Optimal Placement of Phasor Measurement Units: A Literature Review

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***Abstract*—The increasing availability of phasor measurement units (PMUs) at substations enables the synchronized measurements to various applications, such as the monitoring of system state under normal operations or the protection and control of power systems during abnormal operation. The objective of the optimal PMU placement (OPP) problem is to determine a minimal set of PMUs such that the whole system is observable. To solve the OPP problem, mathematical programming, heuristic, and meta-heuristic optimization techniques, have been proposed. This paper provides a comprehensive literature review on the OPP problem and the solution methodologies. Due to the vast number of publications in this field, the most representative papers are reviewed.**

***Index Terms*—Conventional optimization, heuristic optimization, meta-heuristic optimization, phasor measurement units, observability, optimal PMU placement.**

I. Introduction

SECURE operation of power systems requires close monitoring of the system operating conditions. The measurements received from numerous substations are used in control centers to provide an estimate for all metered and un-metered electrical quantities and network parameters of the power system, detect and filter out measurement and topology errors. Until recently, the available measurements were provided by SCADA, including active and reactive power flows and injections and bus voltage magnitudes. The utilization of global positioning system (GPS), in addition to sampled data processing techniques, for computer relaying applications, has led to the development of PMUs. Phasor measurement units are monitoring devices that provide extremely accurate positive sequence time tagged measurements [1]. A PMU installed at a bus can make direct synchronized measurements of the voltage phasor of the installed bus and the current phasors of some or all the branches incident to the bus, assuming that the PMU has sufficient number of channels. With the increasing use of PMUs in recent years, improved monitoring, protection, and control of power networks can be achieved [2], [3], [4]. The intended PMU applications, the relatively high cost of PMUs, as well as the communication facilities cost, which may be higher than that of the PMUs, make the optimal PMU placement problem an important challenge.

Several conventional optimization techniques have been proposed to solve the OPP problem, such as linear programming (LP), nonlinear programming (NLP), dynamic programming, or combinatorial optimization. To overcome the problems of conventional optimization techniques, such as risk of trapping at local optima, difficulties in handling constraints, or numerical difficulties, advanced heuristic and modern metaheuristic optimization techniques have been proposed. A wide range of such strategies can be cited from the OPP literature, like depth first search (DeFS), minimum spanning tree (MST), simulated annealing (SA), tabu search (TS), genetic algorithms (GA), differential evolution (DE), immune algorithms (IA), particle swarm optimization (PSO) or ant colony optimization (ACO).

This paper presents a literature review of the most popular conventional, heuristic and metaheuristic optimization techniques to solve the typical OPP problem. The problem formulation is given in Section II. Solutions to OPP problem, based on mathematical programming, heuristic, and metaheuristic methods, are presented in Sections III, IV, and V, respectively. Section VI concludes the paper.

II. Formulation of Optimal PMU Placement Problem

A PMU is able to measure the voltage phasor of the installed bus and the current phasors of some or all the lines connected to that bus. Figure 1 shows a wide area measurement system based on synchronized phasor measurements. The following rules can be used for PMU placement [5]:

Rule 1: Assign one voltage measurement to a bus where a PMU is placed, including one current measurement to each branch connected to the bus itself.

Rule 2: Assign one voltage pseudo-measurement to each node reached by another equipped with a PMU.

Rule 3: Assign one current pseudo-measurement to each branch connecting two buses where voltages are known. This allows interconnecting observed zones.

Rule 4: Assign one current pseudo-measurement to each branch where current can be indirectly calculated by the Kirchhoff current law (KCL).

This rule applies when the current balance at a node is known.

