Scheduling of demand response program in the presence of retail electricity providers using multi-objective uncertainty-constrained optimization

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This study discusses a new approach to demand response program scheduling (DRP) having retail electricity providers (REPs) with lighter tangible assets. The primary goal of this study is to present an optimal multi-objective function design for integrating REPs into a motivational DRP, while taking into account uncertainty of loads and LMP (location marginal prices). Designing with fuzzy functions are used for load uncertainty and Non-dominated sorting genetic algorithm (NSGA-II) is implemented to find solutions. The optimal compatibility between Pareto front-generated solutions was achieved by using a fuzzy, non-linear attribution method. In order to demonstrate the performance of the proposed model, simulations are performed on the IEEE 24 bus RTS test system. The results have shown that short-run benefits of REPs in electricity markets could be provided and ensured through the designed DRPs.

keywords: *Demand response program, retail electricity providers, locational marginal prices, uncertainty, NSGA-II.*

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1. INTRODUCTION

The space between wholesale electricity markets and final consumers can be bridged by retail electricity providers REPs in market discussions. Besides the forward contracts, the REPs as a mediator role in electricity markets purchase part of the consumer demand through the pool market [1]. Different factors such as volatile loads, price variations, and the effort of market power made by generating companies may bring financial risks to retail electricity providers.

A REP can manage market risks by employing demand response programs. The REPs can propose the selling price in accordance with fixed tariffs, time-of-use price, or actual time price during the contract period. Moreover, due to the risk in the market price, electricity consumers can retain themselves through long-term contracts that are held with REPs. In these circumstances, the REPs are able to perform a blend of methods to control the financial risks to be protected from the wholesale markets' risks [2]. One way to reduce the risk is a well-designed demand response program (DRP). The U.S. DRP is determined as the ability of residential, commercial, and industrial sectors to modify the electrical energy-consumption models as a reaction to variations in electricity costs after a while or to encourage payments to find rational prices and reliability of the network. The DRP could be sorted into two classifications according to this definition [3]: time-based ratios and incentive-based plans. For example, a combination of the time incentive based demand response program, and real-time pricing was presented in [4] in order to decrease the maximum load by energy governance at the customers' side.

For implementing the DRP, consumers must be equipped with smart meters. Finally, DRP could be exploited by the REPs as an alternative which is allowed through smart technology to enhance the anticipated benefit. Moreover, with the modern intelligent technologies in grids and home energy management systems, the DRPs could be effectively used by electricity consumers to moderate some financial risks [5].

Another way to overcome risk is using at peak prices such systems as DG (distributed generation) and ESS (energy storage system) which REPs possess. DG and ESS have lighter tangible assets and when used by ERPs, serve electricity end-users in the distribution level [6]. The effect of ESSs has been studied by many researchers [7, 8] . The authors of [7] have investigated the participation of ESSs in the demand response program by proposing two scheduling algorithms.

Various papers are focusing on REPs for the specification of selling at three short, medium and long-time cycles. References [9, 10] in the long cycle setup present plans to decrease the sum total cost and DPR, intelligent metering technology and to also augment the profits expected from the presented uncertainty model. In addition to that, analysis of studies on middle cycle setups shows that the objective function is minimized cost [11, 12], maximizing benefit [13–15]. Furthermore, the solution technique is based on a hybrid heuristic algorithm or GAMS optimization package. The technique used follows a cross-heuristic problem-solving algorithm or GAMS development plan. Finally, studies on short cycle setups suggest that the factor to increase profit and decrease cost is the objective function. Unlike the two time periods above, real-time pricing, together with stable costs and prices on consumption, are exploited in short cycle setups in place of market prices in short cycles. [16] used real-time pricing in the retail price determination problem in the smart grid to increase retailer profit. The load uncertainty modeling is not considered for LMP in the presented papers. Also, researches have been attempted to introduce DRP in problems of REPs regarding power provision, which follow an optimal pattern with multiple objects. Only, [17] is the only one suggesting an optimized multi-objective design to help retailers plan for managing the load requirements of a body of customers.

In this paper, the short-term scheduling for DRP with asset-light retailers is proposed. The main idea is to determine an optimal for these retail electricity providers to cooperate with them and propose the optimal DRP base on the incentive in the market while having short-time benefits and load uncertainties in mind on locational marginal prices (LMP).It is assumed that the DISTCO's do not participate in the DRP, and only REPs and consumers are involved. Short DRP schedules for light-asset retailers providing electricity for customers use a multi-objective optimization design with practical restrictions in performance. Short-term DRP scheduling of the light-asset retailers who provide the electricity consumers is formulated through a multi-objective optimization model with practical operational constraints. This type of scheduling supports the REPs to decrease the peak periods at the nodes that they provide to the customers. Here, NSGA-II is utilized for multi-objective optimization. By creating a crowding distance sorting, design, it keeps the solutions diverse. The results of sum paper such as [18–22] demonstrated that all three algorithms were able to find a good approximation of the Pareto set of solutions, but differed in the rate of convergence to the optimal solutions. Table 1 shows the references by optimal solutions:

The innovation of this work can be organized as follows:

- Provide an optimal incentive-based DRP to electricity retailers to reduce the financial losses in the market .
- Formulating the short-term scheduling for DRP in the form of an optimization model with multiple objectives .
- The load uncertainty on the LMPs is characterized.

In addition, the main contributions are illustrated as follows:

- Only the retailers and the customers are involved in the proposed DRP.
- Consideration of energy generation and storage unit's effect in the DRP to handle the market price by the electricity retailer.
- Investigation of the demand-side reserve role in the energy market.

