Optimal Allocation of Measurement Devices for Distribution State Estimation Using Multiobjective Hybrid PSO–Krill Herd Algorithm

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***Abstract*— This paper proposes a new multiobjective hybrid particle swarm optimization (PSO)–krill herd (KH) Pareto-based optimization algorithm to optimize number and location of the measurement devices for accurate state estimation (SE) in smart distribution networks. Three objectives are considered to be minimized: 1) the total cost; 2) the average relative percentage error (APE) of bus voltage magnitude; and 3) APE of bus voltage angle. As the objective functions are conflicting with respect to each other, a multiobjective Pareto-based nondominated sorting hybrid PSO–KH optimization algorithm is proposed. In this approach, the random variation in loads and the metrological error of the measurement devices are also taken into account. The proposed algorithm minimizes the cost and enhances the accuracy of the distribution state estimator for better monitoring and control of the system. Furthermore, the impacts of distributed generation on SE performance are also investigated. The feasibility of the proposed algorithm is demonstrated on IEEE 69-bus system and practical Indian 85-bus radial distribution network. The results obtained are compared with conventional KH algorithm and PSO, with well-known multiobjective nondominated sorting genetic algorithm and also with an existing technique based on dynamic programming method for validation.**

***Index Terms*— Distribution system state estimation (DSSE), hybrid particle swarm optimization (PSO)–krill herd algorithm (KHA), multiobjective optimization (MOO), nondominated sorting approach.**

I. Introduction

RECENTLY distribution systems have been subjected to increasingly integration of distributed generation (DG) and frequent changes in network configuration which are creating new problems of monitoring, control, and reliability issues in smart grid environment. The active injections of renewable sources and loading conditions result bidirectional power flow and exacerbation of voltage unbalance in a distribution network [1]. The bidirectional power flow occurs when the DG generation exceeds local load, and it has stronger impact on voltage profile of the distribution network. Furthermore, the network configuration of the smart distribution network will be changing dynamically to achieve minimum power loss and voltage deviations. The real-time monitoring of distribution network is becoming more and more challenging due to the increasing dynamics and changing behavior of actors in distribution systems. Therefore, the knowledge about the system states is required more accurately and reliably for online monitoring and control of the distribution networks. To resolve these issues, meter placement techniques have been used widely in distribution systems for state estimation (SE). In a power system, measurement devices can be placed at every location to estimate the states of the system, but it is not economically acceptable. Fundamentally, in a distribution system, the number of real measurements is significantly smaller than the pseudomeasurements [2]–[4]. Therefore, SE technique is used to obtain the status of the network more accurately from the available measurements. SE is a digital filtering algorithm which can accurately determine the states of the system from the noisy data. However, due to the limited number of real-time measurements, accurate SE in distribution systems is more challenging. So, a large number of pseudomeasurements (historical data) retrieved from *a priori* knowledge are necessary to maintain observability of the network and convergence of the SE algorithm. Additionally, the accuracy of pseudomeasurements is comparatively low. As a consequence, estimation accuracy is not as much accurate as is expected. Therefore, some additional meters need to be appended at appropriate location in distribution systems to achieve better estimation accuracy.

In recent years, many alternative methods have been proposed by various researchers for enhancement of SE accuracy using meter placement techniques in distribution networks. Baran *et al*. [5] introduced a rule-based meter placement strategy and proposed three empirical rules based on observations, i.e., meters have to be placed at all the main switches and fuse locations that has to be monitored, meters have to be placed at feeder line sections and on normally open tie switches used for feeder reconfiguration. This method of meter placement gives a good compromise between the accuracy and computational complexity, but it does not guarantee to get optimal number of meters with minimum cost.

In [6], a heuristic-technique-based meter placement method is introduced. The optimization problem is designed as a

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nonlinear combinatorial constraint optimization problem, and the objective function minimizes the mean of the weighted sum of the variance of the estimated quantities. The constraints imposed on this optimization problem are that the system would be observable with established accuracy with a minimum number of meters. The authors have proposed dynamic programming (DP) following a step-by-step approach to find the optimal number of meters with required accuracy level.

Liu *et al.* [7] proposed a meter placement technique in SE using genetic algorithm (GA). The objective function considered for this optimization problem is the minimization of the total cost combined with the specified accuracy index of the SE. The authors have used relative voltage and phase angle deviation as performance index for this optimization problem. Furthermore, an optimal tradeoff solution is obtained between phasor measurement units and smart metering devices using GA. Pegoraro and Sulis [8] proposed DP-based meter placement technique to find the optimal placement of the measuring devices. The authors have considered both the network parameter uncertainty and decay of metrological characteristic of the measurement devices in distribution system SE (DSSE). Sing *et al.* [9] addressed an ordinal optimization-algorithm-based meter placement scheme in distribution network. In this approach, the meters are placed progressively until the errors are below the prespecified thresholds in 95% of the simulated cases. However, the solution obtained using ordinal optimization algorithm may not be a global optimal solution, but it results at least one of the suboptimal solution. Shafiu *et al.* [10] have used a heuristic technique to deploy certain number of voltage measurements to reduce the standard deviations in estimated voltage at unmonitored buses. This method reduces error only in voltage magnitude not in phase angle. The major disadvantage of these optimization algorithms is that the solution obtained may not be guaranteed a global optimal solution because these are based on sequential placement of measurement devices to achieve required SE accuracy. The sequential meter placement techniques may not achieve minimum number of meters with required accuracy level. From the literature survey, a tradeoff solution between bus voltage magnitude and phase angle with respect to the total cost of the meter in multiobjective framework has not been discussed.

Therefore, in this paper, the meter placement problem is considered as a multiobjective Pareto-based optimization problem for distribution SE (DSE) has been attempted for the first time. A further step toward the optimal placement of measurement devices that can guarantee a certain quality of SE in active distribution network (in the presence of DGs) has also been investigated. The main objective of the optimization process is to find the number and location of measurement devices that can guarantee specified threshold limits. In this paper, voltage magnitude measurement (VMM) device and power flow device have been considered for estimation of system states. In distribution networks, placing voltage and power flow meters is usually more economical than Phasor Measurement Unit (PMUs). Therefore, in this paper, PMU has not been considered for SE in distribution networks. However, the phasor measurement unit-based SE is more efficient than the present state estimator which is based on data collected via Supervisory Control and Data Acquisition (SCADA) and Remote Terminal Unit (RTUs). Since the synchronized phasor signals give state variables in particular phase angles which can improve the accuracy of the state estimator. In SE without the use of PMU, the phase angle difference of all the buses is determined with respect to a reference angle. Therefore, accurate evaluation of the real phase angle is not possible without PMUs.

The multiobjective optimization problem can be solved in two ways: 1) by using weighted sum approach, i.e., transferring the multiple objectives into single objective using weighting approach and 2) Pareto-based nondominated sorting approach can also be used to optimize all objective functions [12]. In this paper, Pareto-based nondominated sorting approach has been implemented using a new hybrid particle swarm optimization (PSO)–krill herd (KH) optimization algorithm to find the optimal number and position of measurement devices to improve the SE quality.

A hybrid PSO–KH optimization algorithm is proposed to find the optimal meter locations. The PSO is hybridized with KH algorithm (KHA) to find the near global optimal solution. The objective of the optimization problem is to find the optimal balance between the default measurements, pseudomeasurements, and real measurements with established accuracy.

The main contribution of this paper is summarized as follows.

1) A new hybrid PSO–KH as multiobjective Pareto-based optimization algorithm is proposed for the meter placement problem.
2) A tradeoff solution between the relative errors in voltage and phase angle estimates is established with the total cost of meters in a multiobjective framework to achieve best compromised solution between the cost and SE errors.

The rest part of this paper is organized as follows. The meter placement problem is formulated in Section II. The proposed hybrid PSO–KHA for meter placement is described in Section III. In Section IV, the test and simulation conditions are explained. The simulation and results are discussed in Section V, and finally, the conclusion of this paper is presented in Section VI.