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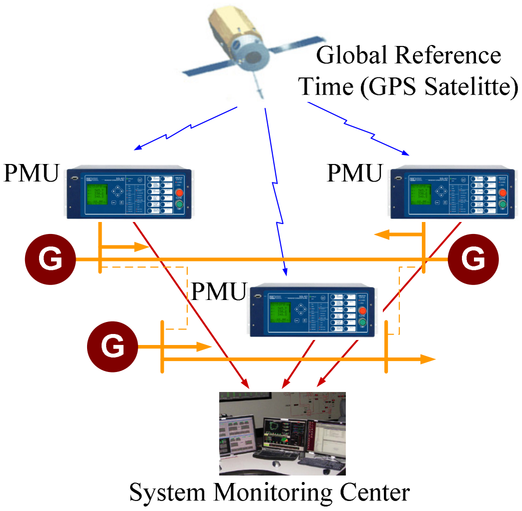

Fig. 1. Wide area measurement system based on synchronized phasor measurements.

The objective of the optimal PMU placement (OPP) problem is the strategic choice of the minimum number n_p of PMUs and the optimal location $S(n_p)$ of the n_p PMUs in order to ensure complete observability and satisfy a preset redundancy criterion. The OPP problem can be formulated as [6]:

$$\min_{n_p}\left\{\max R\left(n_p, S(n_p)\right)\right\} \quad (1)$$

s.t.

$$O_{bs}\left(n_p, S(n_p)\right) = 1 \quad (2)$$

where $R\left(n_p, S(n_p)\right)$ is the redundancy measurement index and O_{bs} is the observability evaluation logical function [6].

The optimal solution n_{p_min} is difficult to be obtained directly, due to (i) the large-scale nature of the OPP combinatorial optimization problem and (ii) the dependence of system observability on two factors: the number of PMUs and the placement set. Computationally, the OPP problem is highly nonlinear, discontinuous and multi-modal, having a nonconvex, nonsmooth, and nodifferentiable objective function. The observability conditions that have to be met for selecting the placement of PMU sets are [6], [7]:

Condition 1: For PMU installed at a bus, the bus voltage phasor and the current phasors of all incident branches are known.

Condition 2: If one end voltage phasor and the current phasor of a branch are known, then the voltage phasor at the other end of the branch can be calculated.

Condition 3: If voltage phasors of both ends of a branch are known, then the current phasor of this branch can be directly obtained.

Condition 4: If there is a zero-injection bus without PMU and the current phasors of the incident branches are all known but one, then the current phasor of the unknown branch can be calculated using KCL.

Condition 5: If the voltage phasor of a zero-injection bus is unknown and the voltage phasors of all adjacent buses are known, then the voltage phasor of the zero-injection bus can be obtained through node voltage equations.

Condition 6: If the voltage phasors of a set of adjacent zero-injection buses are unknown, but the voltage phasors of all the adjacent buses to that set are known, then the voltage phasors of zero-injection buses can be computed by node voltage equations.

The measurements obtained from Condition 1 are called direct measurements. The measurements obtained from Conditions 2-3 is also called pseudo-measurement. The measurements obtained from Conditions 4-6 are called extension-measurements.

III. Mathematical Programming Methods

A. *Integer Linear Programming (ILP)*

A linear programming (LP) problem in which all the design variables must take integer values is called integer linear programming (ILP) problem.

The objective of method [8] is the minimization of strategically located PMUs that eliminate measurement criticality in the entire system. The placement problem is then extended to incorporate conventional measurements as candidates for placement. Furthermore, the same formulation can be used to determine optimal locations when a desired level of local redundancy is considered. This allows design of measurement systems with different degrees of vulnerability against loss of measurements and bad data.

The objective of [9] is the proper placement of PMUs for a given budget. This issue is addressed via a special case of ILP, known as binary integer programming (BIP), considering the presence of injection and power flow measurements. Furthermote, loss of single PMUs is taken into account to minimize the vulnerability of state estimation to PMU failures.

A generalized formulation [10], considering situations with and without zero injections, shows that the problem of optimal PMU placement can be modelled linearly and solved by ILP for full and incomplete observability. A simplification of [10] is proposed in [11].