This paper is organized as follows sections: Section 2 discusses the multi-objective model to achieve the best short-time DRP scheduling with REPs. This section describes the objective functions and constraints. Section 3 models the uncertainties of the LMPs load. Sections 4 and 5 present optimal multi-objective algorithms, and simulation. Description of the test system and simulation results are in section 5. In section 6 the relevant conclusions are introduced.

2. THE PROPOSED FRAMEWORK

The REPs can employ new instruments and approaches or make use of different strategies to reduce risks linked to the severe market price variations. In this regard, this paper targets to present how a REPs with few generation units, as well as storage employ the DRPs to manage the varieties on the power energy market. Ref [6] was introduced the REPs with light physical assets as an asset-light retailer. If strategies applied by REP to avoid short-term financial or economic losses are well-premeditated, they can obtain additional profits for the REPs. In the smart grids, the DRPs can be exploited for flexible load management to reduce peak load and the purchased energy cost [?]. This study ideally aims to define a model for specifying the financial incentives per hour, which are proposed in the short term. The fundamental goal of this study is to formulate a model to determine the hourly financial incentives suggested to the consumers for a short-term horizon. The short-term DRP scheduling of the asset-light retailers who provide the electricity consumers is analyzed in this paper as a multi-criteria optimization problem that has practical operational limitations. In this model, to avoid the high network costs in the long-term, the REPs have several options to moderate their daily profit. The asset-light REPs contain a lighter tangible asset like DG units as well as ESSs in the distribution network. Batteries have different technology with its economic and technical characteristics. It must be determined which battery type is suitable for a distribution grid. The batteries discussed here are of NaS Sodium-sulfur) and Zn-Br (Zinc-bromine) types [23].

The highest demand offers are determined by the*DG* units' dispatching accords of ESSs for the day ahead. These intentions can affect the optimal financial incentives offered to customers to persuade them to adapt their consumption profile. In order for clarity and simplicity, the assumptions are given below:

- Here REPs are thought of as price taker in the large-scale power provision market. The considered REPs are pricey-taker, which means that it cannot change the electricity prices in the market. Prices in the market behave as an exogenous parameter.
- DGs and ESSs in this model that belong to the retailer, submit power demand offers, and are against providing the large-scale market with their products and power repositories.
- The different types of battery technology are considered.
- The uncertainty of the battery technological behavior for optimal battery planning is taken into account. Fuzzy logic is applied to resolve this decisive problem.
- The load is considered as uncertain parameter. This uncertainty is defined as stochastic models [24].

A. Fuzzy Logic Based Uncertainty Modeling

Different battery technologies show different behavior due to their different characteristics; however, the technical and economic behavior is not deterministic. The uncertainty of the behavior should be considered in a comparative study. Figure

Table 1. Comparing optimization methods

Algorithm	Reference [18]	[19]	[20]	[21]	[22]
Particle Swarm Optimization (MOPSO)	√	√	√	√	√
Non-dominated Sorting Genetic Algorithm (NSGA-II)	√	√	√	√	√
Multi-objective Shuffled Complex Evolution Metropolis (MOSCEM-UA)	√	√	-	-	-
ε-Constraint Method	-	√	-	-	-
Weighted Metric Method	-	√	-	-	-
Multi-Objective EAs (MOEAs)	-	√	-	-	-
Differential Evolution Multi-Objective Optimization (DEMO)	-	√	-	√	-
Other	-	√	-	-	-
Best algorithm	∼NSGA-II	-	NSGA-II	DEMO	NSGA-II

1 shows the uncertainty of the deposit price charts in form of boxes. Each box has data segments. For example, the data as an example, average (median), the interquartile range (middle fifty), and range4 (except outliers) is presented [24].

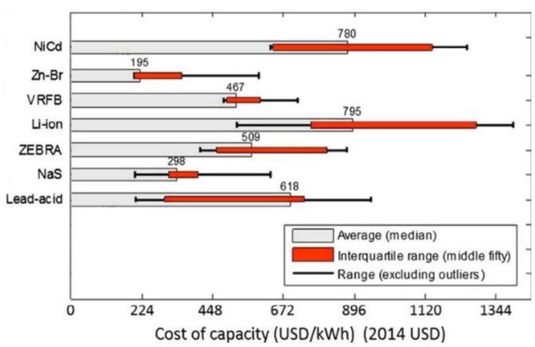

Fig. 1. Variations of capacity cost as well as the average.

The range (except outliers) or the middle fifty is used for modeling uncertainty, while the median data is used in deterministic studies. Thereof, using fuzzy logic we have defined two amounts for each factor. Figure 2 presents the range (apart from outlying sections) and triangular fuzzy amounts for the fifty at the center. The two models indicate that the average price is allotted to the optimal membership function [25].
The middle fifty models contain possible situations. When using the model of range (excluding outliers), the uncertainty intensifies [26, 27].

B. Battery Technologies

Rechargeable batteries are categorized into several types based on their structures, used materials, and the mechanism of storage. Any kind of battery has its planning criteria. Capacity cost in $/kWh, power rating investment cost in$/kW, prices of battery replacement in $/kWh, yearly O & M costs in $/kW, total efficiency, maximum depth of charge limit, and the total length of life, indicated in the number of charge/discharge cycles, are the critical considerations for optimal battery sizing. We have concentrated on Sodium-sulfur batteries' (NaS) and batteries with Zinc-Brome (ZnBr) characteristics of this research. Reference [28] gives a complete review of these technologies with detailed technical and economic considerations.

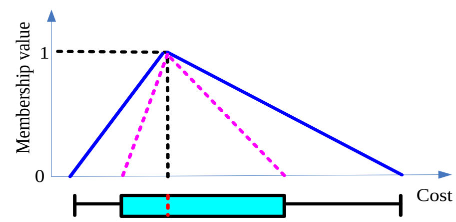

Fig. 2. Dedication of triangular fuzzy membership to a box plot.

