

14. PESGRE_2020_Demand Response Management_Pravat_dkk

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Demand Response Management using Non-Dominated Sorting Genetic Algorithm II

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Abstract—In a smart grid environment, economic operation means not only economic scheduling of generation but also scheduling the load. Incentive-based Demand Response (DR) programs assume a noteworthy job in improving grid operation and reliability as well as cost management. Such a program enables utilities to decrease electrical energy use amid peak hours, which place burden on the electrical grid and result in high electricity prices or system outage as an after effect of issues present in the distribution system. This paper focus on the basic advantages of Demand Response Management (DRM) in smart households which includes optimization of customer loads leading to minimization of the bill borne by the customer. It also includes different methods (algorithms) to accomplish a lower inconvenience posed to the consumers. This is accomplished by an elitist Non-dominated Sorting Genetic Algorithm (NSGA II) and the result is compared with another optimization technique called Strength Pareto Evolutionary Algorithm (SPEA II). These will result to a profit-based environment; both to the consumers, and utility in an electricity market.

Keywords—Demand Response, Non-Dominated Sorting Genetic Algorithm II, Pareto-optimal solution, Strength Pareto Evolutionary Algorithm II

I. INTRODUCTION

Time-based tariff is one of the major advantages of smart grid applications. Earlier the customers used to pay a fixed charge for the kWh of energy they have consumed and for a desired peak load value. But now they can adjust their usage to extract maximum benefits from the flexible tariff. This whole process requires an advance energy management system, an open electricity trading market, and financial incentives. They can then be utilized for regulating the power consumption of the consumer appliances and it may involve economies of scale.

Smart grids have the capability of accessing smart appliances in order to optimize the energy usage whenever required. For instance, the coffee maker will be supplied power during morning hours while the washing machines will be given supply during night time. They can communicate with other loads on the smart grid that are present in the vicinity or neighborhood, in order to regulate the energy usage for optimization of DR [1]. Such an arrangement has been illustrated in Fig. 1. Smart grid concept hasn't been implemented at a national level yet. They are presently being tested at various levels. Once they are implemented nationally, they could save a considerable amount of money, over the next few years, for the utility companies as well as for the consumers.

Paper [2] describes the importance of DRM and the implementation of DRM in a micro grid (MG). In this work, the authors have considered an industrial commercial MG

with one PV source, two Diesel Generators, and one battery with an assumption that the utility grid uses dynamic pricing. Another paper [3] focuses on load scheduling which is a major part of Demand-side Management. In this paper a distributed framework for the demand response-based cost minimization is proposed. In [4], the authors take care of a similar issue in an efficient manner, utilizing a stochastic method. They have assumed that each appliance has an adaptable begin-time, yet a fixed span and vitality utilization. Conversely, the authors in [5] propose an energy plan where the begin-time and the end-time are known from before and the energy utilization changes regularly. They have proposed an appropriate calculation to find out the optimal energy utilization plan utilizing instruments from various hypothesis. In this methodology, the clients are charged depending on their day to day utilization of electricity, the overall improvement being successive, and all clients need to communicate their schedules to the other different clients in the framework. Each one of the appliances are expected to have a place within a similar class. In [6], the authors have proposed an energy utilization scheme which works by arranging the appliances into two different classes; and in [7]-[8], the authors have proposed a plan with four classes. The appliances are modeled as utilizing power from a utility network and having a lot of constraints. Be that as it may, the working occasions of the appliances are thought to be known from before, and the energy utilization can be changed continuously.

The multi-objective problem of demand response is solved in this work through an elitist Non-dominated Sorting Genetic Algorithm II (NSGA II). This heuristic optimization technique has significant practical value as it is not derived from any axioms or theorems of mathematics. Its strength includes preserving the elitism and diversity of the solutions. Elitism ensures that the best solutions among the generated population in the next iteration is retained; Diversity ensures that the termination at the global minima/maxima, avoiding false termination at any local minima /maxima.

The rest of the paper is organized as follows: Section II describes the steps for achieving the Pareto optimal solution. Section III details the steps of multi-objective optimization based on NSGA II. Section IV describes the simulation results and Section VI concludes the paper.

