Sādhanā (2021)46:101
https://doi.org/10.1007/s12046-021-01626-z

A hybrid genetic algorithm (GA)–particle swarm optimization (PSO) algorithm for demand side management in smart grid considering wind power for cost optimization

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MS received 4 October 2020; revised 2 February 2021; accepted 22 March 2021

Abstract. Demand side management (DSM) program is a key feature of smart grid and extensively used for its reliable functionalities and benefits of customers on electricity bill reduction. A DSM approach based on load shifting for a typical day is considered in this paper for a hierarchical smart grid structure. Renewable energy source such as wind energy is considered here along with conventional power generators. All the participants of electricity market: utility operator, customers and aggregator, wish to get monitory benefits in electricity market. It is quite challenging to ensure benefits to each participant simultaneously. To address the challenge, a multi-objective problem is framed. Further, using weighted sum technique, the multi-objective problem is transformed to a single objective. In this paper, a hybrid genetic algorithm (GA)–particle swarm optimization (PSO) (hybrid GA–PSO) algorithm is proposed to solve the problem developed. The objective of the proposed algorithm is to minimize cost of electricity bill and optimally allocate generation and load demand of a day-ahead market. The proposed hybrid algorithm is used to combine the strength of both GA and PSO algorithms and to help improve its performance by increasing the convergence speed and avoid trapping into local minima. In order to balance between exploration and exploitation a decision parameter: fusion factor, is introduced in this algorithm. The simulation results prove that the current approach is able to give financial advantage to all the participants of the electricity market simultaneously while optimally allocating load and generation profile for a day. It also helps to reduce peak to average ratio (PAR) of load demand and improves the efficiency and economy of smart grid. The results have also been compared with a few existing optimization techniques to show effectiveness of the current optimization algorithm.

Keywords. Demand side management (DSM); peak to average ratio (PAR); Genetic algorithm (GA); Particle Swarm Optimization (PSO); smart grid; aggregator.

1. Introduction

There are numerous factors in the world: climate change, increase in carbon emission of industries, decrease in fossil fuels, growing energy demand and blackouts, that cannot be addressed within the scope of existing grid of electricity. Existing grid of electricity is unidirectional in nature whereas the next generation grid, which is popularly known as smart grid, provides bi-directional flow of electrical power and information between the electricity source networks and customers. The new generation grid is called intelligent because it is designed to overcome the shortcomings of the existing grid of electricity. It provides feasible, reliable and environment-friendly electrical power to consumers [1]. Smart grid helps to reduce peak demand of load, which in turn helps to cut down the cost of electricity consumption. On the other hand, it helps in integration of renewable energy sources to the system in an easier way and improves transmission efficiency. Smart grid also helps in quick restoration of electricity after disturbances [2, 3]. Demand side management (DSM) is an aspect of smart grid that provides smart control of load consumption by customers, which in turn helps to shift energy use from peak periods to non-peak periods. Thus, DSM helps in reducing carbon emission, improves efficiency of electricity grid and reduces cost of electricity bill

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Published online: 06 May 2021

for the consumers or customers. The following services are provided by DSM program: peak clipping; load shifting; strategic conservation; valley filling; flexible load shape and strategic load growth as discussed in [4–6]. Load shifting is the mostly used DSM technique.

Among the broad classifications of demand response mentioned in [7], three main demand response programs are ancillary service and economic and emergency demand response schemes. Transfers of electricity to load centres considering the reliability issues that are imposed by industry regulators on utilities are being assisted by ancillary service demand response program [8, 9]. Economic demand response program [10] is employed by utilities to decrease cost of electricity generation during peak hours of load demand of a day. Emergency demand response program [11–13] provides financial incentives to include customers in the program so that they can intimate the customer at short notice to shed the non-essential load to prevent blackouts and reduce the overload conditions. Implementation of DSM needs the details of information exchange between the utility operator and the customers. Establishing smooth communication among a large number of generation units and customers is difficult, as a result of which there is a requirement of an entity that can fill the gap and make efficient communication among them. Aggregators [14] do it efficiently and also negotiate with the utility operator for the customers. Though DSM techniques have been discussed widely in [14], the profit of an aggregator is not addressed. In [8–14] the major focus was in the domain of technical benefits and improvement of DSM, but it is also required to address the monetary benefits related to DSM.

To escalate DSM program in smart grid, different heuristic algorithms are used by researchers in their research works. Ant colony optimization [15] and mutation-based ant colony optimization [16] algorithms are used in DSM to optimize cost of electricity by optimizing load profile. In [17], a heuristic-based evolutionary algorithm has been discussed to solve a DSM problem based on load shifting technique in smart grid in a day-ahead market. Genetic algorithm (GA) [18] is a global search algorithm that depends on survival of the fittest. The technique involves genetic operators: selection, mutation and crossover, to get new and better solutions as compared with the previous generations continuously till the termination criterion is achieved. GA-based DSM is presented for optimum allocation of power usages in smart grid in [19] and to reduce peak to average (PAR) ratio and minimize cost of energy in [20]. Particle Swarm Optimization (PSO) algorithm [21] belongs to the group of Swarm-based algorithms and it is inspired by the social behavior of bird flocking. PSO algorithm is presented to optimize load pattern in order to optimize cost using DSM program in [22, 23] and to get the near-optimal sharing schedule within community to reduce the total electricity cost in [24]. The works described in [15–24] have contributed remarkably in the area of DSM program but the main focus was on optimization of single-objective problem at a time.

The tri-level structure of the smart grid model is shown in figure 1. Basically, utility operators, aggregators and customers are the three entities of electricity market. Utility system tries to minimize operational cost of electricity generation. Aggregators try to maximize their profit by giving less incentive to the customers, whereas customers try the best to adjust the usages of load in order to earn more incentive from aggregators [25]. As each entity tries to maximize individual profit, there is a need for a multi-objective optimization problem that can fulfill demand of all the entities of electricity market simultaneously. Pareto optimality based on Artificial Immune algorithm is used to optimize multi-objective problems in [25], where it optimizes the profit of all the participants of electricity market. While dealing with multi-objective problems with three or more objective functions, pareto optimality suffers frequently as discussed in [26, 27].