C. Objective Functions

The objective functions are considered as REP's payoff and total peak demand as follows.

C.1. REP's Payoff based Objective Function

The retail electricity providers through their facilities of production/depositories in the distribution grids and DRP_s, can help short-time payoffs grow. Employing this model, the REPs will tend to use their resources when the costs are at their highest. The first equation shows the ESSs' charging energy is a market-provided and the LMPs' uncertainty is used to estimate the charging price. The costs of startup and polynomial function make up charges of DG units [29]. The first objective function that will be maximized is as follows:

$$Payoff_x = \sum_{b\in\Omega_x}\sum_{t=1}^{T}\left[\sum_{c\in\Omega_x^{b-c}}\left[\begin{array}{l}(R_c^t.(I_c^t-\Delta I_c^t)) - LMP_b^t.w_d^t - \\ CG(t) - CDG(t) - CESS(t) - FI(t)\end{array}\right]\right] \quad (1)$$

Where,

$$CG(t) = \sum_{g\in\Omega_x^{b-G}} (\alpha_g.u_g^t + \beta_g.P_g^t + \gamma_g.(P_g^t)^2 + c_g^{start}.v_g^t) \quad (2)$$

$$CDG(t) = \sum_{i\in\Omega_x^{b-DG}} c_g^p.P_g^t \quad (3)$$

$$CESS(t) = \sum_{s\in\Omega_x^{b-ESS}} c_s^{\deg}.P_s^{out,t} \quad \textbf{(4)}$$

$$FI(t) = \sum_{c\in\Omega_x^{b}} (Fi_b^t.\Delta I_c^b.m_c^t) \quad \textbf{(5)}$$

Where t indicates the time duration (per hour), b indicates buses, c indicates the end consumers, g indicates the number of DG_s, s is the number of ESSs, p_g shows the g^{th} DG unit power product(kW), u_g is the binary variance showing the g^{th} DG unit commitment state (1 means the unit is working), v_g is the binary variance that indicates g^{th} DG initialization state (1 means the unit begins working at t^{th} time), $p_s^{(in/out)}$ is the charging and the discharging status of ESSs power during the time periods (kWh), m_c is the binary variance of the time periods at which the retailers should provide their customers incentives (1 means the retailers are to send incentives to customer c^{th}). FI indicates fiscal incentives of DR in DAM(dollar per kilowatt-hour), $\triangle_1$ is the decrease in demand anticipated for c^{th} consumer(kilowatts), T is the time horizon for scheduling (in number of time periods), α, β, andγ are polynomial values for coefficients of g^{tj} manageable DG unit (dollar per hour, dollar per kilowatt-hour, dollar per $((kilowatt - hour)^2)$, c_g^{start} indicates the cost of startup the g_{th} controllable DG unit (dollar), c_g^p is production cost of the g_{th} uncontrollable DG unit (dollar per kilowatt-hour) and R_c is the electricity price offer by retailers.

C.2. Peak Demand based Objective Function

Given the high upstream market price at peak time, the secondary target function is considered to prevent the peak load from increasing due to the high market price. The secondary objective function is to reduce the total load of buses under the retail contract second objective function aims to minimize the overall maximum load of all nodes served by REPs, according to Eq. (6).

$$CF2 = \sum_{b=1}^{N_b} M_b \quad \textbf{(6)}$$

Where M_b is the peak demand at bus b.
The stochastic models of loads are generated by using Eq. (7) [30]:

$$L(h) = L_m(h) + \sigma(h).N_h(0,1) \quad \textbf{(7)}$$

Where L_m is expected load, (σ) is standard deviation are given in Fig. 3. h index is hour and $N_h(0,1)$ are independent values drawn from the normal distribution.

D. Constraints

The constraints of the proposed objective functions are explained as follows:

D.1. Purchase Limit

Eq. (8) is applied to the objective function (6) and serves to lower the highest charge per bus.

$$w_b^t = \sum_{c\in\Omega_x^{b-c}} (I_c^t - \Delta I_c^t) + \sum_{s\in\Omega_x^{b-ESS}} p_s^{in,t} - \sum_{s\in\Omega_x^{b-ESS}} p_s^{out,t} - \sum_{g\in\Omega_x^{b-G}} p_g^t - \sum_{g\in\Omega_x^{b-DG}} p_g^t \ \forall t, \forall b \quad \textbf{(8)}$$

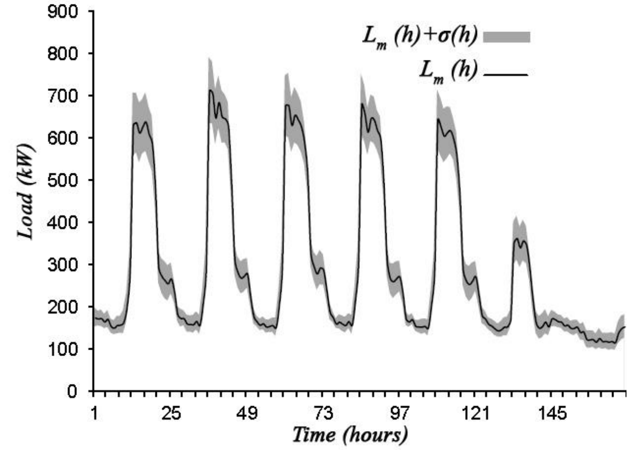

Fig. 3. Stochastic model of the customer load [30].

$$w_b^t - M_b \leq 0 \ \forall t, \forall b \quad \textbf{(9)}$$

Where w_b is the electrical energy which is provided by large-scale trader at the bus b (kilowatt).