II. PARETO OPTIMAL SOLUTION FOR MULTI-OBJECTIVE OPTIMIZATION

In general, to solve an optimization problem through Genetic Algorithm, a set number of candidate solutions are evolved towards a better set of solutions. These candidates are called individual, creature or phenotype. They can be altered and mutated in order to modify their properties. In [9] the authors have shown that instead of representing the solution in binary

i.e., 0 and 1, we can also use other types of encoding. In each iteration, the population is referred to as generation. So, for the population of randomly selected individuals the evolution process starts by calculating the fitness of each individual in the population. The fitness is defined as the magnitude of the objective function of the optimization problem. The individuals having more fitness values are selected and their genomes are modified, i.e., mutated and recombined to get a new generation which is then utilized in the next iteration. The iteration is terminated when an acceptable value of fitness is achieved for the population or after a certain number of generations have been produced.

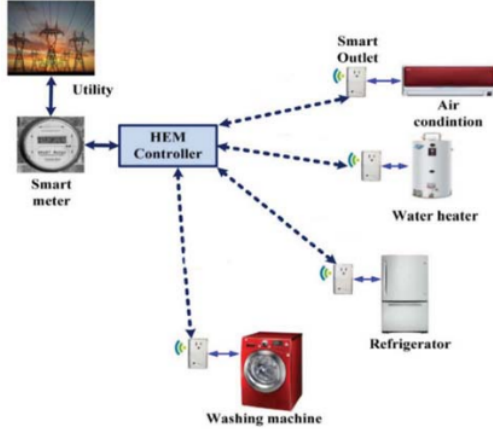


Fig. 1. Smart appliances connected to a home energy management system.

A. Dominance

Dominance is a measure to choose the best solutions from the pareto-optimal front. Solution i dominates solution j which implies that solution i is giving better result than solution j on a particular objective. Mathematically, it is described as:

The individual i dominates j if and only if any of the following is true:

- i is feasible and j is not
- i and j are both not feasible, but i has a smaller overall constraint violation
- i and j are both feasible and i dominates j (usual Pareto domination)

For a minimisation problem, x^1 dominates x^2 if $F_m(x^1) < F_m(x^2)$ for at least one $m = (1, 2, \dots, M)$ where, M = Number of objective functions.

B. Crowding distance

Crowding distance is a measure which sets the priority of solutions on the pareto-optimal front when contradiction arises in choosing the best feasible solutions to the optimization problem [10]. In other words, it is used to estimate the density of solutions surrounding a particular solution i . The solution having higher crowding distance is selected for next iteration's population. To find the crowding distance following algorithm is used:

1. Form a cuboid surrounding i^{th} solution where d_i is the perimeter of the cuboid

2. To perform crowding sort on front F i.e. (F, α_c) , measure the number of solutions present in the front

$$l = |F| \quad (1)$$

Assign $d_l = 0$ (initial value), $l \in F$

3. For each $m=1, 2, \dots, M$ sort the solutions of front F in inverse order of the fitness values
4. Indices after sorting is returned and stored in $l^m = \text{sort}(F_m, \alpha)$
5. For $m=1, 2, \dots, M$; assign the largest distance to boundary solution
6. For rest of the solutions, we have to find the crowding distance as:

$$d_{l^m} = d_{l^m}^{prev} + \frac{F_m^{l^m+1} - F_m^{l^m-1}}{F_m(mx) - F_m(mn)} \quad (2)$$

where,

$F_m(mx)$ denotes the maximum fitness value in objective function m

$F_m(mn)$ denotes the minimum fitness value in objective function m

F_m^l denotes the fitness value of the solution stored in index l under the objective function m

d_l is the crowding distance of the solution stored in index l

7. Include the updated crowding distance for the previous fitness function in the next iteration

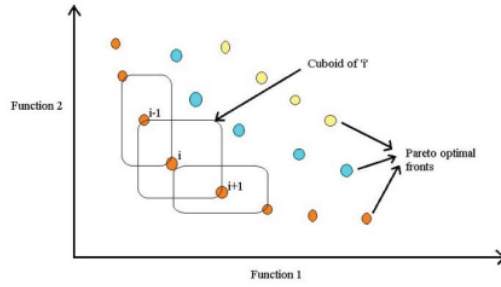


Fig. 2. Figure showing the concept of crowding distance calculation.