Among various meta-heuristic optimization algorithms, PSO [21] is one of the most popular algorithms that effectively solves various optimization problems. PSO is easy to implement and it shows fast convergence. However, PSO has some limitations such as trapping into local optimum, poor global search ability and premature convergence; as a result it cannot effectively solve complex optimization problems whereas mutation operation in the GA [28] ensures that trapping at local optima is avoided. However, it makes the convergence slower. Both GA and PSO algorithm have a couple of advantages and disadvantages.

2. Novelty of the paper

In this paper, a multi-objective demand side management (MODSM) problem based on weighted sum is formulated to maintain fairness among all the participants: utility system, customers and demand response aggregators of electricity market. The multi-objective problem is converted into one objective by giving priorities to different objectives of the participants of electricity market using scalar weights, which helps to reduce the time of

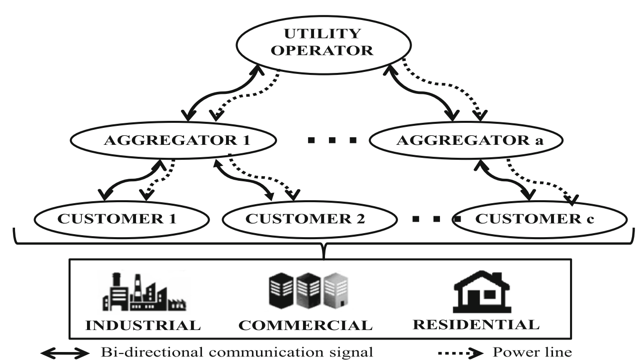

Figure 1. Operation framework of the smart grid structure.

computation. In the problem formulated one also needs to ensure reducing PAR load demand and optimizing the cost of electricity bill by allocating load demand and generation profile for a typical day optimally. In order to overcome the drawbacks of both GA and PSO algorithms mentioned in the previous section and to balance between exploration and exploitation, a hybrid GA–PSO algorithm is proposed in this paper to solve the complex MODSM problem. The hybrid GA–PSO algorithm combines the strength of both algorithms and helps to enhance the convergence speed and avoid trapping into local minima. It is the fusion of the concept of velocity and position update rules of PSO algorithm and the concept of selection, crossover and mutation of GA algorithm. To balance between exploration and exploitation a decision parameter: fusion factor, is introduced. It is the deciding factor of the proportion at which new population will be generated from both the techniques, i.e. using PSO and GA.

3. System modelling

For a typical day, a DSM approach based on load shifting for a hierarchical tri-level smart grid structure is considered as shown in figure 1. For the current system, an utility operator, a set of customers and an aggregator to deal with both the entities and to provide DSM service in the electricity market are considered. The utility operator supplies electrical power to the customers. The aggregator holds the position of intermediate level between utility operator and customers and provides bi-directional flow of electricity and information between them [14]. Throughout the day the load demand of a customer varies with respect to time and as per consumption, which is tracked through a smart meter installed at the customer end [29]. The power generated from renewable energy sources varies based on the environmental conditions. It is always required to regulate electricity generation in order to adjust supplied power and load demand.

3.1 *Objective of all participants of the tri-level smart grid structure*

3.1a *Objective of utility operator:* Utility operator provides incentives to aggregators for providing DSM service to a set of customers. The utility operator tries to reduce both the cost of electricity generation and the part of its profit given to the aggregator. Thus, objective of utility operator is formulated as [14, 25] follows:

minimize

$$F_{UTILITY}(g_c) = \sum_{t \in T} [f_1(g_{c,t}) + \alpha f_2(g_{c,t})], \qquad (1)$$

where $f_1(g_{c,t})$ is the cost of generation with DSM program; $\alpha f_2(g_{c,t})$ is the bonus for aggregator from utility operator and it is expressed as [25]

$$f_{bonus} = \alpha f_2(g_{c,t}) = \alpha \sum_{t \in T} [f_0(g_{c,t}) - f_1(g_{c,t})], \qquad (2)$$

where $f_0(g_{c,t})$ signifies the conventional generation cost without considering DSM program and α is the bonus coefficient; α can be varied from zero to one, i.e. $0 \le \alpha < 1$. In (2), α signifies the percentage of profit that will be given to the aggregator by the utility operator. If α increases, the bonus drawn by aggregator will also increase.

3.1b *Objective of aggregator:* The aggregator communicates with the set of customers and encourages them to participate in DSM program. In this process, the aggregator monitors the daily load consumed by the customers and tracks electricity generation profile. The customers get incentive on their electricity bill for the inconvenience faced by them at time of load shifting [14]. The aggregator tries to maximize its profit by drawing more bonus from utility operator and giving less incentive to the customers by convincing them to participate in DSM process. Thus, objective of the aggregator is expressed as [14, 25] follows:

maximize

$$F_{AGGRE}(g_c, l_a) = \sum_{t \in T} \{\alpha f_2(g_{c,t}) - [-\beta_1 (l_{a,t} - g_t)^2 + \beta_2]\}, \qquad (3)$$

where the second part is the amount given to the customers as compensation, which is expressed as [25]

$$f_{compensation} = \sum_{t \in T} [-\beta_1 (l_{a,t} - g_t)^2 + \beta_2], \qquad (4)$$

where β_1 and β_2 are coefficients of compensation ($\beta_1 > 0; \beta_2 > 0$); $l_{a,t}$ is the actual load demand and g_t is the scheduled generation, which includes scheduled power generated from conventional generators and renewable energy sources. It is calculated as $g_t = G_c + g_{res,t}$ where G_c is the power anticipated from traditional generators and considered as fixed for each time instant; $g_{res,t}$ is the power generated from renewable sources of energy and it is time-varying in nature. The power generated from the renewable energy system will be absorbed first and the remaining power demand will be fulfilled by the conventional generators. In this paper, wind power is used as a source of renewable energy. In (4), β decides the amount of compensation that can be given to the customers. When the actual load demand follows the scheduled generation completely, i.e. $l_{a,t} = g_t, f_{compensation}$ must be equal to zero.

