The Role of PSO Meter Placement in Distribution State Estimation

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Abstract: - Optimal meter placement with state estimation plays a major role in monitoring and controlling of Distribution System. The objective of this work is to optimize the number of necessary measurements and Remote Terminal Units, subject to the constraints of the system observability requirements for best voltage estimation. A global optimization algorithm and Particle Swam Optimization is proposed to fulfil the requirement. The parameter values are estimated using the Hybrid Artificial Neural Network based state estimation technique of injecting pseudo measurements at un-metered buses. The algorithm is simulated for IEEE and Indian standard bus distribution systems and the results are presented. The effectiveness and flexibility of PSO are demonstrated by validating the results with Mathematical techniques and the effectiveness of estimator.

Key-Words: -Branch and Bound technique, Meter Placement, Particle Swarm Optimization, Power Distribution Systems, State Estimation.

1 Introduction

With the increase in complexity of power distribution systems, optimal data collection has become important for ensuring accurate performance of various control functions. Distribution state estimation (SE) [1] [2] [3] [4] [5] is used to facilitate data collection. It was performed by processing a set of measurement data consisting of power line flows and bus voltage measurements. The RTUs collect these measurements and transmit them to the control centre through telemeter lines.

State Estimation of electric power system [6] was first introduced by Fred Schweppes of MIT in 1969. At the same time, power system meter placement has been addressed by different authors in the past. Koglin [7] developed a criterion for state estimation accuracy with respect to different interesting quantities. The algorithm named Koglin was proposed on the basis of measurement elimination procedure which is clearly based on the measurement sensitivity as the performance criterion. Baran et al. [8] developed rule based meter placement to identify the data requirements for real-time monitoring and control of distribution systems. Souza et al. [9] presented a methodology to place optimal meter for real-time power distribution system monitoring where Genetic Algorithms technique was employed to achieve a trade-off between investment costs and real-time monitoring capability. 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. Wang et al. [11] developed a revised branch-current-based three-phase distribution system SE algorithm for studying the impact of meter placement on the proposed estimator. Shafiu et al. [12] developed a heuristic approach to identify the best locations for placing voltage measurements for distribution SE with distributed generation. This method identifies the bus bars on which a given number of voltage measurements are to be made, so as to minimize the standard deviation of the voltages at those bus bars in the network which do not have a measurement.

Muscas et al. [13] proposed an optimization algorithm for energy dispatching and protection coordination in modern electric distribution networks by choosing the optimal number and position of the measurement devices. The goal of the proposed dynamic programming procedure is to guarantee minimum cost and accuracy required to the measured data. Cecchi et al. [14] designed the software and hardware instruments to perform network reconfiguration and meter placement studies for unique and flexible Instrumentation and Measurement system. Tian et al. [15] presented the power system observability and the rules of PMU placement. Several algorithms of PMU placement as well as their differences and relations are discussed in details Moradi et al. [16] proposed optimum number and location of two types of switches (locations of CBs and sectionalizes) in distribution systems based on multistage version of a discrete PSO. The algorithm was tested using the RBTS BUS 4 and the IEEE 123-node feeder standard test system to check the convergence rate and the ability of the proposed algorithm in finding the near global minimum. A comparative study of state estimation, an important task, was addressed in [17] [18], which dealt with the intelligent meter placement algorithm in power system. This method also allows the cost optimal selection of meters so that the system remains observable under measurement losses, branch outages, bus splitting and any other pre-defined contingency. The intelligent algorithm proposed in this work using Genetic Algorithm is tested for IEEE 6 and 14 bus systems and the results are more effective when compared with results of the quantitative analysis.