III. NON-DOMINATED SORTING GENETIC ALGORITHM II

Demand Response aims at controlling the consumer load for optimum use of electricity. This helps in maintaining a healthy grid and in return consumers get an incentive for handling their inconvenience. So, our main objective focusses on:

$$\text{Minimize } (P, st) = \sum_{i=1}^T C(P_{dgi}, P_{gridi}, t_i) + \sum_{l=1}^L I_l(st_l)$$

$$\text{Subject to : } \sum (P_{dgi} + P_{gridi} + P_{pvi}) = P_{li}$$

$$P_{dg \min} \leq P_{dg} \leq P_{dg \max}$$

$$st_{l \min} \leq st_l \leq st_{l \max} \quad (3)$$

where,

$$C(P_{dgi}, P_{gridi}, t_i) = (aP_{dgi}^2 + bP_{dgi} + c) \times t_i + (P_{gridi} \times c_{gridi} \times t_i) \quad (4)$$

$$I_l(st_l) = Ast_l^2 + Bst_l + Cst_l$$

P_{dgi} is power generated by Diesel Generator units in i^{th} time interval

P_{gridi} is power extracted from the grid in i^{th} time interval

P_{pvi} is power extracted from the solar PV panel in i^{th} time interval
 P_{li} is the total power consumed by the load in i^{th} time interval
 t_i denotes duration of i^{th} time interval
 $C(P_{dg}, P_{grid}, t_i)$ is the cost function
 T is the total number of time intervals
 L is the total number of loads
 st_i is the duration for which i^{th} load is shifted
 $I_i(st_i)$ is the inconvenience function
 a, b, c are the parameters for the cost function associated with Diesel Generator
 A, B, C are the parameters for the inconvenience function associated with each load

Steps of the NSGA II algorithm are as follows:

1. Initialize the Parent set P_t with random values in the feasible set
2. Do certain mutation and crossover to form the Offspring set Q_t
3. Application of Genetic Algorithm to find P_{t+1} and Q_{t+1} which will be going to the next iteration
 - 3.1. Form $R_t = P_t \cup Q_t$ (5)
 where, R_t is the union set of parent set and offspring set
 - 3.2. Perform non-dominated sorting to R_t in order to identify different fronts F_i
 After finding F_1 , delete the solution set from R_t and do the non-dominance checking on remaining elements of R_t . Repeat till $R_t = \phi$
 - 3.3. Initialize $P_{t+1} = \phi$, $i = 1$ (6)
 - 3.4. if $|P_{t+1}| + |F_i| < N$ (7)
 $P_{t+1} = P_{t+1} \cup F_i$
 $i = i + 1$
 else
 goto 3.5
 - 3.5. Perform crowding distance sort (F_i, α_c) on the current front which is not included in P_{t+1} . Append ($N - |P_{t+1}|$) solutions to $|P_{t+1}|$ having higher order of crowding distance
 - 3.6. Form Q_{t+1} from P_{t+1} using Crowding Distance Tournament Selection (CDTS)
 - 3.6.1. Make random pairs of the solutions (i, j)
 - 3.6.2. For each pair, check $rank(i) < rank(j)$
 True: $Q_{t+1} = i$
 False: if $d_i > d_j$
 $Q_{t+1} = i$
 else
 $Q_{t+1} = j$
 (If solutions are in same front, rank is same. If solution i is in F_1 and solution j is in F_2 , $rank(i) < rank(j)$)
 - 3.7. Perform mutation and crossover on Q_{t+1}
 - 3.8. Calculate the fitness value of different objective functions
 - 3.9. Check for convergence criteria
 True: goto 4
 False: goto 3.1
4. end

This method of solving the multi-objective problem helps to maintain two important aspect of the journey to the optimal solutions: Elitism preserving and Diversity preserving [11].

IV. SIMULATION RESULTS

A. System Configuration

The microgrid system of Fig.3 has been considered as our test system. It consists of Diesel Generator as well as a PV system interconnected to the grid.

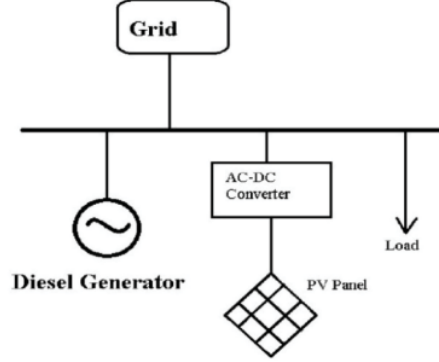


Fig. 3. The system considered for DR computation.

