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Research Paper

Securing Reliability Constrained Technology Combination for Isolated Micro-Grid Using Multi-Agent Based Optimization

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Abstract: The determination of a suitable technology combination for an isolated micro-grid (IMG) based on hybrid renewable energy resources (HRES) is a challenging task. The intermittent behavior of RES leads to an adverse impact on system reliability and thus complicates the planning process. This paper proposes a two-fold approach to provide a suitably designed HRES-IMG. Firstly, a reliability-constrained formulation based on load index of reliability (LIR) is developed with an objective to achieve a minimum levelized cost of energy (LCOE). Multi-state modeling of HRES-IMG is carried out based on hardware availability of generating units and uncertainties due to meteorological conditions. Modeling of battery storage units is realized using a multi-state probabilistic battery storage model. Secondly, an efficient optimization technique using a decentralized multi-agent-based approach is applied for obtaining high-quality solutions. The butterfly-PSO is embodied in a multi-agent (MA) framework. The enhanced version, MA-BFPSO is used to determine optimum sizing and technology combinations. Three different technology combinations have been investigated. The combination complying with LIR criterion and least LCOE is chosen as the optimal technology mix. The optimization is carried out using classic PSO, BF-PSO, and, MA-BFPSO and obtained results are compared. Further, in order to add a dimension in system planning, the effect of uncertainty in load demand has also been analyzed. The study is conducted for an HRES-IMG situated in Jaisalmer, India. The technology combination comprising of solar, wind, and battery storage yields the least LCOE of 0.2051 $/kWh with a very low value of LIR (0.08%). A reduction in generator size by 53.8% and LCOE by 16.5% is obtained with MABFPSO in comparison with classic PSO. The results evidently demonstrate that MA-BFPSO offers better solutions as compared to PSO and BF-PSO.

Keywords: Isolated Micro-Grid, Levelized Cost of Energy, Multi-Agent System, Renewable Energy Sources, Reliability.

1 Introduction

THE global power generation scenario is undergoing a metamorphosis with increasing inclination towards deployment of renewable energy sources (RES) based generators [1]. Amidst a broad spectrum of RES technologies, solar and wind based generators have particularly grabbed the attention due to their ample availability. They are also seen as a powerful alternative to grid expansion in isolated locations. However, the stochastic behavior of these sources is one of the major obstacle in their deployment for stand-alone applications [2]. The hybridization of these resources in combination with storage can effectively curb the effects of intermittency. A hybrid renewable energy sources based isolated micro-grid (HRES-IMG) is deemed to be capable of ensuring the reliability for stand-alone applications. Besides intermittency, another criterion which largely affects the planning of HRES-IMG is the high capital cost associated with RES. Although, a steep decline in cost has been witnessed in recent years, it remains high when compared to

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Fig. 1 Categorization of literature survey.

conventional fossil fuel based generation. Despite high cost, integration of RES is justified as they present a major de-carbonization solution in agreement with the climate protocols.

Thus, planning of HRES-IMG seeks elaborate analysis due to intermittency issues and high costs. Further, for standalone applications, it becomes all the more challenging as the HRES-IMG is solely responsible for maintain reliability standards. An inadequate planning may lead to a compromise on reliability and costs. The planning of HRES-IMG is a highly constrained, non-linear, combinatorial optimization problem. Thus, use of competent optimization technique is crucial to solve this problem with efficacy.

1.1 Literature Survey

Looking into exhaustive nature of the planning problem, a systematic literature survey is elementary to effective problem formulation. The literature survey carried out in this paper is classified under three subdivisions as presented in Fig. 1.

A significant contribution has been reported in literature for handling the intermittency issues associated with RES. Paliwal *et al.* [3-5] have suggested that an effective way of dealing intermittency is to use a combination of solar/wind/battery storage for standalone applications. The reliability benefits in islanded micro-grid have been studied by Costa and Macos [6]. Khalili *et al*. [8] have proposed a formulation for distribution system targeting multiple objectives. The planning of solar, wind and battery storage has been proposed in [7], [9-11]. However, in these papers only meteorological parameters have been considered. The hardware availability of generating units has not been considered. Oboudi *et al*. [12] have considered hardware modeling also. However, storage integration has not been taken into account. A broad spectrum of reliability indices has been used for analyzing system adequacy. The most popular indices are LOLP [5, 13] and EENS [14]. System well-being indices have also been used for assessment of reliability [4, 15].

As per economic evaluation of HRES-MG, levelized cost of energy (*LCOE*) has been used in several planning formulations [16-17]. Lamye *et al*. [18] and Lozano *et al*. [19] have determined optimum configuration based on energy cost. A cost-benefit analysis considering storage as a system component has been reported in [20-21]. An economic evaluation framework considering cost competitiveness of micro-grid configurations has been proposed by Som and Chakraborty [22]. The economic evaluation parameters such as payback period [23] has also been employed. A ranking based approach for finding out best option has been used by Singh and Parida [24].

The determination of optimal technology combination involves evaluation of large number of possible alternatives. This calls for state-of-art optimization technique to ensure high planning standards both in terms of cost as well as reliability. Analytical techniques such as mixed integer non-linear programming models [25-26] and Bender's decomposition method [27] have been used for optimal system design. As compared to analytical techniques, artificial intelligence techniques offer ease of implementation and high computational speed. Thus, these techniques are particularly suitable for HRES-MG which have complex and non-linear design. Gabbar *et al.* [28] have used PSO to plan a nuclear-renewable micro-grid based on minimization of net present cost. PSO [29] has also been used to determining component sizes for islanded MG. Elattar and Elsayed [30] have proposed a modified moth flame optimization for determining the size and placement of generators. Lu and Wang [31] have utilized dynamic programming for the sizing of hybrid systems. A hybridization of phasor PSO and gravitational search optimization [32] has also been used.

In recent times, multi-agent (MA) systems have attracted the attention of researchers for MG optimization. MA systems have the capability of parallel processing, thus are more suitable for complex optimization problems. Lee *et al.* [33] have used MA-PSO for determining optimum battery size. Liu *et al.* [34] employed MA-chaotic search PSO for optimizing MG operation Elamine *et al*. [35] have implemented MA-back propagation PSO to maximize benefits in smart MG. Moshseni *et al*. [36] have used MA system for sizing of multi-carrier MG. In a recent work by Dai *et al.* [37], a solar-battery based electric vehicle charging station has been designed using MA-PSO.

Table 1 presents a summary of literature review conducted on HRES micro-grids. The literature has been studied based on type of technology used, hardware and climatological modeling. The attention

Table 1 Summary of literature review.