A.A. Razi [19] implemented a method in response to the goal of placement of remote terminal units which are in charge for data acquisition and control in a power distribution system. In this light, a new practical methodology based on the robust decision making method, analytical hierarchical process, was proposed to simply and, at the same time, to profoundly exploit some practical aspects which have not been considered before in cases of placements. Shafiee [20] proposed a new algorithm that uses the minimum variance criterion (MVC) and a sequential method for optimal meters placement, the SVD method, for observability analysis and finally the WLS method for harmonic estimation. It minimizes the number of measurement devices and the error of estimation, which was tested on the Mazandaran transmission network in Iran, so as to make the system fully observable. Junqi Liu [21] presented the concept of robustness to their previous work in the optimal meter placement procedure, so that the distributed measurement system can provide accurate estimates in the occurrence of either loss of data or degradation of metrological performance of the measurement devices also. Tests performed on a small UKGDS 16-bus distribution network are presented.

This paper extends the author's work of comparison with numerical techniques [22-23] to propose optimal meter placement and state estimator algorithm for radial distribution network through an intelligent PSO approach. The algorithm identifies the minimum number of meters required by considering the meter cost to make the system observable. The proposed algorithm is tested with the IEEE and the TNEB distribution system. The superiority of the PSO is validated by comparing the tested result with numerical techniques.

2 Meter Placement State Estimation Methodology

The population based stochastic optimization algorithm which came from the nature of the social behaviour of flocks of birds is termed as Particle Swarm Optimization. Kennedy and Eberhart [24] introduced the algorithm in 1995 by the several variants of the PSO. If the parameters are adequately selected [17], then a convergence of the PSO algorithm is guaranteed. A wide range of optimization problems are solved by the PSO because of its easy implementation. The PSO algorithm consists of a swarm of particles flying through the search space. Each particle's position is a potential solution to the problem. Each particle's velocity is modified based on its distance from its personal best position and the global best position. The Binary Particle Swarm Optimization BPSO [25] is a variant of the PSO, which was adapted to search in binary space. In the BPSO, the component values of a particle's position Xii are restricted to the set {0, 1}. The velocity, $V_{i,}$ is interpreted as a probability to change a bit from 0 to 1, or from 1 to 0 when updating the position of the particles. This can be done using a sigmoid function defined as (1):

$$sig(x) = \frac{1}{1+e^{-x}} \tag{1}$$

Hence, the equation for updating positions is the probabilistic update equation (2), namely [5]:

$$x_{i,j}(t+1) = \begin{cases} 0 \ if \ \ r_i(t) \geq sig(V_{i,j}(t+1)) \\ 1 \ if \ \ r_i(t) < sig \ (V_{i,j}(t+1)) \end{cases} \tag{2}$$

Where r_i (t) ~ U (0, 1) is a random number between 0 and 1 and Vi the velocity of particle i, that is updated as the following equation (3):

$$V_{i,j}(t+1) = wV_{i,j}(t) + c_1 r_{1,j}(t)$$
$$(y_{i,j}(t) - x_{i,j}(t)) + c_2 r_{2,j}(t)(\hat{y}_j(t) - x_{i,j}(t)) \tag{3}$$

Here, $X_{i,j}(t)$ is the current position of the particle. $V_i(t)$ is the current velocity of the particle. Y_i (t) is the personal best position of the particle (pbest). This is the best position visited so far by the particle i and it is the global best position of the Swarm (gbest) and it seems to be the the best position visited so far by the entire swarm. And it also acts as the inertia weight serving as a memory of previous velocities such that the inertia weight controls the impact of the previous velocity [26] [27]. The cognitive component represents the particle's own experience which is the best solution. The social component represents the belief of the entire swarm as the best solution. C1 and C2 are acceleration constants and r1(t) , r2(t) ~ U(0,1), where U(0,1) is a random number between 0 and 1. This paper makes use of a binary PSO to optimize the number of RTU and meters.

The PSO [26-29], as an optimization tool, provides a population-based search procedure in which individuals, called particles, change their positions with time. When particles fly around in a multidimensional search space, the position of the particle is adjusted by its own experience, which is termed as pbest, and the experience of neighboring particles, which is termed as gbest. The optimum position is obtained by making use of the best position encountered by itself and its neighbors. By use of the set of particles neighboring the particle and its experience, the swarm direction of a particle is determined.

