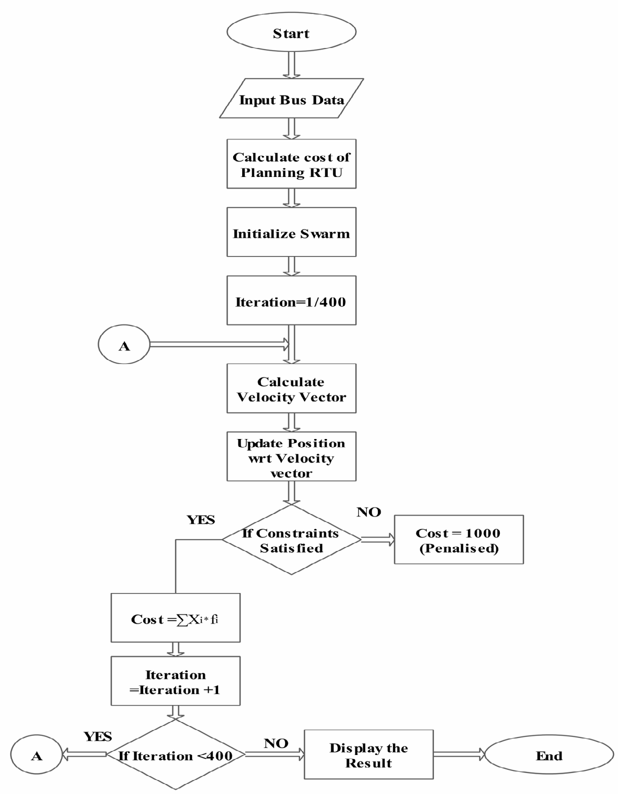

Fig. 2: PSO binary algorithm flowchart

4 Test Cases & Meter Placement

In this paper we plan to install a new metering system to make a distribution system observable. To validate the proposed approach, the optimization procedure has been applied to IEEE standard networks [26]. Cost of RTU is taken as 1 unit and cost of meter is taken as 0.2 units. The PSO algorithm is tested with IEEE 37 and IEEE 123 Bus distribution systems. To check the effectiveness and flexibility of PSO, it is verified by comparing the result with Branch and Bound technique. The program has been developed using MATLAB for PSO and Branch and Bound Optimization.

4.1 PSO Optimal Meter Placement

The PSO Algorithm tested for IEEE 13, 34, 37, 61,123 standard different node systems is to make the system observable with total meter cost, location and optimal number of meters. Table 1 shows the results for optimal meter placement obtained by the proposed PSO technique with the location of meter and total investment cost. Table 2 shows the results for meter position branches in IEEE 13 bus system. Table 3 shows the results for meter position branches in IEEE 34 bus system. Due to page limitation only meter location in branches for IEEE 13 and 34 bus systems is displayed in table 2 and 3.

Table 1
Test Results for IEEE Systems

Test System	Total Cost	RTU Placement Buses	No. of Meters
IEEE 13	8.79	1,4,6,9,10,13	6
IEEE 34	18.8	2,5,7,11,13,17,21,24,26,29, 31,33	12
IEEE 37	20.4	1,3,6,10,13,14,19,21,24,28, 31,35	12
IEEE 61	35.4	2,5,8,11,14,17,19,21,25,28, 31,33,35,37,39,41,44,46,49, 52,55,58,60	23
IEEE 123	69.4	1,2,6,8,14,15,20,22,24,28,3 1,33,37,39,41,43,47,52,56,5 8,62,65,68,71,74,76,78,82,8 5,88,90,92,94,95,98,103,10 5,107,110,114,116,118,119, 121	44

Table 2
Meter position in IEEE 13 Bus Systems

S.No	Meter Placement Branches	RTU Location Bus
1	1--2	1
2	3--4	4
3	5--6	6
4	8--9	9
5	10--11	10
6	10--7	10
7	10--12	10
8	7--13	13

Table 2
Meter position in IEEE 34 Bus Systems

S.No	Meter Placement Branches	RTU Location Bus
1	2--3	2
2	4--5	5
3	6--7	7
4	7--8	7
5	10--11	11
6	11--12	11
7	9--13	13
8	13--14	13
9	13--15	13
10	16--17	17
11	17--18	17
12	17--19	17
13	20--21	21
14	21--22	21
15	23--24	24
16	25--26	26
17	26--27	26
18	28--29	29
19	30--31	31
20	31--32	31
21	31--34	31
22	32--33	33

