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Appraisal of eco-friendly Preventive Maintenance scheduling strategy impacts on GHG emissions mitigation in smart grids

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A B S T R A C T

The electricity sector as a crucial source of GHGs (Greenhouse Gases) plays a pivotal role in energy and climate policies. In this regard, specialists endeavor to present a comprehensive and efficient plan including environmental as well as economic aspects. However, in a smart energy system, an ability to control both supply-side and demand-side is provided. This paper presents a methodology of economic and emission PM (Preventive Maintenance) scheduling while concentrating on DRRs (Demand Response Resources) as one of the aspects of smart environments to handle emitted GHGs and expenditures. The nominated structure aims to minimizing system expenditures as well as GHGs emissions over the time horizon. In one hand, PM scheduling is a highly complicated problem and, DRRs consideration makes it even more complicated; overcome this complexity, the problem is implemented in GAMS (General Algebraic Modeling System) environment. Furthermore, the compromise between multifarious targets is performed by Entropy technique to reflect system conditions, while arbitrary compromising cannot be an acceptable solution. In order to evaluate the capability of DRRs in declining GHGs as well as expenditures, it has been applied to IEEE-RTS. The results indicate that considerable reduction is occurred by increasing the number of DRRs in the system.

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1. Introduction

Over the past century, human activities have released large amounts of pollutants and other GHGs (greenhouse gases) into the atmosphere. The majority of GHGs originates from fossil fuels burning to produce energy especially in electricity sector. Hence, optimal planning of electricity sector ranging from short-term to long-term is contemplated as a crucial issue in energy policy decisions.

Generation PM (Preventive Maintenance) scheduling is an essential requirement of power system planning which plays an important role in reducing unanticipated events ratio, improving system performance, and prolonging capital expenditures (Ghazvini et al., 2013; Mollahassani-pour et al., 2015a). Generally, target of the PM problem is contemplated based upon economic criterion (Mollahassani-pour et al., 2015a; Abirami et al., 2014; Canto, 2008; Marwali and Shahidehpour, 1998; Saraiva et al., 2011) or reliability criterion (Ekpenyong et al., 2012; Reihani et al., 2012; Schlünz and Van Vuuren, 2013; Volkanovski et al., 2008; Yare and Venayagamoorthy, 2010). On the other hand, generation PM scheduling is a large scale, non-convex and mixed integer combinatorial optimization problem which has been solved via multifarious mathematical and heuristic techniques; mathematical techniques include branch and bound (Booth, 1983; Dopazo and Merrill, 1975; Egan et al., 1976), dynamic programming (Yamayee et al., 1983; Zurn and Quintana, 1975), benders decomposition (Canto, 2008; Marwali and Shahidehpour, 1998). The heuristic methods are Tabu search (El-Amin et al., 2000), fuzzy logic (El-Sharkh et al., 2003), evolutionary programming (El-Sharkh and El-Keib, 2003), simulated annealing (Saraiva et al., 2011; Schlünz and Van Vuuren, 2013), genetic algorithm (Reihani et al., 2012; Volkanovski et al., 2008), particle swarm optimization (Yare and Venayagamoorthy, 2010; Samuel and Rajan, 2015), ant colony (Foong et al., 2008), clonal Selection (El-Sharkh, 2014; Elyas et al., 2013). Currently, in most cases, GAMS (General Algebraic Modeling System) as a commercial solver is also implemented to solve such a complicated problem (Mollahassani-pour et al., 2015a; Conejo et al., 2005; Mollahassani-pour et al., 2015b).

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Nomenclature

Variables

$E^i(.)$	Emissions function of a unit in a period
$E^i_k(.)$	Generation of k^{th} segment in linearized emission curve of a unit
$f^L(.)$	Active power flow of a line in a period
$\overrightarrow{f^L}(.)$	Vector of active power flows in a period
$\overrightarrow{g}(.)$	Vector of generated active power in a period
$G^i_c(.)$	Generation cost function of a unit in a period
$G^i_k(.)$	Generation of k^{th} segment in linearized generation cost curve of a unit
inc^b_{opt}	Incentive of DRPs in b^{th} bus at a period
$loss(.)$	System losses in a period
$Pr^b_0(.)/Pr^b_{DR}(.)$	Electricity price of b^{th} bus in a period before/after implementing DRPs
pen^b_{opt}	Penalty of b^{th} bus in a period
$\overrightarrow{r}(t)$	Vector of load curtailments
$r^b(.)$	Load curtailment of b^{th} bus in a period
$rl^i(.)$	Reservation level of a unit in a period
$u^i(.)$	Commitment status of a unit in a period
$z^i(.)$	Maintenance status of a unit in a period
$\sigma^b_k(.)$	Award of k^{th} segment in linearized total incentive curve of b^{th} bus
$\phi^b(.)$	DRPs status of b^{th} bus in a period
$\rho(\Delta D^b(.))$	Total incentive to customers' of b^{th} bus in a period
$\varpi^i(.)$	Maintenance starting time

Parameters

$D^b(.)/D^b_{DR}(.)$	Demand of a bus before/after implementing DRPs in a period
$\overrightarrow{D^b}(.)$	Vector of demand in a period
$E(t,t)/E(t,j)$	Self/cross elasticity
$\underline{E}^i$	Lower limit on the emission of a unit
$\overline{f}^L$	Maximum capacity of a line
$\underline{G}^i_c$	Lower limit on the generation cost of a unit
$\overline{G}^i_k(.)$	Maximum generation in k^{th} segment
$\overline{inc}^b(.)/\underline{inc}^b(.)$	Maximum/minimum incentive level in b^{th} bus
$\overline{N}_{DRR}(.)$	Maximum number of DRRs in a period
$\overline{P}^i(.)/\underline{P}^i(.)$	Maximum/minimum generation capacity of a unit
s^T	Node branch incidence matrix
$SRC(.)$	System reserve capacity in a period
ε	Accepted level of expected curtailments
$\hbar^b_1, \hbar^b_2, \hbar^b_3$	Incentive coefficient of DRPs in b^{th} bus
Λ^i_k	Slope of k^{th} segment in linearized generation cost curve
Γ^i_k	Slope of k^{th} segment in linearized emission curve
π^b_k	Slope of k^{th} segment in linearized incentive curve
μ^i_c	Reserve capacity cost of a unit
$\underline{\sigma}^b_{inc}$	Lower limit on award of b^{th} bus
$\overline{\sigma}^b_k(.)$	Maximum award in k^{th} segment
λ^i_c	Maintenance cost of a unit
ψ^i	Maintenance duration of a unit
$\upsilon(.)$	Maximum number of under inspection units in a period
ξ	Nominal potential for participating customers in DRPs

Set

N_G	Number of generating units
N^i_{SE}	Number of segment for the piecewise linearized emission curve
N^i_{SF}	Number of segment for the piecewise linearized generation cost curve
N^b_{SI}	Number of segment for the piecewise linearized total incentive curve
T	Scheduling time horizon
Ω_B	Number of buses
Ω_L	Number of lines