Ref.	Technology	Hardware modeling	Climatological modeling	Optimization technique	Objective	Reliability analysis	Site
[4]	SPVG, WG, Storage	Yes	Yes	PSO	Minimize Cost	Yes	Jaisalmer, India
[5]	SPVG, WG, Storage	Yes	Yes	BF-PSO	Minimize Cost	Yes	Jaisalmer, India
[7]	SPVG, Diesel, Storage	No	Yes	Artificial Bee Colony	Minimize Cost	No	Egyptian 45-bus, Meshed System of Alexandria
[9]	WG, SPVG, FC, MT, Storage	No	Yes	PSO	Minimize Cost, Losses	Yes	Ekbatan residential complex, Tehran, Iran
[10]	SPVG, WG, Storage	No	No	Grey Wolf Optimizer	Minimize Cost, Losses	No	Satara, Maharashtra, India
[11]	SPVG, Storage	No	Yes	GA	Losses	No	Not Specified
[13]	WG, SPVG, FC, Storage	No	Yes	E-constraint	Minimize Cost	Yes	Specific Location in 25° Latitude.
[14]	WG, SPVG	No	Yes	Exchange Market Algorithm	Minimize Cost	Yes	Not specified
[15]	WG, SPVG, Storage	Yes	Yes	PSO	Minimize Cost	Yes	Jaisalmer, India
[16]	WG, SPVG, Diesel Generator, FC, Storage	No	Yes	NSGA-II	Minimize Cost, Emissions	Yes	Chania Region, Crete, Greece
[17]	WG, SPVG, Diesel Generator, FC, Storage	No	Yes	Scenario-based	Minimize Cost, Emissions	No	Bonaire Island
[18]	WG, SPVG, Concentrated Photovoltaic Panels (CPV)	No	Yes	Hybrid GA-PSO	Size, Energy Management	No	Laayoune Region
[19]	SPVG, Diesel Generator, Storage	No	Yes	HOMERPro	Minimize Cost	No	Gilutongan Island, Cordova, Cebu, Philippines
[20]	WG, Storage	Yes	Yes	Hybrid Tabu Search/PSO	Minimize Cost	Yes	13.8-kV Distribution Network
[21]	SPVG, WG, Diesel, Storage	No	Yes	Decomposition–Coordination Algorithm	Minimize Cost	Yes	Kythnos Island, Greece
[22]	SPVG, FC, BM, Storage	No	Yes	Real-Valued Cultural Algorithm	Minimize Cost	Yes	Residential Locality, India
[24]	SPVG, WG, FC	No	Yes	Mixed Integer Non-Linear Programming	Minimize Cost	No	15-Node Distribution System
[26]	WG, Storage	No	Yes	Mixed-Integer Non-Linear Programming	Minimize Cost	Yes	6-Node and 30-Node System
[27]	SPVG, WG, Storage	No	Yes	Benders Decomposition, Mixed Integer Non-Linear Programming	Optimal Dispatch, Emissions, and Social Factors		
[28]	SPVG, WG, FC, nuclear, BM, Storage	No	Yes	PSO	Minimize Cost	Yes	Not Specified
[29]	SPVG, WG, Pumped Storage	No	Yes, Homer	PSO	Minimize Cost, Reliability	Yes	Small Tropical Island
[30]	SPVG, WG, FC, BM, hydro, MT	No	Yes	Modified Moth Flame Optimization	Minimize Cost, Real Power Loss, Voltage Deviation, Pollution Emission	No	IEEE 69 Bus Radial Distribution System
[31]	No generators, Battery, Ultracapacitor	NA	NA	Simulated Annealing	Minimize Cost	No	Study for Plug-In Electric Vehicles
[32]	SPVG, WG	No	Yes	Hybrid Phasor Particle Swarm Optimization And The Gravitational Search Algorithm	Minimize Loss, Maximize Profit	No	IEEE 69 Bus Test System
[33]	SPVG, WG, Storage	No	Yes	MA-PSO	Minimize Cost	No	USA
[34]	SPVG, WG, MT, Storage	No	Yes	MA-Chaotic Search PSO	MG Operational Cost, Environmental Impact, Risk	No	Not Specified
[35]	WG, Storage	No	Yes	MA-Weighted Back Propagation PSO	MG Operational Cost	No	Not Specified
[36]	SPVG, FC, Storage	No	Yes	MA	Minimize Cost	Yes	Hendurabi Island in the Persian Gulf
[37]	SPVG, Storage	No	Yes	MA-PSO	Minimize Cost	No	Shanghai, China

SPVG: Solar PV generator, **WG:** Wind generator, **FC:** Fuel cell, **MT:** Micro-turbine, **BM:** Bio-mass.

has also been paid to objective function and optimization technique used for addressing planning problem. The research gaps identified on the basis of the literature survey have been discussed in subsequent section.

1.2 Research Gaps

The extensive literature survey conducted on planning of HRES-IMG reveals the following research gaps:

i. The output from solar and wind based generators is subjected to hardware availability status of generating units and climatological parameters. There are very few papers, which provide the blending of hardware availability and intermittency of RES in planning structure.

ii. Majority of papers are focused on determination of component sizing for a particular generation technology. Analysis of different technology combinations in order to determine the optimum one has not been widely reported.

iii. There are not many studies which incorporate reliability evaluation as a component of system planning. This is indispensable for an IMG.

iv. Although, a wide-ranging artificial intelligence techniques have been employed for addressing optimal sizing problem of HRES-IMG, they are accompanied by some inherent limitations. Though, they present a great computational ease and simplified approach, they have a tendency to get trapped in local optimal. This may result in sub-optimal planning. To overcome this issue, the application of MA systems has been reported in few studies. However, to the best of the author's knowledge, an integrated framework assimilating all the components of system planning in MA framework has not been proclaimed.

1.3 Contributions and Organization

Based on the above research gaps, the contributions put forward by this paper are as follows:

i. Incorporation of multi-state output model of RES based generators in system planning. The multi-state model integrates respective forced outage rates (FOR) of generators as well as climatological parameters.

ii. Development of a reliability constrained planning framework aimed at determining optimal component sizes for different technology combinations.

iii. Implementation of a highly efficient optimization technique involving parallel processing, Multi Agent-based Butterfly PSO (MA-BFPSO) algorithm. The MA-BFPSO not only reduces the computational time but also provides high-quality solutions. To establish the effectiveness of technique, a comparison has been carried out with standard PSO and Butterfly- PSO (BF-PSO).

iv. Analysis of technology combinations under the effect of load uncertainty.

The paper is organized as follows: Section 2 explains multi-state system modeling. Section 3 elaborates the description of reliability constrained planning framework. Section 4 explains salient features of multi-agent based BFPSO. In Section 5, a study illustrating the application of MA-BFPSO for obtaining appropriate technology mix has been conferred. Section 6 presents pertinent conclusions and prospects of prospective work in this field.

2 Multi-State Modelling (MSM) of HRES-IMG

In the present work, the planning of HRES-IMG has been investigated considering a combination of the following system components:

a) Solar PV based generator (SPVG),
b) Wind generator (WG),
c) Battery storage system (BSS).