D.2. Real Power Generation Limit

The proposed model assumes that the generated electricity of DG units is as high as their maximum installed capacity. The lower and upper bounds of any DG unit limit the active power output as follows:

$$P_g^{\min}.u_g^t \leq P_g^t \leq P_g^{\max}.u_g^t \quad \textbf{(10)}$$

Where $p_g^{Min/Max}$ indicates the highest and lowest electricity outputs by the g^{th} DG unit (kilowatt). Constraint (12) demonstrates the relation between the unit commitment and binary decision variables of the startup, shut down.

D.3. Battery Limit

The charging/discharging power of a battery has been enclosed by the capacity and the rated power of ESS [?].

$$p_s^{out,t} \leq R_s^{out,\max}.k_s^t \quad \textbf{(11)}$$

$$p_s^{in,t} \leq R_s^{in,\max}.h_s^t \quad \textbf{(12)}$$

$$E_s^{\min} \leq E_s^{stored,t} \leq E_s^{\max} \quad \textbf{(13)}$$

$$E_s^{\text{storedt}} = \eta_s^{in} \cdot P_s^{m,t} - \frac{1}{\eta_s^{out}} \cdot P_s^{\text{outt}} + \lambda E_s^{\text{storsdt-1}} + (1-\lambda) E_s^{\text{unitiny}}$$
$$\lambda = \begin{cases} \lambda = 0 & t = 1 \\ \lambda = 1 \text{ other} \end{cases} \quad \textbf{(14)}$$

$$k_s^t + h_s^t \leq 1 \quad \textbf{(15)}$$

where $E_s^{(min/max)}$ is the minimum/maximum levels of sth ESS storage (kWh), $R_s^{(in,min/max)}$ is the minimum/maximum rate of the sth ESS charging (kW/h), $R_s^{(out,min/max)}$ is the minimum/maximum rate of s^{th} ESS_s discharge (kW/h), and k_s is

the binary variable indicating the status of the sth ESS discharging. (1 means it is being discharged), h_s is a binary variable which indicates charging status of the sth ESS (1 means it is being charged) and E_s^{stored} is the storage level of the s^{th} ESS at the end of each time (kWh).
Eq. (14) indicates the discharging and charging power at each point in the cycle. The imposed limit of Eq. (15) excludes the simultaneous charge/discharge activities in any period.

D.4. Financial Incentives Limitation

The incentives of the DRP are suggested only for hours that the customer when the expected customer load consumption is higher than the average. A stream of revenue could be reached with the customer within this step. Each kWh, which is less than the forecasted load is rewarded by the REPs for the hours that the retail electricity providers offer financial incentives. The limitation is expressed as below:

$$\begin{aligned} &\Delta I_c^t = m_c^t \cdot f_c\left(Fi_c^t\right) \\ &m_c^t \cdot Fi_c^{\min} \leq Fi_c^t \leq m_c^t \cdot Fi_c^{\max} \end{aligned} \quad (16)$$

3. IMPACT OF LOAD ON LMPS

Locational marginal price is referring to the marginal price of providing the subsequent increment of electrical power at a particular bus while regarding the marginal cost of production and the physical features of the transmission system. The distinction among the prices of the produced energy $c(p)$ and the consumers' benefits $B(p)$ is social welfare:

$$SocialWeifare : \sum B(p) - C(p) \quad (17)$$

The clearing cost is managed by optimizing (18) using Independent System Operator (ISO) having system limitations in mind. Usually $B(p)$ does not have a specific, or an uncomplicated equation. $B(p)$ is consequently overlooked and the function below is decreased to the minimum (in accordance with the negative symbol) [31]:

$$\min\left(\sum_{i=1}^{n} C_i(p)\right) \quad (18)$$

where $C_i(p)$ is the function for all of the power generators' costs, determined by this formula: $C_i = ap^2 + bp + c_0$ Where n represents the number of power generators and the produced power is represented by P. DCOPF [32] may solve the formula [33]. Below is the Lagrange function for the programming of the problem.

$$\begin{aligned} l = &\sum_{i=1}^{n} C(I_i) + \sum_{i=1}^{n} \pi_i \left[I_i - \sum_{j=1}^{n} Y_{ij}(\theta_i - \theta_j)\right] + \\ &\sum_{i=1}^{n}\sum_{j=1}^{n} \mu_{ij}\left[P_{ij}^{\max} - Y_{ij}(\theta_i - \theta_j)\right] \end{aligned} \quad (19)$$

In (18), is the LMP for the bus i, is the bus angle i, Y_{ij} is the component of row i and column j in the admittance matrix, is the coefficient associated with the spot price and I_i is the injected power. It should be noted that DC load stream determines that the power loss costs are overlooked [31, 32].

4. MULTI-OBJECTIVE SOLUTION METHODOLOGY

Non-dominated sorting-based technique has been integrated into the genetic algorithm for optimizing the multiple-criteria problems. The multiple-criteria solution process is adjusted through taking into account the constraint of Pareto solutions. Therefore, in this study, the multi-objective problem has been analyzed through the programmed NSGA-II, since it has been shown to be one of the most efficient algorithms which is exposed to some limitations. The formulae of the problem with m objective functions subject to several conditions that are usually contradicted together is estimated in the following way:

$$Optimize \quad [F_1(x,\ u), F_2(x,\ u), ..., F_{NP}(x,\ u)] \quad NP = 1, 2, ..., m \quad (20)$$

In order to operate this process, primary population is provided via randomly producing the control variables. The objective functions are assessed and this is followed by applying a non-dominated sorting process to estimated solutions for getting a Pareto set.
Comparison pattern could obtain the most effective Pareto set. For categorizing the largest solutions in the optimum Pareto set, sorting procedure has been exploited. In order to choose the largest compromised solutions on the basis of the problem needs, fuzzy based decision mechanism has been employed.

