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Demand Side Management Strategy for Multi-Objective Day-Ahead Scheduling Considering Wind Energy in Smart Grid

Kalim Ullah [1], Taimoor Ahmad Khan [1], Ghulam Hafeez [1,*], Imran Khan [1,*], Sadia Murawwat [2], Basem Alamri [3], Faheem Ali [4], Sajjad Ali [5] and Sheraz Khan [1]

1 Department of Electrical Engineering, University of Engineering and Technology, Mardan 23200, Pakistan
2 Department of Electrical Engineering, Lahore College for Women University, Lahore 54000, Pakistan
3 Department of Electrical Engineering, College of Engineering, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia
4 Department of Electrical Engineering, University of Engineering and Technology, Peshawar 25000, Pakistan
5 Department of Telecommunication Engineering, University of Engineering and Technology, Mardan 23200, Pakistan
* Correspondence: ghulamhafeez393@gmail.com (G.H.); imran@uetmardan.edu.pk (I.K.)

Abstract: Distributed energy resources (DERs) and demand side management (DSM) strategy implementation in smart grids (SGs) lead to environmental and economic benefits. In this paper, a new DSM strategy is proposed for the day-ahead scheduling problem in SGs with a high penetration of wind energy to optimize the tri-objective problem in SGs: operating cost and pollution emission minimization, the minimization of the cost associated with load curtailment, and the minimization of the deviation between wind turbine (WT) output power and demand. Due to climatic conditions, the nature of the wind energy source is uncertain, and its prediction for day-ahead scheduling is challenging. Monte Carlo simulation (MCS) was used to predict wind energy before integrating with the SG. The DSM strategy used in this study consists of real-time pricing and incentives, which is a hybrid demand response program (H-DRP). To solve the proposed tri-objective SG scheduling problem, an optimization technique, the multi-objective genetic algorithm (MOGA), is proposed, which results in non-dominated solutions in the feasible search area. Besides, the decision-making mechanism (DMM) was applied to find the optimal solution amongst the non-dominated solutions in the feasible search area. The proposed scheduling model successfully optimizes the objective functions. For the simulation, MATLAB 2021a was used. For the validation of this model, it was tested on the SG using multiple balancing constraints for power balance at the consumer end.

Keywords: hybrid demand response programs; smart grid; renewable energy sources; multi-objective genetic algorithm

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1. Introduction

Smart grid networks need accurate forecasting of renewable energy sources (RESs) such as solar and wind energy [1–4]. Thus, some prediction models have been developed to address this issue [5–9]. Due to climatic condition, RESs are uncertain and depend on the weather conditions. To avoid such problems, energy storage systems (ESSs) can be used as a backup source to balance the demand at the user end [10–12]. However, there are several problems with ESSs, such as the maintenance cost, low capacity, charging and discharging cycle limitations, and high operational cost; therefore, their integration with RESs becomes necessary in order to provide balanced power to the end-users [13].

In SGs, the end-users connected with smart meters so that there is a bi-directional communication between the end-users and the utility through the smart grid operator (SGO). By using this information, the SGO sets the DSM strategy for the consumers and sends penalty and incentive signals through which consumers can change their loads to benefit both the utility and consumers [14]. DSM is a strategy used for resource scheduling [15], reliability [16], and household appliances [17] to optimize different objective functions in the SG by load curtailing and shifting, peak clipping, etc. The DSM strategy also maximizes the load factor by managing the relationship between power generation and demand [18–20].

The DSM strategy was used with the involvement of RESs to optimize the net cost of SGs in [21]; this problem was tackled using the distributed algorithm (DA). Besides, to facilitate the RESs penetration in SGs, MCS through robust optimization was employed. The SG's optimal operation in relation to the market electricity price was presented in [22] considering energy prices to maximize the penetration of WTs and ESSs, respectively. The coordination of the output RES power and DLs based on customers' real-time thermal rating was presented in [23]. In the distribution grid, the operational cost, loss of load expectation, and pollution emission were considered as a tri-objective optimization problem using the two-stage optimization algorithm (TSOA) [24].

Some research work has been conducted on multi-class and multi-objective scheduling [25–28]. For instance, in [29], the stochastic optimization scheduling of large-scale sources with peak clipping in the SG in two stages was solved; the authors used Bender's decomposition approach (BDA) to solve this problem. The authors developed multi-type and multi-state models for resilience assessment and enhancement in [30,31]. The energy management problem of the SG was tackled considering the operational cost and pollution emission in [32]; this problem was solved using MOGA technique. The availability of the RES objective function was added in [33] with high RES penetration and the DSM strategy. The authors used multiple techniques to solve this problem, and the results were compared after the successful implementation. The RESs' and loads' optimal scheduling with the regulation of the voltage to optimize the reliability and cost of the SG was presented in [34,35].