3.1c *Objective of customers:* Customers get a comprehensive idea of their electricity consumption from the smart meter data [29]. Consumers may move non-essential loads or essential loads to some extent, in order to draw monetary benefits from the aggregator. It is very clear that DSM implies dissatisfaction to customers and the degree of discomfort increases as the difference between the forecasted and actual load rises. The objective of the set of customers is to maximize its profit and it is formulated as [14, 25] follows:

maximize

$$F_{CUSTOMER}(l_a) = \sum_{t \in T} \{[-\beta_1 (l_{a,t} - g_t)^2 + \beta_2] - \gamma (l_{a,t} - l_{f,t})^2\}, \tag{5}$$

where $\gamma(l_{a,t} - l_{f,t})^2$ is the dissatisfaction of customers, which is expressed as [25]

$$f_{dissatisfaction} = \sum_{t \in T} \gamma (l_{a,t} - l_{f,t})^2, \tag{6}$$

where γ signifies the in-elasticity coefficient of load demand and $\gamma > 0$; $l_{a,t}$ signifies the actual load consumption; $l_{f,t}$ is the forecasted electricity demand of customers. In (6), large value of γ corresponds to more discomfort at customer end; $f_{dissatisfaction}$ is equal to zero when actual load consumption is equal to forecasted load demand.

All the cost coefficients, i.e, bonus coefficient (α), coefficients of compensation (β) and in-elasticity coefficient (γ), have significant effect on the profit drawn by individual participants of electricity market. The effect of variation of cost coefficients on the profit drawn by utility operators, aggregators and customers is widely discussed in the results section.

3.2 *Constraints*

Equations (1)–(6) are subject to the following constraints.

3.2a *Power balance constraint:* The sum of conventional power generated ($g_{c,t}$) and power generated using renewable energy source ($g_{res,t}$) must be equal to the total load demand (l_t), neglecting the transmission losses:

$$\sum_{t \in T} g_{c,t} + \sum_{t \in T} g_{res,t} = \sum_{t \in T} l_t.$$

3.2b *Generation capacity constraint:* The power provided by the conventional generators and renewable energy source should be within certain limits:

$$g_{res,t(min)} \le g_{res,t} \le g_{res,t(max)},$$
$$g_{c,t(min)} \le g_{c,t} \le g_{c,t(max)},$$

where $g_{res,t(min)}$ and $g_{c,t(min)}$ are the minimum limits of power obtained from renewable energy source and conventional generators, respectively; $g_{res,t(max)}$ and $g_{c,t(max)}$ are maximum limits of power obtained from renewable energy source and conventional generators, respectively.

3.2c *Load demand capacity constraint:* The aggregated load demand (l_{at}) must be within certain limits:

$$l_{t(min)} \le l_{a,t} \le l_{t(max)},$$

where $l_{t,(min)}$ and $l_{t,(max)}$ are minimum and maximum limit of load demand, respectively.

3.3 *PAR ratio*

When it comes to system performance, PAR ratio (PAR) [25] is an important factor to analyse the system behaviour. PAR is expressed as

$$PAR = \frac{Load_{peak}}{Load_{avg}}, \tag{7}$$

where $Load_{avg}$ is the average load demand and $Load_{peak}$ is the peak load demand. When the peak load is reduced and the portion of decrease in load is shifted to other off-peak periods, it results in decrease in PAR. As a result, generation cost reduces. Reducing PAR and illustrating its effect on reduction of generation cost is one of the objectives of the current work. It is explained in tabular form in the results section.

4. Problem formulation

4.1 *MODSM*

All the participants of electricity market try to get benefit from the use of DSM program [30] in the system. For utility operators, it can reduce the cost of operation of electricity generation. The aggregator can maximize its profit and the customers can get significant reduction in electricity bill. Thus, to provide unbiased preference to all the participants, a multi-objective problem is formulated. For a typical day (24 h), the MODSM problem [25] can be expressed as follows:

minimize

$$F_{UTILITY}(g_c) = \sum_{t \in T} [f_1(g_{c,t}) + \alpha f_2(g_{c,t})], \tag{8}$$

$$-F_{AGGRE}(g_c, l_a) = \sum_{t \in T} [-\alpha f_2(g_{c,t}) - \beta_1 (l_{a,t} - g_t)^2 + \beta_2], \tag{9}$$

$$-F_{CUSTOMER}(l_a) = \sum_{t \in T} [\beta_1 (l_{a,t} - g_t)^2 - \beta_2 + \gamma (l_{a,t} - l_{f,t})^2]. \tag{10}$$

4.1.1 *Constraints* Equations (8)–(10) are subject to the following constraints:

$$\sum_{t \in T} g_{c,t} + \sum_{t \in T} g_{res,t} = \sum_{t \in T} l_t;$$
$$g_{res,t,(min)} \le g_{res,t} \le g_{res,t,(max)};$$
$$g_{c,t(min)} \le g_{c,t} \le g_{c,t(max)};$$
$$l_{t(min)} \le l_{a,t} \le l_{t(max)}.$$

4.2 *Significance of weighted function and formulation of single objective*

Each participant of the electricity market has individual objective as shown in (8)–(10) and these objectives are interrelated. Therefore, all the objectives must be fulfilled simultaneously in order to achieve the collective goal. A weighted function is defined as $\lambda_i f_i(X)$ for ith objective, where λ_i is a scalar quantity and shows the weight allocated to the respective objective function. The current problem of multi-objective is combined to a single objective function [31] using weights λ_i and functions f_i. It helps to reduce computational time. Therefore, the sum of objectives is represented as follows:

minimize

$$F_{total}(g_c, l_a) = \lambda_1 F_{UTILITY}(g_c) + \lambda_2[-F_{AGGRE}(g_c, l_a)] + \lambda_3[-F_{CUSTOMER}(l_a)], \tag{11}$$

where the range of λ_i is $0 < \lambda_i \leq 1$ and $\lambda_1 + \lambda_2 + \lambda_3 = 1$. Magnitude of weights can be selected based on the choice of giving relative importance to the objectives of the multi-objective problem. For the selection of values of weights different approaches are suggested in [27, 32], which are basically techniques to arrange objectives based on their priorities and preferences. To address the problem shown in (11) a hybrid GA–PSO algorithm is proposed for optimization, which is discussed in the next section.