A. Non-Dominated Sorting

Sorting through non-dominated techniques to achieve the best Pareto series is applied to the multi-objective expansion. F1 and F2 are supposed solutions in one optimal Pareto series. Evaluation of these solutions leads to two probabilities: either one of them overpowers the other one or none of them. When the conditions are met, design A shows the example of u1 overpowering u2:

$$\begin{aligned} &\forall i = 1, 2, \ldots, m \quad F_i\left(u_1\right) \leq F_i\left(u_2\right) \\ &\exists j = 1, 2, \ldots, m \quad F_j\left(u_1\right) \leq F_j\left(u_2\right) \end{aligned} \quad (21)$$

The best solutions of Pareto sets are identified through the sorting process. There are solutions found which are non-dominated and are considered the most efficient fronts of Pareto series.

B. Fuzzy-based Decision Making Rule

A decision is designed on which the optimal solution for Pareto sets is concluded. Decision making, using fuzzy logic may obtain the most efficient answer for Pareto series. Equation (22) shows providing for the membership function for the i_{th} objective [34?] solution for the j_{th} set.

$$\mu_i^j = \begin{cases} 1 & F_i^j < \min\left(F_i\right) \\ \frac{\max(F_i) - F_i^j}{\max(F_i) - \min(F_i)} & \min\left(F_i\right) \leq F_i^j \langle \max\left(F_i\right) \\ 0 & F_i^j > \max\left(F_i\right) \end{cases} \quad (22)$$

Equation (??) calculates the Pareto front set q_{th}.

$$\mu_{opt} = \sup \left\{ \frac{\sum_{p=1}^{m} W_p \, \mu_p^q}{\sum_{q=1}^{N_{PFS}} \sum_{p=1}^{m} W_p \, \mu_p^q} \right\} \quad \textbf{(23)}$$

where wg indicates the weight relation to the pth fitness objective function and NPFS the sum total of solutions for the optimal Pareto sets. Standardized rates determine the desired solutions.

C. Optimization Procedure

Control variances take part in the suggested multi-objective REPs design. The determination procedure is used for the algorithm to begin with attainable values for ESSs power deposit, production rate of DG units, financial motivation and every time presents the nominees for recombination and mutation operations [35]. One of the control variables is Mb which is obtained by constant dispersions. The highest demand at every bus during planning to supply demands and costs for ESSs is taken into account. Throughout the determination process, there are binary control variables produced at random. A few of these explain how affiliated DG units are committed, and others are concerned with financial motivations to decrease demand. The flowchart for a suggested approach to REPs multi-objective problems in short-run commerce is presented in Fig. 3.

5. SIMULATION RESULTS

In this section, to engage electricity providers the IEEE 24 bus accuracy examination is adapted. The assumption is that every retailer serves loads on many buses. In addition, the allocation grid, which is linked to that particular bus helps to determine the assets. The buses to which a retailer serves load and is linked are represented in Fig. 4 by red lines.
The retailers work as a transmitter and serve the consumers in the allocation grids. Retailers establish the procedure which corresponds to LMPs subject to chance variation and the uncertainty which exists in the way the load is consumed. Rechargeable batteries are placed into different categories according to their composition and depository mechanics. Every category is different in their programming aspects. The Data of ESSs features of retailers are taken from [28]. The buses to which the retailers serve load may contain single or multiple ESSs. Features of DG units belonging to individual retailers are shown in Table 2. Four retailers which are arranged as load-servers and are charge-receivers are selected to evaluate the best cycle. The evaluation systems have buses assigned at which the retailers deal with 30 customers.
Fig. 5 represents the demand of each customer cluster with no uncertainty. Additionally, the consumers have contracts with power distributors and rates are determined beforehand. Fig. 6 illustrates the rates of contracts between costumers and retailers. This chapter deals with the day-ahead, the probabilistic LMP and demands for charge to design a 24-hour schedule.

Table 3 shows the data used to determine the best DR cycles. The assumption is that the retailers may be suitable in a quadratic regression function. This table also shows the function coefficients that represent how flexible the final consumers are towards fiscal motivations at times of decreasing demand.

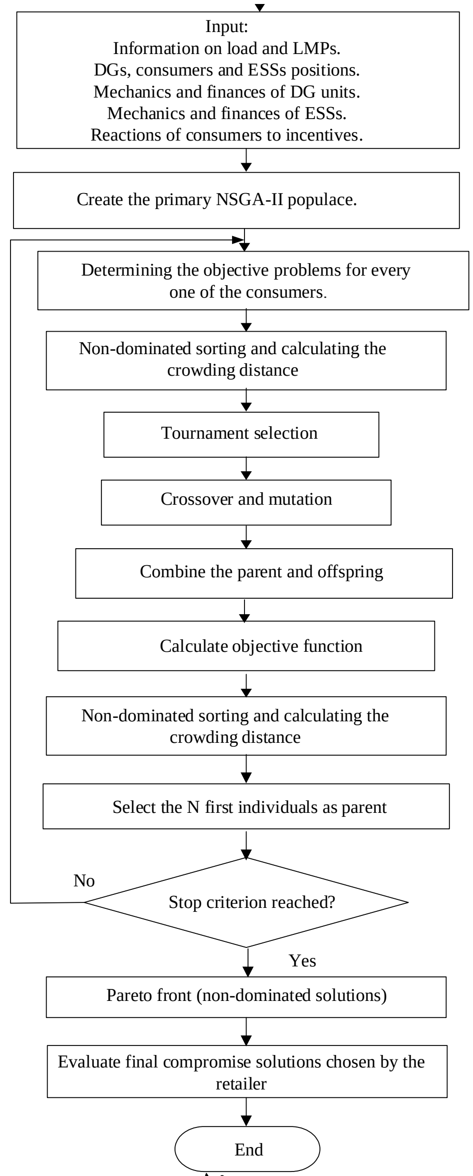

Fig. 4. Flowchart for an optimization function with multiple criteria for the market.