Many researchers have performed plenty of work on scheduling problems in the distribution grid from different viewpoints [36–39]. Some of the existing studies are discussed in detail as follows:

In [40], the multi-objective scheduling problem consisted of the emissions and cost in the SG in the presence of DERs, ESSs, and DRPs. The authors used the epsilon constraint method for the Pareto set solution and the fuzzy mechanism to pick the optimal solution. To reconfigure the distribution grid, a multi-objective optimization problem was investigated by integrating the taxi cab method (TCM) and the MOPSO algorithm.

The operational cost, pollution emission, and customer satisfaction (CS) objective functions were considered in the SG using the epsilon constraint method in [41]. In [42], the optimal dispatching problem in a microgrid was solved for the environment, economic, and CS indices using a dominance-based evolutionary algorithm (DBEA), and the best solution was obtained through fuzzy clustering and grey relation projection (GRP). In [43], a brief overview of SGs regarding the power distribution industry was given. Different technologies were discussed and explained to bring more potential and strength to the distribution grids. Besides, the impacts of many features on SGs were also taken into consideration, such as reliability, DSM implementation, the security of SGs, metering, the integration of RESs with SGs, etc.

The integration of RESs is uncertain and sometimes cannot meet the demand due to their uncertain behavior, so prediction and control models are needed [44–48]. Furthermore, in [49], electric vehicle (EV) batteries' extra capacityto meet the demand of end-users was discussed. Moreover, the integration of EVs and the SG was adopted using communication technologies and protocols to efficiently manage energy in the SG using different mechanisms and techniques. The integration of DSM in the SG for carbon emission reduction was discussed in [50]. The authors presented the DSM operational mode, energy production profile, storage, and consumption, and finally, the study was concluded by explaining the benefits of DSM implementation. The DSM strategy and approaches evaluated in this study were peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, flexible load shape, TOU, and DRPs, respectively.

In the above studies, some key objective functions of SGs were covered using different approaches. Some researchers tracked single-objective problems, which were solved through single-objective optimization algorithms; others tracked multi-objective problems, which were solved through multi-objective algorithms. However, some gaps remain open. Different from our recent work [51], in which wind speed is predicted via probability distribution function. The multi-objective optimization problem is solved via DSM strategy consisting of objective functions: (1) operating cost and pollution emission minimization, (2) Load curtailment cost minimization, and (3) Coordination between WT output power and shiftable loads. In this work, MOGA is adopted to solve a tri-objective optimization problem consisting of the following objective functions: (1) minimizing the operating cost and pollution emission; (2) minimizing the cost of load curtailment; (3) minimizing the deviation between the WTs' output power and demand. As the problem in the proposed study is a tri-objective optimization problem, random weights are considered for MOGA selection, providing multiple non-dominated solutions in the feasible search area. Besides, wind speed is predicted via monte Carlo simulations. This problem is solved in two phases: in the first phase, in the feasible search space, non-dominated solutions are obtained using the MOGA, and in the second phase, the optimal solution is picked among the non-dominated solutions using the DMM. The contributions of the proposed study are summarized as follows:

- Proposing a new demand side management strategy, a hybrid scheme of demand response programs based on real-time pricing and real-time incentives to solve the SG scheduling problem.
- Solving the SG day-ahead scheduling problem using the multi-objective genetic algorithm to obtain the Pareto set solution and the decision-making mechanism to find the optimal solution in the feasible search area.

The remainder of this work is organized as follows: Section 2 illustrates the system model. The methodology is discussed in Section 3. The numerical and simulation results are explained in Section 4. The conclusion of the proposed study is presented in Section 5.

2. Proposed System Model

2.1. Wind System Model

The modeling of the wind RES is briefly analyzed considering the wind speed, and the prediction of the wind speed is necessary before integrating it with the SG. In this study, Monte Carlo simulation was used for wind speed prediction [52]. The WTs' power generation consists of the rated, cut-in, and cut-off speeds and is modeled in Equation (1) [53].

$$P(VW) = \begin{cases} 0 & V_W < V_{c\_i} \\ P_R \frac{(V - V_{c\_i})}{(2V_r - V_{c\_i})} & V_{c\_i} \le V_W < V_r \\ P_R & V_r \le V < V_{c\_o} \\ 0 & V \ge V_{c\_o} \end{cases} \tag{1}$$

where P_R and VW represents the WTs' rated power and wind speed and V_{c_i}, V_r, and V_{c_o} indicate the WTs' speed in different operational regions [54].

2.2. EESs' Technical Constraints

In order to reduce the energy generation and demand difference, the most common solution is to involve ESSs in the energy management of the SEDG. In most applications, batteries are used as the ESSs. The state of charge (SOC) represents the charging and discharging energy relationships of the ESSs. From the SOC, charging, and discharging, the lifetime of the batteries can be expressed. The SOC of the ESSs at time t can be modeled using Equation (2) [55].

$$\mathrm{SOC(h)} = \mathrm{SOC(h-1)} + \mathrm{W_{ESSs}(h)} \tag{2}$$

$$\mathrm{SOC}^{\min} \leq \mathrm{SOC}(\mathrm{h}) \leq \mathrm{SOC}^{\max} \tag{3}$$

where Equation (3) shows ESSs maximum and minimum SOC.