5. Hybrid GA–PSO algorithm

5.1 *Classical PSO and GA*

PSO algorithm [21] is based on the social behavior of birds flying in flocks. The candidates (i.e., particles) of a group communicate among themselves to improve the chance of getting the best position of a bird in the flock [33]. Each particle follows the best fitness value in the search space and records as $B_P(\tau)$, i.e. local best position of the bird, and the best fitness obtained so far of the flock, $B_G(\tau)$, i.e. global best position of the bird [34]. Some drawbacks of PSO algorithm are slow convergence rate, less accuracy of convergence and falling into local minima point. GA developed by John Holland is based on Darwinian evolutionary theory [18]. It is a global search algorithm. The technique involves genetic operators: selection, mutation and crossover, to get new and better solutions until the termination criterion is achieved. Mutation operation in the GA [28] ensures that trapping at local optima is avoided. However, it makes the convergence slower. Both GA and PSO algorithms have a couple of advantages and disadvantages. In this work, a combination of both algorithms is proposed to extract better outcome.

5.2 *GA–PSO-based hybrid algorithm*

A hybrid GA–PSO algorithm is proposed in this paper. The proposed algorithm helps in improving convergence accuracy and increases global convergence rate. Exploitation and exploration are two significant features in any meta-heuristic algorithm. The proposed algorithm provides a good balance between these two features in the solution space. The proposed optimization algorithm is basically a fusion of the concept of velocity and position update rules of PSO algorithm and the concept of selection, crossover and mutation of GA algorithm.

5.2a *Fusion factor:* In this proposed algorithm an additional parameter: fusion factor ζ, is introduced. ζ is the deciding factor of the proportion at which new population will be generated from both the techniques, i.e. using PSO and GA. The fusion factor can be varied from 0 to 1. After various trials on setting the value of ζ for the current problem ζ is set to 0.5, which signifies equal mixing of both the techniques in order to get the best possible result. ζP number of particles have undergone velocity, position update operation of PSO and (P–ζP) number of particles have undergone selection, crossover and mutation operations of GA.

5.2b *Description of entire process:* The entire process can be represented as follows. In the search space, P number of particles are randomly generated. g_c and l_a are two design parameters of the current objective function (11), which represent the particles position in the search space. For each particle, fitness is calculated using (11). If current fitness is greater than $f(B_P(\tau))$, particle corresponding to best fitness is taken as $B_P(\tau)$. Further, if current fitness is greater than $f(B_G(\tau))$ then the overall best value of the particle is considered as $B_G(\tau)$. After this, velocity and position of ζP number of particles are updated [23] using (12) and (13):

$$V(\tau+1) = \xi V(\tau) + c_{a1} x_1 (B_P(\tau) - Y(\tau)) + c_{a2} x_2 (B_G(\tau) - Y(\tau)), \tag{12}$$

$$Y(\tau+1) = Y(\tau) + V(\tau+1), \tag{13}$$

where ξ represents inertia weight factor; c_{a1} and c_{a2} represent the acceleration constants; x_1 and x_2 are chosen randomly between 0 and 1. A larger value of ξ results in less exploitation and more exploration. Similarly, a small value of ξ results in less exploration and more exploitation. Exploration and exploitation are two important factors of any optimization algorithm and excessive attention on one may affect the other. In order to balance between exploration and exploitation and to improve global search speed, the parameter ξ is configured to linearly decrease with iteration count [33]. Thus, ξ is expressed as follows:

$$\xi = \xi_{\max} - \frac{\xi_{\max} - \xi_{\min}}{\tau_{\max}} \tau, \tag{14}$$

where ξ_{max} and ξ_{min} represent the final value and initial value of weight factor, respectively; τ is current iteration; τ_{max} is the maximum iteration. For the current system the parameters $\xi_{\max}$, $\xi_{\min}$ [35] are taken to be 0.9, 0.4, respectively, in (14) and the values of c_{a1}, c_{a2} are both set at 1.5 in (12).

(P–ζ P) number of particles are selected for crossover and mutation operation. In crossover, a pair of chromosomes is randomly selected as parent chromosomes and portions of the two parents from the current generation are combined to create two offsprings in order to provide improved solutions. Here, single-point crossover is used where the location of swapping is decided randomly. Crossover rate (r_c) signifies the percentage of offsprings generated from parents. Here r_c is set at 0.8, as large crossover rate means faster convergence. Mutation is a more random process than crossover. The mutation rate (r_m) is set to a very small value, since larger mutation rate may result in premature convergence. Mutation of a chromosome helps produce and include essential features to the existing chromosome in order to get new population. For each chromosome a random number (u) is generated. If $u \leq r_m$, the chromosome gets mutated. Here, r_m is set at 0.001.

Further, the set of particles obtained by PSO and GA is considered as the new set of population and the process is replayed until termination criterion is reached. Figure 2 shows a flowchart of the proposed hybrid GA–PSO algorithm. The detailed algorithm is illustrated in the next section.

5.2c *Algorithm of the proposed hybrid GA–PSO technique:*

1. *Input:* Initialize the number of iterations and population (P) with random position and velocity vectors, generation (g_c) and load demand (l_a) pattern of a typical day as positions of particles.
2. *BEGIN ALGORITHM*.
3. $/ * StartIteration * /$.
4. For each particle calculate fitness using (11).
5. Particle with best fitness is set as $B_P(\tau)$ (local best). If current fitness is better than $B_P(\tau)$, $B_P(\tau)$ gets updated to current fitness.
6. Current fitness of particle is compared to particle's previous best so far, i.e. $B_G(\tau)$(global best). If current fitness is better than $B_G(\tau)$, $B_G(\tau)$ gets updated to current fitness.
7. Generate new generation of particles with the help of following steps:
   - ζP number of particles are generated while updating velocity of particles using (12) and position of particles using (13), where ζ is fusion factor.
   - The remaining number of particles, i.e. (P–ζ P), is generated using basic GA operators: crossover and mutation.
8. The new set of particles created by PSO and GA operators are considered as new population and used to calculate fitness using step 4.
9. Steps 5, 6 and 7 are repeated until termination condition (i.e., until $\tau = \tau_{(max)}$) is satisfied.
10. *Output:* An optimized set of design parameters as position of the flock is obtained as output.
11. *END ALGORITHM*.