Constant correspondence between retailers and consumers regarding electricity provides retailers with such useful understandings. In addition, this table depicts the bus that determines each customer. The best battery types are identified through two case studies in this paper. The primary goal in the first case is to indicate how effective the suggested model and the NSGA-II algorithm are as solutions for transitory problems which the power providers using NaS batteries face. The second case study did the same for providers using Zinc-Bromine batteries.
In order to verify the simulation method, at first, the model has been developed based on the reference paper [33], and a comparative study has been implemented. Then the improved model has been extended.

Case study 1:
This section deals with the optimization problem with multiple

Table 2. Technical characteristics as well as the costs of DG units

Retailer	DG Unite	Capacity (kW)	Minimum Generation (kW)	Initial commitment status	A	B	C	Startup cost	Buses
1	1	156	18	0	14.628	0.1023	0.00003526	16.25	4
	2	95	10	1	11.21	0.0958	0.00006917	18.26	4
	3	182	25	0	115.508	0.086	0.00009066	9.57	5
	4	108	8	0	9.885	0.0983	0.00004431	12.32	5
2	5	300	25	0	9.563	0.0792	0.00014945	15.75	14
	6	180	41	1	10.838	0.0761	0.00024363	6	22
	7	260	15	0	15.938	0.0964	0.00007146	10.5	5
	8	92	10	1	5.738	0.098	0.0002991	18	11
3	9	98	12	0	16.25	0.0946	0.00030041	21.31	22
	10	112	26	0	11.32	0.1032	0.00014991	15.42	6
4	11	218	31	1	13.869	0.0918	0.00014784	18.5	24
	12	163	45	1	10.173	0.0724	0.00029173	12.8	24
	13	184	17	0	19.581	0.0811	0.00018401	9.5	3

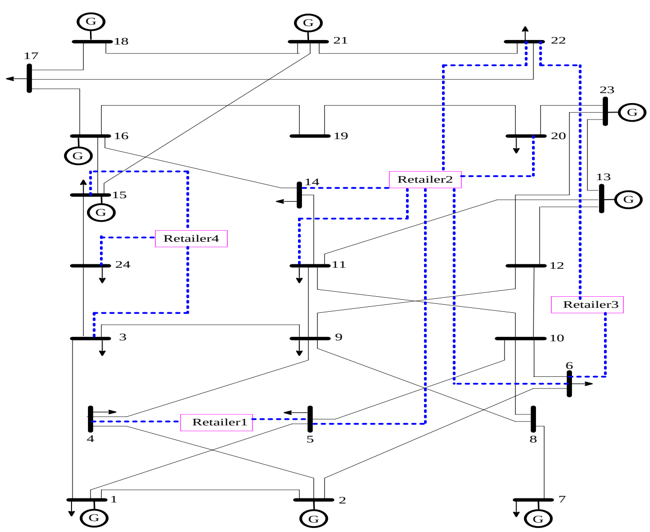

Fig. 5. Flow Modified IEEE 24 bus Reliability case study.

objects using NSGA-II for a solution. The batteries are NaS types. Solution of problem Pareto front is shown in Fig. 7. Experimental reproductions assigned the proper values for algorithm factors. Optimal values regulating crossover and mutation operations were determined and show in Table 4. Fiscal motivations proffered by first retailer are shown in Table 5.

Case study 2: NSGA-II gathered the Pareto fronts from every retailer, using Zinc-Bromine batteries which are shown in Fig. 8. According to the table, retailers 3 and 4 should anticipate day-ahead fiscal failures (i.e. financial damage) in the market. There are procedures to reduce damages, but none can result in any gains. The optimal positions are illustrated in Fig. 8 by the pointers. The comparison is made between the results and the situation that the retailer implements the DR programs and all of the physical assets. Analyzing DR programs or ESSs separately, a short-range replacement of optimal points in the Pareto front is observed. The range is short because ESSs have restricted charges, discharges and capacities and also the limit to which the consumers would decrease their use. In addition, decision makers can have a wider extent to choose from if assets and processes are analyzed with DG units based on distribution grid. Clearly, batteries with a Zinc-Bromine core are better suited for riskier cases than Sodium-Sulfur batteries.

6. CONCLUSIONS

In this paper, the problem of determining the optimal strategy of a retailer's performance in maximizing its profit margin is investigated as the primary objective as well as minimizing the aggregate peak loads under the retailer contract as a secondary objective. The options available to the retailer to meet their contractual committed load include (1) power purchase from the upstream network, (2) power generation by dispersing generation resources or self-storage, and (3) encouraging customers to reduce their consumption. The upstream market uncertainties were also investigated in the simulation considering two Na-S and Zn-Br battery technologies.
Simulation results were presented, including the amount of incentives allocated to customers, the amount of production of distributed generation resources, and the amount of charge and discharge of storage resources at different times of the day in the optimal strategy.
The selected optimal points are expected payoff 1220 ($) in maximum demand 5580(kWh) for retailer (1), expected payoff 1050 ($) in maximum demand 19400 (kWh) for retailer (2), expected payoff -60 ($) in maximum demand 4360(kWh) for retailer (3), expected payoff -725 ($) in maximum demand 5650 (kWh) for retailer (4). By using the proposed framework, the REPs have the ability for trade-off decisions when there are contrary goals as to reducing the highest demand and optimizing the benefits for enhancing motivational DRP in markets.
Fuzzy logic modeling is employed for simulating load uncertainty on the locational marginal prices. $NSGA-II$ has been exploited regarding the complexity and non-linearity of the pro-