2.3. DG Technical Constraints

The minimum up- and down-time of DGs and the ramp-up and down-time limitations of DGs collectively represent the DGs' constraints and are modeled in Equations (4), (7), (14) and (15), respectively.

$$\lambda^{on}(\mathrm{h},\mathrm{sc},\mathrm{d}) + \sum_{t=t+1}^{\min(T,t-1+M^U)} \lambda^{off}(\mathrm{sc},\mathrm{t},\mathrm{d}) \leq 1 \tag{4}$$

$$\gamma^{off}(\mathrm{h},\mathrm{sc},\mathrm{d}) + \sum_{t=t+1}^{\min(T,t-1+M^D)} \gamma^{on}(\mathrm{sc},\mathrm{t},\mathrm{d}) \leq 1 \tag{5}$$

$$\sum_{t=1}^{T} W_d(\mathrm{t},\mathrm{sc},\mathrm{d}) - \sum_{t=1}^{T} W_d(\mathrm{t}-1,\mathrm{sc},\mathrm{d}) \leq R^U \tag{6}$$

$$\sum_{t=1}^{T} W_d(\mathrm{t},\mathrm{sc},\mathrm{d}) - \sum_{t=1}^{T} W_d(\mathrm{t},\mathrm{sc},\mathrm{d}) \leq R^D \tag{7}$$

where γ^{on}, γ^{off}, M^U, M^D, and R^U and R^D represent the on- and off-time of the DGs (i.e., on = 1 and off = 0), the minimum up- and down-time, and the ramp-up and -down of the DGs at time slot t, respectively.

2.4. Demand Side Management: Hybrid Demand Response Programs

A new DSM strategy, H-DRPs based on real-time pricing and incentives, is used, in which three types of consumers participate: (i) consumers with shiftable loads (responsive consumers), (ii) consumers with curtailable loads (responsive consumers), and (iii) non-responsive consumers. From the proposed H-DRPs, the first two types of consumers obtain benefits.

2.5. Objective Functions

2.5.1. First Objective Function

The first objective function of the proposed scheduling model is modeled in Equation (8) as follows:

$$\min F_1 = \left| \begin{array}{l} \sum_{t=1}^{T} \left[\begin{array}{l} \sum_{b=1}^{B} \left\{ \delta {P_{DG}}^2(t,b) + \omega\delta P_{DG}(t,b) + \sigma \right\} \\ + \{C_{su} \times \gamma^{on}(t,b)\} + \left\{ C_{sd} \times \gamma^{off}(t,b) \right\} \end{array} \right] + \\ \sum_{t=1}^{T} \left[\sum_{b=1}^{B} \left\{ \beta {P_{DG}}^2(t,b) + y\delta P_{DG}(t,b) + \phi \right\} \right] + \\ \sum_{t=1}^{T} \left[\{ {\lambda^P}_{Grid} \times P_{Grid}(t) \} + \{ \psi_{Grid} \times P_{Grid}(t) \} \right] \\ + \sum_{t=1}^{T} \left[\begin{array}{l} \sum_{n=1}^{N} \left\{ {C^k}_{op} \times {\mathrm{P_{ESS}}}^{\mathrm{Discharge}}(t,n) \right\} \\ + \sum_{n=1}^{N} {C^k}_{op} \times {\mathrm{P_{ESS}}}^{\mathrm{Charge}}(t,n) \end{array} \right] \end{array} \right| \tag{8}$$

where the DGs' cost factors are represented by δ and σ and the on/off DGs states are represented by γ^{on} and γ^{off}. Besides, the DGs' emission factors are represented by y, β, and ϕ, and the grid market price is shown by λ^P_{Grid}, respectively.

2.5.2. Second Objective Function

The minimization of the load curtailment cost is taken as the second objective function of the proposed scheduling model and is modeled in Equation (9) as follows:

$$\min f_2 = \sum_{c_{load}=1}^{C_{Load}} C_{CLoads} \times D_{CLoads}(t, C_{Load}) \tag{9}$$

where C_{CLoads} and D_{CLoads} represent the bid price offer by responsive consumers who curtail their loads and power consumption by shiftable loads.