II. Problem Formulation

The main objectives of this paper are to determine the optimal number and position of measurement devices to be placed in a given distribution network to achieve an observable system with minimum cost and ensure the state variables to be compliance with predefined accuracy. Three objective functions have been considered to be minimized: 1) the total cost; 2) the average relative percentage error (APE) of bus voltage magnitude; and 3) APE of bus voltage angle. By trial and error basis, it is found that if the number of power flow measurements is higher, then the relative deviation in bus voltage magnitude and angle is lesser and vice-versa, i.e., the objective functions described above are conflicting with respect to each other. Hence, the meter placement problem can be formulated as multiobjective Pareto-based optimization problem which can be solved by using fast non-dominated sorting approach [12], [13]. This paper proposed a hybridized algorithm for placing minimum number of meters ensuring the relative deviations of voltage magnitudes and angles are within the prespecified thresholds for 95% of the simulated cases. Hence, the meter placement problem is based on the minimization of the following objective functions:

$$F_1 = \sum_{i=1}^{nl} C_{\mathrm{pf},i} . P_{\mathrm{pf},i} + \sum_{i=1}^{n} C_{\mathrm{VMM},i} . P_{\mathrm{VMM},i} \tag{1}$$

$$F_2 = \frac{1}{n}\left(\sum_{i=1}^{n}\left|\frac{V_i^a - V_i^{\mathrm{est}}}{V_i^a}\right|\right) \times 100 \tag{2}$$

$$F_3 = \frac{1}{n}\left(\sum_{i=1}^{n}\left|\frac{\delta_i^a - \delta_i^{\mathrm{est}}}{\delta_i^a}\right|\right) \times 100. \tag{3}$$

A. Subjected to Constraints

In 95% of the simulated cases, the maximum relative percentage deviation in voltage magnitude and phase angle is 1% and 5%, respectively [7], [11], and this can be expressed as

$$\left|\frac{V_i^a - V_i^{\mathrm{est}}}{V_i^a}\right| \le 0.01 \tag{4}$$

$$\left|\frac{\delta_i^a - \delta_i^{\mathrm{est}}}{\delta_i^a}\right| \le 0.05 \tag{5}$$

where F_1, F_2, and F_3 are the three objective functions to be minimized, n and nl are the number of buses and lines in a network, C_{pf} and C_{VMM} are, respectively, the relative costs of a power flow measurement device and VMM device are normalized with respect to a conventional unitary cost. Since voltage measurement devices are treated as default measurements, therefore, the costs of a power flow meter and VMM meter are assumed to be same in the optimization process. Throughout the iterative process, the location and the number of default measurements are the same for all algorithm used in this paper. Therefore, it would not affect the cost function. However, different costs can also be assigned to power flow meters or to voltage meters. In practice, the cost of a measuring device depends on specific investment and application scenarios. P_{pf} and P_{VMM} represent the binary decision vectors, if a meter is present in a line or at node then it becomes one or else its value is zero, V_i^a and δ_i^a are the actual bus voltage magnitude and phase angle of ith bus, and V_i^{est} and δ_i^{est} are the estimated bus voltage magnitude and phase angle of ith bus, respectively.

The quality of SE solution deteriorates due to most of the measurements are pseudomeasurements with high variances. But it can be improved by placing some additional real meters with low variances. In this paper, only power flow meters and voltage magnitude meters have been used for SE in distribution networks. Furthermore, branch-current-based DSSE (BC-DSSE) is used for estimation of system states where branch current magnitudes and their phase angles are considered as state variables [14], [15].

III. Krill Herd Algorithm

In this section, the basic of KHA is presented, followed by hybrid PSO–KHA. The nondominated sorting approach for positioning the meters in a distribution network is discussed [9].

A. Krill Herd Algorithm

The KH [16] is a new bio-inspired swarm intelligence algorithm, which is motivated the herding behavior of the krill swarms in searching for the food in nature. The fitness of each krill individual depends on its distances from food position and the density of krill particles. The movement of each krill within the search space is based on three actions:

1) induced movement of krill individuals;
2) foraging motion;
3) random diffusion.

The Lagrangian model of the KHA in a n-D decision space can be expressed as

$$\frac{dL_i}{dt} = M_i + F_i + D_i \tag{6}$$

where M_i is the induced motion of each krill individual, F_i is the foraging motion, and D_i is the random diffusion of the krill individuals.

1) Induced Movement of Krill Individuals: The direction of motion induced is expressed by three effects: local effect, target effect, and repulsive effect. For each krill individual, the movement can be expressed as

$$M_i^{\mathrm{new}} = M^{\max}\alpha_i + w_n M_i^{\mathrm{old}} \tag{7}$$

where

$$\alpha_i = \alpha_i^{\mathrm{local}} + \alpha_i^{\mathrm{target}} \tag{8}$$

$M^{\max}$ is the maximum induced speed, w_n is the inertia weight and its value lies between [0, 1], α_i direction of motion induced by ith krill individual, α^{local} is the local effect produced by the neighbors, and α^{target} is the target direction produced by the best krill individual.

2) Foraging Motion: The foraging motion of krill individual depends on two parameters, one is food location and the second one is on previous food location. The foraging motion for ith krill individual can be expressed as

$$F_i = v_f \phi_i + w_f F_i^{\mathrm{old}} \tag{9}$$

where

$$\phi_i = \phi_i^{\mathrm{food}} + \phi_i^{\mathrm{best}} \tag{10}$$

where v_f is the foraging speed, w_f is the inertia weight of the foraging motion lies between [0, 1], ϕ_i^{food} is the food attractiveness, and ϕ_i^{best} is the effect of the best fitness of the ith krills.

3) Physical Diffusion: It is a random process of the krill individuals to improve the population diversity within the search space. This motion can be expressed as

$$D_i = D^{\max} d \tag{11}$$

where $D^{\max}$ is the maximum diffusion speed and d is the random directional vector, lies between [−1, 1].

4) Movement Process in Krill Herd Algorithm: Based on the above-mentioned movements, the positions of the ith krill individual in the time interval t to $t + \Delta t$ can be expressed as

$$L_i(t + \Delta t) = L_i(t) + \Delta t \frac{dL_i}{dt}. \quad (12)$$

Δt represents the time interval can be defined as

$$\Delta t = C_t \sum_{i=1}^{n_v} (u_i - l_i) \quad (13)$$

where n_v is the number of variables, C_t is a constant number between [0, 2], and u_i and l_i are the upper and lower limits of ith krill individuals.

5) Genetic Operator: To improve the performance of the KHA, genetic operators are incorporated into the algorithm. The genetic operators are crossover and mutation process which are derived from Differential evolution (DE) algorithm.

a) Crossover: The crossover process is controlled by using a parameter called crossover probability (C_p). The position of a krill can be modifying, by interacting each krill individuals with other. In this process, the position of the jth components of the ith krill can be expressed as

$$L_{i,j} = \begin{cases} L_{m,j} & \text{if rand } \leq C_p \\ L_{i,j} & \text{if rand } \succ C_p \end{cases}$$
$$C_p = 0.2 K_{i,\text{best}} \quad (14)$$

where $m \in \{1, 2, 3, \ldots, i-1, i+1, \ldots\ldots N\}$, $L_{m,j}$ represents the jth component of the ith krill individual, C_p is the crossover probability, and $K_{i,\text{best}}$ is the best previously visited position of the ith krill individual.

b) Mutation: The mutation operation is controlled by a parameter called mutation probability (M_p). The mutation process can be formulated as

$$L_{i,m} = \begin{cases} L_{\text{best},m} + \mu(L_{p,m} - L_{q,m}) & \text{rand}_{i,m} \prec M_p \\ L_{i,m} & \text{else} \end{cases}$$
$$M_p = 0.05/K_{i,\text{best}} \quad (15)$$

where $K_{i,\text{best}}$ is the best previously visited position of the ith krill individual and μ is a number lies between 0 and 1.

B. Proposed Hybrid PSO–KH Algorithm

In all modern meta-heuristic algorithms, the balance between the intensification and diversification plays a crucial role for better performance of the algorithms [12]. Intensification refers to a local search around the neighborhood of an optimal or near optimal solution, and diversification refers to the complete exploration of the search space efficiently and effectively. Exhaustive search or excessive diversification increases the convergence time of the searching as well as causing the solution to move around the near optimal solution. On the other hand, excessive exploitation causes the algorithm to trap into a local optima point and it may not reach to global optimal solution. Therefore, a proper balance between the exploration and exploitation is required to ensure faster convergence characteristics and good quality of solution.