Table 3. DR characteristics of end-users

Customers	Baseline load	A2	A1	A0	Minimum incentive	Maximum incentive	Buses
1	1250	659051.76	-38968	511.24	0.0186	0.0514	4
2	1300	-173868.8	23179.4	-433.3	0.0242	0.0526	4
3	950	144351.38	-7783.9	105.7	0.0195	0.0632	5
4	550	34860.79	1292	-41.04	0.0268	0.0578	5
5	1000	507581.06	-38942	620.2	0.0209	0.0676	5
6	780	259722.48	-15808	268	0.0273	0.0493	14
7	1000	17087.38	2198.7	-12.81	0.0364	0.058	14
8	1450	-323228.5	36284.9	-795.4	0.0362	0.0578	14
9	1350	-60611.03	9572.42	-165.8	0.0419	0.0632	20
10	1500	-323835	37347	-860.4	0.0372	0.0587	22
11	1250	-418218.2	47406.3	-1173	0.0404	0.0617	22
12	650	424638.1	-30095	572.8	0.0282	0.0501	22
13	1350	-156061.7	16426	-176.7	0.0289	0.0508	6
14	1500	-687791.4	68344	-1453	0.037	0.0585	6
15	1200	-955117.6	92717	-1944	0.0357	0.0573	5
16	1250	-338477.5	32567.7	-521	0.0265	0.0485	11
17	1200	2157991.5	-201295	4646	0.0378	0.0593	11
18	950	-55310.98	9798.6	-168.9	0.0304	0.0522	11
19	1250	-40451.16	6994.44	-116.4	0.0388	0.0602	11
20	800	37968.77	-29HI	34.51	0.029	0.0509	11
21	1550	-996162.4	84506.6	-1533	0.0267	0.0454	22
22	575	-89542.85	11355.2	-247.4	0.031	0.0659	6
23	1550	-15900.84	8655.4	-211.8	0.0293	0.0547	6
24	1100	207895	-11170	180.3	0.0297	0.064	15
25	605	187256.7	-10889	164.9	0.022	0.0528	15
26	1250	-271774.8	28120.3	-502.2	0.0248	0.0466	24
27	412.5	-199752.3	19079	-334.9	0.0255	0.0536	24
28	698	-154248.6	17154.3	-306.5	0.0246	0.0572	24
29	450.5	-10023.81	3219.4	-85.65	0.0367	0.0717	3
30	495.5	212974.62	-16100	343.5	0.0359	0.0563	3

Table 4. Optimal factors for a24 cycle

Factors	Values
Populace	1500
Repeats	1250
Crossover probability	0.8
Mutation Probability	0.3
Mutation degree	0.03
Mutation intensity	10% of the variance range (max-min)
σ (scope of arithmetic crossover)	0.03

posed pattern. The amended IEEE 24 bus reliability case study discoveries depict that the short-run benefits of REPs in electricity markets could be provided and ensured through the designed DRPs.

On the other hand, with the penetration of renewable resources at the distribution network level, including at the customer level, and the development of the prosumer concept, the creation of a local market mechanism for the purchase and sale of energy is considered at the distribution level.

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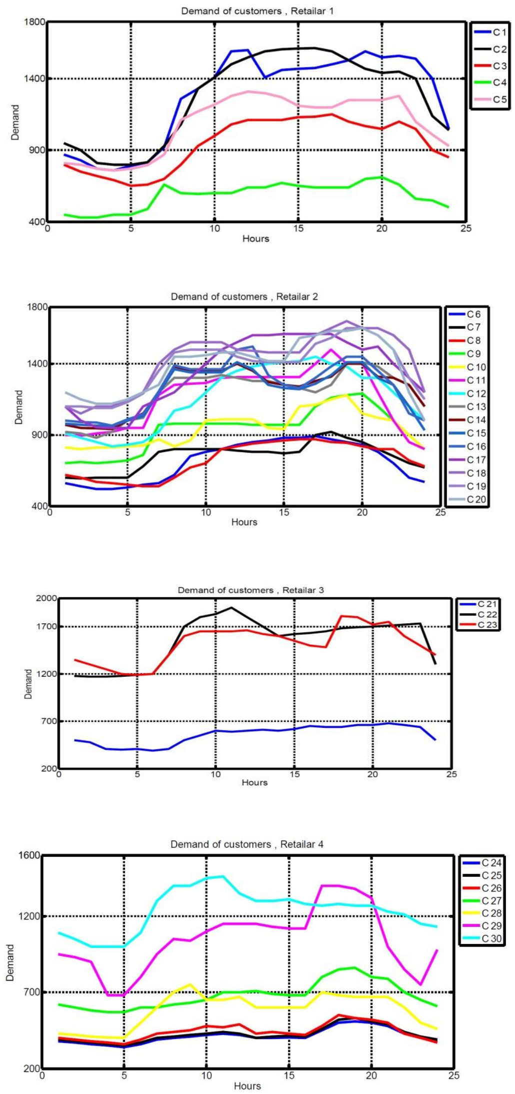

Fig. 6. Demand for any customer group without uncertainty.

