

# Intelligent Algorithmic Multi-Objective Optimization for Renewable Energy System Generation and Integration Problems: A Review

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**Abstract-** Integrated renewable energy is now becoming an option for sustainable growth of humanity. Because it provides the uninterrupted energy supply to small, and micro grids, as well as it penetrates the larger conventional energy grid to decrease the emissions and active losses. Combining renewable sources to conventional grid results in an integrated renewable energy system. Sometimes for smaller loads hybrid renewable energy systems (HRES) can be used as an alternative. This whole integration of different renewable energy systems (RES) which can be grid connected or off grid, requires optimization of various factors like total levelized cost of energy, total CO<sub>2</sub> emission (life cycle), total percentage of grid penetration etc. Hence, these kinds of problems include a large data regarding, energy resources, their annual availability, use pattern of the energy. Therefore to solve these complex problems one has to use intelligent computer algorithms, because of less calculation time and better accuracy than any other means. This paper highlights an updated literature regarding algorithmic multi-objective optimization for generation and integration side problems of renewable energy resources to satisfy electrical and in some cases thermal demand also. It will be helpful to the researchers working in the field of multiobjective optimization and integrated RES.

**Keywords:** Grid integration, Levelized cost, Objective function, Constraint condition, Intelligent Algorithm.

## 1. Introduction

Limitations of a single renewable source came into the picture in the late 20th century, causing the unreliability in energy supplies, fluctuation of the energy generation throughout the year, and insufficiency of a single renewable source to satisfy increasing energy demand. This situation generated the requirement of integration of two or more than two renewable energy sources, and in some cases the combination of renewable sources with some conventional energy sources, or with the grid. This gave rise to multiple problems, while deciding the size of the hybrid renewable system like deciding the total cost percentage of the

renewable energy in the grid, unavailability of a particular renewable resource for a particular period of time, whether to use the storage system or not [1]. To decide the optimal energy mix for an integration problem, which varies from location to location [2], irrespective of the same components, requires use of some computer algorithms, to find the global optimal solution in each case. This technique mainly includes the use of different intelligent algorithms, such as Genetic Algorithm (GA), Evolutionary Algorithm (EA), Ant colony optimization Algorithm (ACO), Simulated Annealing Algorithm (SA), Particle Swarm Optimization Algorithm (PSO) etc., which give a non-dominated solution [3], for the problem. These techniques determine the space for the cost-

quality trade-off for the renewable energy power supply. There are multiple inbuilt open access algorithmic software tools available for the optimization of the grid connected as well as for hybrid renewable energy systems. Yet they emerge with the limitations of components, as well as objective functions. These software include mainly Hybrid-2, improved hybrid optimization using genetic algorithm (iHOGA), and hybrid optimization of multiple electric renewables (HOMER) [4].

## 2. Generalized Form of a Multiobjective Optimization Problem

In a multiobjective optimization problem one has to optimize n objective functions simultaneously, with some equality and inequality constraints, which can be written as follows [5],

$$\text{Min or Max } F(\bar{x}) = [f_1(\bar{x}) \dots f_n(\bar{x})] \quad (1)$$

$$\text{Subject to constraints: } \bar{G}(\bar{x}) = 0 \quad (2)$$

$$\bar{H}(\bar{x}) \leq 0 \quad (3)$$

Where F(x) is objective function, containing n objectives, and equation (2) and equation (3) are equality and inequality constraints respectively.

The answer of this multiobjective optimization problem is actually in the form of set of solutions, means which are equally feasible and one solution cannot dominate other solutions, unless there is a user defined criteria given which is known as trade off criteria. Such sets of non-dominated solutions are shown by the Pareto optimal front [6]. While in some cases Pareto optimal front may not be used.

## 3. Types of Multiobjective Optimization Problems in RES

Types of problems occurred while optimizing the renewable energy systems mainly classified as, 1) Generation (Supply-Demand) side optimization problems and 2) Integration (Distribution Network) side optimization problems,

### 3.1. Generation Side Optimization Problems

Generation or Supply-demand side optimization problems mainly include, problems related to the energy costs, and emissions produced during generation of energy, formation of a hybrid renewable energy system (HRES).