The KHA used in this paper has proven its capability to find the global regions in a reasonable amount of time. However, it is seen that the conventional KHA is not efficient in performing the local searches effectively. Therefore, hybrid KHA is proposed to improve the local search capability of the KHA and also to achieve better balance between the intensification and diversification during the searching process. In order to achieve improvisation in local searching process, the KHA is hybridized with the PSO algorithm to get near global optimal solution.

Basically, PSO [15] is a population-based multipoint evolutionary algorithm. The searching process in PSO starts with a population of particles move in a search space by following the current optimum particles and changing their positions and velocity to find the best particle position. During its movement, particles distribute information among them to search in a good area of the search space. The local search capability and the neighborhood search ability provide hybrid KHA to search in a good area of the search space. These two features added to the hybrid KHA to get near global optimal solution.

C. Proposed Multiobjective PSO–KH Algorithm

The simultaneous optimization of the multiple objectives needs a compromised solution because no solution can improve itself in one objective without worsening the other objectives. In order to get a better compromised solution, nondominated sorting approach, i.e., Pareto-optimality principle has been adopted [12]. This principle states that in a nondominated Pareto front, all solutions are equally important, i.e., no solution is inferior to other. In multiobjective optimization (MOO) problem, the solution relies on a set of solutions rather than a single solution like single-objective optimization problem. In this paper, nondominated sorting approach has been incorporated with hybrid PSO–KH in order to achieve the best tradeoffs solution between the objective functions.

In this paper, hybrid multiobjective PSO–KHA is proposed. In PSO–KHA, the krills individuals are ranked based on the nondominated sorting approach and to get good spread in the Pareto optimal solution crowding distance operator has been used [13]. Both the strategies are described as follows.

1) Nondominated Sorting Approach: For the meter placement problem, three objective functions have been considered to be optimized, they are: 1) the total cost; 2) Average relative percentage error (APE) of bus voltage magnitude; and 3) APE of voltage phase angle. Since the objective functions 1), 2) and 1), 3) are conflicting with one another, so a compromised solution has to be established to find the best optimal solution. Therefore, nondominated sorting technique has been incorporated into this optimization problem. In multiobjective case, each solution is compared with others to check its dominating nature. For solution $s^{(1)}$ to be dominating solution $s^{(2)}$, the following hold.

1) Solution $s^{(1)}$ is better than $s^{(2)}$ in all objectives.
2) Solution $s^{(1)}$ is strictly better than $s^{(2)}$ in at least one objective.

If any of the above conditions are satisfied, then solution $s^{(2)}$ is said to be dominated by $s^{(1)}$.

Algorithm 1 Pseudo Code of Proposed Hybrid PSO-KHA

```
k ◄—1 {Initialization}
Initialize parameters
D^max, M^max, W_f, W_max, W_min, C1 and C2 (Refer Table I)
For i = 1 to P do (P◄— number of krill individuals)
    Generate Solution (x_i(k))
    {Evaluate and update best solutions}
end for
{Find}
F_gbest ◄— best fitness
x_gbest ◄— best position of Krill
{Main loop}
Repeat
    Sort population of Krills
    PSO ◄— {Update velocity and position of Krills using PSO}
    For i = 1 to P do
        Calculate motions value and genetic operators
        M_i ◄— Motion induced by other Krill individuals
        F_i ◄— Foraging motion
        D_i ◄— Physical or random diffusion
        Crossover
        Mutation
        {Update Krill position}
        {Evaluate fitness of Krills}
    end for
    {Find}
    F_best ◄— Current best fitness
    F_worst ◄— Current worst fitness
            If F_best ≺F_gbest
            F_gbest = F_best
            x_gbest = x_best
        else
            F_gbest = F_gbest^old
        end if
x_gbest ← Save best individual x (k)
Stop condition ← Check stop condition
k ◄— k+1
Until stop condition = false
Post-procession of the results.
```

2) Crowding Distance: The crowding distance operator is used to find the density of solutions that are surrounding a particular solution [9].

From the above two definitions, it can be stated that solution $s^{(1)}$ is said to be better than another solution $s^{(2)}$ (krill individuals), if it has satisfied any one of the following criteria: 1) the rank of solution $s^{(1)}$ has to be smaller than solution $s^{(2)}$ or 2) if both the solutions belong to same front (same rank), then the crowding distance of solution $s^{(1)}$ has to be larger than that of solution $s^{(2)}$. The steps of the proposed algorithm are as follows.

Step 1: Initialization—initialize the parameters of the algorithm

$$D^{\max}, M^{\max}, W_f, W_{\max}, W_{\min}, C1, \text{ and } C2.$$

Step 2: Fitness evaluation for the following.

1) Randomly generate number of power flow meters and their locations for each krill individuals in the population.
2) Evaluate the fitness functions using weighting approach for each krill individual.
3) Rank the evaluated population based on the nondominated sorting scheme.
4) Sort the population according to their fitness values and calculate the best and worst fitness value, i.e., best and worst krills among the population.

Step 3: Generate new krills using PSO.

Step 4: For each krill individual calculate the following motions:

1) induced motions;
2) foraging motions;
3) physical diffusions.

Step 5: Update the position of the krill individuals in the search space.

Step 6: Genetic operator—apply crossover and mutation operator to the updated positions.

Step 7: Evaluate the objective functions based on the new positions of the krill individuals and sort them based on the nondominated sorting scheme.

Step 8: Calculate the current best and worst krill.

Step 9: Repeat steps 3–8 for maximum generation times.

Step 10: Use fuzzy theory to find the best compromised solution [24].

The initial value of the parameters used in the proposed algorithm is decided based on the nature of the optimization problem. For unimodal cost functions smaller value for maximum induced speed ($M^{\max}$) and inertia weight (W_f) is recommended and for multimodal case higher values is recommended for better performance of the algorithm. In this paper, the value of $M^{\max}$ and W_f is considered as 0.025 and 0.9, respectively. The other parameters are decided based upon the repeated trial of tests. In PSO, the appropriate value of $w_{\max}$ and $w_{\min}$ is 0.9 and 0.4 and the values are independent to problems as recommended by many papers. The most appropriate value of C1 and C2 (i.e., C1 = C2) is 2 [18]–[20]. For population size of different values like popsize = 10, 20, and 50 have been tried. For the IEEE 69-bus system and Indian 85-bus system, there is no much variation in results for taking different population sizes (popsize) is observed. Finally, it is found that popsize = 20 is sufficient for getting near optimal value. The parameter values are provided in Table I.

After the initialization of the parameters and positions of the krill particles, the fitness value of the krill is evaluated using weighting sum approach. The weighting sum method has been used extensively for MOO to provide multiple solution points by varying the weights consistently. The value of weights is significantly relative to other weights and also relative to its corresponding objective function value. It is also stated that if the weights are representing the tradeoff between the objective function (paired comparison method), then it is better to retain the original units of the objectives without transferring them between 0 and 1. This approach only provides a basic approximation of one's preference function.

TABLE I
PARAMETER VALUES OF KH, PSO, AND NSGA-II

KHA [20]	PSO [22]	NSGA-II
Population size=20	Population size=20	Population size=20
D^{max} (maximum diffusion speed) $\in$ [0.002 0.01]	C1=2,C2=2	Crossover rate (P_c)=0.8
$C_t \in [0, 2]$	W_{max}=0.9, W_{min}=0.4	Mutation rate (M_c)=0.02
V_f (foraging speed)=0.02ms^{-1}	No. of generations=50	No. of generations=50
W_f (inertia of the foraging motion) =0.9	-	-
M^{max} (maximum induced speed)=0.025ms^{-1}	-	-

Even if the weights are acceptable *a priori*, but the final solution may not reflect accurately the initial preferences. Therefore, the decision maker has to choose an appropriate combination of weights to reproduce a representative part of the optimal Pareto front.