6. Mapping of proposed hybrid GA–PSO technique for cost optimization

In this section, a mapping of hybrid GA–PSO technique for cost optimization is discussed. Here, hybrid GA–PSO works as an optimization tool to find the best solution in the search space. Electricity generation and load profile of a particular day are used as design variables. Searching for optimized profile of generation and load pattern using DSM for a particular day to optimize cost of electricity and to provide incentive to all the participants of the electricity market simultaneously is the objective of the proposed hybrid algorithm.

- Initialize the maximum number of population (P) and maximum number of iterations $\tau_{\max}$ for the smart grid model. Also, define the parameters $\xi_{\max}$, $\xi_{\min}$, c_{a1}, c_{a2} and ζ.
- At the starting of the algorithm a few random values of the particles, i.e. generation and load pattern, are produced randomly in a specified range $(g_{c,t(min)} \leq g_{c,t} \leq g_{c,t(max)},\ l_{t(min)} \leq l_{a,t} \leq l_{t(max)})$ for the DSM problem for 24 hours.
- For each design variable (generation (g_c) and load (l_a)) fitness is calculated using (11), which is the MODSM problem. In each iteration, fitness is monitored and updated towards the optimized performance.
- In each iteration, particle with best fitness of particle is considered as $B_P(\tau)$. Current fitness is compared to $B_P(\tau)$. If current fitness $> B_P(\tau)$, $B_P(\tau)$ is updated to current fitness.
- Particle's overall previous best is known as $B_G(\tau)$. If current fitness $> B_G(\tau)$, $B_G(\tau)$ is updated to current fitness.
- ζP number of particles are generated while updating velocity of particles using (12) and position of particles using (13).
- The remaining number of particles, i.e. (P–ζP), is generated using basic GA operators: crossover and mutation.
- The principal goal of the hybrid GA–PSO technique is to minimize the electricity cost of generation. The hybrid GA–PSO algorithm provides optimized design variables (i.e., optimized generation and load profile)

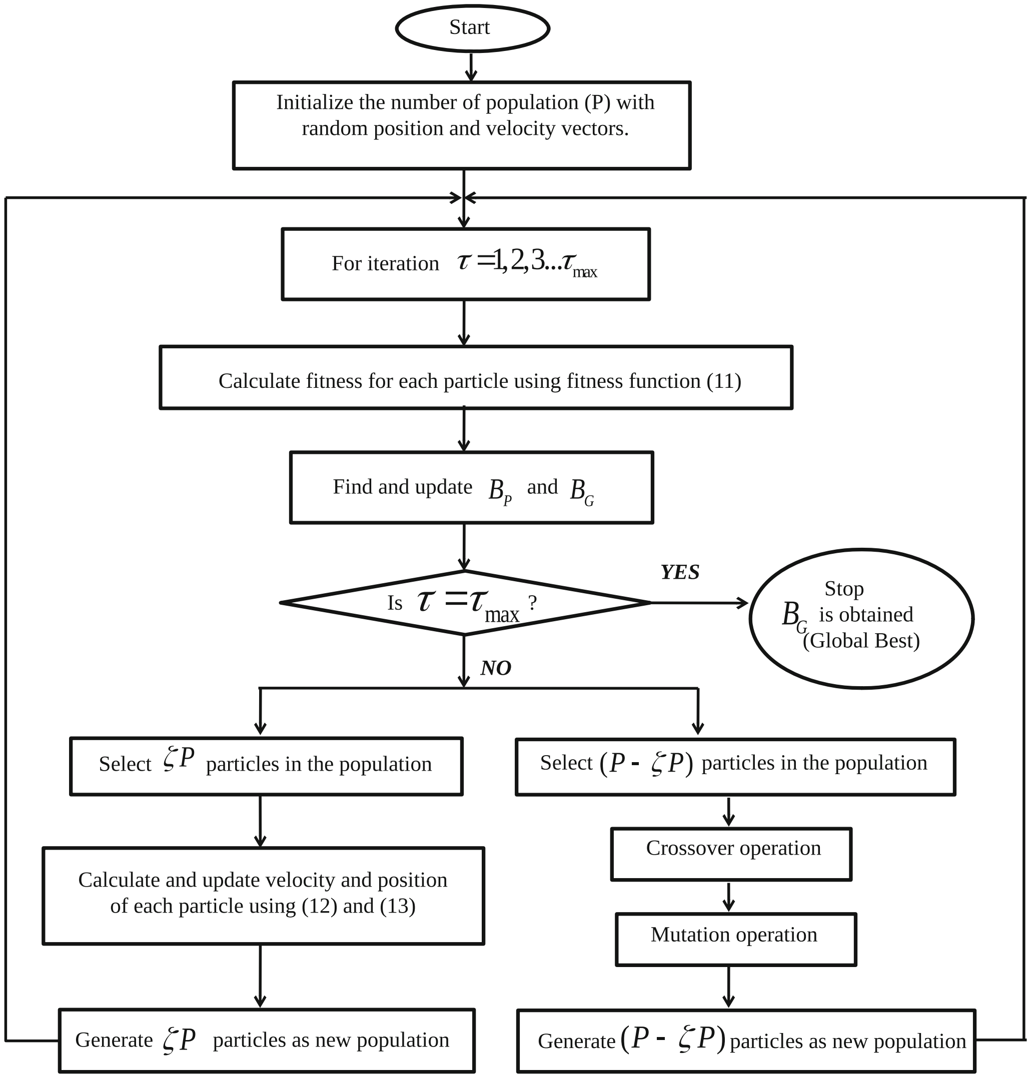

Figure 2. Flowchart of hybrid GA–PSO algorithm.

as global best. Thus, the solution will achieve a global optimal solution.