Indices

b	Bus index
i	Unit index
L	Transmission line index
k	Segment index for linearized generation cost, emission, and total incentives curves
t	Time index

In previous studies, PM scheduling has been usually structured as a single objective problem to merely minimize operating expenditure of generating units without considering environmental aspects as well as the impact of other significant factors (Mollahassani-pour et al., 2015a; Abirami et al., 2014; Canto, 2008; Samuel and Rajan, 2015; El-Sharkh, 2014). However, with the advent of smart grid, new targets may impose to the traditional PM problem as in (Mollahassani-pour et al., 2015b). On the other hand, from modeling point of view, a multi objective decision making problem can be solved by two popular techniques: *i)* methods which replicate the problem into a single objective optimization problem via a weighted technique (Mollahassani-pour et al., 2015b; Abdollahi et al., 2012) and, *ii)* methods which utilized multifarious approaches with a priori/posteriori articulation of preferences like bounded objective function, Lexicographic, normal boundary intersection and, etc. (Aghaei et al., 2012; Manzardo et al., 2014; Marler and Arora, 2004; Munoz Moro and Ramos, 1999). However, regarding references (Kannegiesser and Günther, 2014; Liu and Huang, 2013; Ren et al., 2013, 2015), utilizing the concept of sustainable supply chain model can be appropriate for determining the most proper maintenance scheme based upon DMs' (Decision Makers') preferences.

This paper has been concentrated on weighted approach while efficacious weighted coefficients has been utilized instead of arbitrary weighting coefficients (Abdollahi et al., 2012). Once arbitrary weighting coefficients are applied to the multi targets problem, the system conditions will be ignored, and the DM's opinion will impose to the system. However, multifarious techniques are utilized to determine efficient weighting coefficients such as UNBP (Unequivocal Normalization-Based Paradigm) (Pourakbari-Kasmaei et al., 2014), the Eigenvector, Weighted Least-Square, Entropy (Tzeng and Huang, 2011), PROMETHEE (Vinodh and Girubha, 2012), ELECTRE (Figueira et al., 2016), Analytic Hierarchy Process (AHP) including fuzzy AHP (Kilincci and Onal, 2011; Ren and Sovacool, 2014), grey AHP (Sahoo et al., 2016) and, etc. In this paper, Entropy method as one of the weighting approaches is utilized to find the effective weighted objective by handling a trade-off between different targets in the deregulated environment. In fact,

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Entropy weighted coefficients reflects the collective notions of DMs as well as system conditions.

In order to over the defects of the previous researches, this paper proposes a multi objective security constrained PM problem under a smart grid environment emphasizing on DRRs (Demand Response Resources). Smart grid technologies will enable the grid to better adapt to demand side behaviors by implementation of DRPs (Demand Response Programs) which can be utilized smoothening the load profile, declining GHGs, as well as deferment of additional investments for supplying peak demand (Lund et al., 2015). Therefore, impacts of DRPs from short term to long term scheduling of power system studies are extremely significant. Generation PM scheduling is addressed as a long-term scheduling in power system studies which is affected by DRPs. In previous studies of PM problem, impacts of bid strategy DRPs have been investigated while performing in all load buses with similar incentives (Mollahassani-pour et al., 2015b). However, the focus of this research is on voluntary programs including DLC (Direct Load Control) and, EDRPs (Emergency DRPs) while customers are not penalized by ISO (Independent System Operator) if they do not curtail their demand.

The rest of this research is organized as follows. The hierarchy of MOPM incorporating DRRs from ISO perspective is presented in section 2. The proposed formulation of $\mathrm{MOPM^{DRRs}}$ is also elaborated in section 2. Section 3 illustrates the model using a modified IEEE Reliability Test System (RTS). Section 4 provides concluding remarks.

2. Multi objective PM scheduling associated with DRPs

This section provides the problem formulation of multi objective PM scheduling associated with DRPs, while considering technical constraints. First, the hierarchy of the model is explained then, the complete formulation of the problem as well as utilized approach to compromise between multifarious targets is presented.

2.1. Model features

"System expenditures" including operation and maintenance cost, reserve cost, and total incentive due to participating in DRPs and "*generated GHGs*" are considered as targets of the proposed model which replicated into a single target problem via Entropy approach. The crucial challenge is to link the virtual power plants, i.e. demand side resources, and conventional generating units into PM problem in a way that the economic and environmental benefits of DRPs, as well as improving energy efficiency become observable. In the proposed structure, characteristics of demand side resources including nominal potential of customers in DRPs' participation, number of achievable DRRs, permissible incentive limits, and price elasticity of demand are submitted to the ISO. Furthermore, characteristics of supply side resources, system demand, and transmission network are also called by ISO to perform $\mathrm{MOPM^{DRPs}}$. Therefore, the optimum inspection scheme, commitment status of units, levels of energy and reserve are determined over the time horizon while total expenditures and emitted GHGs are minimized simultaneously by implementing Entropy weights. ISO also determines the optimum award which paid to customers for participating in DRPs in per bus, and the most suitable locations for performing DRPs. In order to clarification, the main contributions of the research are listed in the following:

- *Impacts of voluntary DRPs including DLC/EDRPs into multi objective PM to lessen GHGs as well as expenditures have been investigated.*
- *Best locations of DRPs implementation are nominated to create the most reduction in GHGs as well as cost.*
- *Nominal and actual potential for customers' participation in DRPs are determined from ISO perspective. In fact, nominal potential of DRPs implementation means maximum achievable potential of DRRs in per bus, and actual potential is the realistic achievable potential of DRPs.*
- *The effective weighting coefficients based upon system conditions is determined by Entropy technique.*

More details about proposed structure are provided in Fig. 1 which represents the hierarchy of $\mathrm{MOPM^{DRPs}}$ (Multi Objective security constrained PM scheduling incorporating DRPs). Regarding Fig. 1, it is obvious that $\mathrm{MOPM^{DRPs}}$ problem based upon Entropy weights has been solved by three phases:

- Phase A: The base structure of MOPM problem associated with DRPs is presented in phase A. In fact, MOPM problem is replicated into single objective one based upon DM notion.
- Phase B: Multifarious solutions of $\mathrm{MOPM^{DRPs}}$ based upon different opinions are computed in this phase. Afterwards, regarding the aggregated DMs' notions and utilizing Entropy technique, the weighting coefficients of total expenditures as well as generated GHGs, i.e. w^{Eco} and w^{Env}, are calculated.
- Phase C: The final solution of $\mathrm{MOPM^{DRPs}}$ can be found by implementing Entropy weighting coefficients.