2.1 PSO Meter Placement Problem

The initial development of the PSO is based on continuous-valued search spaces. The first discrete PSO to operate on the binary search space was developed by Kennedy and Eberhart [29] [30].The binary PSO can be applied to the real value optimization problem after a real-binary transformation using the gray code. 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. The 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 present in the algorithm. Due to this randomness, it becomes difficult to satisfy the constraint under a real time programming. To overcome this limitation, the original PSO algorithm is used for solving the continuous optimization problems with some changes in the algorithm. First of all, the range of the particles is restricted to [0, 1]. Then the velocity is calculated using the normal procedure; but while updating the position of the particles, it is rounded off to either 0 or 1.

Penalty function methods, which add a penalty to the objective function, discourage search in infeasible areas of the search space. Constraints like switch position and breaker positions are also considered in the algorithm. If the constraints are not satisfied, then the algorithm takes the basic cost as penalized. The algorithm for the flow chart was written in MATLAB 6.1 .The line data for the test system is the input to the algorithm with the existing contingencies like switch position, breaker position etc. Next the cost of the RTU and the meter are to be assigned. After feeding these as inputs, the programme is executed to search for the position and the optimal number of meters to be placed in the system based on the assigned constraints.

Observability Analysis

The basic idea followed in Observability analysis was either by topological or numerical approaches. The graph theory was followed to determine network observability based on the measurement type and location without any floating point arithmetic [29] [30]. The decoupled measurement Jacobian matrix and the associated gain matrix are followed for Numerical approaches. The same scheme is used to find all the observable islands for the unobservable system. A similar procedure is adopted to place pseudo-measurements to make the whole network observable. The algorithms rendering the identical results require less number of computations by avoiding the solution of measurement equations. These algorithms were utilized and applied in the development of topological approaches and hybrid algorithms for observability analysis. The authors made use of observability algorithm presented to make the system observable before executing the meter and used the algorithm proposed by the author [23] for the PSO RTU position and numbers.

Algorithm for Observability and Pseudo measurements

1) Determine the values of all state variables, if a subset of the available measurements represented by H is sufficient.
2) If the set of available measurements represented by H makes the problem observable, determine which critical measurements cannot be removed to keep the problem observable.
3) Assuming that the state is observable for the given value of H, determine the set of redundant measurements that can be used to replace a given measurement in H so that the problem remains observable.
4) If the state is not observable in the given value of H, identify the observable islands and the observable state variables.
5) If the state is not observable, identify the irrelevant measurement injections.
6) If all state variables are not observable given H, obtain the minimum subset of pseudo-measurements such that they make all state variables observable.
7) Specify the minimal data required to update the results if initial measurements are lost or new measurements become available.

2.2 Swarm Tuned ANN Estimator

An artificial neural network [31-32] is composed of a series of interconnected nodes, which aims at simulating the complex mapping between the input and output. A 3-layer feed- forward ANN basically consists of input units, hidden units and output units. The ANN is characterized by the ability of self-learning and error tolerance. With the appropriate activation functions and trained weights, the ANN can approximate any smooth, non-linear function or relationship between the input and the output. The training process is carried out on a set of data including both input and output parameters. Usually, the data is split into two parts, namely training samples and testing samples. The learning procedure is based on the training samples and the testing samples are used to verify the performance of the trained network. During the training, the weights in the network are adjusted iteratively till a desired error, depicted as equation (4), is obtained.

$$E=\sum_{i=1}^{m}\sum_{k=1}^{n_0}\left(t_i^k-y_i^k\right)^2/2 \tag{4}$$

Where, t_i and y_i represents the actual and the predicted function values respectively, m is the number of training samples and no is the number of output nodes.