A procedure for multistage PMU placement in a given time horizon, using an ILP framework, is presented in [12]. The zero injection constraints can be modelled as linear constraints. The OPP problem has multiple solutions and two indices are proposed to further rank these multiple solutions. The bus observability index (BOI) gives a measure of the number of PMUs observing a given bus and the system observability redundancy index (SORI) gives the sum of all BOI for the system.

In [13], a two level approach partitions the spanning tree of the network into two or more sub-networks using ILP. The ILP has been formulated based on eigenvectors of the adjacency matrix of the spanning tree. After decomposition, PMUs have been placed optimally in the subnetworks in order to minimize their installation cost.

B. Integer Quadratic Programming (IQP)

Quadratic programming (QP) concerns the optimization of a quadratic objective function, linearly constrained. In integer quadratic programming, all design variables take integer values.

Method [14], is an integer quadratic optimization process that minimizes the number of PMUs needed to maintain complete network observability for normal operating conditions as well as for the outage of a transmission line or PMU and maximizes the measurement redundancy at all system buses. It was applied on various IEEE test systems, considering the outage of a single transmission line or PMU. Another IQP approach [15], determines the solution of OPP problem, using the connectivity matrix to represent the network topology and formulate the optimization problem.

C. Greedy Algorithm

A combinatorial optimization algorithm that takes the best immediate, or local, solution while finding an answer, is called greedy algorithm.

A virtual data elimination pre-processing method and a matrix reduction algorithm have been introduced to reduce the size of the placement model and the computational effort for the determination of the optimal placement set [16].

IV. Heuristic Methods

A. Depth First Search (DeFS)

An algorithm that marks all vertices in a directed graph in the order they are discovered and finished, while partitioning the graph into a forest, is called depth first search algorithm (DeFS). This method uses the Conditions 1 to 3 of Section II. It is based on the criterion of ‘depth’ and is non iterative.

In [17]-[18], the OPP optimization problem is solved using PSAT, a MATLAB based toolbox, and DeFS method is compared with other methods. Another DeFS method is proposed in [19]. The DeFS algorithm is computationally faster, but the solution is not optimum, because the optimization criterion is stiff and unitary.

B. Minimum Spanning Tree (MST)

A modified depth first approach is the minimum spanning tree (MST) method. The MST algorithm improves the DeFS approach, which also has fast computing characteristics, and improves DeFS’s complex and weak convergence. It changes optimization rules from "find a slip road linking the bus up to" to "search for the maximum coverage of the bus network". Many simulations have been performed with the IEEE-14 and IEEE-30 bus systems [19] as well as the China's Yunnan Power grid [20].

V. Metaheuristic Methods

A. Simulated Annealing (SA)

Simulated Annealing (SA) is a technique that finds a good solution to an optimization problem, by trying random variations of the current solution. A worse variation is accepted as the new solution with a probability that decreases as the computation proceeds. T*he slower the* cooling schedule, or rate of decrease, the more likely the algorithm is to find an optimal or near-optimal solution.

The proposed SA method in [21] suggests a simple objective function that takes into account the distribution and installation cost of the measuring devices.

The concept of depth of unobservability and how it affects the number of PMUs is presented in [22]. Test results have shown that this method guarantees a dispersed placement of PMUs around the system and ensures that the distance between unobserved and observed buses is not too great. SA technique is utilized to solve the pragmatic communication-constrained PMU placement problem.

The SA algorithm is adopted in [23] to find the sensitivity constrained optimal PMU placement for system observability. A discrete objective function is minimized subject to the constraint that the system be topologically observable and PMUs be placed on buses with higher sensitivities. An observability topology analysis method is used to calculate parameter sensitivities of every bus in the system. The above method can be extended to consider the concept of unobservability depth [24].