2.2. Model formulation

In this section, targets as well as technical constraints of $\mathrm{MOPM^{DRPs}}$ are presented which modeled in GAMS (General Algebraic Modeling System) environment and developed as an MILP (Mixed Integer Linear Programming) problem. The advantages of MILP method include global optimality, direct measure of the optimality of a solution and more flexible and accurate modeling capabilities. CPLEX as one of the popular MILP solver of GAMS is utilized to solve the proposed structure.

2.2.1. Objective function

The linearized objective of $\mathrm{MOPM^{DRPs}}$ is presented in Eq. (1). w^{Eco} and w^{Env} are considered as weighting coefficients which determined based upon DMs' notion.

$$
\begin{aligned}
Min: w^{Eco}\sum_{t=1}^{T}\Bigg\{\sum_{i=1}^{N_G}\Bigg(\Bigg\{\underline{G}_c^i u^i(t)+\sum_{k=1}^{N_{SF}^i}G_k^i(t)\Lambda_k^i\Bigg\} \\
+z^i(t)\lambda_c^i+rl^i(t)\mu_c^i\Bigg)+\sum_{b=1}^{\Omega_B}\Bigg(\underline{\sigma}_{inc}^b\phi^b(t)+\sum_{k=1}^{N_{SI}^b}\sigma_k^b(t)\pi_k^b\Bigg)\Bigg\} \\
+w^{Env}\sum_{t=1}^{T}\sum_{i=1}^{N_G}\Bigg(\underline{E}^i u^i(t)+\sum_{k=1}^{N_{SE}^i}E_k^i(t)\Upsilon_k^i\Bigg).
\end{aligned}
\tag{1}
$$

The first term in Eq. (1) is the cost of energy production in generating units which is non-linear in nature. Nevertheless, it can be correctly approximated by a set of piecewise blocks as Eq. (2) which can't be recognizable from the nonlinear model if enough segments are utilized (Mollahassani-pour et al., 2015b).

$$G_c^i(t)=\underline{G}_c^i u^i(t)+\sum_{k=1}^{N_{SF}^i}G_k^i(t)\Lambda_k^i. \tag{2}$$

The second and third terms in Eq. (1) are maintenance

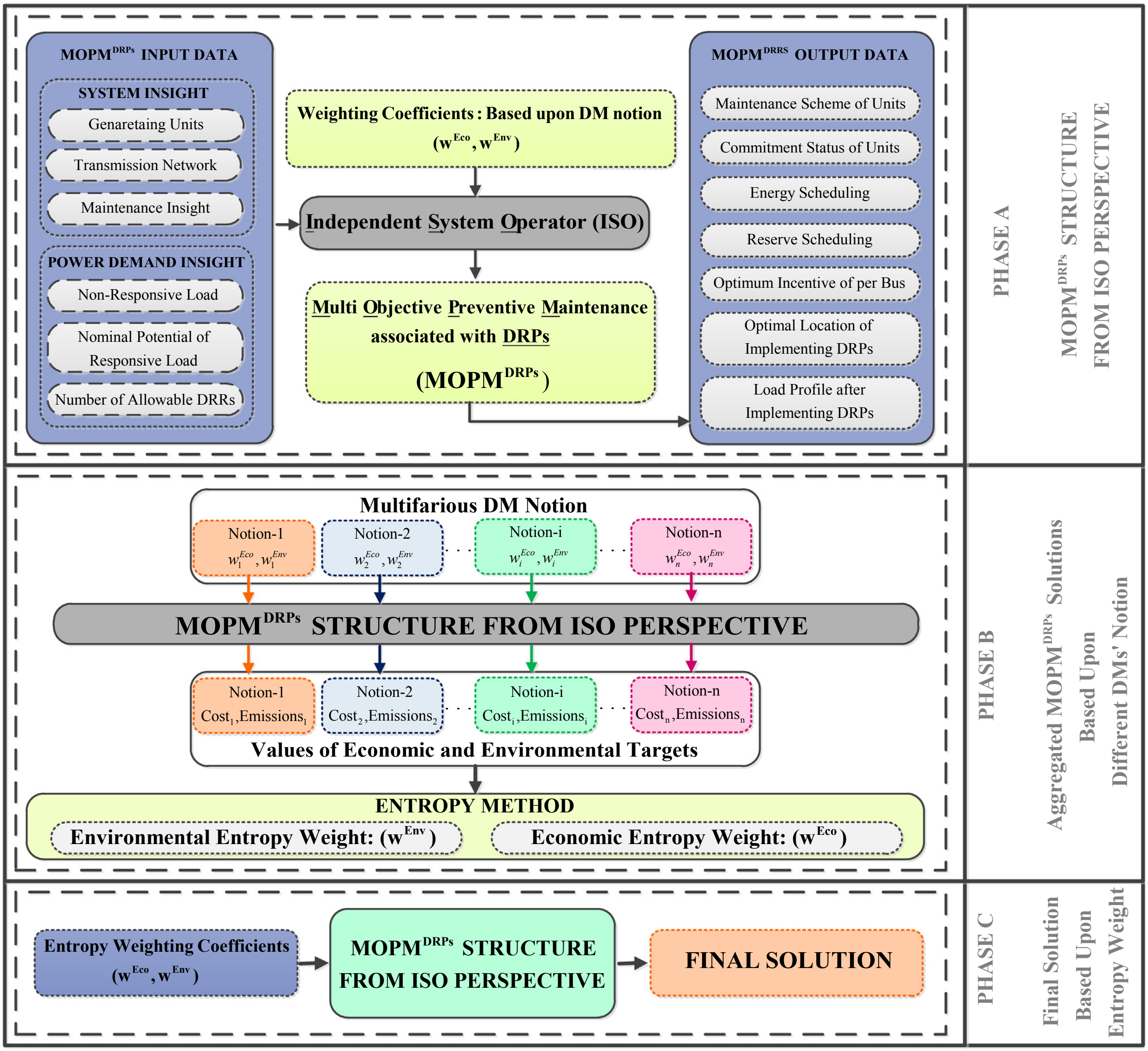

Fig. 1. The hierarchy of MOPM associated with DRPs.

expenditures and reserve capacity cost, respectively. Participation level of a unit in reserve provision, i.e. $rl^i(t)$, is determined so that system total expenditures are minimized. The fourth term is total incentive cost due to participating in DRPs. The linear responsive load economic model is formulated as the following (Aalami et al., 2010; Moghaddam et al., 2011):

$$D^b_{DR}(t) = \xi D^b(t) \times \left(1 + \sum_{j=1,}^{T} E(t,j) \frac{Pr^b_{DR}(j) - Pr^b_0(j) + \tau^a(j) inc^b_{opt} + \tau^e(j) pen^b_{opt}}{Pr^b_0(j)}\right). \tag{4}$$