The neural network is trained by minimizing the above error function in a search space based on weights. The best weight is tuned using particle swarm. The PSO generates possible solutions and measures their quality by using a forward propagation through the neural network to obtain the value of the error function. This error value is used as the particle's fitness function to direct it towards the more promising solution. The global best particle is corresponded to the desired trained network after adequate iterations. A PSO based training algorithm can be summarized with the following steps:

Step 1) Define the network structure, the parameters of the PSO and the fitness function.
Step 2) Encode the candidate weight solution.
Step 3) Initialize the position (weights) and the velocity of each particle randomly in the predefined range.
Evaluate the fitness of each particle according to the previously defined error function.
Step 4) Identify the personal best fitness value and update the corresponding position for each particle; Identify the global best fitness value and update its position.
Step 5) Update the velocity and the position for the whole particle swarm according to respective equations.
Step 6) If the stopping condition is not satisfied, go to step 4. Otherwise, terminate the iteration and obtain the best weight setting from the global best solution.

To train the multilayer ANN, it is necessary to generate a number of input-output patterns at different loading conditions. The different loading conditions in the system have been achieved by varying the KW and the KVAR loads in the system within a certain range with respect to the base loading pattern. In this work, the loads have been varied within the range of 25–150% of the base loading pattern. For each of these loading patterns, a Power System Simulation Package -PSCAD Fortran compiler was simulated and the data is stored in a specified location. Thus, a large number of input-output patterns can be generated by varying the load. In this work, 30,000 patterns have been generated. Out of these 30,000 patterns, a majority have been used for the training of the ANN and the remaining patterns have been used for testing the performance of the ANN. For each input-output pattern, the input pattern consists of the real power line flow (P_{ij}), the reactive power line flow (Q_{ij}) and the line current (I_{ij}) and the output pattern consists of the bus voltage magnitudes. Hence, the numbers of input and output nodes are with respect to the system node.

3 Tested Results

In this paper, a new metering system was installed to make the distribution system observable. To validate the effectiveness of the proposed algorithm, a PSO optimization procedure has been applied to the IEEE standard networks [33]. The cost of RTU is taken as 1 unit and the cost of meter is taken as 0.2 units. The PSO algorithm is tested with the IEEE and the Tamil Nadu Electricity Board (TNEB) Bus distribution systems. To check the effectiveness and flexibility of the PSO, it is verified by comparing the result with the Branch and Bound technique. The program has been developed using MATLAB for PSO and Branch and Bound Optimization.

3.1 PSO Optimal Meter Placement

The PSO Algorithm is tested for the IEEE-13, IEEE-34, IEEE-37, IEEE-61 and the IEEE-123 node systems 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. The position of particle to make the IEEE-37 bus system observable is shown in Fig.1.

Table 1 - Test Results for IEEE Systems

Test System	Total Cost	Meter Placement Buses	No. of Meters
IEEE-13	8.4	1,4,6,7,11	5
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	1,2,6,8,14,15,20,22,24,28,31,33,37,39,41,43,47,52,56,58,62,65,68,71,74,76,78,82,85,88,90,92,94,95,98,103,105,107,110,114,116,118,119,121	44

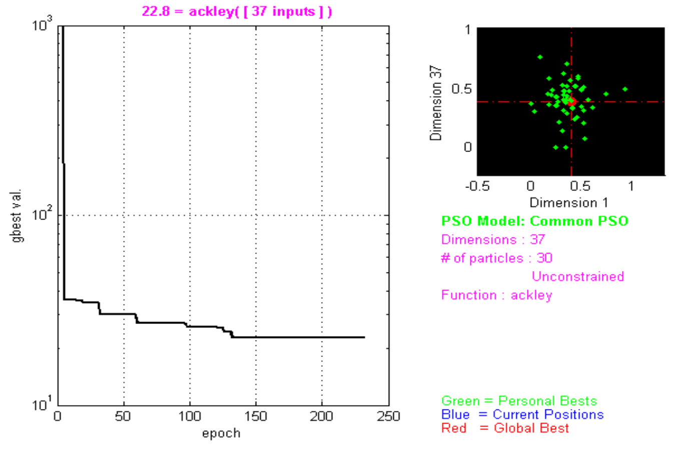

Fig. 1 PSO optimization particle position for IEEE-37 Bus System

The algorithm is tested for an Indian system in the Tamil Nadu Electricity Board (TNEB). The system has 17 nodes with 6 meters to make the system observable, with a total meter cost of 9.6 units. Table 2 shows the results for optimal meter placement obtained by the proposed PSO technique with the location of meter and total investment cost. Fig. 3 represents the one line diagram of the TNEB 17 bus distribution feeder, where M represents the optimal location of meter placement.