2.5.3. Third Objective Function

The deviation between the WTs' output power and demand minimization is considered as the third objective function of the proposed scheduling problem of the SG. By adopting the H-DRPs, the minimization of the deviation between the WTs' output power and demand is modeled in Equation (10) as follows:

$$\min F_3 = \sum_{sc=1}^{SC} \rho_{sc} \sum_{h=1}^{H} \left| \sum_{n}^{N} D_n(\mathrm{h}, \mathrm{n}) - W_{WT}(\mathrm{sc}, \mathrm{h}) \right| \tag{10}$$

where ρ_{sc}, D_n, and P_{WT} represent the probability of the scenario, responsive consumers' demand, and the power of the WTs, respectively. The responsive consumers' demand (D_n) consists of shiftable loads and fixed loads and is modeled in Equation (11) as follows:

$$D_n(\mathrm{h}, \mathrm{n}) = [D_{Fix}(\mathrm{h}, \mathrm{n}) + D_{DL}(\mathrm{h}, \mathrm{n})] \tag{11}$$

where D_{Fix} and D_{DL} are the fixed and shiftable loads. After shifting loads from h to h′, the new shiftable loads can be modeled in Equation (12) as follows:

$$D_{DL}(\mathrm{h}, \mathrm{n}) = \sum_{h'} \sum_{n=1}^{N} D_{DL}(\mathrm{n}, \mathrm{h}, \mathrm{h}') - \sum_{h'} \sum_{n=1}^{N} D_{DL}(\mathrm{n}, \mathrm{h}, \mathrm{h}') \tag{12}$$

where D_{DL} shows the demand of shiftable loads. Moreover, the shiftable loads' response level is modeled in Equation (13) as follows:

$$0 \le \sum_{n=1}^{N} D_{DL}(\mathrm{n}, \mathrm{h}, \mathrm{h}') \le \varsigma \sum_{n=1}^{N} D_{DL}(\mathrm{h}, \mathrm{n}) \tag{13}$$

where ς indicates the response level of the consumers.

3. Methodology

3.1. Multi-Objective Genetic Algorithm

To solve multi-objective scheduling problem, MOGA is adopted, which is based on particles' velocity and position [56]. MOGA search for non-dominated solutions of the proposed multi objective problem in the feasible search area, then each particle/gene in the feasible search space organized and ranked according to its position. The Pareto-set-solution-based particles are ranked as 1, and other solutions in the feasible area are ranked according to their positions. The ranks of each particle can be obtained using Equation (14) as follows:

$$R_{assigned} = 1 + N_s \tag{14}$$

$R_{assigned}$ represents the rank assigned to the particles, and N_s indicates the number of particles/solutions, respectively. In this study, the problem was considered as a tri-objective optimization problem, for more than one objective function, and Equation (15) is used as follows:

$$f(z) = k_1 f_1(z) + \ldots + k_i f_i(z) + \ldots. + k_j f_j(z) \tag{15}$$

where $[k_1, k_2 \ldots\ldots k_i]$, z, and $f_i(z)$ represent random weights, the string, and the ith objective function. In this study, the weights considered are random weights, which provide multiple non-dominated solutions in the feasible search space, and in order to pick the best solution in the non-dominated solutions, the DMM is used. For the evaluation of the weighting factors, the selection procedure is used with random weights to search for Pareto optimal solutions in the feasible search area by utilizing various search directions. The following are the steps used for the implementation of the MOGA for the proposed tri-objective day-ahead scheduling problem:

1. Initialization: Initializing the proposed tri-objective function using Equations (8)–(10), the upper/lower limits for defining the feasible area, the size of the population, and the total iterations.
2. Evaluation: Calculating the proposed tri-objective function using Equations (8)–(10).
3. Selection: Applying the MOGA selection feature, combining the tri-objective problem with the scaler fitness function.
4. Implementation: The following are the implementation steps:
    a. Rank assigned to each particle using Equation (14).
    b. To each solution in the feasible search space, assigning the row fitness function, which helps in finding the average of solutions to find the rank 1 solutions.
    c. Applying crossover and mutation to create new strings.
    e. Checking the condition: satisfied?
    f. If yes, then converge to the optimal solution.
    g. If no, then go back to Step 1.
5. Termination test: The Pareto set solution is determined in Phase 1, and the optimal solution is picked in Phase 2. The DMM is applied to pick the optimal solution. The MOGA flowchart is shown in Figure 1. The computational time and number of iterations of the MOGA for the proposed case studies are shown in Table 1. The proposed technique for the scheduling problem was implemented using MATLAB 2021a.

Table 1. Computational time and max number of iterations of the MOGA for the proposed case studies.

Case Studies	Number of Iterations	Computational Time
Case Study 1	100	45
Case Study 2	100	40
Case Study 3	100	60