The multi-state modeling of SPVG, WG, and BSS has been dealt with the author in their previous work [3-5]. Readers are encouraged to refer to these references in order to enable an enhanced understanding of MSM. However, for the purpose of imparting clarity to this paper, a brief description of MSM is deliberated along these lines:

Step 1: Availability Modelling: Availability model of SPVG and WG units is built up based on their respective forced outage rates (FORs).

Step 2: Meteorological modeling: For each time segment *t*, solar irradiance and wind speed are modeled using Beta and Weibull probability density functions (pdfs) respectively.

Step 3: Multi-State Modelling: For each time segment, an MSM is formulated by combining models obtained from Steps 1 and 2.

Step: 4: For *t*-th time segment, the output power obtainable from SPVG and WG is evaluated for each state of MSM.

Step 5: Based on load and output power from generators, battery charge/discharge status is evaluated for each state of MSM in *t*-th time segment. The evaluation of battery state of charge (SOC) is done based on the battery model derived from [4] as follows:

$$SOC^{t+1} = SOC^{t} \pm \frac{E^{t}_{charge/discharge}}{C_{BSS}} \quad (1)$$

where, SOC^t and SOC^{t+1} represent the battery SOC for *t*-th and *t*+1-th time segment respectively, $E^t_{charge/discharge}$ is energy flow through battery during *t*-th time segment, kWh, wherein the positive and negative signs correspond to charging and discharging operations respectively, and C_{BSS} is battery capacity, kWh.

Step 6: Based on Step 5, multi-state probabilistic battery state model (MSPBSM) comprising of different states of battery state of charge (SOC) and their respective probabilities is obtained [3-5]. The minimum and maximum limits of battery SOC is constrained by

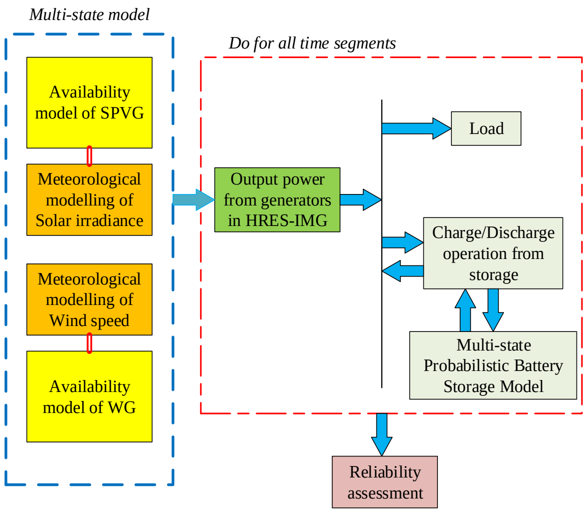


Fig. 2 Schematic of multi-state model.

the manufacturer.

Step 7: Steps 3-6 are repeated for all time segments. By assessing system states, the reliability evaluation indices are calculated. A schematic of multi-state model is presented in Fig. 2.

3 Description of Reliability Constrained Planning Formulation

Reliability and cost are the most important design criteria for HRES-IMG. Thus, in this paper a reliability constrained planning framework has been presented. The levelized cost of energy (LCOE) has been used as the objective function [4]. LCOE has been specifically chosen for its ability to provide a comparison between different technology combinations. For addressing the reliability issue, the optimization framework is subjected to a reliability constraint; Load index of reliability (LIR). The objective function and constraints are briefly discussed in succeeding sub-sections.

3.1 Objective Function

Minimize *LCOE* (2)

$$\text{where } LCOE = \frac{LCC}{\sum_{n=1}^{N_p} E_n / (1+r)^n} \tag{3}$$

The life cycle cost (*LCC)* is defined as the net present value of total costs incurred over the lifespan of project [15]. It comprises of different cost components as expressed by (3).

$$LCC = Cost_{cap} + Cost_{OM} + Cost_{\mathrm{Re}\,p} + Cost_{UL} + Cost_{social} - Cost_{salvage} \tag{4}$$

where, $Cost_{cap}$ is capital costs of components, $Cost_{OM}$ is NPV of operation and maintenance costs, $Cost_{Rep}$ is NPV of replacement costs incurred over planning years, $Cost_{UL}$ is NPV of cost of unmet load, $Cost_{social}$ is NPV of social cost of carbon emissions, and $Cost_{salvage}$ is NPV of salvage value of components. All costs are in k\$. E_n is energy supplied during *n*-th planning year, N_p is number of planning years, and *r* is nominal discount rate.

3.2 Constraints

3.2.1 Constraint on System Reliability Index LIR

In this paper, the reliability metric used is called as load index of reliability (LIR) which is defined as the percentage of unserved load to the total load during study period [38].

$$LIR \le LIR_{\max} \tag{5}$$

3.2.2 Constraint on BSS SOC

$$SOC_{\min} \le SOC \le SOC_{\max} \tag{6}$$

where, $SOC_{\min}$ and $SOC_{\max}$ are lower and upper limits for SOC, respectively

3.2.3 Constraints on Component Sizing

$$C_{SPVG_{\min}} \le C_{SPVG} \le C_{SPVG_{\max}} \tag{7}$$

$$C_{WG_{\min}} \le C_{WG} \le C_{WG_{\max}} \tag{8}$$

$$C_{BSS_{\min}} \le C_{BSS} \le C_{BSS_{\max}} \tag{9}$$

where, $C_{SPVG_{\min}}$ and $C_{SPVG_{\max}}$ are respectively lower and upper limits of solar generator capacity, kW, $C_{WG_{\min}}$ and $C_{WG_{\max}}$ are respectively lower and upper limits of wind generator capacity, kW, $C_{BSS_{\min}}$ and $C_{BSS_{\max}}$ are respectively lower and upper limits of battery capacity, kWh.

3.2.4 Constraint on Power Balance

For all time segments, the balance between the available and consumed power in IMG must be maintained.

a) BSS discharging mode:

$$P_{SPVG}^t + P_{WG}^t + P_{BSS_{dis}}^t = L_{sup}^t \tag{10}$$

b) BSS charging mode

$$P_{SPVG}^t + P_{WG}^t = L_{sup}^t + P_{BSS_{ch}}^t + P_{unutilized}^t \tag{11}$$

where, P^t_{SPVG} and P^t_{WG} represent the output power available from SPVG and WG during *t*-th time segment. $P_{BSS_{ch}}^t$ and $P_{BSS_{dis}}^t$ is the power flow through BSS during charging and discharging mode respectively, L^t_{sup} is the load supplied during *t*-th time segment, $P^t_{unutilized}$ is the power which remains unutilized due to excess generation in IMG.

Based on (10), the unmet load for *t*-th time segment can be calculated as:

$$L_{unmet}^t = L^t - L_{sup}^t \tag{12}$$

where, L_t and L^t_{unmet} represent the load demand and unmet load respectively for *t*-th time segment.

3.2.5 Constraint on Power Flow through BSS

The power flow through BSS is constrained by minimum and maximum limits specified by the manufacturer.

$$P_{BSS_{dis\_\max}} \le P_{BSS}^t \le P_{BSS_{ch\_\max}} \tag{13}$$

where, $P_{BSS_{dis\_\max}}$ and $P_{BSS_{ch\_\max}}$ represent the maximum power flow limit specified by the manufacturer during discharge and charge operation, respectively.