Table 2 - Test Result For TNEB System

Test System	Total Cost	Meter Placement Buses	No. of Meters
TNEB 17	9.6	2,6,9,11,14,15	6
TNEB 40	25.8	2,5,8,10,12,15,16,19,20, 24,25,31,33,34,36,37,39	17

3.1.1 Branch and Bound Meter Placement

The Branch and Bound algorithms [BB] [34] are mathematical optimization methods to solve non convex problems. They maintain exact upper and lower limits on the globally optimal objective value. The algorithms terminate with a condition stating that the suboptimal point found is suboptimal. The BB Algorithm is tested for the IEEE-13, IEEE-34, IEEE-37, IEEE-61 and the IEEE-123 standard systems with different distribution systems. The test results are tabulated in Table 3 to make the system observable with a total meter cost and the total number of meters.

Table 3 Test Results for IEEE System

Test System	Tota l Cost	Meter Placement Buses	No. of Meters
IEEE 13	9	2,4,6,9,10,13	6
IEEE 34	19.2	2,5,7,11,13,17,22,23,25, 28,33,34	12
IEEE 37	20.6	2,3,6,9,13,17,19,22,24, 28,31,35	12
IEEE 61	37.4	2,5,8,11,13,17,19,21,25,27,3 1,33,35,37,39,41,43,45,48,5 1,54,57,59,61	24
IEEE 123	72.4	2,4,6,8,14,15,20,22,24,28,31 ,33,37,39,41,43,47,51,52,56, 58,62,65,68,71,74,76,78,82, 85,88,90,92,94,95,98,103,10 5,107,110,114,116,118,119, 121,122	46

The algorithm is also tested for the 17 node TNEB system with 6 meters to make the system observable with a total meter cost of 9.6 units. Table 4 shows the results for optimal meter placement obtained by the Branch and Bound technique with the location of meter and the total investment cost.

Table 4 Test Result for TNEB System

Test System	Total Cost	Meter Placement Buses	No. of Meters
TNEB 17	9.6	2,6,9,11,14,15	6
TNEB 40	25.8	2,5,8,10,12,15,16,1 9,20,24,25,31,33,3 4,36,37,39	17

3.1.2 Discussions

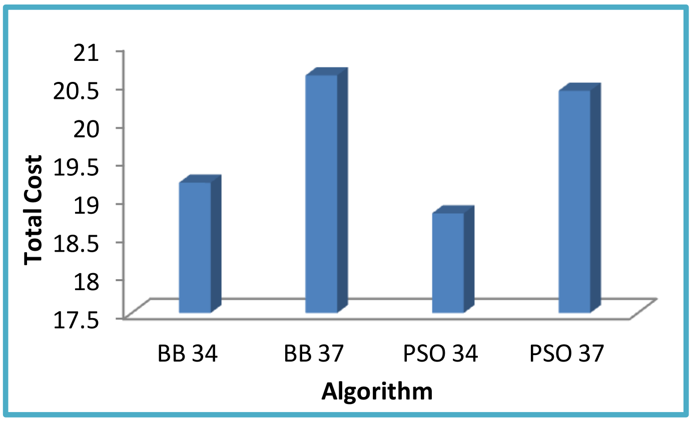

Fig. 2 Comparison of Total cost with PSO and BB Methods

The power system state estimation plays a major role in the accurate monitoring of the power system operation and control. Enormous research works were carried out in this area using different approaches [17]. The recent development was carried out in the development of meter placement algorithm in power distribution system including DG. This paper results the optimal meter placement algorithm which will try to minimize the cost of the meter by identifying the location of the meter. The comparison of the above simulation results for the PSO algorithm (Fig. 2) indicates that, for a minimum number of buses it gives the same result. When the number of buses increases above 20, the total cost is reduced. Test results in IEEE- 61 and IEEE-123 bus systems indicate that the total number of meters also reduces with minimum cost. However, for higher number of buses, the time for computation to get accurate result is more than the lesser number of buses.