Since we focus on voluntary DRPs including DLC and EDRPs, so $pen^b(t)$ is considered equal to zero in Eq. (4). If ISO pays "inc^b_{opt}" \$ as an incentive to customers for 1 *Mwh* load reduction in maximum level of load curve, the total incentive for voluntary DRPs can be presented as (Abdollahi et al., 2012):

$$\rho\left(\Delta D^b(t)\right) = \tau^a(t) inc^b_{opt}\left(D^b(t) - D^b_{DR}(t)\right); \quad where\ \tau(t) = D^b(t) \Big/ \overline{D^b}. \tag{5}$$

By substituting Eq. (4) in Eq. (5), $\rho(\Delta D^b(t))$ is simplified and formulated as a quadratic function of incentive as given in Eq. (6), which can be also presented as a piecewise linear model by Eq. (7). The status of customers' participation in DRPs is shown by $\phi^b(t)$, which is one if the customers of b^{th} bus partake in DRPs and otherwise takes zero.

$$\rho\left(\Delta D^b(t)\right) = \hbar_1^b(t) inc_{opt}^{b^2} + \hbar_2^b(t) inc_{opt}^b + \hbar_3^b(t). \tag{6}$$

$$\rho\left(\Delta D^b(t)\right) = \underline{\sigma}_{inc}^b \phi^b(t) + \sum_{k=1}^{N_{SI}^b} \sigma_k^b(t) \pi_k^b. \tag{7}$$

The fifth term is emitted GHGs in generating units. Basically, emissions produced by generating units are presented as a polynomial function of their production which is usually contemplated as a quadratic function (Mollahassani-pour et al., 2015b), and can be approximated by a set of piecewise blocks as presented in Eq. (8).

$$E^i(t) = \underline{E}^i u^i(t) + \sum_{k=1}^{N_{SE}^i} E_k^i(t) \Upsilon_k^i. \tag{8}$$

2.2.2. Constraints

Some technical constraints in conjunction with MOPM^{DRPs} are considered as follows:

i) Generation constraints

- *Power balance:* Generated power from committed units should satisfy the required demand including responsive and nonresponsive load as well as system losses (Shiraki et al., 2016).

$$\sum_{i=1}^{N_G} P^i(t) = loss(t) + \sum_{b=1}^{\Omega_B} (1-\xi) D^b(t) + \sum_{b=1}^{\Omega_B} \xi D^b(t) \times \left(1 + \sum_{j=1}^{T} E(t,j) \frac{Pr_{DR}^b(j) - Pr_0^b(j) + \tau^a(j) inc_{opt}^b + \tau^e(j) pen_{opt}^b}{Pr_0^B(j)}\right). \tag{9}$$

- *System reserve capacity:* To encounter any unanticipated operating conditions such as unexpected outage of units or sudden increase in demand, the specified reservation amount must be considered. System reserve is usually a pre-specified amount that is either equal to the largest unit capacity or a given percentage of the forecasted load.

$$\sum_{i=1}^{N_G} u^i(t) \overline{P}^i(t) \geq SRC(t) + loss(t) + \sum_{b=1}^{\Omega_B} (1-\xi) D^b(t) + \sum_{b=1}^{\Omega_B} \xi D^b(t) \times \left(1 + \sum_{j=1}^{T} E(t,j) \frac{Pr_{DR}^b(j) - Pr_0^b(j) + \tau^a(j) inc_{opt}^b + \tau^e(j) pen_{opt}^b}{Pr_0^b(j)}\right). \tag{10}$$

$$0 \leq rl^i(t) \leq \left(\overline{P}^i(t) - \underline{P}^i(t)\right) u^i(t); \quad where \ \sum_{i=1}^{N_G} rl^i(t) \geq SRC(t). \tag{11}$$

In Eq. (10), the i^{th} unit on/off status is symbolized by $u^i(t)$ which is one when the unit is on and otherwise it takes zero.

- Power generation

$$\underline{P}^i(t) u^i(t) + \sum_{k=1}^{N_{SF}^i} G_k^i(t) \leq \overline{P}^i(t) u^i(t) - url^i(t); where: 0 \leq G_k^i(t) \leq \overline{G}_k^i(t). \tag{12}$$

- *Customers' incentive limits:* The amount of incentive is subjected to Eq. (13). Depending on ISO purpose from implementing DRPs, the amount of incentive can be restricted during problem lead time between $\underline{inc}^b(t)$ and $\overline{inc}^b(t)$.

$$\underline{inc}^b(t) \phi^b(t) + \sum_{k=1}^{N_{SI}^b} \sigma_k^b(t) \leq \overline{inc}^b(t) \phi^b(t); \quad where: \ 0 \leq \sigma_k^b(t) \leq \overline{\sigma}_k^b(t). \tag{13}$$

- *Limited number of DRRs:* The maximum number of locations which can be participated in DRPs is limited by Eq. (14).

$$\sum_{b=1}^{\Omega_B} \phi^b(t) \leq \overline{N}_{DRR}(t) \quad \forall t \in T. \tag{14}$$

ii) Maintenance constraints

- *Maintenance duration:* Each unit must be maintained for specified time as follows:

$$\sum_{t=1}^{T} z^i(t) = \psi^i \quad \forall i \in N_G. \tag{15}$$

- *One time maintenance:* Each unit is taken under maintenance just once during the time horizon. $\varpi^i(t)$ is maintenance starting variable which takes one if the unit inspection starts at the beginning of period t, and otherwise is zero.

$$\sum_{t=1}^{T} \varpi^i(t) = 1 \quad \forall i \in N_G. \tag{16}$$

- *Maintenance continuity:* The maintenance of a unit must be performed in successive periods.

$$z^i(t) - z^i(t-1) \leq \varpi^i(t) \quad \forall i \in N_G, \forall t \in T. \tag{17}$$

- *Connection and maintenance status:* It represents the relation between maintenance status and commitment state of a unit.

$$z^i(t) + u^i(t) \leq 1, \quad \forall i \in N_G, \forall t \in T. \tag{18}$$

- *Maintenance exclusion:* The impossibility of maintaining two pre-specified units at the same interval is considered by Eq. (19).

$$z^i(t) + z^j(t) \leq 1 \quad \forall t \in T. \tag{19}$$

- *Maintenance precedence:* The order of generating units' maintenance is symbolized by precedence constraint. Equations (20) and (21) should be satisfied if the maintenance of i^{th} unit is prior to the maintenance of j^{th} unit.

$$\varpi^i(t) + \varpi^j(t) \leq 1 \quad \forall t \in T. \tag{20}$$

$$\sum_{\tau=1}^{t} \varpi^i(\tau) - \varpi^j(t) \geq 0 \quad \forall t \in T. \tag{21}$$

- *Maintenance coincidence:* Number of the generating units which can be maintained simultaneously is limited due to technical limitations.