Each objective function value in (2)–(4) is evaluated based upon the initial position of the power flow meters for all the krill individuals using DSE algorithm. The obtained fitness values are ranked using nondominated sorting technique. Then the best and worst krills are determined based upon the overall fitness value of each krill. In order to achieve better performance, the position of the krills is first updated using PSO discussed in Section III. After the first updation, KHA is implemented to find the new updated position of the krill particles. During the evaluation of the fitness, the constraints violation checking is also carried out. For each Monte Carlo step, the APE in bus voltage magnitude and angle is determined at each bus. For a particular number of meters and their locations, if in 95% of the simulated cases, the relative errors in voltage and phase angle estimates are brought down below the prespecified thresholds, then the value of the objective functions is determined and stored. On the contrary, if in 95% of the cases, the estimation errors are not below the specified thresholds, then for that particular meter location a higher value of the objective functions is assigned. So that in the next immediate generation of the algorithm, this particular solution will be removed from the list because of nondominated sorting and crowding distance approach. Then the above procedure is repeated until the convergence is achieved.

D. Robust Optimal Meter Placement in Distribution Networks

The multiobjective hybrid PSO–KHA is based on the fact that the selected optimal solution of different alternatives in a decision space is robust with respect to estimation noise. In view of this, the meter placement problem is formulated as multiobjective Pareto-based optimization problem. The most interesting application of the proposed approach is that a tradeoff solution between the relative errors in voltage magnitude and phase angle is established with respect to the total cost of meters to achieve best compromised solution between the cost and SE accuracy. The hybrid PSO–KHA is applied to address the whole problem of robustness of the DSE technique to obtain an optimal meter placement that takes into account different metrological characteristics of the measurement devices, random load variations and measurement uncertainties. This algorithm does not enumerate all feasible solutions due to the computational complexity and is possible because of its efficient exploration and exploitation capability. Therefore, this algorithm is able to find the near global optimal solution. Furthermore, an overall optimization is performed in which each combination of default meters and power flow meters under random load variations as well as for different metrological characteristic of the real meters is reported. Additionally, it is observed that the maximum deviations in voltage and phase angle estimates are significantly lower than the other algorithms used in this paper.

The robustness of the proposed approach of meter placement is also tested in presence of DGs in distribution network. In the simulation study, it is assumed that the DGs output is a random variable following Gaussian distribution. The optimal location and number of meters in the presence of DGs under various operating scenarios has been tested to find a robust meter placement that can guarantee a desired level of accuracy for SE.

IV. TEST AND SIMULATION CONDITIONS

To analyze the effectiveness of the proposed algorithm, the following test and simulation conditions have been considered in this paper in MATLAB 2014b environment.

BC-DSSE algorithm is used for the estimation of system states [14], [15]. For testing, the base case load flow is run to obtain the reference or true values of the quantities to be measured. The uncertainty of the measurements is obtained by adding errors following the normal distribution to the reference values obtained from base case load flow solution. In SE, four types of measurements with different accuracies are considered such as substation measurements, real measurements, pseudomeasurements (historical data), and virtual measurements [22]. The measurement uncertainties are considered based on maximum percentage of error associated with the measurements. The following conditions are considered for the measurement uncertainties.

1) *Substation Measurements:* These measurements are called default measurements because these are already present in the substation. In this test, one VMM meter and one power flow meter are assumed to be present at the substation. The maximum error of 1% is considered for substation measurements.
2) *Real Measurements:* For real measurements, power flow meters are used which measures both real and reactive power in a line. Different metrological errors in real measurement devices are considered such as 1%, 3%,

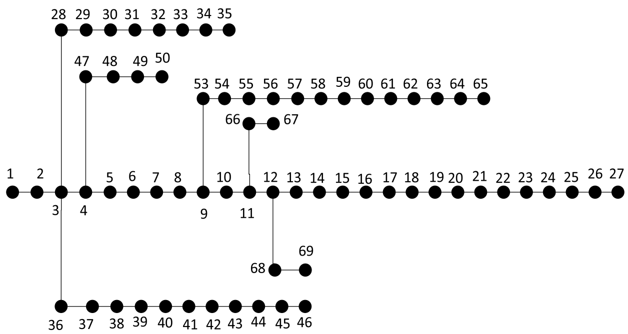

Fig. 1. Single-line diagram of IEEE 69-bus system.

and 5% to observe the impact of metrological error on SE accuracy and number of devices required.

3) *Pseudomeasurements:* The accuracy of the pseudo-measurements is relatively low because it is derived from the historical load data. Therefore, the maximum percentage error considered for this is 50% [22].

4) *Virtual Measurements:* The zero injection buses are modeled as virtual measurements with low variance of 10^{-7} [23].

In this paper, the stochastic nature of loads and generators are taken into consideration for better visualization of the proposed technique. Different network conditions are simulated by considering the load demands and generator output as stochastic variables following the Gaussian distribution around the mean values with prefixed standard deviation. Additionally, Monte Carlo algorithm is used to study the impacts of measurement uncertainties on SE performance. In order to consider the measurement uncertainties, Monte Carlo algorithm has been used to generate 1000 number of different network state from each network condition by applying the instrument uncertainty to the measured data. Thus, total number of cases considered in this simulation is 100×1000.

Furthermore, the results obtained using various methods considered in this paper are not optimized with respect to the position of the voltage meters, because voltage meters are treated as default measurements available at the substation and DG locations. Therefore, it is not optimized, but the power flow meters are considered in the optimization process for better estimation of system states. The power flow measurements are better compared to only current magnitude, voltage magnitude, and pseudomeasurements in estimating the system states. Moreover, in order to improve the accuracy of the voltage phase angle, power flow meters are appended in distribution network at appropriate locations.

The test conditions assumed in this paper is summarized as follows.

1) The number of operating conditions, NC $= 100$.
2) The standard deviation assumed for the NC operating conditions is $\pm 10\%$ of the base value.
3) Number of Monte Carlo trials MC $= 1000$.
4) Metrological errors of measurement device: 1%, 3%, and 5%.
5) The total test cases of 100×1000 have been studied.

The number of power flow meters required and their positions in the presence of DGs are also investigated in this paper. In the simulation study, the location of DGs is kept fixed [25], [26] and it is assumed that the DGs output is a stochastic variable following the Gaussian distribution with prefixed standard deviation, and moreover, all DGs are generating real power to the network. The impacts of DG on

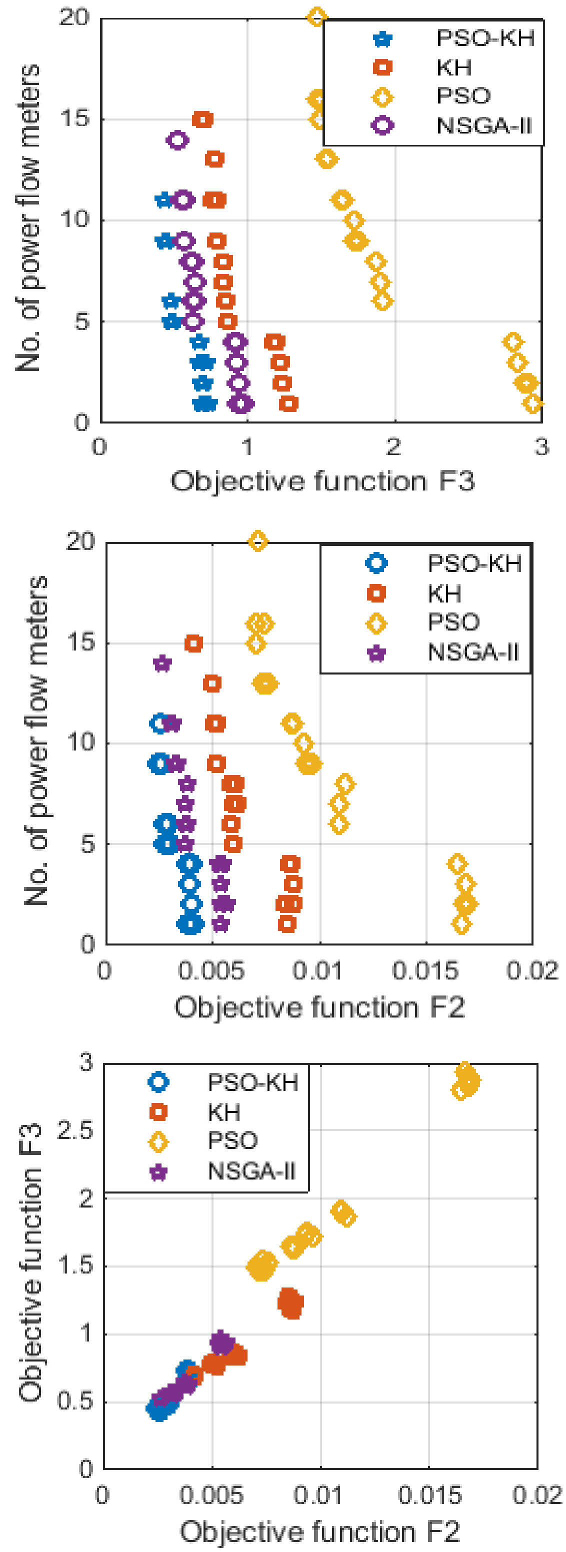

Fig. 2. Optimal Pareto-front plot of IEEE 69-bus system: 1% error in real measurements and 50% in pseudomeasurements.