**3.1.1. Objective Functions:** Many studies have been carried out regarding the multiobjective optimization of supply demand side renewable problems but most of them contain limited number of objectives, as minimization of loss of power supply probability, which is a ratio of shortage (demand minus generation) to the demand [7]. Minimization of total life cycle cost of energy [8] [9], minimization of greenhouse gas (GHG) emissions, minimization of only CO<sub>2</sub>

[10]. Maximization of grid penetration by maximizing renewable energy generation [6].

**3.1.2. Constraints:** The constraints regarding supply demand side optimization are strongly related to the system capacity. Demand satisfaction constraint, maximum unmet load, state of charge of the battery if used [11] [12], rated output of generator [13], hydrogen availability (H<sub>2</sub> electrolyzer) if used, useful area, initial investment cost, are some conditions which are considered as important [14].

**3.1.3. Variables:** Variables in the supply-demand problems are, global daily average incident solar radiation, area of PV panel, average annual wind speed, flow of water in streams, efficiencies of power generating equipment(s) [15], along with these variables some variables like daily waste generation, production of biogas per day [16] are used for the thermal power fulfilment along with the electrical power.

### 3.2. Integration Side Optimization Problems

These problems are generally associated with the planning of distribution network structures for integrated systems, renewable penetration percentage in the grid, network topology changes, components allocations and upgradations.

**3.2.1. Objective functions:** In these types of problems which are considered by researchers are mainly as, Minimization of network power losses, which includes resistive and inductive losses, resistive and inductive loss index [17]. Maximization of voltage stability, this condition has been expressed in some literatures in the form of voltage stability index, load sustainability limit or stability margin, and in some cases minimization of total variation of voltage [18]. Minimization of total harmonic distortion levels this includes minimization of current and voltage total harmonic distortion (THD) minimization [19]. Minimization of total distribution side costs which includes the planning, operational and maintenance costs [20]. Maximizing the system reliability, or minimizing system failures [21]. Minimizing the power purchased from the conventional grid or increasing the renewable energy penetration [22], minimizing GHG emission.

**3.2.2. Constraints:** Limiting conditions occur while optimizing the several functions at a time. In this case, conditions are, bus voltage range, number of taps, line flow constraint [23], thermal overloading constraint [24], feeder capacity constraint, power flow equality constraints [25][26].

**3.2.3. Variables:** Slack bus power [27], load bus voltage magnitude, phase angles, reference voltage, distribution network line parameters are variables observed while studying problems [28].

#### 4. Intelligent Algorithmic Optimization for Generation Side Problems

Intelligent algorithms generally having the property of giving global optimal solution rather than a local one best, so they are useful over the ordinary algorithms. Each intelligent algorithm has its advantages as well as disadvantages for a given scenario. However, the superiority of a particular algorithm over another can be compared by parameters like number of non-dominated solutions given, and smoothness of Pareto optimal front, and number of objectives which can be optimized simultaneously [29]. Use of algorithms is very common for optimization of generation side problems, but many of the optimization problems are limited to the two components which mainly consist of wind and solar PV, and therefore one cannot analyse the actual performance of an intelligent algorithm. Due to this reason literature reviewed in this paper deals with more than two components. For optimization of generation side problems first one has to verify the resources which will provide the energy then writing the governing equation for the each individual resource is necessary, which further leads to identifying the variables, constrains governing the energy output from that particular resource, then loading schedule and availability of a particular resource need to be identified before going to optimization task.

M. Trivedi [30] developed a multiobjective demand scheduling for a combination nuclear power plant- hydro power plant with renewable power plants, using genetic algorithm, the results show that the GA is capable of optimizing highly nonlinear scheduling problems. R. Dufo-López, and J. L. Bernal-Agustín [31] minimized total cost, unmet load and CO<sub>2</sub> emission of a hybrid renewable energy system using multiobjective EA (MOEA), and GA algorithms. The maximum net present cost for the non-dominated solutions was observed up to 60% over the lowest net present cost of the non-dominated solution. Saif et al. [32] used multiobjective optimization method for capacity planning of PV-Wind Diesel-Battery hybrid system with minimization of total levelized cost and emissions, uniqueness of this optimization was that, when unused energy level is 0% the solution with the least cost went close to the solution with least emission. O. Ekren, B. Y. Ekren [33] used simulated annealing algorithm (SA) for optimization of PV-Wind-Battery hybrid system for minimization of total cost, of the system. The study shows that using SA instead of using inbuilt optimization software results in 10.13% improvement in the objective function. Bilal et al. [34] designed hybrid battery-wind-PV system for minimization of total cost, and loss of power supply probability, for the site of Potou, it was observed from the simulations using GA that the loss of power supply probability increases with increasing share of wind energy production. Katsigiannis et al. [35] used non dominated sorting genetic algorithm (NSGA-II) for optimization of small scale standalone hybrid energy systems, two main case studies were analysed of which one system was having battery storage, and the other one having hydrogen storage, the results shows that battery storage was better than H<sub>2</sub> storage in both cost and emission criteria applied. M. Fadaee