A stochastic simulated annealing (SSA) method for solving the OPP problem to satisfy topological observability, is presented in [25]. The placement of PMUs results in a measurement system without critical measurements. The critical measurement free system can detect any single measurement bad data. Critical measurement identification is included as a penalty function. A similar method is suggested in [26]. The SA method is used to solve the OPP problem in such a way that the volume of initial information, based on the SCADA and PMU measurements, is sufficient to determine all the state vector components for load flow calculations without iterations [27]. In this case, the number of PMUs should be minimal.

The modified simulated annealing (MSA) method in [28], makes it possible to reduce the search space drastically, compared with the SA method, by:

– Modifications in the initial temperature and the cooling procedure to consider the current state of solution sets.
– A direct combination (DC) technique, using an effective heuristic rule to select the most effective sets in the observability sense.
– A Tabu search method, in which the heuristic rule used in DC method is also used to reduce the searching spaces effectively.

A hybrid genetic algorithm and simulated annealing (HGS) method for solving optimal placement of PMUs and RTUs in multi-area state estimation, is presented in [29]. Each control area includes one PMU and several RTUs. Voltage and current phasors are measured by the PMUs, while conventional measurements (power injections and flows) are measured by the RTUs. Pairs of power injection and flow measurements are placed to observe the raw data of boundary bus and tie line for data exchange in wide-area state estimator. The critical measurement identification procedure is used to provide critical measurement free areas. To reduce the number of conventional measurements and RTUs, a PMU is placed at the bus with the highest number of connected branches. The conventional measurements and RTUs are optimally placed to minimize the corresponding installation cost. The results are compared with the SA approach.

An SA method using the model of Markov chain, which is a series of test solutions generated at one time is proposed and compared with other heuristic methods in [19]. The speed of SA method is dependent on the number of network buses and connected branches to each node. Another comparison of SA algorithm to others using the PSAT toolbox is presented in [11], [29].

B. Genetic Algorithm (GA)

A genetic algorithm (GA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems.

The GA method suggested in [30] solves the OPP problem using different PMU placement criteria, such as the absence of critical measurements and critical sets from the system, maximum quantity of measurements received as compared to the initial one, maximum accuracy of estimates, minimum cost of PMU placement, and transformation of the network graph into tree.

In [31] the OPP problem was solved using a GA approach. The accuracy of the estimator was assessed using as fitness function for the GA the inverse of the cumulative differences between estimated and real power flows in the system. Presence of PMUs, produces a 4-time increase of the fitness function.

A GA method that determines the minimum number and places of PMUs, as well as the minimum number of phasors measured by a PMU, in order to guarantee the minimum number of PMUs, is presented in [32]. This characteristic gives a marked degree of realism to the method, not present in other techniques which suppose that PMUs measure the phasor currents at all adjacent branches. A very distinctive aspect of the method is the way the individuals are codified in the GA. This codification permits a rapid and clear quantification of the fitness value of each individual.

In [33] a non-dominated sorting genetic-based algorithm (NSGA) is presented, which can successfully solve the PMU placement problem with two competing objectives: minimization of the number of PMUs and maximization of the measurement redundancy. The optimization is carried out without any preference information given with respect to the objectives. The result of the search process is a set of (ideally Pareto-optimal) candidate solutions, from which the decision-maker may choose the most desirable one. The important advantage of the algorithm is that provides the entire Pareto-optimal front, instead of a single point solution, and can lend itself to application in an entire class of problems, where multi-objective optimization on a prohibitively large enumerative search space is required.

In [7] the OPP problem is formulated using topology based algorithms and solved using branch and bound and genetic algorithms. Simulated annealing is combined with a genetic algorithm in [29] for optimal PMU and RTU placement.

C. Tabu Search (TS)

Tabu Search (TS) is a combinatorial search technique for solving optimization problems by tracking and guiding the search.

A novel topological method based on the augment incidence matrix and TS algorithm, is proposed in [6]. The solution of the combinatorial OPP problem requires less computation and is highly robust. The method is faster and more convenient than conventional observability analysis methods using complicated matrix analysis, because it manipulates integer numbers. A TS method on meter placement to maximize topological observability is presented in [34].