7. Significance of hybrid GA–PSO algorithm on DSM in smart grid

In this paper, DSM program is formulated as a multi-objective problem based on weighted sum. The population-based meta-heuristic optimization technique hybrid GA–PSO is used as an optimization tool. The hybrid GA–PSO does not suffer from falling into local minima point. It also helps in improving convergence accuracy and to increase global convergence rate. Achieving a suitable trade-off between exploration and exploitation is an essential task, which provides fairness to them. The proposed algorithm can optimize energy generation and load demand for a selected day at the same time. This optimized profile of generation and load pattern can further help to reduce PAR, cost of electricity generation and to lower electricity bill. In the process, it can help to reward all the participants of the electricity market: utility operators, aggregators and customers.

8. Simulation and results

The proposed algorithm is executed in NI LabVIEW©2015 in a system with processor i5-3230M CPU @ 2.60 GHz. The cost function is simulated for 15 times with an iteration count of 100 for each optimization algorithm. The number of population is set at 50.

8.1 *Analysis for cost optimization for DSM*

To validate the proposed optimization algorithm, the cost optimization of a smart grid model is used. For a typical day, for reference load and electricity generation profile, UK Grid Watch data [25] is used in this paper. Here day-ahead load demand and generation data of 24 hours is forecasted and fed to the system for further processing. Average electricity price of 0.18 £/kWh is considered as flat pricing, which signifies that electricity price is constant throughout the day. A model is considered from [36] and for the conventional generators a quadratic cost function is considered, which is expressed as

$$C(g_{ct}) = 2 + 3(g_{ct}) + 1.2(g_{ct})^2. \tag{15}$$

The output power of wind turbines is calculated as [37]

$$P_{wind} = 0.5C_w(\eta, \phi)\rho A_d v_w^3, \tag{16}$$

where air density ρ and the swept area A_d are set at 1.225 kg/m^3 and 1257 m^2, respectively; v_w is wind speed; C_w is performance coefficient and it can be calculated using the blade pitch angle ϕ and the blade tip speed ratio η. The parameters of wind turbine are considered as mentioned in [37].

Due to various factors like pressure and temperature of air, humidity, seasons, etc., the wind speed varies throughout the day. Thus power generated from it also varies throughout the day. The maximum and rated wind speed are set at 30 and 15 m/s, respectively. If wind speed is more than the maximum wind speed, for the safety reasons, the wind turbines will be stopped forcefully, as severe wind speed stresses the blades of the turbine. When wind speed is less than the maximum wind speed but more than the rated wind speed, the power generated form wind turbine will be the rated power and it will remain constant. For a typical day, power generation from the wind turbines ($g_{res,t}$) is forecasted in Figure 3 as discussed in [25]. Initially, the electricity generated from the wind turbines will be absorbed. The power generated from conventional generators will be used to compensate the remaining portion of demand of electrical power. For supply of wind power 2500 number of wind turbines are used with a capacity of 2.75 MW each [25].

For the simulation of the current system the bonus coefficient (α) is chosen as 0.6 in (2), which shows that 60% of the profit of the utility operator will be given as incentive to the DR aggregator. The compensation coefficients are set as follows: β_1 = 2, β_2 = 80 in (4) and inelasticity coefficient γ_c = 3 in (6). It is considered that 20% of load can be varied for customers.

Figure 4 shows the optimized conventional generation pattern for a specific day with PSO and hybrid GA–PSO algorithms. At off-peak hours, peak generation increases from 20.8 to 21.8 GW on using classical PSO and it further increases to 23.33 GW on using the proposed hybrid GA–

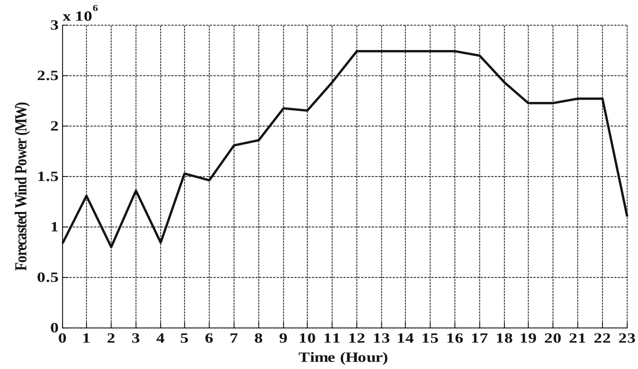

Figure 3. Projected wind power for a typical day.

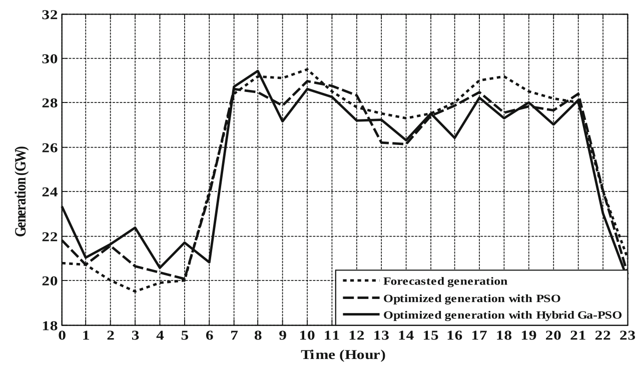

Figure 4. Optimized conventional generation pattern of a typical day with PSO and hybrid GA–PSO.

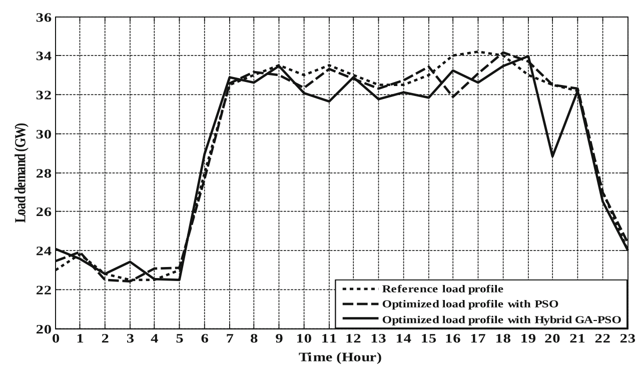

Figure 5. Optimized load demand pattern of a typical day with PSO and hybrid GA–PSO.

Table 1. Profit made by different participants of electricity market using hybrid GA–PSO algorithm.

Electricity market participants	Amount
Savings of utility (£)	163,000
Profit of aggregator (£)	380,034
Savings in electricity bill (£)	1,501.46

Table 2. System performance with PSO and hybrid GA–PSO algorithms.