$$\sum_{i=1}^{N_G} z^i(t) \leq \upsilon(t) \quad \forall t \in T. \tag{22}$$

iii) Line flow constraints

Practically, generating units are in different regions of network which may affect the maintenance scheme. Transmission security constraints in PM scheduling can be handled either by TM (Transportation Model) or other power flow models. Since TM is a linear model, it is easier to be solved and may lead to feasible solutions but not necessarily an optimal one which is modeled by (23). Equation (23a) shows the power balance in per bus, while the permissible level of load curtailment should be equal or smaller than the summation of responsive and non-responsive load as given in Eq. (23b). The power flow through transmission lines must be lower than the maximum capacity of the line which is represented by (23c). In (23d), ε is the allowable un-served energy which is determined by ISO. Although increasing in maximum un-served energy level, decreases the operating cost as well as system total cost, but causes to attenuate system reliability level.

$$s^T \overrightarrow{f^L}(t) + \overrightarrow{g}(t) + \overrightarrow{r}(t) = (1-\xi)\overrightarrow{D^b}(t) + \xi\overrightarrow{D^b}(t) \times \left(1 + \sum_{j=1}^{T} E(t,j) \frac{Pr_{DR}^b(j) - Pr_0^b(j) + \tau^a(j) inc_{opt}^b + \tau^e(j) pen_{opt}^b}{Pr_0^b(j)}\right). \tag{23a}$$

$$0 \leq r^b(t) \leq (1-\xi)D^b(t) + \xi D^b(t) \times \left(1 + \sum_{j=1}^{T} E(t,j) \frac{Pr_{DR}^b(j) - Pr_0^b(j) + \tau^a(j) inc_{opt}^b + \tau^e(j) pen_{opt}^b}{Pr_0^b(j)}\right). \tag{23b}$$

$$\left| f^L(t) \right| \leq \overline{f^L} \quad \forall t \in T, \forall L \in \Omega_L. \tag{23c}$$

$$\sum_{b=1}^{\Omega_B} r^b(t) \leq \varepsilon \quad \forall t \in T. \tag{23d}$$

2.3. Weighted approach

Multi objective optimization is the problem of optimizing several objective functions which is usually replicated into a single target optimization problem via arbitrary weighting coefficients (Abdollahi et al., 2012). However, per objective has a different meaning which cannot be assumed to have equal weights. Therefore, finding the appropriate weight for per target is extremely substantial. Various techniques are utilized to regulate weighting coefficients such as the Eigenvector method, Weighted Least-Square method, Entropy method, AHP (Analytic Hierarchy Process) and, etc (Tzeng and Huang, 2011; Esmaeel Nezhad et al., 2014). which structured based upon performance matrix. The importance of i^{th} objective is determined by j^{th} DM which causes to organize a performance matrix as presented in Table 1.

One of the target weighting measures which has been proposed by researchers is the Shannon Entropy concept (Shannon, 2001). Entropy technique is a method of finding out which target affects more significantly during optimization process by ranking them. Indeed, Entropy method has its benefits of ease to apply and required less information for ranking in comparison with other techniques (Collaboration and harmoni, 2005). Utilizing the Entropy, nonnegative weights of objectives, i.e. w_i, between zero and one are suitably chosen. First, in order to achieve the Entropy weight, the decision matrix should be normalized as Eq. (24):

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}}, \quad \forall i \in n, \forall j \in m. \tag{24}$$

By normalizing decision matrix, multifarious scales and units among various objectives are transformed into common measurable units to allow for comparisons of different objectives. Then, entropy variable, i.e. h_i, should be calculated as Eq. (25), where h_0 is the entropy constant. Finally, the rank of importance of i^{th} objective, i.e. Entropy weight, is obtained as Eq. (26), where d_i is the degree of diversification (Lotfi and Fallahnejad, 2010).

$$h_i = -h_0 \sum_{j=1}^{m} p_{ij} ln\left(p_{ij}\right), \quad where: h_0 = -1/ln(m). \tag{25}$$

$$w_i = \frac{d_i}{\sum_{r=1}^{n} d_r}, \quad where: d_i = 1 - h_i. \tag{26}$$

3. Numerical study

3.1. Test system description

The proposed framework of MOPM^{DRPs} problem has been applied to the IEEE-RTS with a scheduling horizon of 52 weeks, as depicted in Fig. 2. The system includes 26 thermal units;

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Table 1
Structure of the performance matrix.

	Objective 1	. . .	Objective *i*	. . .	Objective *n*
DM 1	x_{11}	. . .	x_{1i}	. . .	x_{1n}
. . .	. . .	. . .	. . .	. . .	. . .
DM j	x_{j1}	. . .	x_{ji}	. . .	x_{jn}
. . .	. . .	. . .	. . .	. . .	. . .
DM m	x_{m1}	. . .	x_{mi}	. . .	x_{mn}
Weight	$\boldsymbol{w_1}$	…	$\boldsymbol{w_2}$	…	$\boldsymbol{w_n}$

Table 2
Price elasticity of demand.

Self-elasticity				Cross elasticity		
Peak	Off-peak	Valley		Peak	Off-peak	Valley
−0.22	–	–	Peak[a]	0.01	0.04	0.034
–	−0.15	–	Off-peak[b]	0.04	0.03	0.03
–	–	−0.08	Valley[c]	0.034	0.03	0.04

[a] Peak period: Loading higher than 88% of maximum demand.
[b] Off-peak period: Loading between 75 and 88% of maximum demand.
[c] Valley period: Loading lower than 75% of maximum demand.

15 oil namely O_1-O_{15}, 9 coal so-called C_{16}-C_{24}, and 2 nuclear as N_{25}-N_{26}. The peak load is 2100 MW, and system reserve capacity is considered 400 MW that is equal to the largest unit capacity (Mollahassani-pour et al., 2015b). More required data including operating and maintenance insights as well as transmission lines' characteristics are adopted from (Subcommittee, 1979). Emission and generation cost curves are both approximated by 20 linear segments between the minimum and maximum units' capacity (Mollahassani-pour et al., 2015b). It is assumed that 3 generators can be inspected simultaneously due to the technical limitations. The network losses is disregarded during the scheduling time horizon. Furthermore, no un-served energy is allowed by ISO.

Nominal potential of DRPs is considered 10% of total load in per bus. The elasticity of load is extracted from (Abdollahi et al., 2012) with some modifications as presented in Table 2. Furthermore, minimum and maximum values of incentive in per bus are considered equal to $0.1Pr_0^b$ and $5Pr_0^b$, respectively. The focus of this research is on voluntary programs with equal values of $Pr_0^b(t)$ and $Pr_{DR}^b(t)$. Total incentive curves are also approximated by 20 linear segments between minimum and maximum values of incentive.