4 Discussion on Different Variants of PSO

The planning problem of HRES-IMG is a constrained, non-linear, discrete combinatorial optimization problem. Various optimization techniques such as GA, PSO, Tabu Search, Ant colony optimization have been employed by researchers for efficient system planning. However, these techniques are centralized in nature. Thus, they suffer from a very significant drawback that even a small update requires change in whole structure. This leads to high computational time.

This paper presents the application of an efficient optimization technique, MABFPSO, developed and duly validated in previous work by author [39]. The development of MABFPSO and its validation through benchmark functions has been explained in detail by author in [39]. In this paper, MABFPSO has been employed for solving the optimal planning problem of HRES-IMG. The obtained results are compared with classic PSO and BF-PSO. A brief discussion on implementation of classic PSO, BF-PSO and MA-BFPSO is presented here.

4.1 Classic PSO

PSO involves a swarm of particles comprising of initial population of random solutions. The velocity and position of particles for k-th iteration are modified based on personal best (pbest) and global best (gbest) using the following equation [4]:

$$\begin{aligned} Velocity_{id}(k+1) = {} & w_k Velocity_{id}(k) \\ & + C_1 r_1 [Pbest_{id}(k) - Position_{id}(k)] \\ & + C_2 r_2 [gbest_d(k) - Position_{id}(k)] \end{aligned} \quad (14)$$

$$Position_{id}(k+1) = Position_{id}(k) + Velocity_{id}(k+1) \quad (15)$$

where, $Velocity_{id}$, $Position_{id}$, $Pbest_{id}$, and $gbest_d$ represent velocity, position, personal best and global best respectively of d-th dimension of i-th particle, w_k is inertia weight for k-th iteration, C_1 and C_2 are acceleration coefficients, and r_1 and r_2 are random variable (0 to 1).

4.2 Butterfly PSO(BF-PSO)

The BF-PSO [40] is an upgraded form of classic PSO. It imitates the intelligence and information sharing pattern which the butterflies display while searching for nectar search. BF-PSO incorporates three additional parameters *viz.* sensitivity, probability of food, time-varying probability coefficient (μ).

The sensitivity and probability are evaluated as follows:

$$Sensitivity_k = e^{-(N_{\max} - N_k)/N_{\max}} \quad (16)$$

where, N_{max} is maximum number of iterations and N_k is k-th iteration count.

$$Probability_k = F_{gbest,k} / \sum F_{pbest,k} \quad (17)$$

where, $F_{pbest,k}$ and $F_{gbest,k}$ are values of personal and global best solutions respectively in k-th iteration, and $Probability_k$ is the probability of k-th iteration.

Incorporating $Sensitivity_k$ and $Probability_k$, Eqs. (14) and (15) are reframed as shown below:

$$\begin{aligned} Velocity_{id}(k+1) = {} & w_k Velocity_{id}(k) \\ & + Sensitivity_k (1 - Probability_k) C_1 r_1 [Pbest_{id}(k) - Position_{id}(k)] \\ & + Probability_{kg} C_2 r_2 [gbest_d(k) - Position_{id}(k)] \end{aligned} \quad (18)$$

$$Position_{id}(k+1) = Position_{id}(k) + \mu_k Velocity_{id}(k+1) \quad (19)$$

where, $Probability_{kg}$ is the probability of global best. μ_k is time varying probability coefficient which is estimated as:

$$\mu_k = random \times Probability_k \quad (20)$$

where, *random* is the random number [0, 1].

4.3 Multi-Agent Based Butterfly PSO (MA-BFPSO)

Though BF-PSO ascertains improved performance in comparison with classic PSO, it is centralized in nature. This is a major shortcoming associated with other conventional optimization techniques as well. Multi-agent system (MAS) provides a way of overcoming this problem wherein each agent has different understanding of best solution. Thus, MAS and BF-PSO have been integrated [39] to form MA-BFPSO method for solving complex optimization problem. The procedure for implementing MA-BFPSO is as follows:

i. A lattice-like structure is created in which each agent is fixed on a lattice-point as shown in Fig. 3. Each agent is designated by a circle. The data in circle is indicative of position of agent in the environment. The size of lattice L is $L_{sz} \times L_{sz}$, where L_{sz} is an integer and suffix '*sz*' represents the size. The size of lattice represents total number of particles in BF-PSO.

ii. Using Competition and Cooperation Operator, each agent contests and collaborates with their neighbors in lattice. If the fitness of particle $\alpha_{i,j}$ is better in comparison with its neighbors, it continues to occupy the same position (i, j) in the lattice. Else, if β be the particle with best fitness in the neighborhood, then (i, j) is occupied by a new agent γ which is calculated as:

$$\text{New agent } \gamma \text{ at position } (i, j) = \beta + \text{rand}(0,1).(\beta - \alpha_{i,j}) \quad (21)$$

iii. As each agent only senses its local environment, it contests and collaborates only with its neighbors. The ability of agent to communicate with its neighbors enables the slow diffusion of information from the local agent lattice to global agent lattice.

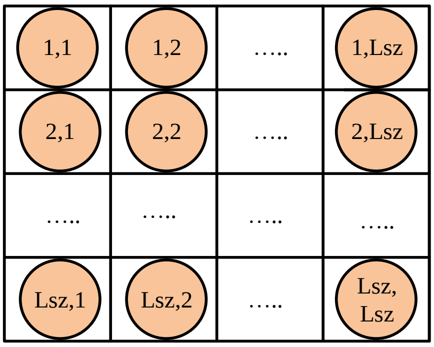


Fig. 3 Lattice structure for agent [39].

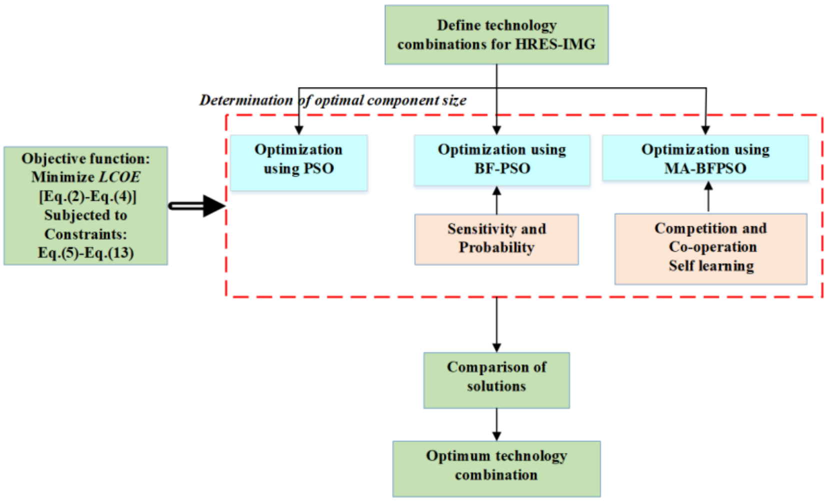


Fig. 4 Schematic representation of methodology.