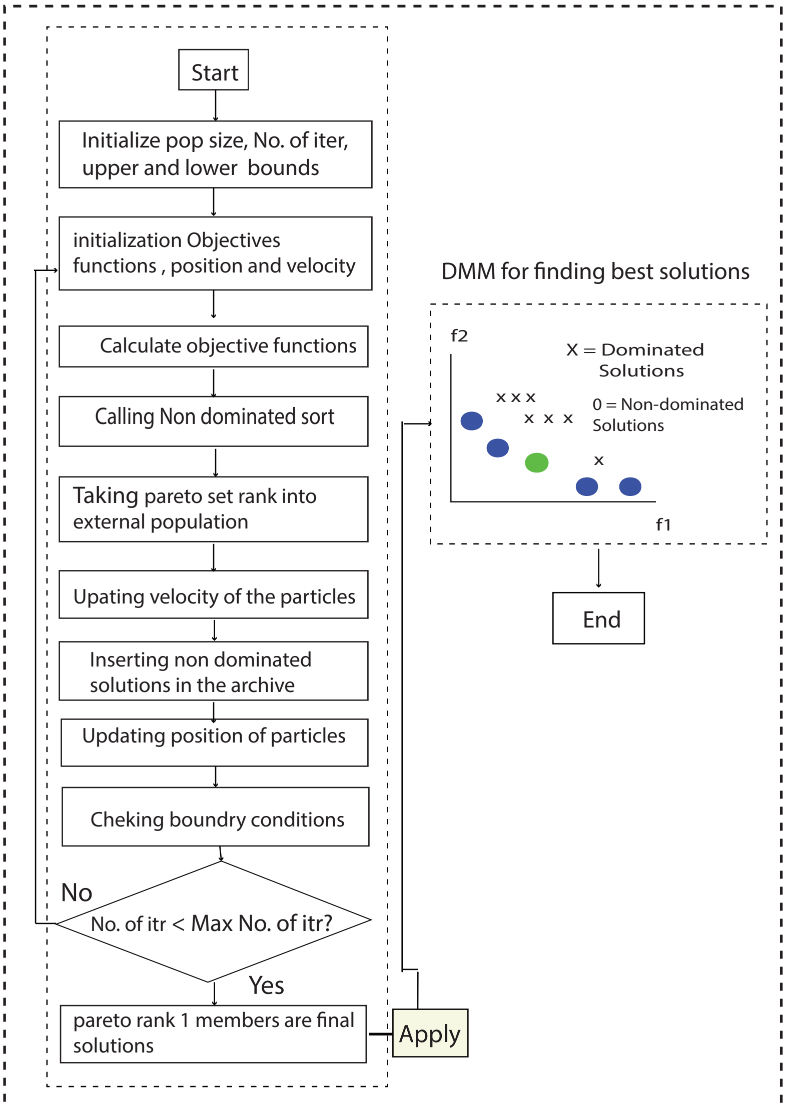

Figure 1. MOGA flowchart.

3.2. Decision-Making Mechanism

Decision-making is important to choose the optimal solution amongst the Pareto set solution while considering multi-objective optimization in the SG. Different methods and tools can be used such as the analytical hierarchy process (AHP), the technique for order preference by similarity to ideal solution (TOPSIS), the fuzzy approach, and the Knee set for finding the optimal solutions. In this study, the best solution amongst the Pareto set solution/non-dominated solutions was picked through the DMM. In this mechanism, the ideal point is considered, and based on the distance from that ideal point, the best solution is obtained. The best solution sample used in the proposed scenario using the decision-making mechanism is modeled in Equations (16)–(18), respectively.

$$\kappa_N{}^m = \frac{F_N{}^{\max} - F_N(\mathrm{m})}{F_N{}^{\max} - F_N{}^{\min}} \tag{16}$$

$$P_{ideal} = [\min \quad \kappa_1{}^m \quad \kappa_2{}^m \quad \kappa_3{}^m \ldots\ldots\ldots\ldots\ldots \kappa_N{}^m] \tag{17}$$

$$\min D(\mathrm{m}) = \sqrt{\left| \begin{array}{l} [\kappa_1{}^1 - \min \kappa_1{}^1]^2 + [\kappa_1{}^1 - \min \kappa_2{}^2]^2 + \\ \ldots\ldots\ldots\ldots + [\kappa_N{}^m - \min \kappa_N{}^m]^2 \end{array} \right|} \tag{18}$$

where $F_N{}^{\min}$ and $F_N{}^{\max}$ indicate the minimum and maximum value of the Nth objective functions and $\kappa_N{}^m$ and $F(m)$ indicate the mth solution of the Nth objective functions and the objective function value in the mth solution, respectively. The MOGA and decision-making mechanism implementation steps are shown in Figure 2.