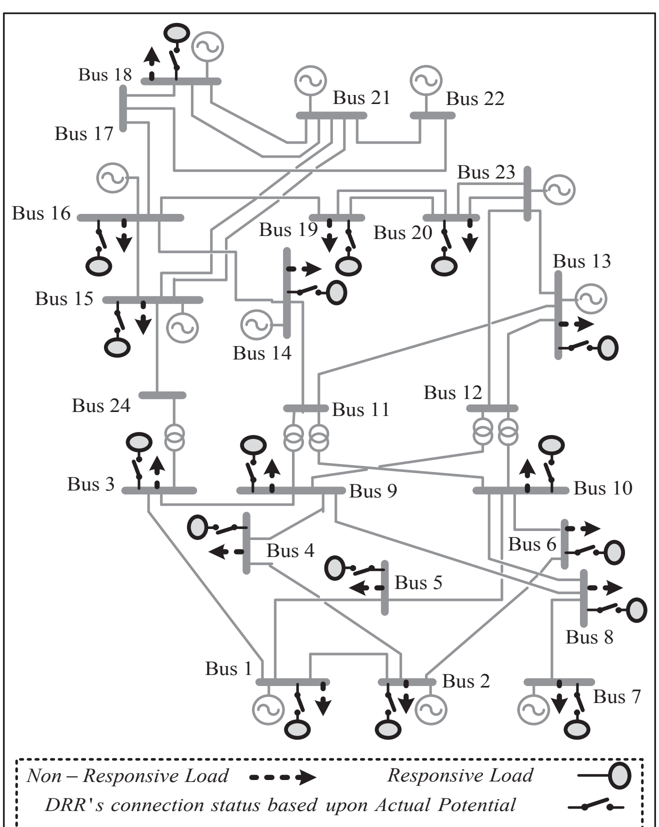

Fig. 2. The modified 24-bus reliability test system considering DRRs.

3.2. Simulation results and discussions

To scrutinize impacts of voluntary programs on MOPM scheduling, multifarious scenarios are contemplated as follows. All cases are performed in GAMS environment and solved using CPLEX 12.5.1.0. Moreover, regarding Entropy method, eleven DMs are considered which alter their opinions about preferences of objectives by changing weighting coefficients from zero to one with increasing of 0.1 in per step.

- *Case #A: The IEEE-RTS without DRRs Considerations*

In this case, MOPM problem has been solved without DRRs considerations. Applying CPLEX 12.5.1.0, the problem is handled and, different expenditures as well as emissions are calculated based upon divers DMs' opinions, as shown in Fig. 3.

Indeed, in a high order of cost coefficient, i.e. w^{Eco}, most economical units i.e. N_{25}-N_{26}, are participated in both reserve acquisition and demand satisfaction to regulate system expenditures in minimum level. Therefore, due to decreasing generation level of low cost units, expensive units are also cooperated to satisfy the required demand. This issue causes to increase the emitted GHGs of units as presented in Fig. 3. On the other hand, by declining the weighting factor of expenditures and increasing the weighting factor of generated GHGs, most environmental units i.e. N_{25}-N_{26}, are cooperated more in demand satisfaction to lessen pollution. Consequently system expenditures, as presented in Fig. 3, will be increased. Utilizing obtained results and implementing Entropy technique, Entropy weights of expenditures and emissions are calculated equal to 0.187 and 0.813, respectively. Applying Entropy weights into MOPM, optimal solutions are computed equal to 240.513 m$ and 123.253 mlbs. Table 3 shows operation and reserve expenditures as well as emissions of final solution in Case #A.

- *Case #B: The IEEE-RTS with DRRs considerations and without limitation on number of DRRs*

In Case #B, economic and environmental impacts of DRPs implementation have been scrutinized, while DRRs are available in all load buses. Based upon DMs' notions and utilizing Entropy technique, efficient weighting factors for expenditures and emitted GHGs are obtained equal to 0.179 and 0.821, respectively, in Case #B. By applying Entropy weights, optimal expenditures is obtained equal to 239.45 m$/yr. Although, an additional expenditure, i.e. total incentives, has been imposed to the system in Case #B; however total cost as well as emissions are declined 1.06 m$ and 1.68 mlbs per year, respectively, in comparison with Case #A. Table 4 represents operation, reserve and, total incentive expenditures, SO_2 and NO_x emissions, as well as percentage of variations in comparison with Case #A. As shown in Table 4, due to demand side resources' impacts, operation cost of system is declined considerably in Case #B in comparison with case #A.

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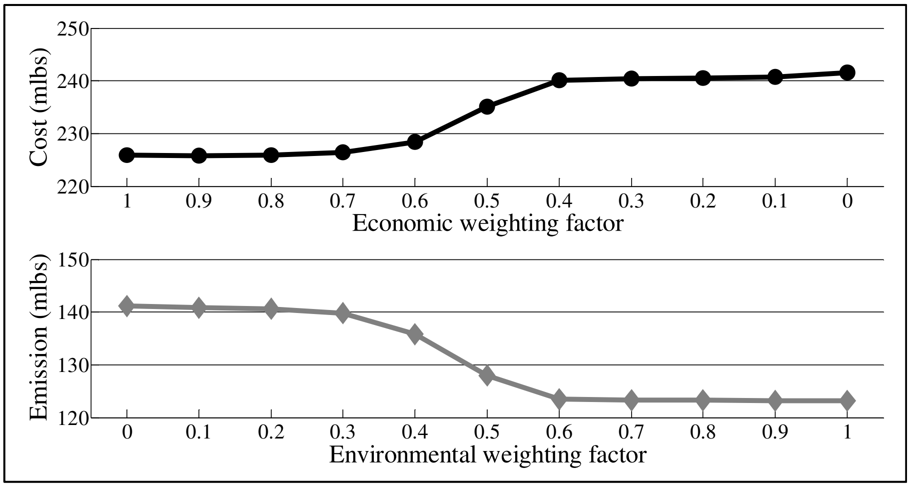

Fig. 3. Multifarious levels of emission and cost in Case #A.

Table 3
Optimal solution for case #A.

Expenditures (million $)	Operation & maintenance	Reserve capacity	Total cost
	177.546	62.967	240.513
Emissions (million lbs)	Emitted NO_x	Emitted SO_2	Total emissions
	88.038	35.215	123.253

Table 4
Optimal solution for Case #B.

Expenditures (million $)	Operation & maintenance	Reserve capacity	Total incentive	Total cost
	175.138	62.075	2.240	239.453
$\frac{\text{Case \#B} - \text{Case \#A}}{\text{Case \#A}}$ (%)	−1.37	−1.41	–	−0.44
Emissions (million lbs)	Emitted NO_x	Emitted SO_2	Total emissions	
	86.834	34.733	121.567	
$\frac{\text{Case \#B} - \text{Case \#A}}{\text{Case \#A}}$ (%)	−1.36	−1.36	−1.36	

Optimal awards for per MWh which paid to customers due to participation in DRPs in multifarious locations have been provided in Table 5. Maximum and minimum incentives are highlighted in Table 5.