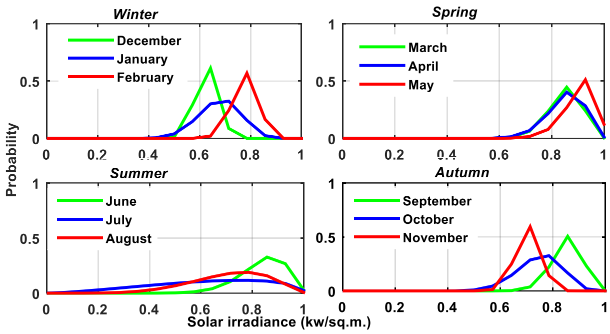


Fig. 5 Beta PDF for time interval 1:00–2:00 p.m.

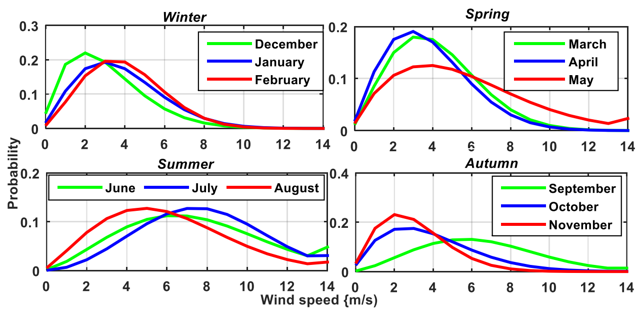


Fig. 6 Weibull PDF for time interval 1:00–2:00 p.m.

The computational efficiency can be increased if diffusion of information can be accelerated. This can be achieved by making use of BF-PSO Operator. Thus, each agent upgrades its position in the search space using (18) and (19) based on its personal experience as well as the experience of best agent in the environment.

iv. In order to enable the agent to learn through its own experience, a Self-Learning Operator is used. A small lattice sL of size $sL_{sz} \times sL_{sz}$ is generated, such that $sL_{sz} < L_{sz}$. Steps (ii) and (iii) are iteratively done on sL. Finally, $\alpha_{i,j}$ is replaced by the agent with best fitness.

Based on Sections 2, 3, and 4, a complete schematic depicting the methodology is depicted in Fig. 4.

5 Case Study and Discussions

The reliability constrained formulation is implemented for an IMG assumed to be situated in Jaisalmer, Rajasthan, India. Jaisalmer is an excellent location for solar and wind based generation projects. The peak system load has been considered as 300 kW. The sequential load profile has been obtained from [41]. The solar irradiance and ambient temperature for the site have been derived from [42] and wind speed data has been derived from [43]. As an illustration, the probability distribution of solar irradiance obtained through Beta pdf has been presented in Fig. 5. Wind speed distribution obtained from Weibull pdf has been presented in Fig. 6. The pdfs have been presented for time segment 1:00–2:00 pm for four different seasons. Such pdfs are obtained for all other time segments. The technical and economic parameters considered in the analysis have been derived from [4].

For determining the optimum technology combination, the following three combinations have been analyzed:

Combination-I: SPVG-BSS
Combination -II: WG-BSS
Combination -III: SPVG-WG-BSS

The optimal sizing problem for the above three combinations is solved using PSO, BF-PSO, and MA-BFPSO. The tuned operational parameters of PSO, BFPSO, and MABFPSO are presented in Table 2. $L_{sz} \times L_{sz}$ is equivalent to the population size in traditional PSO. The determination of component size is subjected to reliability constraint LIR_{max} = 3%.

Figs. 7, 8, and 9 present a comparison of convergence characteristics of the three techniques for Combination-I, Combination-II, and Combination-III, respectively. It can be observed for all three cases that MA-BFPSO fetches least LCOE in comparison with the other two techniques. PSO and BF-PSO are trapped in local

Table 2 Tuned parameters.

Parameter	PSO	BF-PSO	MA-BFPSO
Swarm size (Lattice size $L_{sz}\times L_{sz}$ in case of MA-BFPSO)	20	20	20
C_1	2	2	2
C_2	2	2	2
Inertia weight (w)	0.4-0.9	0.4-0.9	0.4-0.9
Probability factor	-	0.0-1.0	0.0-1.0
Sensitivity factor	-	0.0-1.0	0.0-1.0
Size of small lattice $sL_{sz}\times sL_{sz}$	-	-	5

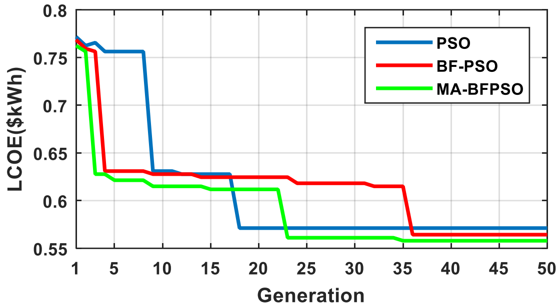


Fig. 7 Convergence characteristics for Combination-I.

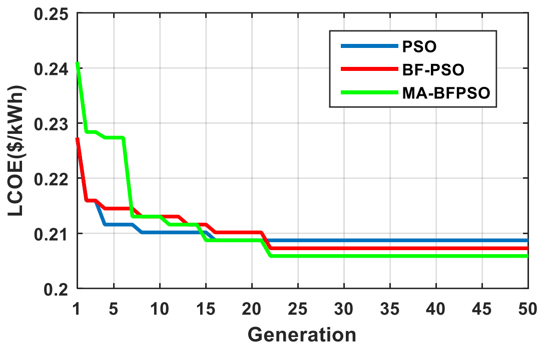


Fig. 8 Convergence characteristics for Combination-II.

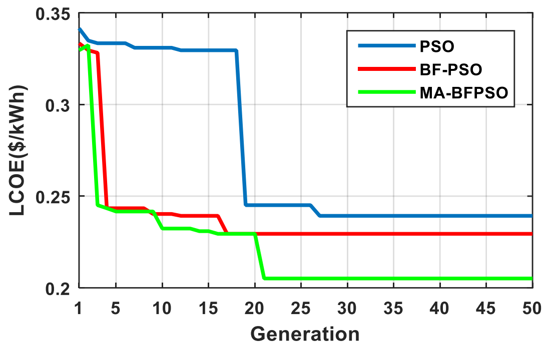


Fig. 9 Convergence characteristics for Combination-III.

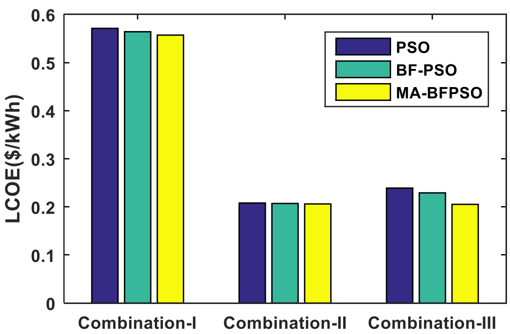


Fig. 10 Comparison of LCOE for Combination-I, II, and III.