TABLE II
DG INSTALLATION BUS AND CAPACITY

Test system	Bus Number	DG capacity in MW (Base Value)
IEEE 69-bus [25]	50 61	0.180 0.270
Practical Indian 85-bus[26]	45 61	0.277 0.290

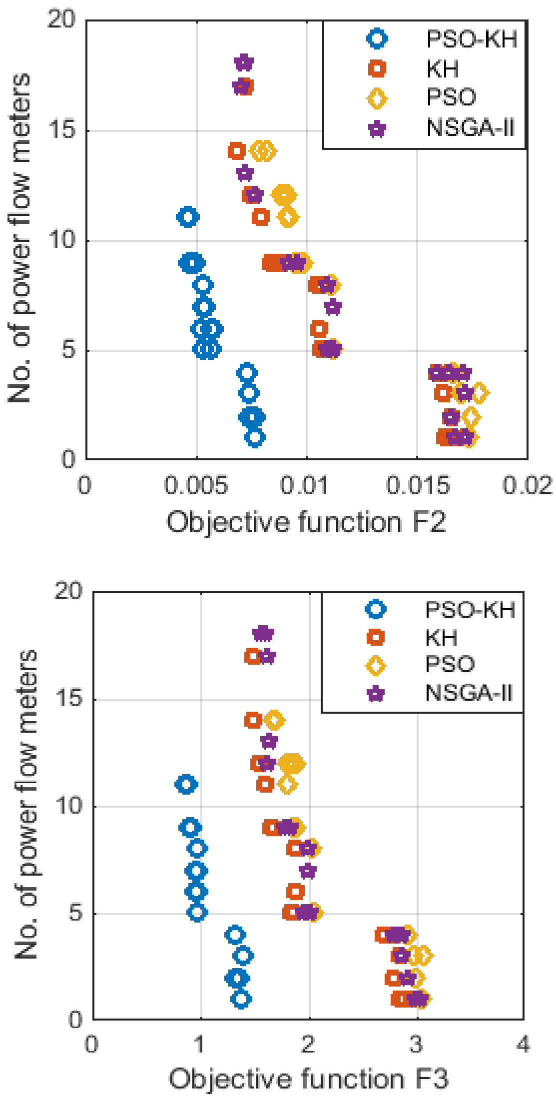

Fig. 3. Optimal Pareto-front plot of IEEE 69-bus system: 3% error in real measurements and 50% in pseudomeasurements.

SE accuracy are presented in the following section of this paper. Moreover, the results reported considering DG refer only to a particular case, and the impact of possible power flow inversion has not been considered in this paper.

To validate the performance of the proposed hybrid PSO–KHA, the results are compared with some well-known

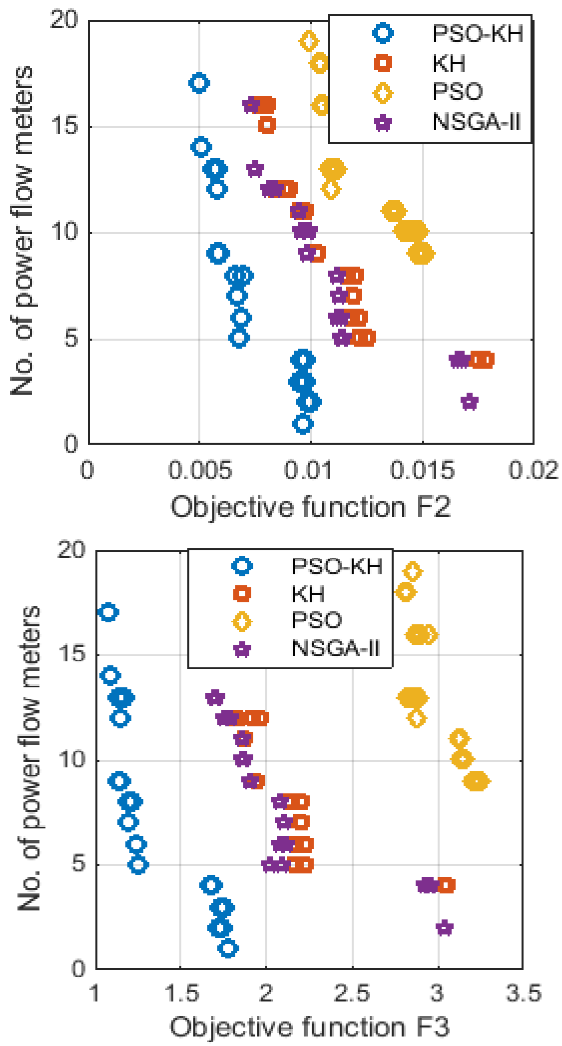

Fig. 4. Optimal Pareto-front plot of IEEE 69-bus system: 5% error in real measurements and 50% in pseudomeasurements.

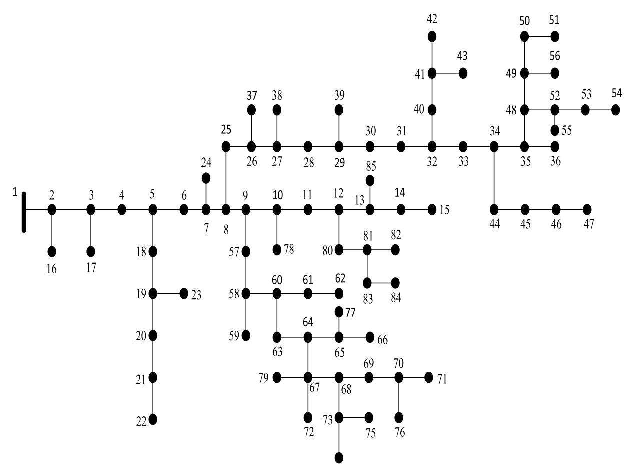

Fig. 5. Single-line diagram of Indian 85-bus radial distribution network.

existing algorithm such as conventional KH, PSO, and non-dominated sorting GA (NSGA-II). Furthermore, the proposed approach of meter placement technique has also been compared with an existing technique in the literature, based

TABLE III
IEEE 69-BUS SYSTEM: OPTIMAL LOCATION OF THE POWER FLOW METERS UNDER DIFFERENT LOADINGS INCLUDING METROLOGICAL ERRORS OF THE FLOW METERS