Performance of system	Reference profile	Optimized profile with PSO	Optimized profile with hybrid GA–PSO
PAR	1.151	1.140	1.133
Total generation (GWh)	615.6	611.83	610.01
Average generation (GW)	25.65	25.49	25.41
Cost of generation (M£)	29.37	29.34	29.206

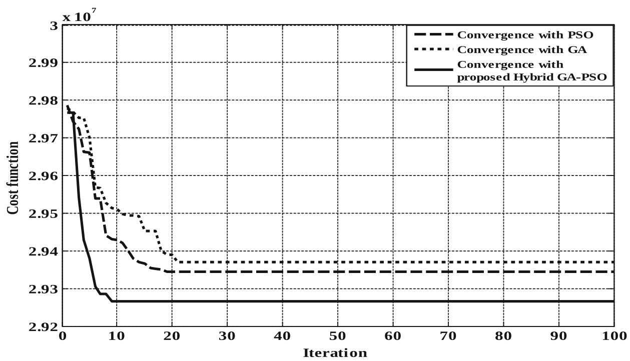

Figure 6. Cost convergence characteristics with different optimization algorithms.

Table 3. Performance analysis of optimization algorithms for demand side management problem in smart grid.

Algorithm	PSO	GA	Hybrid GA–PSO
Best	29,344,854.01	29,369,372.26	29,265,255.29
Worst	29,344,927.12	29,369,409.42	29,265,376.11
Mean	29,344,821.68	29,369,388.26	29,265,287.73

PSO algorithm. On the other hand, at peak hours, peak generation decreases from 29.5 to 28.95 GW on using PSO whereas, on using hybrid GA–PSO, it further decreases to 28.61 GW. Thus, for the current system, the proposed hybrid GA–PSO algorithm effectively optimizes the generation profile as compared with classical PSO while minimizing the cost.

Figure 5 illustrates the forecasted load profile and optimized load profile for the selected day using PSO and hybrid GA–PSO algorithms. After optimization using PSO, it is noticed that, during the off-peak period, peak load demand increases from 23 to 23.45 GW (1.92% more) and during the peak period, peak load demand decreases from 34.2 to 33.07 GW (3.3% less). However, using proposed hybrid GA–PSO algorithm, it is noticed that during the off-peak period, peak load demand increases from 23 to 24.1 GW (4.56% more) and during the peak period, peak load demand decreases from 34.2 to 32.60 GW (4.67% less). Therefore a part of load demand is shifted from peak period to the off-peak period, which shows smart distribution and efficient utilization of load demand throughout the day for the smart grid model. The comparative analysis clearly shows that for the same system improved results can be obtained using the proposed hybrid GA–PSO algorithm than those by the classical PSO algorithm.

Table 1 shows that with the proposed hybrid GA–PSO algorithm, utility system can make a savings of 163,000 £, aggregator can get a profit of 380,034 £ and there is a saving of 1501.46 £ amount in electricity bill for the customers. Table 1 summarizes that all the participants of electricity market draw profit simultaneously when the proposed hybrid GA–PSO algorithm is applied to the MODSM problem.

Table 2, demonstrates the comparative study of PAR, total generation and average generation in reference profile and using classical PSO and proposed hybrid GA–PSO algorithms. For a fixed load demand, the load shift from peak period to off-peak period results in significant decease in generation cost. Particularly for the current system, the simulated results reveal that the PAR reduces from 1.151 to 1.14 in case of PSO and it further reduces to 1.133 using the proposed hybrid GA–PSO algorithm. As a result, cost of electricity generation reduces from 29.37 (M£) to 29.34 (M£) using PSO and it further reduces to 29.206 (M£). Therefore, the analysis shows the effectiveness of the

Table 4. Comparative analysis among different techniques of optimization.

Optimization tool	Decrease in PAR (%)	Decrease in total generation (%)	Decrease in average generation (%)	Decrease in cost of generation (%)
Artificial immune algorithm (AIA) [25]	5.33	0.21	0.25	0.19
Particle swarm optimization (PSO)	0.87	0.61	0.62	0.10
Hybrid GA–PSO algorithm	1.74	0.9	0.94	0.5

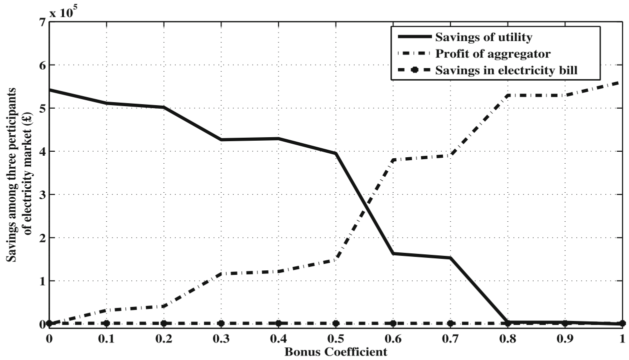

Figure 7. Significance of bonus coefficient among all three participants of electricity market.

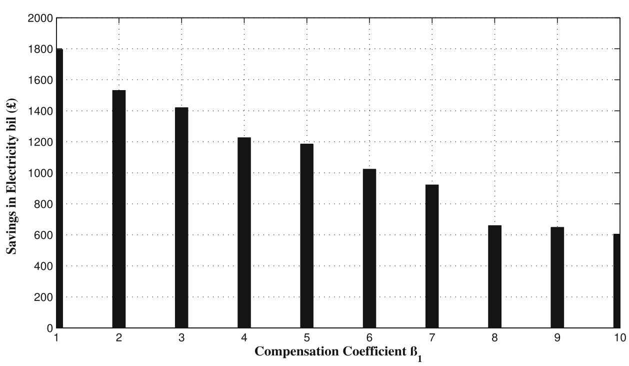

Figure 8. Effect of compensation coefficient on savings of electricity bill.