Table 3 Optimal sizing results.

Technology combination	Solar [kW]	Wind [kW]	BSS [kWh]	*LIR* [%]	*LCOE* [$/kWh]
Combination–I: SPVG-BSS					
PSO	787.5	-	739.2	2.957	0.571
BF-PSO	787.5	-	818.4	0.822	0.564
MA-BFPSO	787.5	-	765.6	1.30241	0.557
Combination–II: WTG-BSS					
PSO	-	800	92	1.1619	0.208
BF-PSO	-	800	897.6	1.499	0.207
MA-BFPSO	-	800	871.2	2.68	0.206
Combination–III: SPVG-WG-BSS					
PSO	300	300	765.6	0.654	0.239
BF-PSO	300	300	739.2	0.974	0.229
MA-BFPSO	195	360	792	0.080	0.2051

optima whereas MA-BFPSO offers a higher quality solution.

A comparison of LCOE for all three combinations is presented in Fig. 10. Table 3 presents the optimal sizing results for all three combinations. It is evident from Fig. 10 and Table 3 that least LCOE is attained by Combination- III i.e. SPVG-WG-BSS. This ascertains the fact that a combination of different generation technologies can provide an effective and economical alternative.

It can also be observed from Table 3 that not only does the Combination-III gives minimum LCOE, but also offers the best solution in terms of system reliability. The LIR attainable with Combination-III is 0.080 which is only 2.98% and 6.142% respectively in comparison with the best solution offered by Combination-I and Combination- II. The analysis of component sizing obtained with MA-BFPSO w.r.t. PSO and BF-PSO is presented in Table 4. It can be observed from Table 4, for all the combinations, maximum reduction in LCOE is obtained through MA-BFPSO. Combination-III offers a substantial reduction of 53.8% in SPVG size. Though there is an increase in size of WG by 16.67% and BSS by 3.33%, the LCOE sees a major drop by 16.5% in comparison with PSO.

Fig. 11 presents a comparison of LIR and EENS for solutions obtained through three techniques. It can be observed that LIR and EENS with MA-BFPSO is well within the defined reliability standard LIR_{max}.

The variability associated with SPVG and WG restricts their standalone application in the absence of BSS. BSS contributes significantly in ascertaining the reliability standard of IMG. In order to emphasize this fact, Fig. 12 presents the contribution of BSS in supplying load for all three technology combinations. It can be seen from Fig. 12 that BSS supplies 45%, 29%, and 22% of load share for Combination-I, II, and III respectively. It can also be seen that a combination involving SPVG and WG both not only fetches the lowest LCOE but also reduces the dependency on BSS. Nevertheless, the integration of BSS is essential if an IMG is to be planned based on only RES.

The planning of HRES-IMG is utterly challenging due to heterogeneous mixture of sources and their variable nature. Besides the intermittency of RES, the variation in load can further complicate the planning process. The load demand may vary due to seasonal conditions, social scenarios or any other unforeseen factor. If the IMG is planned with some redundancy to cater to an increase in load demand, this may lead to unutilized power. As the excess power cannot be fed back to grid in case of IMG, this will lead to wastage and consequent

Table 4 Analysis of component sizing obtained with MA-BFPSO.

Parameter	Compared to PSO	Compared to BF-PSO
Combination–I: SPVG-BSS		
Change in generator size [%]	0	0
Change in BSS size [%]	3.44	-6.89
Change in LCOE [%]	-2.53	-1.26
Combination–II: WTG-BSS		
Change in generator size [%]	0	0
Change in BSS size [%]	-6.06	-3.03
Change in LCOE [%]	-0.97	-0.485
Combination–III: SPVG-WG-BSS		
Change in generator size [%]	-53.8 (SPVG), 16.67 (WG)	-53.8 (SPVG), 16.67 (WG)
Change in BSS size [%]	3.33	6.67
Change in LCOE [%]	-16.5	-11.65

Positive value indicates increment, Negative value indicates decrement.

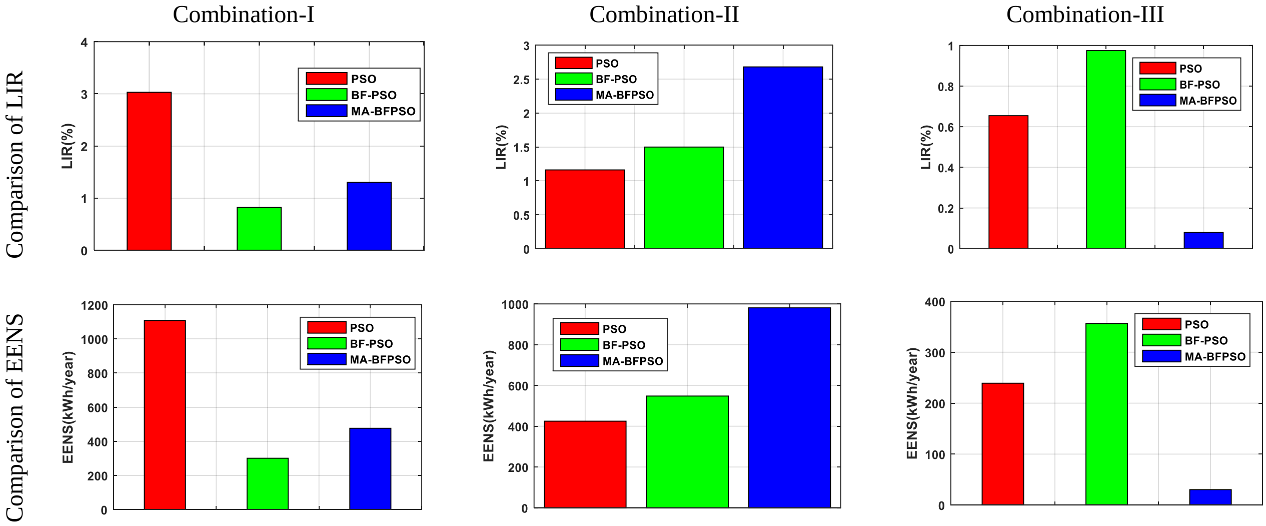


Fig. 11 Comparison of LIR and EENS for Combination-I, II, and III.