To check the effectiveness of the PSO, the total cost of the meter for the PSO and the Branch and Bound method is compared with the IEEE-34 and the IEEE-37 bus systems. Fig.3 expresses the comparison of the PSO with Dynamic Programming, Integer Programming and the Branch & Bound Techniques. The comparison analysis is considered for the RTU cost, time and accuracy for sample IEEE system in percentage as output.

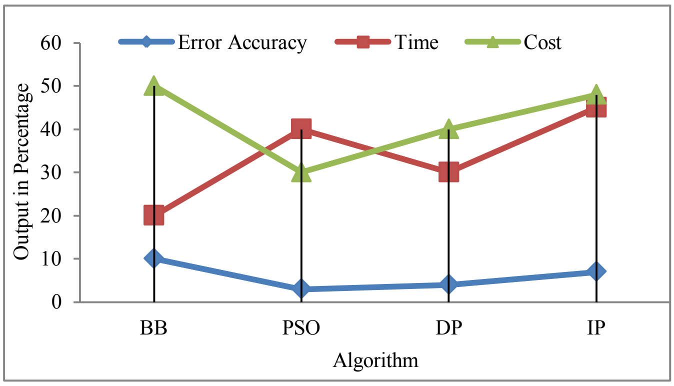

Fig. 3 Comparative analysis of PSO with Numerical Algorithm

It clearly proves the effectiveness and flexibility of the PSO with numerical techniques whereby the total cost is nominal with same meter to be installed, so that the system is observable at different locations. Various authors have discussed distribution system optimal meter placement without considering the meter investment cost, whereas the cost of meter is considered in this paper for optimization. The execution time for the proposed algorithm is slightly high when compared with other algorithms. This limitation will not affect the efficiency of the work, because this algorithm is not executed in real time monitoring the system. The major limitation of the work is that the status of the Switch position was not considered for calculation.

3.2 Swarm Tuned ANN Estimated Output

The proposed system is modelled in PSCAD with all specified parameters and meters. The different measured value from multimode meter setup in PSCAD is observed by the RTU in the respective bus number. The collected value like bus voltage, line current, real power line flow, reactive power line flow and angle from the RTU is transmitted through radio link and received by another radio link. The received signal is connected to the RTP recorder .The output from the recorder device is connected to the plotter to plot the value with respect to real time. To create error in measured value, the variable input slider is connected to the recorder. Different analyses were made to estimate the bus voltage.

The measured values through the PSO algorithm at different bus numbers are taken as input for the estimator. The pseudo-measurements are taken by the estimator for unmeasured bus numbers. The percentage absolute error is calculated for measured and estimated value. The accuracy of the proposed scheme is acceptable in the presence of the noisy field measurements. The estimated output is accurate when compared with paper [35], where the random historical data is considered as pseudo-measurements. If the concept is to implement in real time, it is very important to execute the result quickly. This work satisfies that criteria, when compared with paper [35] [36] the execution time is quite fast because of the swarm tuner ANN. Figure 4 presents the overall analysis of the proposed hybrid estimator in conversion to percentage for error accuracy and complete performance, which includes time, cost, observability, complexity, constraints and loss of measurements.