Moreover generation pattern and reserve scheduling in Case #B have been altered in comparison with Case #A due to customers' participation in voluntary programs. This issue has been provided for maximum and minimum level of demand, i.e. week #51 and week #38 in Table 6. Referring to Table 6, it can be concluded that DRPs affect the generation pattern as well as reserve allotment.

It should be mentioned that, required demand in Case #B is increased 1.46% in period #38 in comparison with Case #A, due to more tangible cross elasticity of demand. However, required demand in week #51 has been declined 210 MW due to customers' cooperation in DRPs, while multifarious awards which paid by ISO depend on customers' location in the system.

- *Case #C: The IEEE-RTS with DRRs considerations and limitation on number of DRRs*

In this case, besides implementing DRPs in MOPM, demand side resources are also limited to a few locations. This case is performed in two different analyses as follows:

- *Case #C.1. Single optimal allocation*

In this analysis, the most proper location for implementing DRPs is specified, which means that $\overline{N}_{DRR}$ is considered equal to one. By applying CPLEX 12.5.1.0 and, utilizing Entropy method, efficient weighting factors for expenditures and emissions are obtained equal to 0.186 and 0.814, respectively in Case #C.1. Afterwards, Entropy weighted $MOPM^{DRPs}$ problem is handled and, bus #15 is selected as the best location for customers' participation in DRPs.

Table 5
Optimal value of incentive in Case #B.

Bus no	Award ($/MWh)	Bus no	Award ($/MWh)	Bus no	Award ($/MWh)	Bus no	Award ($/MWh)	Bus no	Award ($/MWh)	Bus no	Award ($/MWh)
#1	4.902	#4	4.866	#7	5.025	#10	4.762	#15	4.292	#19	4.525
#2	4.888	#5	4.866	#8	5.003	#13	4.651	#16	4.505	#20	4.484
#3	4.658	#6	4.866	#9	4.717	#14	4.63	#18	4.405		

Table 6
Comparison the generation pattern and reserve allocation in Cases #A and #B.

Unit no	Generation pattern				Unit no	Reserve allocation			
	Period #38		Period #51			Period #38		Period #51	
	Case #A	Case #B	Case #A	Case #B		Case #A	Case #B	Case #A	Case #B
O_1	0	0	2.4	0	O_1	0	0	9.6	0
O_2	0	0	2.4	0	O_2	0	0	9.6	0
O_3	0	0	2.4	0	O_3	0	0	2.6	0
O_{10}	25	25	25	25	O_{10}	75	75	75	75
O_{11}	25	0	0	25	O_{11}	75	0	0	67
O_{12}	25	25	25	25	O_{12}	36.5	31.899	75	75
O_{13}	0	0	68.95	0	O_{13}	0	0	128.05	0
C_{16}	0	15.2	42.56	15.2	C_{16}	0	60.8	33.44	60.8
C_{17}	15.2	15.2	57.76	0	C_{17}	60.8	60.8	18.24	0
C_{18}	15.2	15.2	54.72	15.2	C_{18}	60.8	60.8	21.28	60.8
C_{19}	15.2	15.2	48.81	15.2	C_{19}	60.8	60.8	27.19	60.8
C_{20}	149.087	140.36	155	155	C_{20}	5.913	14.64	0	0
C_{21}	149.962	144.925	155	155	C_{21}	5.038	10.075	0	0
C_{22}	144.925	144.925	155	155	C_{22}	10.075	10.075	0	0
C_{23}	144.925	139.887	155	154.4	C_{23}	10.075	15.113	0	0.6
C_{24}	350	0	350	350	C_{24}	0	0	0	0
N_{25}	400	400	400	400	N_{25}	0	0	0	0
N_{26}	0	400	400	400	N_{26}	0	0	0	0

Table 7
Optimal solution for Case #C.1.

Expenditures (million $)	Operation & Maintenance	Reserve capacity	Total incentive	Total cost
	177.234	62.954	0.23	240.418
Emissions (million lbs)	Emitted NO_x	Emitted SO_2	Total emissions	
	87.881	35.152	123.033	

Table 8
Optimal solution for Case #C.2.

Expenditures (million $)	Operation & maintenance	Reserve capacity	Total incentive	Total cost
	176.364	62.453	1.131	239.948
Emissions (million lbs)	Emitted NO_x	Emitted SO_2	Total emissions	
	87.446	34.978	122.424	

Optimal award which is paid to customers in bus #15 is obtained equal to 4.243 $ per MWh. Optimization results of Case #C.1 is provided in Table 7. As presented in Table 7, total expenditures as well as GHGs are both declined slightly in comparison with Case #A due to existence of DRRs in only one location.

- *Case #C.2. Multiple optimal allocation*

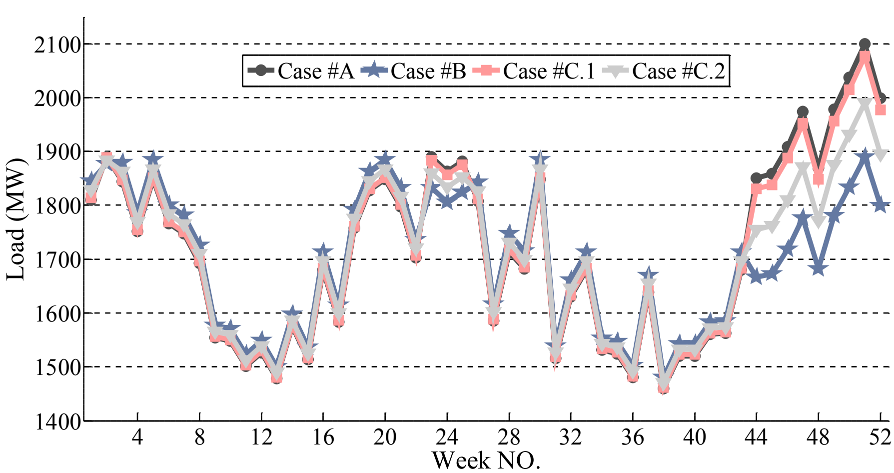

Fig. 4. The impact of demand side resources on load profile.

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Table 9
Technical characteristics of load profile.

Characteristics	Case #A	Case #B	Case #C.1	Case #C.2
Peak (MW)	2100	1890	2076.95	1990.587
Reduction (%)	–	10	1.09	5.21
Load factor amount	0.8186	0.9014	0.8269	0.8595
Improvement (%)	–	10.11	1.003	4.99
Peak to valley ratio	1.438	1.276	1.421	1.353
Reduction (%)	–	11.26	1.18	5.91

Table 10
Optimal value of incentive in Case #C.2.