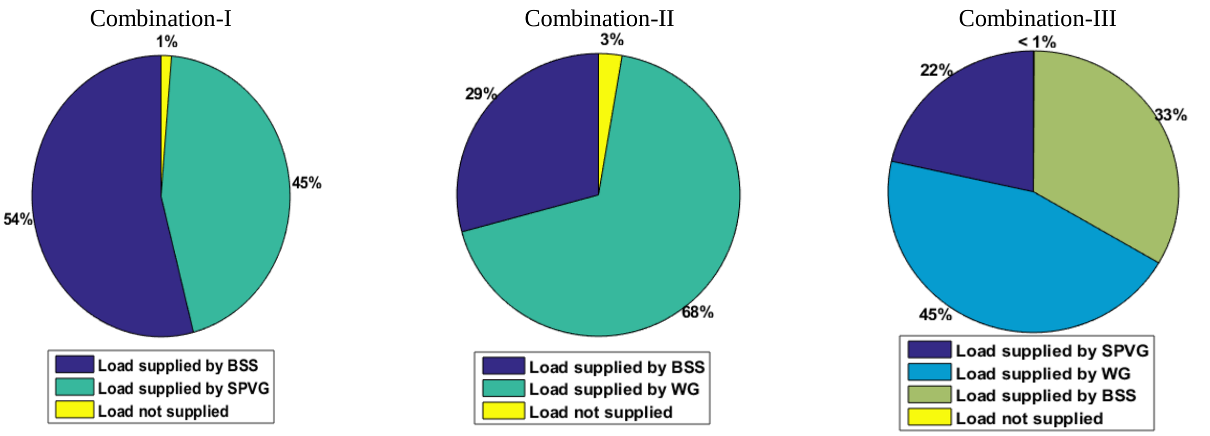


Fig. 12 Load share from different technologies for Combination-I, II, and III.

uneconomical operation. On the other hand, if the resources are constrained to deliver only the present load, the reliability of IMG may suffer if there is an increase in load demand. Thus, an IMG has to be planned in such a way so as to absorb a slight increase in load effectively and doesn't lead to an unreasonably high dumping of power under light load conditions.

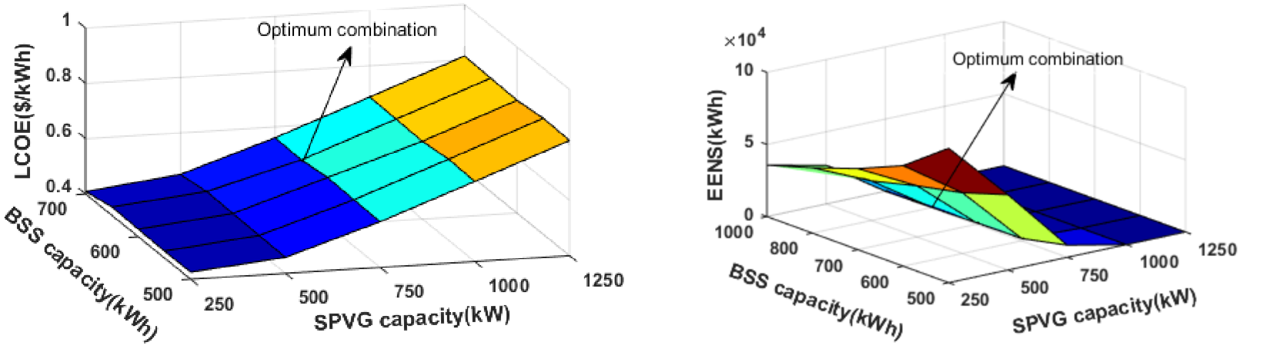
Above factors necessitate sensitivity analyses so as to impart greater clarity to system planning. In this paper, following sensitivity analyses have been conducted for all three combinations:

i. Impact of variation of component sizing on economic parameter LCOE and reliability parameter EENS.
ii. Impact of variability in load on unutilized power and reliability parameter.

Figs. 13(a) and (b) demonstrate the impact of variation of SPVG and BSS on LCOE and EENS. Figs. 14(a) and (b) demonstrate the impact of variation of WG and BSS on LCOE and EENS. Figs. 15(a) and (b) demonstrate the impact of variation of WG and BSS on LCOE and EENS with SPVG capacity fixed at optimal value i.e. 195 kW.

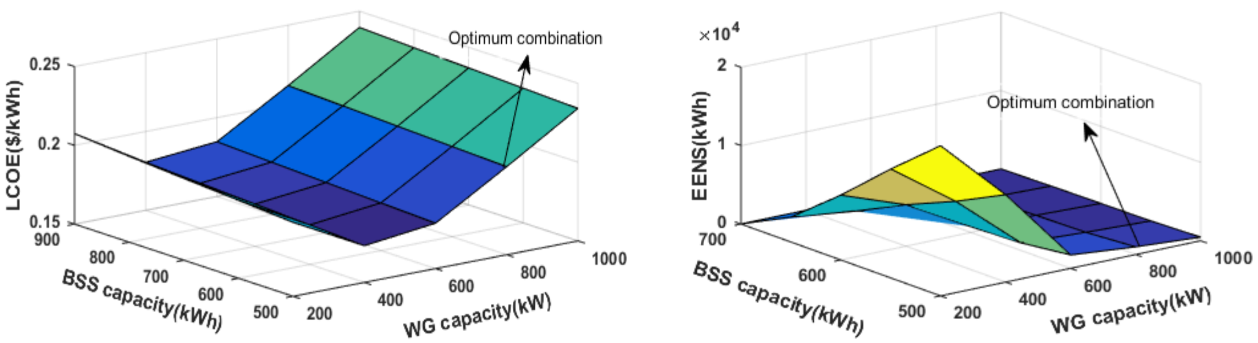
It is evident from these figures that there is a non-linear relationship between the component sizing and their consequent impact on EENS and LCOE. An increase in component size does not guarantee a proportionate decrease in EENS. This is accredited to the variability of RES.

Taking the analysis further, the impact of variation of



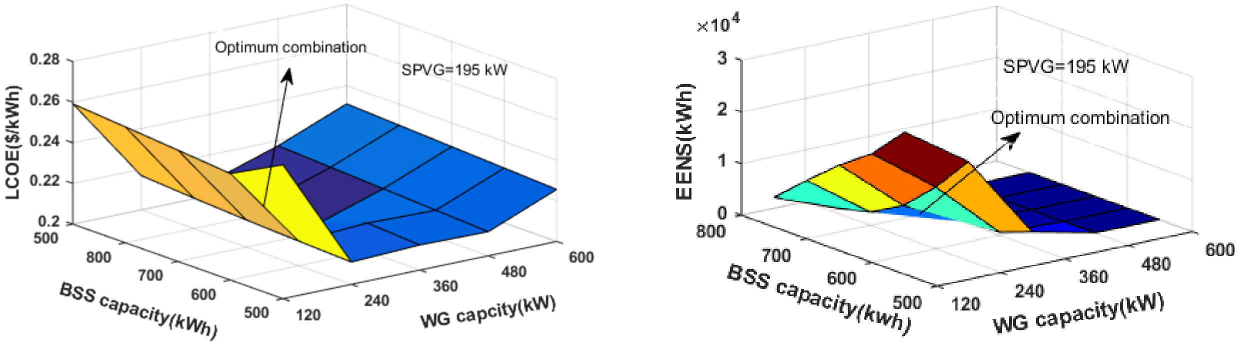
(a) (b)

Fig. 13 Impact of variation of SPVG and BSS capacity.