Metrological Errors	Algorithm	Default Measurements (node/line number)	location of flow meters(Line number)	No. of flow meters	Objective functions value			Max. error in bus voltage magnitude (V) (%)	Min. error in bus voltage magnitude (V) (%)	Max. error in bus voltage angle (δ) (%)	Min. error in bus voltage angle (δ) (%)
					F_1	F_2	F_3				
1%	**Proposed PSO-KH**	**1/1**	**1,7,24,54,66**	**5**	**6**	**0.0028**	**0.4947**	**0.0381**	**0.0001**	**5.7922**	**0.0068**
	KH	1/1	1,9,17,23,32,47, 56,61,63	9	10	0.0052	0.7837	0.0399	0.0017	6.9994	0.0287
	PSO	1/1	1,18,28,37,56, 65,42, 49	8	9	0.0112	1.8731	0.0475	0.0007	7.9249	0.0641
	NSGA-II	1/1	1,5,19,27,54	5	6	0.0037	0.6273	0.0772	0.0013	9.3022	0.0086
	DP [8]	1/1	1, 11, 19, 37, 44, 57	6	7	0.0067	0.9891	0.0561	0.0012	8.4751	0.0099
3%	**Proposed PSO-KH**	**1/1**	**1,11,18,43,52**	**5**	**6**	**0.0053**	**0.9782**	**0.0417**	**0.0009**	**5.9154**	**0.0096**
	KH	1/1	1,2,4,12,21,24, 30,59,67	9	10	0.0084	1.6767	0.0479	0.0023	7.8239	0.0485
	PSO	1/1	1,13,17,25,31,39, 45,51,59,64,65	11	12	0.0091	1.7990	0.0638	0.0011	11.6239	0.1988
	NSGA-II	1/1	1,3,10,19,27,30, 32,4,45,49,54,65	12	13	0.0077	1.6130	0.0488	0.0019	10.3332	0.2269
	DP [8]	1/1	1, 7, 19, 27, 37,41,47,59	8	9	0.0071	1.5289	0.0529	0.0021	9.2621	0.1269
5%	**Proposed PSO-KH**	**1/1**	**1,7,14,21,28, 33,49,53,61**	**9**	**10**	**0.0058**	**1.1491**	**0.0523**	**0.0014**	**6.3172**	**0.0224**
	KH	1/1	1,5,11,30,35, 41,47,52,61	9	10	0.0102	1.9423	0.0927	0.0033	9.6717	0.2137
	PSO	1/1	1,5,18,30,34,35, 44,47,50,56,63,67	12	13	0.0109	2.8704	0.0838	0.0041	12.7865	0.3022
	NSGA-II	1/1	1,4,9,14,20,32,38, 40,43,45,51,57,65	13	14	0.0075	1.7001	0.0776	0.0032	12.4533	0.3009
	DP [8]	1/1	1,7,19,27,39, 45,53,58,61,66	10	11	0.0112	1.7325	0.0612	0.0071	10.3241	0.3067

on DP [8]. For the comparison of results with this existing method, first, the objective function considered in [8] has been taken into consideration and the optimal number and location of the meters are determined using DP. After doing so, (1)–(3) are solved to determine the three objective function values. Moreover, the constraints and accuracies considered for both the techniques are same for comparison purpose. However, the network parameter uncertainties have not been considered in both the techniques.

V. SIMULATION RESULTS AND DISCUSSION

A. IEEE 69-Bus System

In order to highlight the performance of the proposed algorithm, standard IEEE 69-bus, 12.66 kV radial distribution network has been taken into account. This system comprises of 69 buses and 68 lines, 48 loads and two DGs. The system load information and line parameters are obtained from [27]. The total load of this system is 3.802 MW and 2.692 Mvar, respectively. The single line diagram of the test system is shown in Fig. 1. Furthermore, this system includes 21 number of zero injection buses. The real and reactive power injections at these buses are considered as virtual measurements with higher accuracy level. In addition, there are two real meters kept at the substation which are called as default measurements (one voltage and one power flow meter), provided in Table III.

The obtained results using the proposed algorithm are reported in Table III, and the optimal Pareto-front plots are shown in Figs. 2–4 under different operating scenarios. It is worth noticing that the total number of power flow meters required is 5 using the proposed PSO–KHA when the meter accuracy is considered as 1%. But in case of KH, PSO, and NSGA-II, the total number of flow measurements required is 9, 8, and 5, respectively. The average relative percentage error in bus voltage magnitude and phase angle is obtained as 0.0028% and 0.4947% using PSO–KH, whereas in case of KH and PSO, these are 0.0052%, 0.7837% and 0.0112%, 1.8731%, respectively. Though the same number of meters is obtained for NSGA-II and PSO–KH, the average relative percentage of error obtained using NSGA-II is 0.0037% and 0.6273% which is more compared to PSO–KH. The results shown in Table III are obtained at the final iteration of the iterative process, i.e., at the optimal Pareto front. From the optimal Pareto front, the best compromised solution is obtained using fuzzy theory discussed in [24]. When the results are compared with other technique such as DP, the proposed technique is found to be more superior to existing one because these optimization methods are based on the step-by-step approach. Based upon the results obtained using DP, the total number of meters required is 6, 8, and 10 for 1%, 3%, and 5% meter accuracy value, respectively. The competitive results are shown in Table III, which shows the superiority of the proposed

TABLE IV
IEEE 69-BUS SYSTEM: OPTIMAL LOCATION OF THE POWER FLOW METERS UNDER DIFFERENT LOADINGS INCLUDING METROLOGICAL ERRORS OF THE FLOW METERS (WITH TWO DGs AT BUS NUMBERS 50 AND 61)

Metrological Errors	Algorithm	Default Measurements (node/line number)	location of flow meters(Line number)	No. of flow meters	Objective functions value			Max. error in bus voltage magnitude (V) (%)	Min. error in bus voltage magnitude (V) (%)	Max. error in bus voltage angle (δ) (%)	Min. error in bus voltage angle (δ) (%)
					F_1	F_2	F_3				
1%	**Proposed PSO-KH**	**1,50,61/1**	**1,49,52,59,67**	**5**	**8**	**0.0011**	**0.2653**	**0.0289**	**0.0001**	**5.3122**	**0.0014**
	KH	1,50,61/1	1,27,34,37,51,62,67	7	10	0.0037	0.6123	0.0371	0.0011	8.7895	0.0071
	PSO	1,50,61/1	1,13,24,30,34,49,67	7	10	0.0093	1.6224	0.0421	0.0013	8.0123	0.0341
	NSGA-II	1,50,61/1	1,9,18,29,51	5	8	0.0034	0.5827	0.0569	0.0010	9.4322	0.0571
	DP [8]	1,50,61/1	1,21,39,44,51,66	6	9	0.0039	0.7006	0.0346	0.0018	8.1231	0.0359
3%	**Proposed PSO-KH**	**1,50,61/1**	**1,29,41,53,66**	**5**	**8**	**0.0025**	**0.5386**	**0.0411**	**0.0007**	**5.8923**	**0.0613**
	KH	1,50,61/1	1,29,32,33,41,61,66	7	10	0.0072	1.1604	0.0567	0.0018	8.2213	0.2971
	PSO	1,50,61/1	1,14,41,43,44,51, 56,62,67	9	12	0.0060	1.0535	0.0422	0.0011	9.1325	0.3291
	NSGA-II	1,50,61/1	1,9,21,23,37,38,42, 44,66	9	12	0.0060	1.0211	0.0612	0.0019	9.1009	0.2332
	DP [8]	1,50,61/1	1,11,19,26,41,47, 50,59	8	11	0.0067	1.3628	0.0501	0.0016	9.8975	0.2978
5%	**Proposed PSO-KH**	**1,50,61/1**	**1,3,17,25,34,42,50,63**	**8**	**11**	**0.0063**	**1.0587**	**0.0499**	**0.0010**	**6.5122**	**0.1913**
	KH	1,50,61/1	1,4,22,36,47,54,61,64	8	11	0.0064	1.0667	0.0733	0.0014	10.6567	0.3697
	PSO	1,50,61/1	1,2,5,24,29,33,34,41 ,43,63	10	13	0.0060	1.9560	0.0645	0.0017	12.2564	0.2457
	NSGA-II	1,50,61/1	1,10,21,24,28,33, 34,36,46,49	11	14	0.0061	1.7509	0.0614	0.0019	11.0011	0.2217
	DP [8]	1,50,61/1	1,9,13,23,34,47, 57,63,66	9	12	0.0099	1.5249	0.0607	0.0025	10.1222	0.2423

algorithm over other existing algorithm and techniques considered in this paper. Furthermore, the minimum and maximum APEs in voltage magnitude and angle estimates are also reported in Table III for different methods. The maximum deviations in voltage and angle estimates are found to be significantly lower than the PSO, KH, NSGA-II, and DP algorithm.