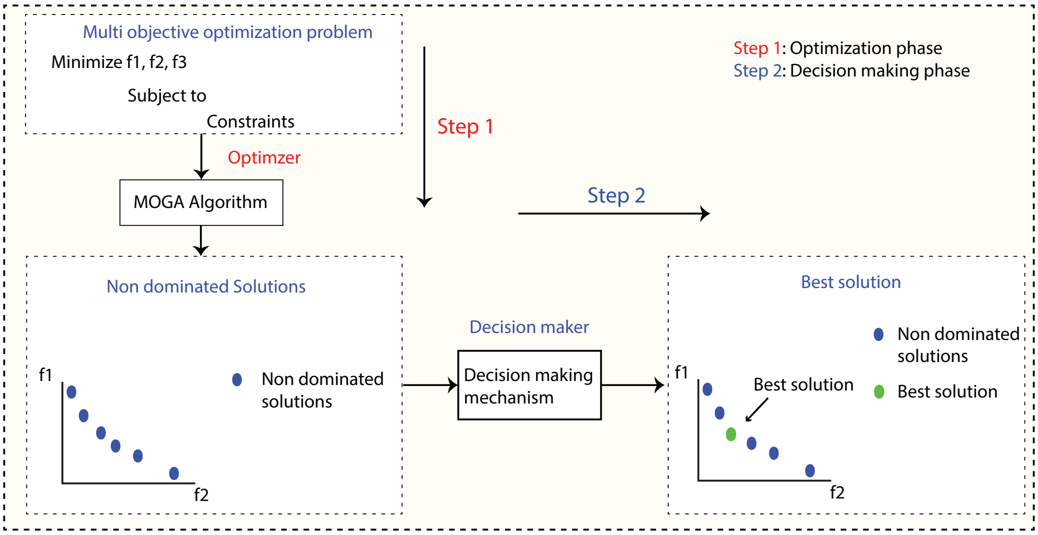

Figure 2. MOGA and decision-making mechanism implementation steps.

4. Numerical and Simulation Results

A new DSM strategy is adopted for solving the scheduling problem in SG using DERs. For the proposed study, wind speed (hourly) is shown in Figure 3 and the speed limits for WTs in different operational regions were considered as 3 m/s, 10 m/s, and 15 m/s. The economic and technical data of the ESSs are illustrated in Table 2, and the technical data of the DGs are illustrated in Table 3. The demand for electricity is shown in Figure 4. Four case studies are adopted for solving the scheduling problem of SG using the H-DRPs and DERs as follows:

Basic case study: Optimization without consideration of the DERs and H-DRPs.
Case Study 1: First and second objective optimization.
Case Study 2: First and third objective optimization.
Case Study 3: Tri-objective simultaneous optimization.

The aim of the proposed case studies was to optimize the objective functions with and without the involvement of the DERs and H-DRPs in order to visualize the impact of the proposed DSM strategy. These case studies are discussed in detail as follows.

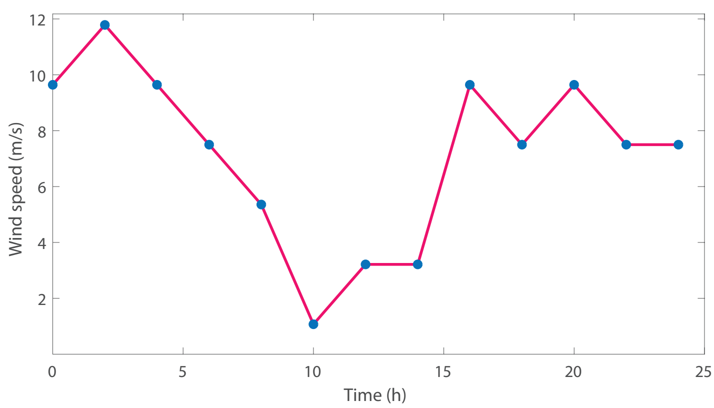

Figure 3. Computational time and number of iterations of the MOGA for each case study.

Table 2. Economic and technical data (ESSs).

Parameters	Numerical Values
ESSs-discharging $(P^{\min})$	0.45 MW
ESSs-charging $(P^{\max})$	0.45 MW
ESSs-charging (efficiency)	92%
ESSs-discharging (efficiency)	96%
ESSs-SOC (max)	100%
ESSs-SOC (min)	15%
ESSs operational cost	USD 20

Table 3. DGs' technical data.

Diesel Generator	Unit	Value
DG-1	$P^{\min}$ (MW)	0
	$P^{\max}$ (MW)	0.70
	Min up-time M^U (h)	2
	Min down-time M^D (h)	2
	Ramp-up R^U (MW)	0.04
	Ramp-down R^D (MW)	0.04
DG-2	$P^{\min}$ (MW)	0
	$P^{\max}$ (MW)	0.75
	Min up-time M^U (h)	2
	Min down-time M^D (h)	2
	Ramp-up R^U (MW)	0.05
	Ramp-down R^D (MW)	0.05
DG-1	$P^{\min}$ (MW)	0
	$P^{\max}$ (MW)	0.85
	Min up-time M^U (h)	1.5
	Min down-time M^D (h)	1.5
	Ramp-up R^U (MW)	0.02
	Ramp-down R^D (MW)	0.08

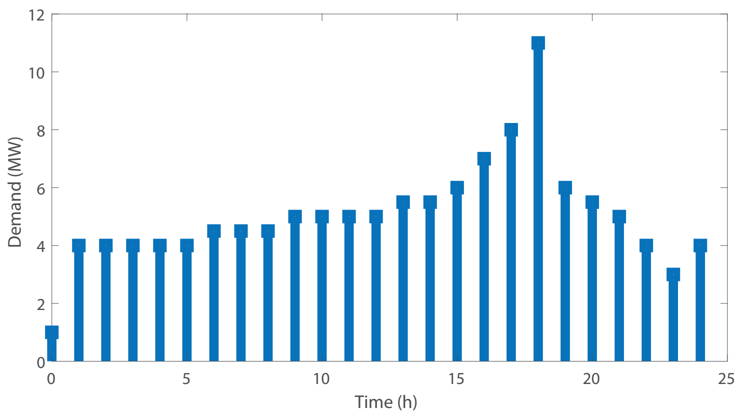

Figure 4. Electricity demand.