and M.A.M. Radzi [36] reviewed evolutionary algorithmic approaches for optimization, and stated that, most used genetic, and PSO algorithms can be used for generalized optimizations for standalone hybrid systems. S. Fazlollahi and F. Maréchal [37] used evolutionary multiobjective optimization algorithm for deciding the individual renewable unit capacity for minimum cost, and CO<sub>2</sub> emissions for integrated thermal energy resources with the renewables they observed that combined production of heat and power (CHP) using biomass based renewables give more economic profitability up to 52% and reduction in CO<sub>2</sub> emission up to 40% compared to base case can be possible. A. J. Litchy [38] applied a real time energy management system for an islanded microgrid using multiobjective PSO algorithm. A relation between the performance and economic operating parameters was established for battery and H<sub>2</sub> electrolyzer, and operating order was developed such that least cost can be achieved with optimal energy provided. Stojiljkovic et al. [39] compared different algorithms performance optimization for a trigeneration based hybrid power system, and found out that PSO, SA and taboo search algorithm (TSA) were superior over GA, ant colony and harmony search algorithms because they require a fewer inputs. Al-Shamma'a and. Addoweesh [40] analysed a case study using GA of a village for a standalone renewable system, with energy components as PV, wind, diesel, and battery. They resulted in a conclusion that a combination of 65% renewables and 35% DG-set will result in the lowest total cost along with the optimize emission. The outputs were also compared with HOMER. M. Sharafi, and T. Y. EIMEkkawy [41] applied optimization for a problem comprising of Wind-PV-Battery-Diesel-Hydrogen tank-Fuel cell combination using dynamic multiobjective PSO (DMOPSO) and estimated that a minimum of 67% of solutions generated by DMOPSO dominates solutions generated by other algorithms. Perera et al. [42] integrated the DG set with a standalone renewable system, using steady state  $\epsilon$ -multiobjective optimization algorithm based on  $\epsilon$ -dominance method, with maximizing the renewable energy capacity, and loss of load probability, with cost minimization. One of the results shows that increasing wind generation capacity in the system, allows user to use higher powered DG sets, whenever there is limitation to the storage bank. Ko et al. [43] used elitist NSGA-II for the optimization of combined renewable heat power supply, for a school building. It was also observed that the higher penetration of renewables above certain limit will not decrease the GHG emissions, instead it will increase the total cost only. This condition was occurred due to differences in operational orders, and component capacities. M. Sharafi [44] Studied and compared (MOPSO) Multiobjective Particle Swarm Optimization Algorithm with the multiobjective genetic algorithm, for optimization of islanded micro grid and concluded that MOPSO performs faster than multiobjective GA (MOGA) for optimization with the same demand, and same number of solution sets. Mohamed et al. [45] studied series and parallel implementations of PSO for a PV-Wind-Battery-and Diesel generator system, with objectives as maximum energy generation with minimum system cost. Study reveals that the parallel implementation of PSO is more time saving than serial implementation. Ming et al. [46] proposed

multiobjective evolutionary algorithm with a localized penalty based-boundary intersection method (MOEA/D-LPBI) used for optimizing the nonlinear, mixed integer problem. Simulation for an optimization of 5 components for minimizing system costs, unmet load, emissions, was carried out. Results show superiority of this algorithm over the preference inspired the co-evolutionary algorithm using goal vectors (PICEA-g) and multiobjective evolutionary algorithm based on decomposition (MOEA/D). Maleki et al. [47] optimized a similar combined heat power optimization problem using PSO and GA for minimum cost objective function, each algorithm was run for 20 times keeping the problem same as earlier. When minimum values of objective functions were compared and relative error calculation was carried out for demand fulfilment using hybrid energy and conventional grid it was 14%, giving PSO a winning edge. R. Singh et al. [48] introduced a new method for the hybrid system analysis which is termed as reformed electric system cascade analysis, taking two constraints at a time and goal programming for the real time optimization of hybrid energy systems for standalone as well as grid connected cases.