D. Differential Evolution (DE)

Differential evolution (DE) is an optimization method that iteratively tries to improve a candidate solution with regard to a given measure of quality.

The algorithm proposed in [35], is an organic integration of Pareto non-dominated sorting and differential evolution algorithm (NSDE). It can realize global multi-objective optimization easily and quickly, can find a lot of Pareto-optimal solutions and can achieve accurate and complete Pareto front. The schemes of PMU placement produced by the approach are flexible, diversified, rational and practical. It has realistic instructive significance for the decision-maker to make decision scientifically according to practical situation. Moreover, it is worth further studying and researching on how to apply NSDE algorithm to PMU optimal placement problem with more objectives and other optimal problems of engineering community.

E. Immune Algorithm (IA)

The immune algorithm (IA) is a search strategy based on genetic algorithm principles and inspired by protection mechanisms of living organisms against bacteria and viruses.

In reference [36], the application of the immune genetic algorithm (IGA) method to the OPP problem is presented. Utilization of the local and prior knowledge associated with the considered problem is the main idea behind IGA. The prior knowledge of the OPP problem was inferred based on the topological observability analysis and was abstracted as some vaccines. The injection of these vaccines into the individuals of generations, revealed a remarkable increase in the convergence process.

F. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is an optimization method that provides a population-based search procedure in which individuals, called particles, change their positions with time. Particles fly around in a multidimensional search space. During flight, each particle adjusts its own position according to its own experience and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. The swarm direction of a particle is determined by the set of particles neighboring the particle and its history experience.

In [37], a modified discrete binary version of particle swarm algorithm (BPSO) is used, as an optimization tool to find the minimal number of PMUs for complete observability. By developing a new rule based on analysis of zero-injections, an improved topological observability assessment, based on topological analysis, is implemented. A BPSO algorithm, with the objective of minimum PMU installation costs, is introduced in [38]. A number of factors may influence the cost, such as the communication conditions at the located bus and the number of adjacent branches at the bus. The latter factor has been proved to be more qualified than conventional methods.

In [39], the GA algorithm is effectively combined with the PSO algorithm to achieve the optimal solution. The cross and mutation operations in GA are used to decrease the searching scope of the PSO method and improve the quality of initial PMU placement, thus accelerating the solving process. In addition, a speedy observability analysis method, called the pseudo measurement, is put forward.

A modified BPSO algorithm is used to obtain the minimal number of PMUs and their corresponding locations while satisfying associated constraints [40]. A similar methodology for the OPP problem using the BPSO algorithm is proposed in [41]. An attractive property of this formulation is that any available conventional measurements can also be taken into account. The optimization process tries to minimize the number of PMUs needed to maintain complete system observability and to maximize the measurement redundancy at all system buses. A similar BPSO algorithm is also suggested in [42].

A hybrid algorithm based on BPSO and immune mechanism is introduced in [43]. It provides a speedy and general analyzing method of power network topology observation based on the properties of PMU and topological structure information of the power network. The feature of the proposed algorithm is the combination of the swiftness in BPSO and the diversity of antibodies in immune system, thus improving its ability of converging in later evolution process.

G. Ant Colony Optimization (ACO)

The classical ant colony optimization (ACO) algorithm is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. A generalized ACO algorithm is proposed in [44]. The mechanism of adaptively adjusting the pheromone trail persistence coefficient and stochastic perturbing is introduced to improve the algorithm on the ability to escape from stagnation behaviour and convergence speed.

VI. Conclusions

The OPP problem is an NP-hard problem. During the last 25 years, numerous optimization techniques have been developed to solve the problem. The proposed techniques can be classified into three main categories: conventional, heuristic, and metaheuristic. The literature review presented in this paper will be useful for the researchers in order to discover and apply new methods for solving the challenging OPP problem.

VII. References

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VIII. Biographies

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