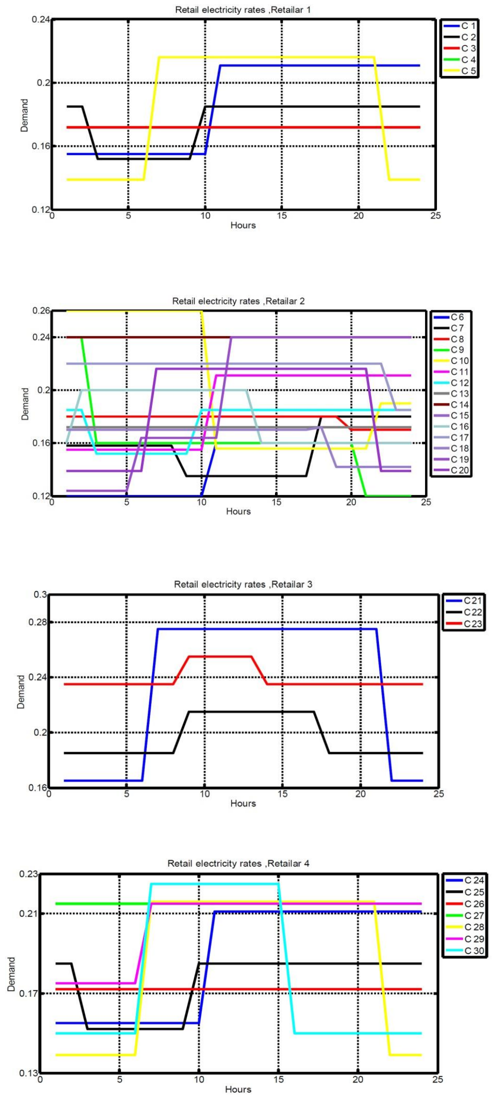

Fig. 7. Demand for any customer group without uncertainty.

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Table 5. The fiscal motivations offered to the customers by first retailer ($) in case 1

bus	C 1	C 2	C 3	C 4
8	-	-	-	0.0634
9	-	0.0549	-	0.0612
10	-	0.0551	-	0.0629
11	0.052	0.0563	-	0.0641
12	0.0514	0.0539	-	0.061
13	0.0503	0.053	-	0.0596
14	0.051	0.0572	-	0.061
15	0.0547	0.0589	-	0.0539
16	0.0512	0.0551	-	0.0608
17	0.0513	0.0564	-	0.0642
18	-	-	-	0.0626
19	0.0543	0.057	-	0.0614
20	-	0.0593	-	0.0653
21	0.0505	0.0585	0.592	0.0684
22	0.0544	-	-	0.0669
23	0.0536	-	-	0.0639

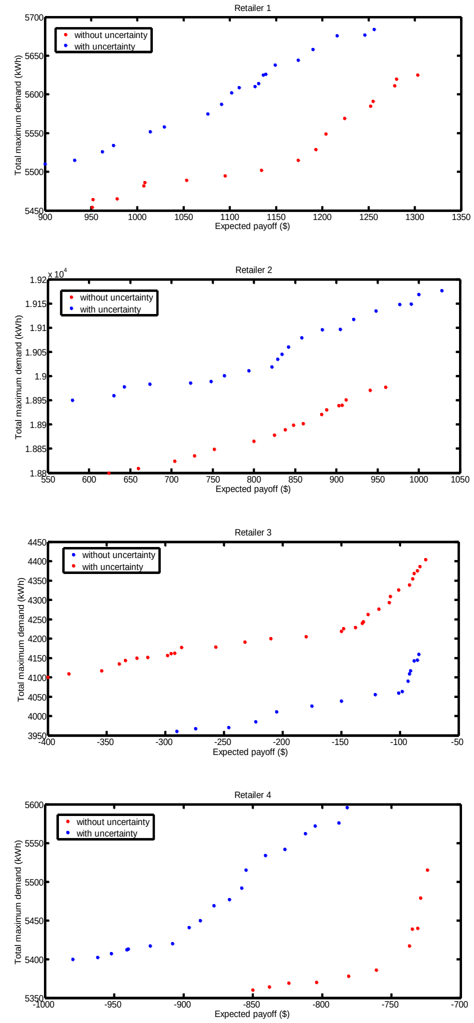

Fig. 8. Pareto front for retailers at case 1.

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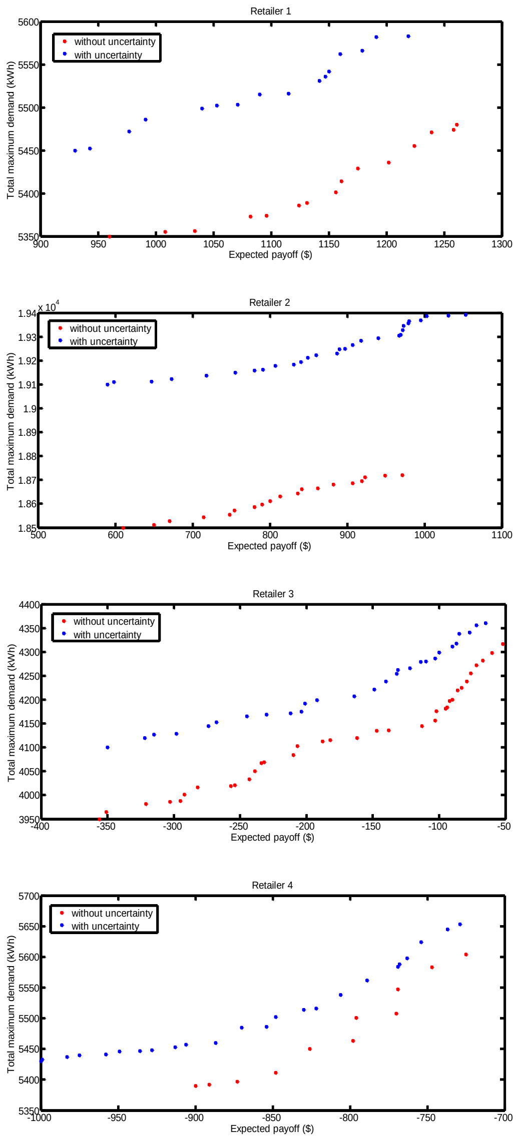

Fig. 9. Pareto front for retailers at case 2.

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