### 5. Intelligent Algorithmic Optimization for Integration Side Problems

Integration side optimization problems for RES generally consist of dealing with distribution network, grid resonance attenuation, [49] generating station optimal placement, real time energy demand fulfilment. [50] The test systems generally used for the distributed network analysis, can be categorized into two types which are, medium voltage level having the range of 6.6 kV to 34.5 kV, and low voltage level having the range of 110 V to 600 V. The multiobjective optimization provides an active network control for the distributed network system, rather than the conventional methods which actually focus on the distributor solely.

Ochoa et al. [51] Proposed time series based maximization of distributed wind energy generation using NSGA algorithm also discussion has been carried that the all solutions given may not be non-dominated, when dealing with probabilistic approaches. A. Soroudi, & M. Ehsan [52] compared performance of different algorithms for multiobjective optimization of distributed generation integration in to the distribution network, and came up with a conclusion that modified NSGA can find more number of optimal solutions as compared to other algorithms like SA, PSO, TSA, and ordinary NSGA. A. Mohsenzadeh and M. Haghifam [53] analyzed simultaneous allocation of conventional and renewable generations in distribution generation with 132/33 kV 9 node system, distribution generation consisting of only diesel and wind systems, and resulted in decreased power loss up to 76%, and unsupplied energy reduced to 25% of original value. Ebrahimi et al. [54] studied the optimization of 2 400-kVAr-SVC 13 bus system using binary PSO for, also it has been proved that binary PSO is more efficient in solving this kind of problems rather than genetic algorithm. Zidan et al. [55] came up with multiobjective approach based on NSGA-II for the optimization of the distributed network with objectives as, minimizing GHG emissions, and costs related to the system,

it has been proved that emission reduction up to 56.94% is possible as compared to base case considered using, 119 bus system. Ameli et al. [56] used MOPSO for maximizing the profit of distributed generation owner and minimizing the distribution companies' costs, it has been concluded that minimizing one quantity results in the minimization of another quantity. P. Kayal and C. Chanda [57] proposed a method using MOPSO for minimizing the voltage deviation, emission, losses and payback period and found out that presence of renewables decreases the losses in system. Also they mentioned that, consideration of power factor in system can affect the system allocations. B. Arandian and M. M. Ardehalia [58] used hybrid shuffled frog leap algorithm (HSFLA) for allocating combined PV- and CHP power allocation in radial and meshed integrated heat and electric network with storages. It was found out that, using HSFLA increase in profit, by 28.36%, 11.89%, 19.96%, 14.73%, 8.21%, and 17.44% in comparison with, GA, modified SFLA, imperial colony algorithm (ICA), ordinary SFLA, improved PSO, and ordinary PSO respectively. Conteh et al. [59] used GA and artificial neural network (ANN) for minimizing the system costs, and meeting the demand respectively. The study emphasizes that, the ANN technique is more effective for load shedding assessments, and system isolation than conventional techniques. Khaled et al. [60] introduced modified PSO technique for optimizing power flow in distribution with a modelled system network of IEEE 30-bus test system. The study represents that the integration of renewables is more effective in case of slight decrement in load. The reduction in losses by 16% for the 5% decrement in the load to be supplied, when renewables are connected to the grid. A. M. Eltamaly and M. S. Al-Saud [61] used nested MOPSO with an IEEE 30 bus system model for optimized allocation of renewables, and minimizing transmission line losses. Zhang et al. [62] proposed a distributed network operator based method to solve the multiobjective optimizations with uncertainty conditions, in this method redundant calculations connected to the optimal location of DG, are omitted. Ravadanegh et al. [63] studied distributed network based approach, it has been discussed that the voltage amplitude can be considered as a main governing parameter, in case of power flow, and losses, this paper deals with the demand mix of industrial, commercial and domestic power.