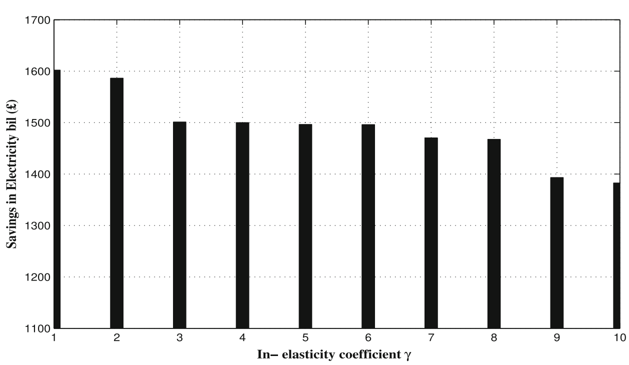

Figure 9. Effect of in-elasticity coefficient on savings of electricity bill.

proposed hybrid GA–PSO algorithm over PSO in terms of system performance.

8.2 *Performance analysis*

In this section, the performance of the proposed algorithm is validated with the help of cost convergence analysis of the current system mentioned in the previous section. Figure 6 demonstrates the comparative analysis of cost convergence behaviour of the current system in the presence of the proposed hybrid GA–PSO algorithm and a few well-known optimization algorithms: PSO [21] and GA [18]. It is observed that in the presence of the proposed hybrid GA–PSO algorithm, the cost function converges faster and reaches the optimal solution within a few number of iterations as compared with PSO and GA algorithms. Thus, the cost convergence profile proves that the proposed hybrid GA–PSO algorithm is very efficient as compared with other existing optimization algorithms.

Since global optimum solution may not be possible every time with optimization algorithms [38], in order to highlight the global optimal quality of the algorithm, the MODSM problem is simulated for 15 times with an iteration count of 100 for each optimization algorithm on the current system. Table 3 shows the simulated best result, worst result and mean value of the 15 individual trials. The results clearly show that the proposed hybrid GA–PSO algorithm gives better result in terms of better mean value than PSO and GA algorithms.

To show the effectiveness of the current approach to improve the performance of current system, a comparative study has been made among a few well-known optimization algorithms: PSO [22] and Artificial Immune algorithm [25] in Table 4. In [39] a well-known algorithm, i.e. PSO, is used to implement DSM and in [25], the Artificial Immune algorithm is used using Pareto optimality to solve the DSM program. Specifically, PAR has decreased by 5.33%, 0.87%, 1.74% on using AIA, PSO, hybrid GA–PSO algorithms, respectively. As a result % decrease in cost of electricity generation is 0.19%, 0.1% using AIA, PSO algorithms, respectively whereas hybrid GA–PSO algorithm provides around 0.56% decrease in cost of electricity generation, which is a significant amount as compared with other techniques. Total and average generation of electricity are decreased in all cases but significant percentage decrease is observed using hybrid GA–PSO, which is around 0.9% and 0.94%, respectively. Therefore, Table 4 shows the superiority of the proposed hybrid GA–PSO algorithm as compared with other existing algorithms.

8.3 *Analysis considering the effect of cost coefficients*

The bonus coefficient (α) signifies the portion of the utility operator savings that will be shared with the demand response aggregator in order to implement DSM in smart grid.

Bonus coefficient (α) can be varied from 0 to 1; $\alpha = 0$ signifies no bonus is given to the aggregator and $\alpha = 1$ signifies 100% incentive is given to the aggregator. From Figure 7 it is clear that the aggregator gets zero bonus at $\alpha = 0$, i.e. utility operator keeps the total savings, and the aggregator gets maximum bonus when α is 100%, i.e. utility operator savings is nil in this case. In this range, as value of α increases, bonus given to aggregator also increases gradually.

From figure 7, it is evident that due to increase in α, there is no significant change in electricity bill reduction at customer end as it is completely independent of α.

Figure 8 shows that at the same level of demand adjustment a smaller compensation coefficient (β_1) means more compensation will be given to customers, i.e. more saving in electricity bill. β_1 is varied from 1 to 10 by keeping other coefficients fixed as mentioned earlier, since $\beta_1 > 0$. As β_1 increases, electricity bill reduction decreases. Therefore, customers get higher benefits at lower level of β_1.

Figure 9 shows how the variation (1–10) of in-elasticity coefficient (γ) effects the reduction in electricity bill. As γ increases, savings of electricity bill reduces. Small value of γ signifies less discomfort to customers, so that customers can save electricity bill more.

9. Conclusion

In this paper, a multi-objective optimization approach is proposed to reduce PAR load demand ratio and to make savings on electricity bill of a day-ahead market in smart grid using DSM. The hybrid GA–PSO algorithm is proposed for optimal allocation of the generation and load profile for a typical day in the electricity market. The results of the proposed hybrid GA–PSO algorithm are validated and compared to those from other optimization techniques. The simulation results prove that the proposed technique optimally allocates generation and load profile for the typical day and effectively reduces PAR; as a result, the cost of generation of electricity reduces. Moreover, with the proposed approach, all the participants of the smart grid for a day-ahead market get monetary benefits due to optimized pattern of load and generation, i.e. utility operator reduces the operational cost, aggregator makes profit and customers save money on their electricity bill simultaneously. The result also illustrates the effect of variation of bonus, compensation and in-elasticity coefficient on individual profit of different participants of the electricity market and savings in electricity bill. From the result, it is very clear that the proposed approach shows better performance and it draws significant and better response of the MODSM program as compared with some existing approaches.

List of symbols

g_c	Power generated from conventional generators
g_{res}	Power generated from renewable energy sources
l_a	Actual load demand
l_f	Forecasted load demand
g_t	Scheduled conventional power generation
$F_{UTILITY}()$	Objective of utility operator
$F_{AGGRE}()$	Objective of aggregator
$F_{CUSTOMER}()$	Objective of customers
$f_0()$	Cost of conventional generators without DSM
$f_1()$	Cost of conventional generators with DSM
α	Bonus coefficient
β_1, β_2	Compensation coefficients
γ	In-elasticity coefficient
λ	Scalar weight
τ	Current iteration
ξ	Inertia weight factor
ζ	Fusion factor
c_{a1}, c_{a2}	Acceleration constants
P	Number of particles
r_c	Crossover rate
r_m	Mutation rate
C_w	Performance coefficient
η	Blade tip speed ratio
ϕ	Blade pitch angle
ρ	Air density

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