For meter accuracy of 3% and 5%, the optimal Pareto front between different objectives is shown in Figs. 3 and 4. It can be observed from the figures that the number of meters requirement is increased compare to previous case, i.e., when 1% accuracy of the meter was considered. Moreover, the objectives F_2 and F_3 values are also increased due to large error incorporated into real measurements, i.e., in power flow measurements. From this, it can be concluded that if the error in power flow measurements is more then it influences the estimation accuracy of the state estimator and also on number of meter requirements. It is important to note that both metrological errors and the location of the measurement devices significantly affecting the accuracy of the state estimator. From Figs. 3 and 4, it is observed that even though the number of meters are the same, SE accuracies are different because the location of meters also influencing the estimation accuracy. The obtained results are reported in Table III, and the optimal Pareto front between objectives 2 and 3 is shown in Fig. 2. It is noticed that the two objectives are not conflicting with each other rather these are correlated. Therefore, the Pareto front curve is not possible between the objectives F_2 and F_3.

The result provided in Table III refers to a passive distribution network, i.e., when there is no DG installed in the network. There are two observation can be made by analyzing the results provided in Table III. The first one is as the accuracy of the measurements decreases the number of power flow meters have to be increased for better SE. The second one is the performance of the proposed PSO–KHA is found to be better due to its efficient searching capability. The hybridization of PSO and KHA brings a higher degree of balance between the intensification and diversification during the search process. Therefore, a new hybrid PSO–KHA has been proposed for the DSE in multiobjective environment to solve the meter placement problem. The obtained results are also compared with PSO, KH, and NSGA-II algorithms to check superiority of the proposed algorithm.

Furthermore, the proposed methodology has also been applied in active distribution network. Two DGs of 0.270 and 0.180 MW are installed at nodes 50 and 61, and it is assumed that both are injecting only real power to the network. Moreover, the results reported considering DG refer only to a particular case because the location of DGs is based on to achieve minimum power loss and voltage deviations [25]. The results obtained in the presence of DGs are reported in Table IV. It is worth noticing that the number of power flow meters requirement is reduced compared to the passive case and moreover, the objective function F_3 value is reduced compared to without DG case. The reason behind is that the DG supplying power to the local load connected to that bus. Therefore, the power drawn by that load from the feeder

TABLE V

INDIAN 85-BUS SYSTEM: OPTIMAL LOCATION OF THE POWER FLOW METERS UNDER DIFFERENT LOADINGS INCLUDING METROLOGICAL ERRORS OF THE FLOW METERS

Metrological Errors	Algorithm	Default Measurements (node/line number)	location of flow meters(Line number)	No. of flow meters	Objective functions value			Max. error in bus voltage magnitude (V) (%)	Min. error in bus voltage magnitude (V) (%)	Max. error in bus voltage angle (δ) (%)	Min. error in bus voltage angle (δ) (%)
					F_1	F_2	F_3				
1%	**Proposed PSO-KH**	**1/1**	**1,13,18,26, 75 79,84**	**7**	**8**	**0.0385**	**1.1077**	**0.1853**	**0.0014**	**5.1722**	**0.0025**
	KH	1/1	1,28,32,35,42,43 ,60,68	8	9	0.0390	1.2449	0.2891	0.0032	6.3321	0.0031
	PSO	1/1	1,8,15,32,48,56, 70,71	8	9	0.0387	1.2911	0.2786	0.0022	6.6143	0.0058
	NSGA-II	1/1	1,18,28,31,40,52 ,64,70	8	9	0.0390	1.2641	0.2399	0.0017	7.8259	0.0037
	DP [8]	1/1	1,17,21,35,39,47 ,51,54,63	9	10	0.0403	1.4231	0.2911	0.0031	8.4322	0.0127
3%	**Proposed PSO-KH**	**1/1**	**1,17,22,30,36,73 ,81**	**7**	**8**	**0.0438**	**1.3355**	**0.2347**	**0.0011**	**5.5217**	**0.0098**
	KH	**1/1**	1,28 ,42,52,58, 73,78,81,84	9	10	0.0430	1.3255	0.4011	0.0010	6.7162	0.0424
	PSO	1/1	1,20,34,40,54,58 ,71,81	8	9	0.0452	1.4298	0.3217	0.0013	7.3192	0.0119
	NSGA-II	1/1	1,13,14,21,26,50 ,58,60,65,77	10	11	0.0431	1.1851	0.3019	0.0019	9.8822	0.0088
	DP [8]	1/1	1,10,21,29,36,45 ,54,59,64,74	10	11	0.0481	1.5728	0.2916	0.0054	7.1842	0.0213
5%	**Proposed PSO-KH**	**1/1**	**1,16,21,24,33,69 ,77,79**	**8**	**9**	**0.0439**	**1.2855**	**0.2896**	**0.0016**	**5.9407**	**0.0711**
	KH	1/1	1,9,19,24,37,53, 63,67,74	9	10	0.0467	1.5213	0.3342	0.0048	7.6721	0.0932
	PSO	1/1	1,6,23,32,68,70, 72,76,79,81,84	11	12	0.0468	1.5478	0.3211	0.0069	8.6434	0.2152
	NSGA-II	1/1	1,20,28,38,40,41 ,43,68,73,76	10	11	0.0459	1.3836	0.2898	0.0089	8.6315	0.1789
	DP [8]	1/1	1,7,16,19,37,43, 44,48,54,59,78	11	12	0.0633	1.5537	0.3219	0.0122	8.0377	0.1587

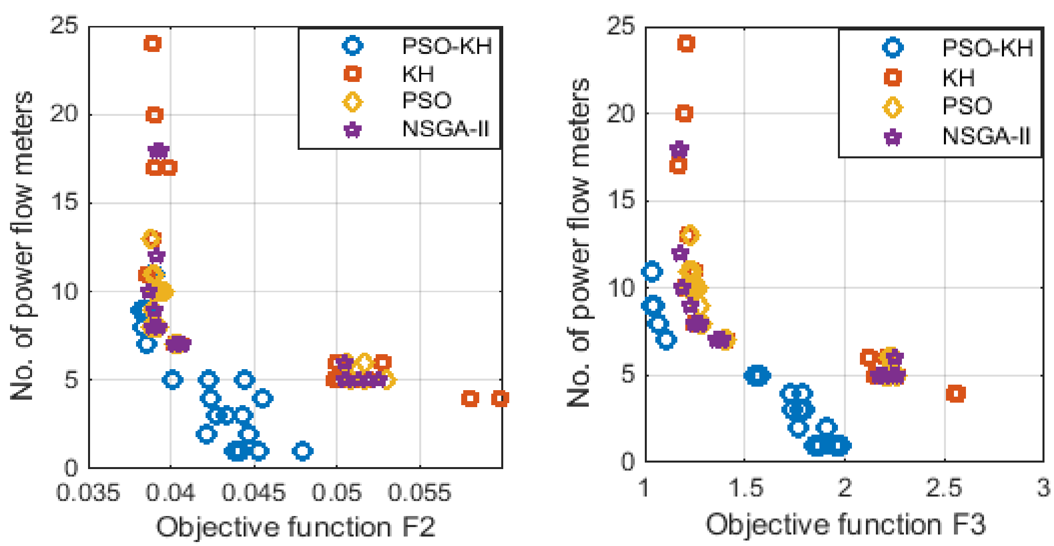

Fig. 6. Optimal Pareto-front plot of Indian 85-bus system: 1% error in real measurements and 50% in pseudomeasurements.

section is reduced, i.e., the current in the lines get reduce. As a consequence, the magnitude of error associated with the flow measurements will reduce. Furthermore, the presence of DG provides more real-time measurements and increases the redundancy level of the system which helps in getting more accurate results.