Basic case study:

In this case, the involvement of the DERs and H-DRPs was not considered, and the system response resulted in high cost and emissions.

Case Study 1:

In this case, the first and second objectives' simultaneous optimization was modeled using the MOGA technique considering the DERs and H-DRPs, as shown in Figure 5. By curtailing curtailable loads, which is the second objective, it directly impacted the first objective function. There was a total of 15 non-dominated solutions, and the optimal solution was picked from the non-dominated solutions through the DMM, which was the sixth solution in the feasible search space. The operational cost of the DERs (ESSs (charging/discharging), DGs, UG) was reduced as compared to the basic case study by charging 0.77% and discharging 0.03%, 3.5%, and 0.05%. Moreover, the pollution emission of the DGs and UG was reduced by 2.1% and 14.5%, respectively.

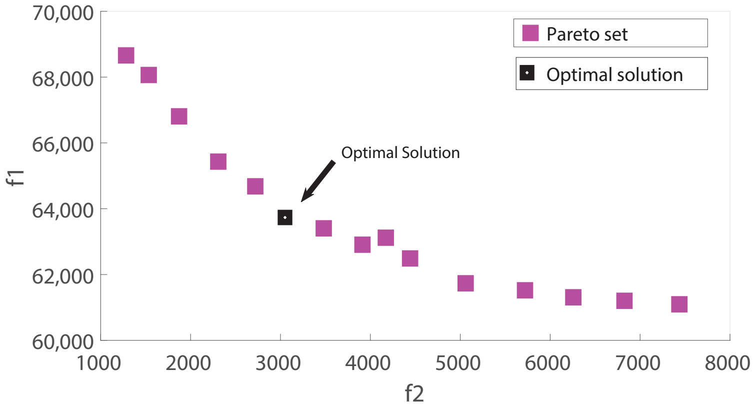

Figure 5. Simultaneous optimization of ($F1$, $F2$).

Case Study 2:

In this case, the first and third objectives' simultaneous optimization was modeled using the MOGA technique considering the DERs and H-DRPs, as shown in Figure 6. By minimizing the deviation between the WTs' output power and demand, which is the third objective, it directly impacted the first objective function. There was a total of 14 non-dominated solutions, and the optimal solution was picked from the non-dominated solutions through the DMM, which was fifth solution in the feasible search space. The cost and emissions were minimized by 2% and 14%, respectively.

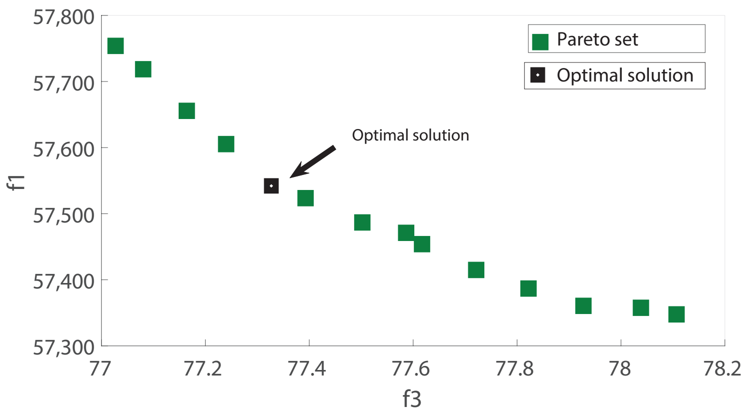

Figure 6. Simultaneous optimization of ($F1$, $F3$).

Case Study 3:

In this case, the first, second, and third objectives' simultaneous optimization was modeled using the MOGA technique considering the DERs and H-DRPs, as shown in Figure 7. By minimizing the load curtailment cost and minimizing the deviation between the WTs' output power and demand, it directly impacted the first objective function. There was a total of 12 non-dominated solutions, and the optimal solution was picked from the non-dominated solutions through the DMM, which was the sixth solution in the feasible search space. Besides, considering the first and second objectives, the operating cost of the proposed system and emission generated by the DERs were minimized by 2.8% and 13% using the MOGA as compared to Case Study 1. Moreover, considering the first and third objective, the operating cost of the proposed system and emissions generated by the DERs were minimized by 2.5% and 13.5% using the MOGA as compared to Case Study 2. The power scheduling of the proposed DERs iss shown in Figure 8.