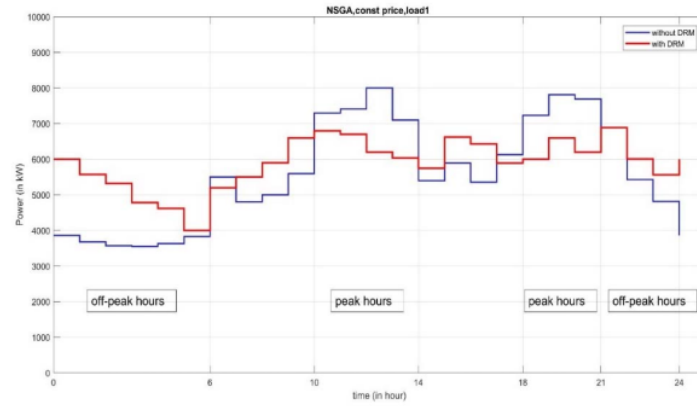
The value of the parameters associated with each unit is as follows:

- $a = 0.02368 \text{ Rs}/(kW)^2h$,
- $b = 16.06 \text{ Rs}/kWh$
- $c = 815.47 \text{ Rs}/h$
- $P_{dg \min} = 100 \text{ kW}$, $P_{dg \max} = 4000 \text{ kW}$
- $L = 10$, $M = 2$
- For load 1:
 $A = 0$, $B = 0.23$, $C = 1$.

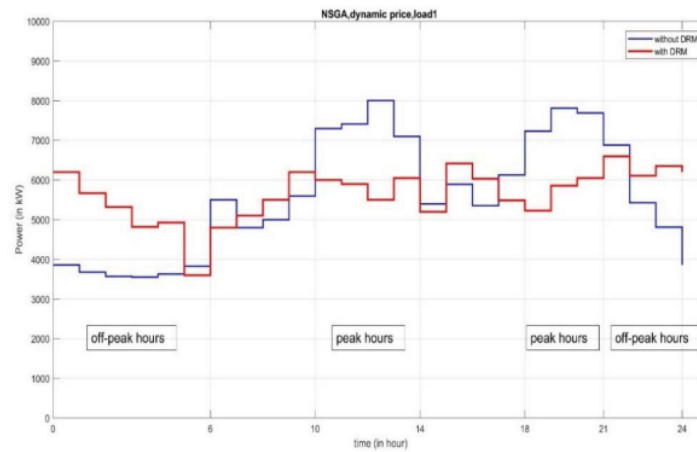
B. Results

Fig. 4 summarizes the load pattern load pattern with and without DRM for load profile 1 using NSGA II, for constant and dynamic grid pricing. It is evident that loads at the peak hours have reduced and shifted to off-peak hours. The peak hours are defined as 10:00 to 14:00 hour and 18:00 to 21:00 hour. Similar curves are obtained for load profile 2, as summarized in Fig. 5, and a similar conclusion can be drawn. It can be clearly observed that the reduction of load is more significant for the dynamic grid pricing scheme as compared to that of the constant grid pricing scheme.

The proposed DRM has the secondary objective (apart from the main objective of peak load shifting) to reward the customers for customizing their loads despite inconveniences. An investigation of cost versus inconvenience in conjunction with two GA's population sizes is illustrated in Fig. 6 and 7. It was found that with a small population size (i.e., 100 in Fig. 6), the application of NSGA II does not lead to significant benefits as compared to SPEA II. The achieved result deviates further from the Pareto front. This situation is made clearer when we compare the results obtained from NSGA II and SPEA II for a larger population (i.e., 500 in Fig. 7).