From the location of the power flow meters shown in Table IV, it can be stated that if the flow meters are placed

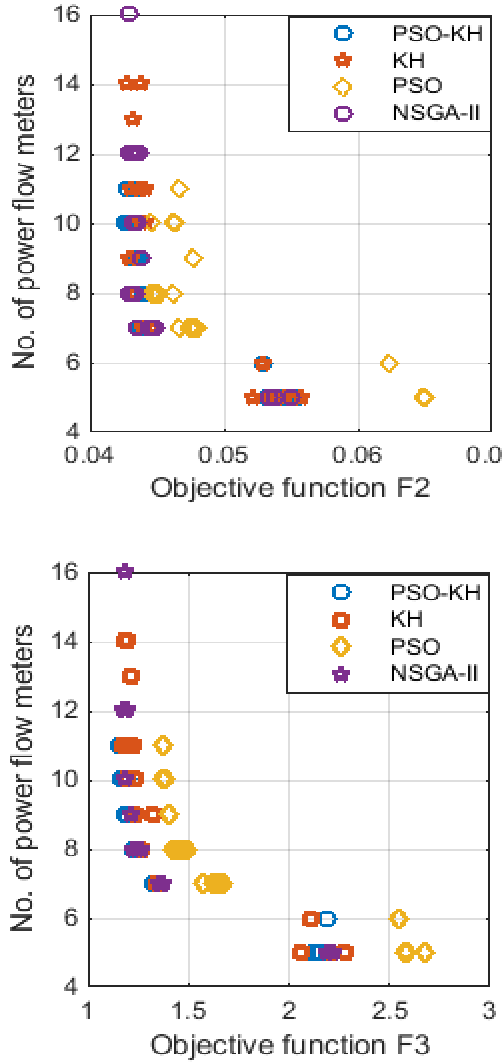

Fig. 7. Optimal Pareto-front plot of Indian 85-bus system: 3% error in real measurements and 50% in pseudomeasurements.

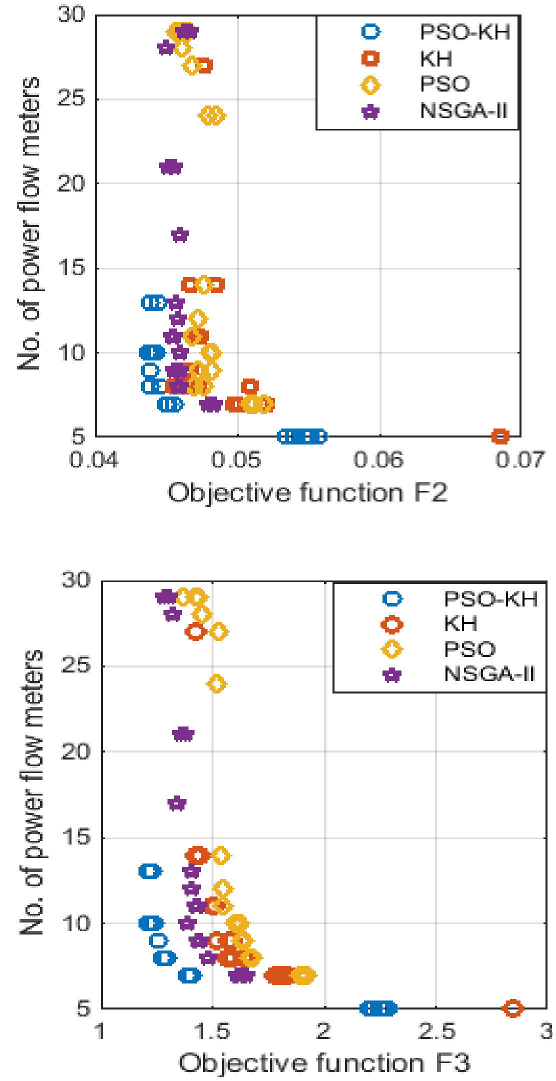

Fig. 8. Optimal Pareto-front plot of Indian 85-bus system: 5% error in real measurements and 50% in pseudomeasurements.

nearer to the sources and in the main feeder, then much better results can be expected than the meters at the laterals or far away from sources. Therefore, in the optimization process, some real meters like power flow meters and voltage meters are kept at the substation and DG location for further improvement in SE accuracy.

B. Practical Indian 85-Bus System

To demonstrate the effectiveness of the proposed algorithm, in a large-scale practical distribution system, Indian 85-bus, 11-kV radial distribution network has been considered in this paper. The system comprises of 85 nodes and 84 branches with two DG sources. The total load of the system is 2.574 MW and 2.622 MVar, respectively. Furthermore, the total number of zero injection buses that it includes is 26. The single line diagram of this system is shown in Fig. 5. The network and load data for Indian 85 bus are taken from [28]. The parameters of the algorithms mentioned in Table I are also applicable for this test system.

The results obtained using the proposed algorithm are shown in Table V. When 1% error in power flow meter and 50% error in pseudomeasurements are considered, the total number of power flow meters required is 7 using the proposed PSO–KHA, whereas in case of PSO, KH, and NSGA-II, the total number of flow meters required is 8, 8, and 8, respectively. The respective objective functions value is also provided in Table V. Furthermore, the optimal Pareto fronts between objective functions are shown in Figs. 6–8, respectively, for different metrological errors of the power flow meters. From the results, it is observed that as the accuracy of the meter is decreased, more number of real meters have to be placed to get better estimation performance because the quality of the estimates decreases with the increase in the error in measurements and this decrease in quality is significant with the increase in error in the real measurements compared to the pseudomeasurements. Therefore, more meters are needed to bring down the relative errors in voltage and phase angle estimates below the prespecified thresholds which is reported in Table V. The result obtained using DP has also been compared with the proposed PSO–KHA, and it is shown in Table V. It is proven that the solution obtained using hybrid PSO–KH is a near global optimal solution.

TABLE VI

INDIAN 85-BUS SYSTEM: OPTIMAL LOCATION OF THE POWER FLOW METERS UNDER DIFFERENT LOADINGS INCLUDING METROLOGICAL ERRORS OF THE FLOW METERS (WITH DGs AT BUS NUMBERS 45 AND 61)

Metrological Errors	Default Measurements (node/line number)	Location of flow meters(Line number)	No. of flow meters	Objective functions value			Max. error in bus voltage magnitude (V) (%)	Min. error in bus voltage magnitude (V) (%)	Max. error in bus voltage angle (δ) (%)	Min. error in bus voltage angle (δ) (%)
				F_1	F_2	F_3				
1%	1,45,61/1	1,9,27,33,44	5	8	0.0347	1.0013	0.1622	0.0009	5.1137	0.0016
3%	1,45,61/1	1,9,34,51,79,81	6	9	0.0411	1.1220	0.2181	0.0011	5.377	0.0064
5%	1,45,61/1	1,9,19,28,46,62,79	7	10	0.0419	1.2124	0.2214	0.0014	5.5231	0.0087

The results obtained in the presence of DGs at bus numbers 45 and 61 are also shown in Table VI. It can also be visualized that the presence of DGs impacts on accuracy of the estimated quantities. It reduces the phase angle error because DG supplies power to the local loads connected to that bus; therefore, the power drawn by the load from the main feeder section is reduced. In Table VI, the results obtained using the proposed hybrid PSO–KHA has been reported. From Tables V and VI, it is observed that both the location and metrological error of the measurement devices significantly affecting the SE accuracy. Therefore, it is necessary to consider these items into account to assure that the state variables comply within predefined thresholds. A best compromised solution between APE in voltage magnitude and angle with the cost of meter is established which is the main advantage of using this Pareto-based MOO technique.

VI. CONCLUSION

This paper proposed an MOO methodology that optimizes the number and location of measurement devices for SE in modern distribution networks. A new hybrid PSO–KH optimization algorithm has been proposed which considers variation in load power demand as well as the uncertainty of the measurement devices using Monte Carlo algorithm. A tradeoff solution between the relative errors in voltage and phase angle estimates is established with the total cost of meters in a multiobjective framework to achieve best compromised solution between the cost and SE errors. Furthermore, the impacts of DG on SE accuracy have also been discussed.

The proposed hybrid PSO–KHA is tested on IEEE 69-bus standard benchmark test system and Indian 85-bus distribution network. The competitive results obtained using the proposed algorithm is compared with the existing algorithm such as PSO, KH, and NSGA-II, and also with an existing method under various operating scenarios of the distribution networks. It is verified that the proposed algorithm is reliable and robust with respect to different metrological characteristics of the devices and load variation. Moreover, it can guarantee in getting global optimal solution. Therefore, the proposed approach of meter placement technique can be used for the planning study of the smart distribution networks.

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