Bus no	Award ($/MWh)	Bus no	Award ($/MWh)	Bus no	Award ($/MWh)
#10	4.762	#13	4.651	#14	4.63
#15	4.292	#18	4.405	#19	4.525

Here, maximum number of accessible DRRs is considered equal to six locations. Regarding DMs' opinions and Entropy technique, weighting factors of expenditures and emissions are calculated equal to 0.188 and 0.812, respectively, in Case #C.2. Different terms of system expenditures and emissions are given in Table 8. Referring to Table 8, total expenditures as well as produced pollution of Case #C.2 have been decreased 0.56 m$ and 0.829 mlbs in comparison with Case #A and increased 0.49 m$ and 0.857 mlbs in comparison with Case #B. In fact, due to performing DRPs in finite locations of system, reduction of cost as well as emission in Case #C.2 is less than Case #B.

Utilizing economic model of DRPs, consumers' consumption is altered during the time horizon due to demand elasticity. The load curve of IEEE-RTS before and after implementing DRPs is displayed in Fig. 4. As presented in Fig. 4, customers in peak periods declines their consumption due to more tangible effects of self-elasticity; while required demand is increased because of more considerable impact of cross elasticity in valley and off-peak periods. It's obvious that the variation of demand in Case #B is more in comparison with Case #C.1 and Case #C.2 due to availability of DRRs in all locations. Furthermore, technical characteristics of load profile have been given in Table 9. It is seen that technical characteristics such as peak reduction, load factor, and peak to valley ratio have been improved in Cases #B-C.2 in comparison with Case #A due to existence of demand side resources. It can be concluded from Table 9 that, implementing DRPs can flatten demand curve, while the load factor value as well as peak to valley ratio guarantees this issue.

Table 10 displays optimum location of implementing DRPs as well as optimum incentive in Case #C.2. Comparing Tables 5 and 10, it can be concluded that optimal incentives are identical in same buses due to similar demand elasticity in both Cases #B and #C.2.

Nominal and actual potentials of customers' cooperation in voluntary programs during peak periods along the scheduling time are provided in Fig. 5. It was expected actual potential of DRPs in multifarious periods has been obtained lower or equal than their nominal ones. Furthermore, it can be concluded that by increasing the number of available demand side resources, participation level of customers in voluntary programs will be increased. As an example, in week #51, i.e. maximum loading period, nominal potential of implementing DRPs is 210 MW. However, by applying CPLEX 12.5.1.0, actual potential in Cases #B-C.2 is obtained equal to 210 MW, 23.05 MW and, 109.41 MW in aforementioned period, respectively. The obtained results guarantee this fact that actual values of DRPs are always equal or smaller than the nominal potential of responsive load.

Maintenance scheme of Cases #A-C.2 is provided in Table 11. As shown in Table 11, demand side resources affect inspection pattern of units. Therefore, it is beneficial to consider DRPs impacts in PM scheduling to determine the most proper maintenance time.

4. Conclusions

This paper offers a novel framework of multi objective PM scheduling under the smart grid environment. DRPs as one of the crucial infrastructure of smart grids technologies have been studied in this work, while affecting the power system' handling. In this paper, the impacts of demand side resources on reduction of air pollutants as well as incurred expenditures have been scrutinized. Therefore, a linearized structure for multi objective PM problem associated with DRPs has been presented. Incurred expenditures including operation, maintenance, and reserve costs, as well as total incentives due to participating in DRPs, and generated emissions are considered as multifarious targets of the suggested model. Here, unlike previous studies that utilized arbitrary weighting coefficients, Entropy method is implemented to replicate the multi objective PM problem into a single objective one. Therefore, multi objective PM problem is firstly performed using the multifarious ranking of objectives which is specified based upon the Decision Maker's opinion. Afterwards, regarding the aggregated DMs'

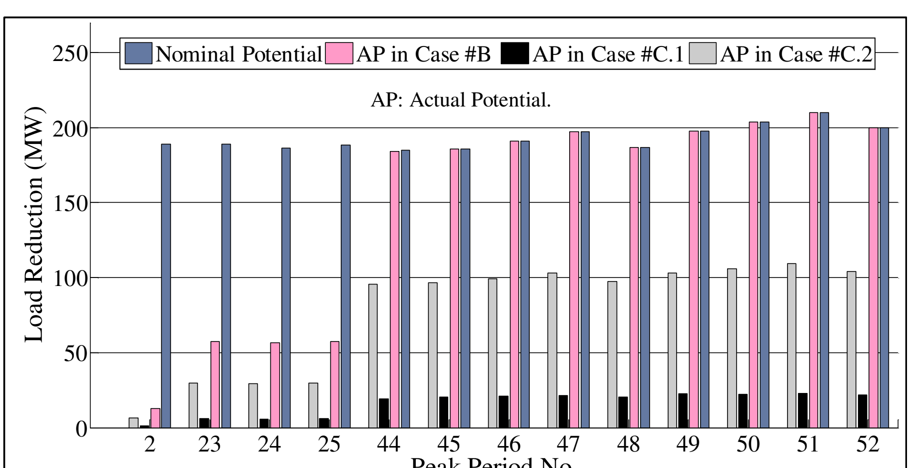

Fig. 5. Expectation of customer's participation in IBPs for optimal multifarious incentives in peak periods.

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Table 11
Start time of maintenance in generating units.

Unit-no		O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9	O_{10}	O_{11}	O_{12}	O_{13}
Cases	# A	2	47	5	2	23	25	12	51	11	20	43	15	45
	#B	42	51	38	2	31	30	1	21	35	44	2	47	7
	#C.1	3	24	42	24	26	1	41	36	49	17	27	20	28
	#C.2	4	26	2	2	4	47	23	49	33	27	37	15	1
Unit-NO		O_{14}	O_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}	C_{23}	C_{24}	N_{25}	N_{26}
Cases	# A	38	47	38	6	1	35	15	29	26	4	33	9	38
	#B	11	33	39	50	6	6	43	26	15	22	38	31	9
	#C.1	5	47	44	21	42	6	15	26	15	4	31	36	9
	#C.2	8	7	13	31	41	34	43	14	26	21	38	8	31

notions, the final weighting factors of system expenditures as well as generated emissions are computed utilizing the Entropy technique. Finally, the optimal solution can be found by performing Entropy weighted problem. The proposed structure within the concept of this paper was applied on IEEE-RTS which conducted in several analyses. Here, $MOPM^{DRPs}$ problem has been performed with and without incentive based programs considerations while different limitations on number of DRRs are also contemplated. It is concluded that by increasing the locations of DRPs implementation, generated contaminants from power plants such as SO_2 and NO_x as well as expenditures are declined tangibly. Furthermore, utilizing the proposed structure, optimum incentive in per location, nominal, and actual potential for participating consumers in incentive based programs are determined. In addition, maintenance scheme, commitment status, reserve and energy scheduling are also specified over scheduling time horizon. It's worth mentioning that, Entropy technique can't reveal the preferences of DMs directly; however, it reflects the overall DMs' willingness with consideration of system's conditions. Therefore, investigating multifarious weighting techniques impacts to select most proper alternative and, environmental effects of DRPs are worth studying in future research of PM problem.

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