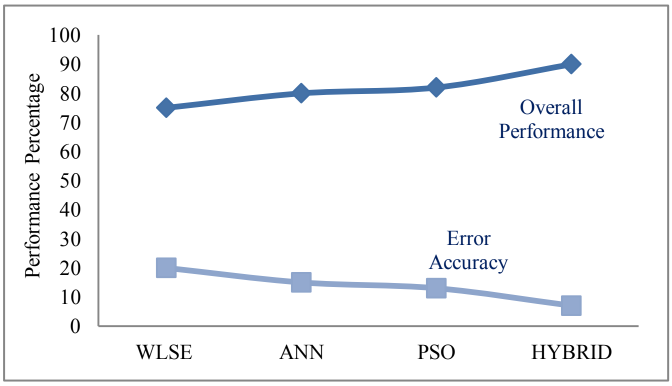

Fig. 4 Comparative Performance Analysis of Proposed Hybrid Estimator

The effectiveness of the hybrid swarm tuned ANN estimator is evident from the above figure, where the error percentage has decreased and the performance graph has increased with other algorithms.

The pie chart representation in Fig.4 indicates the estimated real power and its percentage of flow in lines. For example 102.06 KW power flow in line 1-2 will occupy 37% of the entire flow. The above graph compares the two cases of Gaussian noise. The bus voltage is estimated, considering Gaussian noise injection of 2% at all measured buses

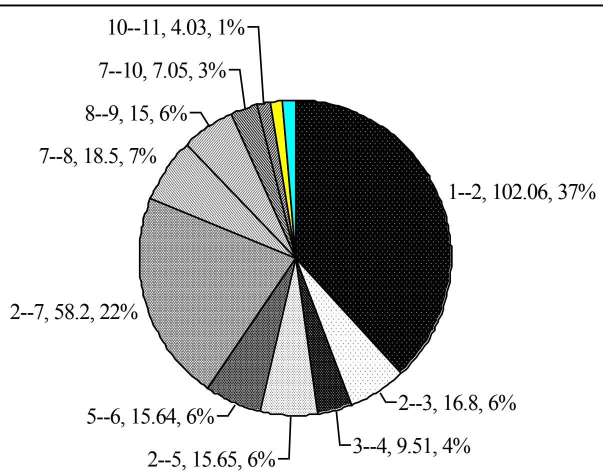

Fig. 4 : Pie Chart representing the estimated real power and its percentage of flow in branches

In the second case, 2% noise is considered at bus numbers 1, 6, 9, 5% at bus numbers 4 and 13 and 10% at bus number 10. The study case clearly indicates that the designed swarm ANN estimator estimates the bus voltage accurately when subjected to any error that occurred in measured value which is shown in Fig. 7.

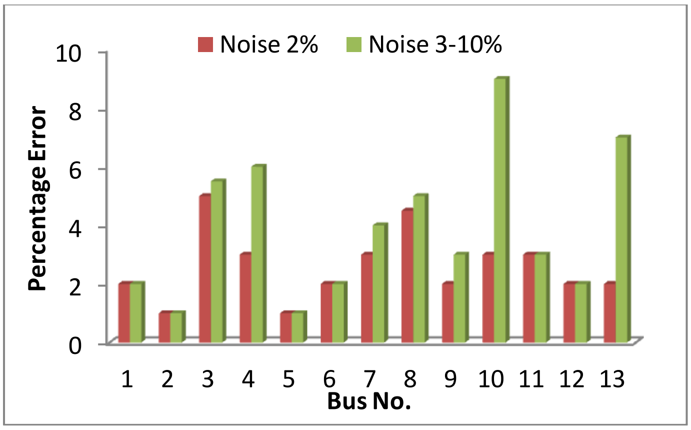

Fig. 7 : Percentage absolute error with respect to different noise level.

4 Conclusion

In this work, a PSO-based optimization technique has been proposed to optimally place meters to monitor and control power distribution systems. It is also extended to estimate the bus voltage using Intelligent Algorithm. The results are simulated for the standard IEEE and the TNEB bus systems and the results imply that the proposed methodology is capable of obtaining optimal metering systems at a minimum cost, satisfying constraints such as network observability and absence of critical measurements. The estimated results and percentage error conclude that the proposed algorithm and the estimator are working with good accuracy when compared with the Branch and Bound technique and other algorithm proposed in the literature. The future scope of this paper is to consider the distributed generation for planning meter placement and to consider more switch position and transformer locations. This paper can also be extended for different hybrid algorithms considering more complicated and complex networks.

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