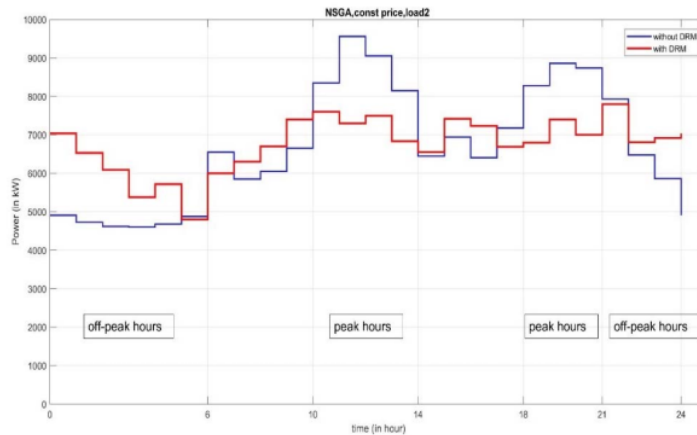


(a)

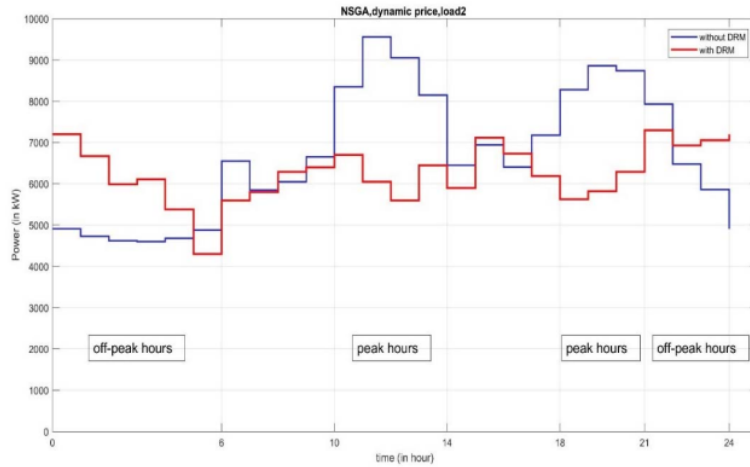


(b)

Fig. 4. The load pattern with and without DRM for load profile 1 using NSGA II for (a) constant grid pricing (b) dynamic grid pricing.



(a)



(b)

Fig. 5. The load pattern with and without DRM for load profile 2 using NSGA II for (a) constant grid pricing (b) dynamic grid pricing.

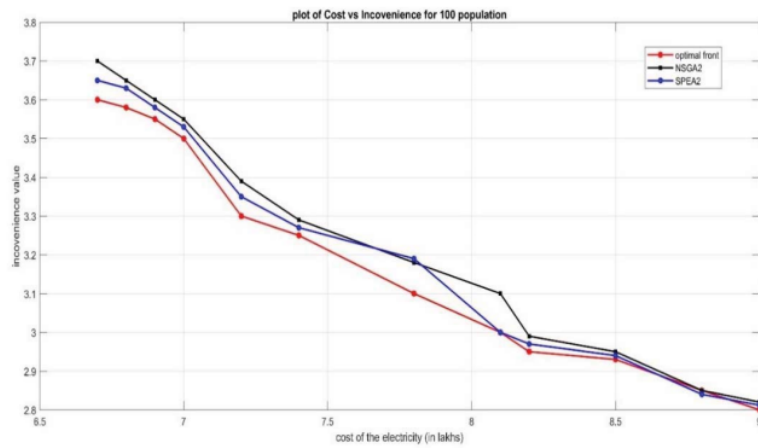


Fig. 6. Plot of Cost vs Inconvenience for NSGA II and SPEA II for a population size of 100.

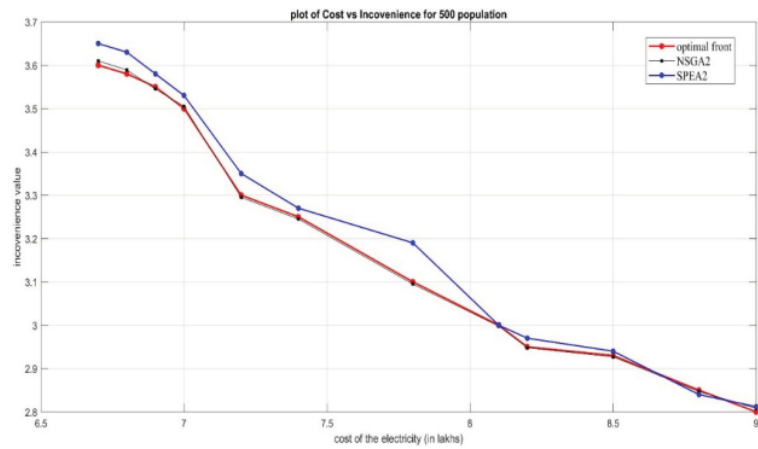


Fig. 7. Plot of Cost vs Inconvenience for NSGA II and SPEA II for a population size of 500.