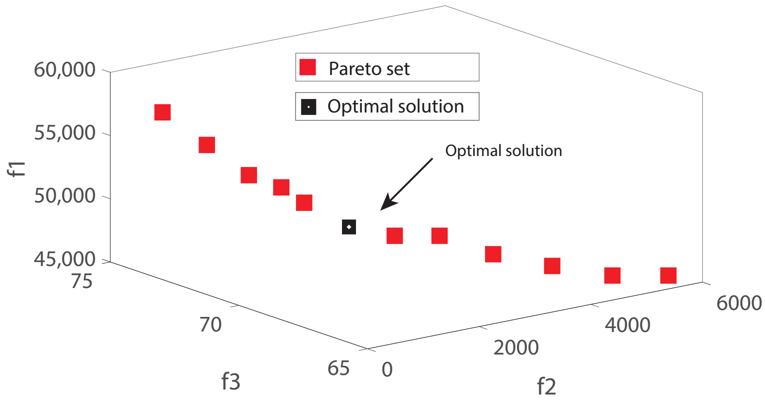

Figure 7. Tri-objective simultaneous optimization of ($F1$, $F2$, $F3$).

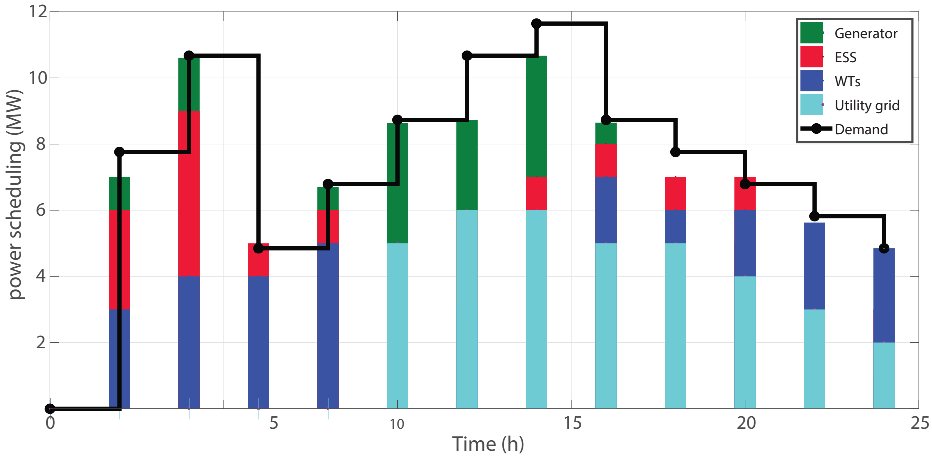

Figure 8. Power scheduling of distributed energy resources.

5. Conclusions

A new DSM strategy was adopted for the day-ahead SG scheduling problem using distributed energy resources. This problem was solved in four different case studies. The simulation results show that, in the basic case study, the involvement of the DERs and H-DRPs was not considered, and the system response resulted in high cost and emissions. In Case Study 1, the operational cost of the DERs (ESSs (charging/discharging), DGs, UG) was reduced as compared to the basic case study by 0.77%, 0.03%, 3.5%, and 0.05%. Moreover, the pollution emission of the DGs and UG was reduced by 2.1% and 14.5%. In Case Study 2, the operating cost of the proposed system and pollution emission generated from the different DERs were minimized by 2% and 14% as compared to Case Study 1. Finally, in Case Study 3, the tri-objective optimization problem was solved simultaneously using the MOGA, considering the first and second objectives, and the operating cost of the proposed system and emissions generated due to the DERs were minimized by 2.8% and 13% using the MOGA as compared to Case Study 1. Moreover, considering the first and third objective, the operating cost and emissions were minimized using the MOGA as compared to Case Study 2 by 2.5% and 13.5%, respectively.

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Nomenclature

$C^k{}_{\mathrm{op}}$	ESS's operational cost
C_{sd}, C_{su}	Start-up and shut-down cost
Em_{DG}	DGs' pollution emission
Em_{UG}	UG's pollution emission
P_{ESSs}	ESS's power generation
P_{DG}	DGs' power generation
P_{UG}	UG's power generation
ρ_{sc}	Probability of s scenario
γ^{on}	On-time of DGs
γ^{off}	Off-time of DGs
SOC	State of charge
$P_W T$	WTs' power
$\lambda_{ESSs-charge}$	ESSs' charge
$\lambda_{ESSs-discharge}$	ESSs' discharge
β, y, ϕ	Emission factors
F_1, F_2, F_3	Objective functions
$\gamma\sigma$	Wind speed prediction scale parameters
P_R	WTs' rated power
$P(VW)$	Total power of WTs
V_{c_i}	Cut-in speed
V_r	Rated speed
V_{c_o}	Cut-off speed
VW	Wind speed
M^U	Min up-time
M^D	Min down-time
W_{PV}	Total power generation of PVs
R^U	Ramp-up time
R^D	Ramp-down time
D_n	Responsive users' demand
D_{nr}	Non-responsive users' demand
sc	Scenario indices
h, H	Time indices
b, B	EES's indices
nr, NR	Non-responsive users' indices
n, N	Responsive users' indices

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