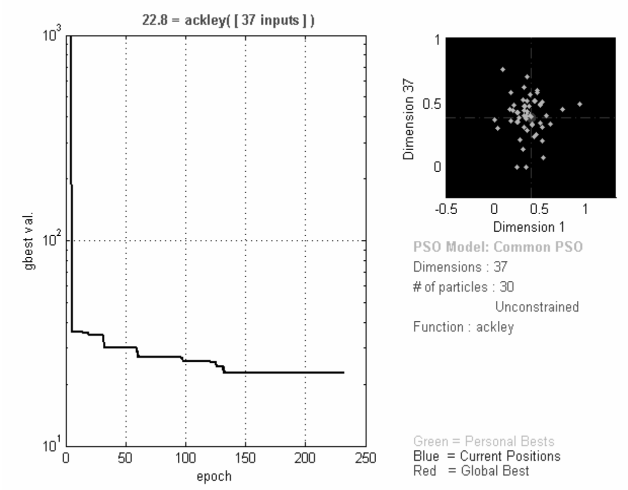

Fig. 3 PSO optimization particle position for IEEE 37 Bus System

The position of particle to make the IEEE 37 bus system observable is shown in Fig.3.

Algorithm is tested for an Indian system of Tamil Nadu Electricity Board (TNEB). The system has 17 nodes with 6 meters to make the system observable with total meter cost of 9.6 units. Table 4 shows the results for optimal meter placement obtained by the proposed PSO technique with the location of meter and total investment cost. Fig 4 represents the one line diagram of TNEB 17 bus distribution feeder, where M represents the optimal location of RTU placement.

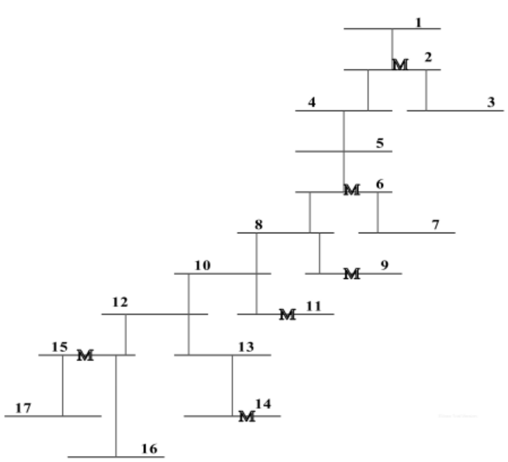

Fig. 4 represents TNEB 17 bus distribution feeder with meter position.

Table 4
Test result for TNEB System

Test System	Total Cost	RTU Placement Buses	No. of Meters
TNEB 17	9.6	2,6,9,11,14,15	6
TNEB 40	24.6	3,5,8,10,11,15,16,19,20,24, 25,31,32,36,37,40	16

The proposed algorithm executed for TNEB 32 node real time feeder assuming zero injection, zero switch position and zero transformers connected. Thirteen number of RTU needed to monitor the feeder .RTUs are placed at bus number 2,6,7,9,12,14,16,19,21,24,26,28,and 31,where line meters are placed at respective branches with investment cost of meter is 20.2 units.

The number of particle taken as input is 26.Figure 5 shows the optimization output and particle position. The green color in inner plot represents the particle position when global best position is occurred. Another plot shows the gbest value and number of epoch .The value 20.2 in the top of the plot represents the total minimum investment cost of RTU/Meter.

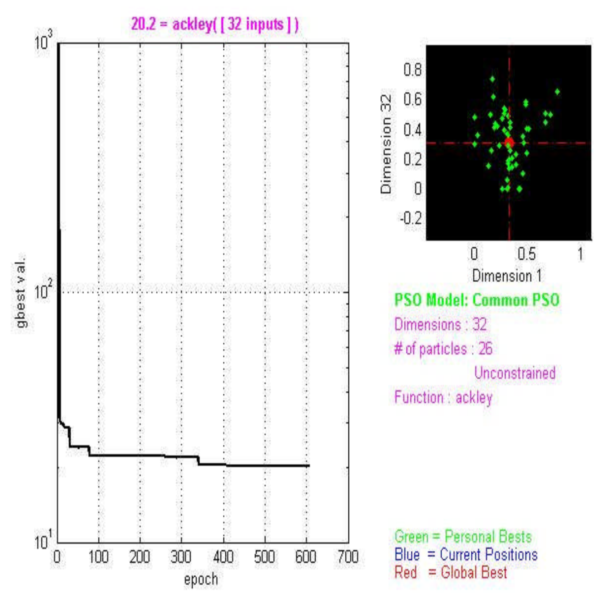

Figure 5 : TNEB 32 node PSO particle position

5 Conclusion

The optimal number/location of RTU and meter by minimizing the total cost in distribution system is formulated using Particle Swarm Optimization Algorithm. The proposed PSO algorithms were tested on IEEE and Indian standard bus distribution systems. The case study results indicate that PSO is superior in all respect. This paper can be extended for loss of branch outages and different hybrid algorithms, considering distributed generation.

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