Fig. 7 shows that the front obtained by NSGA II merges with the reference optimal front and the front obtained by SPEA II deviates somewhat further from the optimal front. It is therefore inferred that when the size of the population is large, NSGA II is a more suitable tool to solve the Demand Response algorithm.

Table 1. A comparison of the parameters associated with DRM using NSGA II.

Quantities	Without DRM	With DRM	% reduction
Total cost of electricity (in lakhs)	8.14	7.4	9.09
Peak demand (in kW)	31500	25700	18.41

Table 2. A comparison of the parameters associated with DRM using SPEA II.

Quantities	Without DRM	With DRM	% reduction
Total cost of electricity (in lakhs)	8.14	7.53	7.49
Peak demand (in kW)	31500	25878	17.84

During 08:00-12:00 hour and 16:00-20:00 hour, the inconvenience is made lower but the cost of power is significantly high. These are called the peak hours of the day here. Schedulable loads can be shifted to the off peak hours like 20:00-24:00 hour depending upon the cost and inconvenience parameter. A comparison of the parameters' values (cost and peak demand) associated with DRM is given in Table 1 and Table 2. The peak hour duration considered is 08:00-12:00 hour. A similar analysis has been done for SPEA II. It can be seen that by implementing DRM (for the dynamic grid pricing case) a reduction of 9.09 % of the total cost of electricity is possible during the peak hours in NSGA II and 7.49 % in SPEA. More importantly, the peak demand is reduced by 18.41 % in NSGA II, and 17.84 % in SPEA. This investigation again shows that that NSGA II performs slightly better as compared to that of SPEA II in both providing incentives to the customers and in shifting/shaving the peak loads.

V. CONCLUSION

The proposed work focuses on a heuristic based Demand Response Management for load scheduling, and consumer satisfaction. Both the SPEA II and NSGA II algorithms are found to give satisfactory convergence at the global minima. Both the algorithms give an optimum captive generation schedule which in overall minimizes the cost borne by the consumers. However, based on the obtained results, it is evident that NSGA II actually performs better in terms of time complexity and accuracy when the size of population is large. In all, it leads to lower cost incurred to the customers, lower load variance, lower peak load, and potentially results in more profits to the utilities.

ACKNOWLEDGEMENT

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REFERENCES

- [1] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid - The new and improved power grid: A survey," *IEEE Communications Surveys and Tutorials*, 2012.
- [2] P. U. Herath, V. Fusco, M. N. Cáceres, G. K. Venayagamoorthy, S. Squartini, F. Piazza, and J. M. Corchado, "Computational intelligence-based demand response management in a microgrid," *IEEE Trans. Ind. Appl.*, 2019.
- [3] L. Gelazanskas and K. A. A. Gamage, "Demand side management in smart grid: A review and proposals for future direction," *Sustainable Cities and Society*, 2014.
- [4] J. Soares, M. A. Fotouhi Ghazvini, N. Borges, and Z. Vale, "A stochastic model for energy resources management considering demand response in smart grids," *Electr. Power Syst. Res.*, 2017.
- [5] M. Parvania, M. Fotuhi-Firuzabad, and M. Shahidehpour, "Optimal demand response aggregation in wholesale electricity markets," *IEEE Trans. Smart Grid*, 2013.
- [6] A. F. Meyabadi and M. H. Deihimi, "A review of demand-side management: Reconsidering theoretical framework," *Renewable and Sustainable Energy Reviews*, 2017.
- [7] S. Nan, M. Zhou, and G. Li, "Optimal residential community demand response scheduling in smart grid," *Appl. Energy*, 2018.
- [8] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response analysis," *IEEE Trans. Smart Grid*, 2012.
- [9] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. S. Fadali, and Y. Baghzouz, "Genetic-algorithm-based optimization approach for energy management," *IEEE Trans. Power Deliv.*, 2013.
- [10] C. R. Raquel and P. C. Naval, "An effective use of crowding distance in multiobjective particle swarm optimization," 2005.
- [11] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, 2002.

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PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6