### Summary of Optimization Approaches

Summary of different algorithmic approaches used for renewable optimization of generation and integration side problems is presented in "Table 1" and "Table 2" respectively,

**Table 1.** Summary of optimization approaches for Generation side problems

Authors	Energy Components	Objective Functions		Algorithms Used	Year
		Maximize	Minimize		
R. Dufo-López, and J. L. Bernal-Agustín [31]	PV, Wind, Battery, Diesel	—	<ul style="list-style-type: none"> <li>• Net present cost</li> <li>• Emissions</li> <li>• Unmet Load</li> </ul>	MOEA, GA	2008
Bilal et al. [34]	PV, Wind, Battery	—	<ul style="list-style-type: none"> <li>• Annual Power cost</li> <li>• Loss of Load Probability (LLP)</li> </ul>	GA	2010
Katsigiannis et al. [35]	PV, Wind, Diesel, Fuel cell, Fuel cell (natural gas), Biodiesel generator, Electrolyzer, Battery	—	<ul style="list-style-type: none"> <li>• Total energy cost</li> <li>• GHG emission</li> </ul>	NSGA-II	2012
S. Fazlollahi and F. Maréchal [37]	Back pressure steam turbine, Biomass integrated gas engine-gas turbine- combined cycle, Biomass Rankine cycle, Synthetic natural gas	—	<ul style="list-style-type: none"> <li>• Investment cost</li> <li>• Operating cost</li> <li>• CO<sub>2</sub> emissions</li> </ul>	EA	2013
A. J. Litchy [38]	PV, IC engine CHP, Fuel cell CHP, H <sub>2</sub> tank, Boiler	—	<ul style="list-style-type: none"> <li>• Total energy cost</li> <li>• GHG emission</li> </ul>	MOPSO, GA	2013
Stojiljkovic et al. [39]	Components related to heating, cooling and electric generation	—	<ul style="list-style-type: none"> <li>• Annual Power cost</li> <li>• Primary energy consumption</li> </ul>	GA, PSO, SA, TSA, ACO	2014
Al-Shamma'a and Addoweesh [40]	PV, Wind, Battery, Diesel	Renewable fraction	<ul style="list-style-type: none"> <li>• (LLP)</li> <li>• system cost</li> </ul>	GA	2014
M. Sharafi, and T. Y. EIMekkawy [41]	Wind, PV, Diesel, Battery, electrolyzer, Fuel cell, Hydrogen Tank	—	<ul style="list-style-type: none"> <li>• Net present cost</li> <li>• (LLP)</li> <li>• Fuel emission</li> </ul>	Dynamic MOPSO	2014
Perera et al. [42]	PV, Wind, Battery, Diesel	—	<ul style="list-style-type: none"> <li>• system cost</li> <li>• fuel consumption</li> <li>• (LLP)</li> </ul>	ε-MO dominance	2015
Ko et al. [43]	PV, solar collector, steam boiler, and other thermal components	Renewable penetration	<ul style="list-style-type: none"> <li>• levelized cost of energy</li> <li>• GHG emissions</li> </ul>	NSGA-II	2015
M. Sharafi [44]	PV, Wind, Battery, Diesel, Electrolyzer, Fuel Cell, H <sub>2</sub> Tank	—	<ul style="list-style-type: none"> <li>• system cost</li> <li>• (LLP)</li> </ul>	MOPSO	2015
Mohamed et al.[45]	PV, Wind, Battery, Diesel	Renewable generation	<ul style="list-style-type: none"> <li>• System Cost</li> </ul>	Pareto based PSO	2016
Ming et al. [46]	PV, Wind, Battery, Diesel	System Reliability	<ul style="list-style-type: none"> <li>• System Cost</li> <li>• Fuel emission</li> </ul>	MOEA/D (LPBI)	2017
R. Singh et al.[48]	PV, Wind, Battery, Diesel, Conventional Grid, Inverter	Renewable Energy fraction	<ul style="list-style-type: none"> <li>• Final Excess Energy</li> <li>• Annual system cost</li> <li>• (LLP)</li> </ul>	RESCA	2018