(a) (b)

Fig. 14 Impact of variation of WG and BSS capacity.



(a) (b)

Fig. 15 Impact of variation of WG and BSS capacity with SPVG capacity=195 kW.

Table 5 Analysis of load uncertainty for LIR.

	LIR [%]				
Load variation / Combination	5%	2.5%	Present load	-2.5%	-5%
SPVG-BSS	16.48	2.77	1.302	0.014	0.0062
WG-BSS	6.4	2.75	2.68	1.12	0.77
SPVG-WG-BSS	1.5	0.932	0.08	0.017	0.0045

Table 6 Analysis of load uncertainty for unutilized energy.

	Unutilized energy [MWh]				
Load / Combination	5%	2.5%	Present load	-2.5%	-5%
SPVG-BSS	49.86	53.36	56.89	60.58	64.3
WG-BSS	326.19	338.1	350.73	396.38	553.89
SPVG-WG-BSS	3.38	4.25	6.28	7.84	10.66

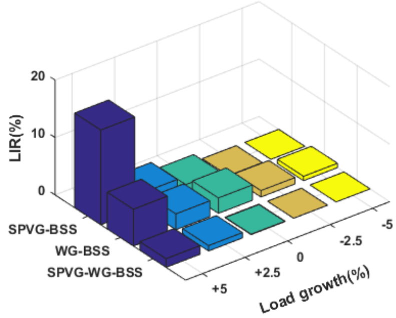


Fig. 16 Impact of load uncertainty on LIR.

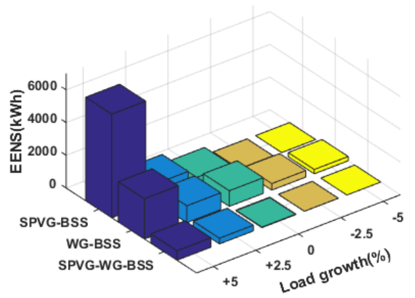


Fig. 17 Impact of load uncertainty on EENS.

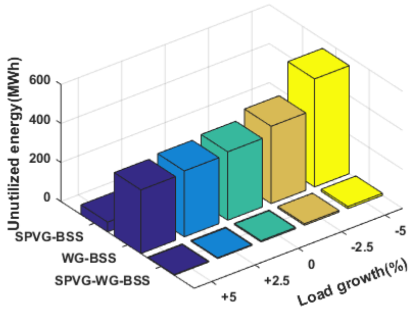


Fig. 18 Impact of load uncertainty on unutilized energy.

load is analyzed. The load is varied by ±5% in the steps of 2.5 %. The increase in load above the expected value will lead to a degradation in system reliability. The decrease in load below the expected value will lead to underutilization of generated power. Table 5 presents the performance analysis of HRES-IMG w.r.t. LIR under varying load condition. The analysis has been carried out for all three combinations. It can be observed from Table 5 that Combination-III: SPVG-WG-BSS presents predominantly superior performance in comparison with Combination-I and II. Combination-I: SPVG-BSS performs worst in terms of reliability when the load growth is considered. The LIR reaches a very high value of 16% in case of 5% load growth. This is due to the fact that solar power is available only during sunshine hours.

Table 6 presents the performance analysis of HRES-IMG w.r.t. unutilized power under varying load condition. Combination-II performs worst in terms of unutilized power in the event of decrease in load demand. Combination-III is undoubtedly a cut above other combinations in terms of reliability and optimum utilization of power.

In order to give a better perception, a pictorial analysis of results for all the three combinations has been presented in Figs. 16, 17, and 18 for LIR, EENS and unutilized energy respectively.

6 Conclusions and Future Scope

The planning of IMG based on RES is an intricate task due to variability associated with these resources. For sustainable planning, it is essential to balance cost structure as well as reliability of IMG. It is important to find the appropriate mix of generation technologies which can provide an economical solution while ascertaining the reliability standards. This calls for assessment of large number of technology combinations. Hence, application of a suitable optimization technique which can furnish high-quality solutions is indispensable.

In this paper, an effective alternative to conventional PSO has been proffered. MA-BFPSO embeds conventional PSO in a multi-agent structure. The algorithm has been applied to determine the optimal technology combinations and component sizing for an HRES-IMG. Adequate consideration has been given to the uncertainties affiliated with RES. The hardware availability of generating units and meteorological conditions have been adequately accounted for by using MSM.

Based on analysis conducted in this paper, the following conclusions can be drawn:

i. MA-BFPSO offered the best results in all three combinations. The reduction in *LCOE* obtained through MA-BFPSO is 1.26%, 0.485%, and 11.65% better as compared to BF-PSO for Combination I, II, and III respectively. When compared with PSO, the improvement is more significant. This is indicative of the fact that MA-BFPSO offers better quality solutions in comparison with PSO and BF-PSO.
ii. Though MA-BFPSO fetched lowest LCOE as compared to PSO and BF-PSO, it is able to sustain system reliability within defined standards for all the three combinations.
iii. Combination-III: SPVG-WG-BSS ensures the most reliable IMG with *LIR*=0.08%. Not only does it offer increased reliability, it does so at the least LCOE of 0.2051 $/kWh. This suggests that a combination of complementary technologies such as solar and wind in conjunction with storage ensures optimum planning of IMG.
iv. The analysis of uncertainty in load demand by ±5% suggests that Combination-III is able to sustain load

variations in much better way as compared to Combination-I and II. Combination-I: SPVG-BSS based IMG presents worst performance in terms of reliability for the increase in load. The *LIR* reaches a very high value of 16.48% which is well above LIR_{max}=3%.

v. In the event of decrease in load, *Combination-III* emerges the winner with least unutilized energy of 7.84 and 10.66 MWH respectively for 2.5% and 5% reduction. This indicates the economic viability of Combination-III.

It can be concluded that instead of a single generation technology, a combination of complementary technologies can offer a superior alternative.

For the planning of micro-grid, the multi-agent based optimization techniques can offer a superior alternative in comparison with classic optimization techniques. In this paper, an attempt has been made to achieve two requisites of system planning: a systematic planning formulation and an efficient optimization technique. Nevertheless, the research can be further extended in the following areas:

i. In addition to component sizing, placement of generators on feeder can also be determined.
ii. Study can be extended with incorporation of more storage technology options such as hydrogen storage.

The planning formulation can be further augmented with multiple objectives.

Intellectual Property

The authors confirm that they have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property.

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P. Paliwal: Conceptualization, Methodology, Software, Formal analysis, Data curation, Investigation, Validation, Writing.

Declaration of Competing Interest

The authors hereby confirm that the submitted manuscript is an original work and has not been published so far, is not under consideration for publication by any other journal and will not be submitted to any other journal until the decision will be made by this journal. All authors have approved the manuscript and agree with its submission to “Iranian Journal of Electrical and Electronic Engineering”.

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