**Table 2.** Summary of optimization approaches for Integration side problems

Authors	Objective Functions		Constraints	Algorithms used	Year
	Maximize	Minimize			
Ochoa et al.[51]	• Wind power Export	• Active power loss • Hazard for protection devices	• Bus voltage drop • Power flow Equality • Radial operation • Branch feeder capacity	NSGA	2008
A. Soroudi , M. Ehsan [52]	—	• Active Losses • Total costs • GHG Emission	• Power flow equality • Voltage Magnitude	Modified NSGA	2011
A. Mohsenzadeh and M. Haghifam [53]	• System Reliability	• Power losses costs • CO <sub>2</sub> emissions • Investment costs • Voltage deviation penalty	• Power flow equality	NSGA-II	2012
Ebrahimi et al. [54]	• Renewable penetration	• Active Losses • Voltage deviation • Cost of power • Emission	• Bus voltage drop • Power flow Equality • Thermal constraints • Power Factor	Binary PSO-fuzzy set theory	2012
Zidan et al. [55]	—	• Total costs • GHG Emission • Active losses	• Bus voltage drop • Power flow Equality • Radial operation • Branch feeder capacity • THD constraint	NSGA	2013
Ameli et al. [56]	• DG owner profit	• Customer interruption cost • Total cost • Cost of power purchase	• Bus voltage drop • Power flow Equality • Branch feeder capacity • Transformer overload • Budget constraint	MOPSO	2014
P. Kayal and C. Chanda [57]	• Average voltage stability	• Payback year • Yearly voltage loss	• Bus voltage drop • Power flow Equality • Branch feeder capacity • DG capacity limit	MOPSO	2015
B. Arandian and M. M. Ardehalia[58]	• Distributors economic profit	• Total cost of power	• Heat flow distribution and pressure limit • Bus voltage drop • Electricity and heat storage • Branch feeder capacity • Balance of electric and thermal loads	Hybrid SFLA	2017
Conteh et al. [59]	• Reliability of power supply	• Total system cost	• Load balance constraint • Bus voltage drop	MOGA& ANN	2017
A. M. Eltamaly and M. S. Al-Saud [61]	—	• Generation and operating cost • Total line losses • Emission	• Voltage stability • Power stability	Nested MOPSO	2018
L. Zhang et al. [62]	• Power reliability	• Voltage Quality • Power loss	• Voltage Limit • Line Capacity	NSGA-II	2018
Ravadanegh et al. [63]	Power Reliability	• O&M cost of energy • Emission	• Voltage Limit • Line Thermal unit	NSGA-II	2018

## 6. Discussions

The multiobjective optimization of hybrid renewable energy systems is necessary for the developing the precise microgrid, structure which can deliver power to forever increasing demand in the future. Various evolutionary algorithms are now being used besides only PSO and GA. This current scenario of developing hybrid microgrids whether for a remote place or as an assisting medium for the conventional grid to supply the continuously increasing power, can result in a more cost saving and green option. For future studies more algorithms which can solve the complex programming regarding the energy optimization should be used to tackle the uncertainty in power supply. In future the simultaneous as well as real-time optimization of available energy sources and their integration will be a prior solution required along with the accuracy, so two or more algorithms can be compared for the time taken to optimize the complex problem and accuracy. Presently one cannot rely on the mere optimization of complex grid scheduling and integrating problem but a real time simulation should be needed to identify the uncertainties more carefully and to minimize them. The integration side problems are generally optimized with bus voltage drop and power flow quality as the vital constraints. Minimization of active power losses is one of the most studied objective, due to cost related with the losses is high. Also some researchers have used various post optimization decision making criteria for cost-quality trade-off for a particular set of solutions. On the other hand generation side optimization problems are considering more environmental constraints rather than technical one, and NSGA category algorithms are now being used for optimizing simple as well as moderate complex system optimization problems. Many studies highlight that integration renewables in the conventional grid resulting in to the less power losses, and emissions of the grid. Integration also giving advantage on the counter side for standalone renewable systems against their limitations for load supply. Installing grid connect renewable with CHP plants also increases system efficiency and generates heat providing capability into the whole network. The system derived by this addition can be a cost effective, yet more reliable system.

## 7. Conclusion

The present study has classified the multiobjective energy optimization problems in two different perspectives rather than a single problem, yet the optimization methods use the same algorithms for different objective functions in two different fields. For both the problems some common objective functions are there like minimization of total emission minimization of system cost and maintenance cost. Most of studies are dealing with only a single sided conflicting objective functions, such as two maximizing or two minimizing, there is a future scope for simultaneously optimizing two sided conflicting objectives. The interrelation between generation side and integration side problems should be established as the focus on a particular objective is different from both the perspective. The future challenges

like wide area monitoring, optimal location and sizing of DG's must need the multiobjective optimization in real time.

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