A Heuristic Multi-Objective Multi-Criteria Demand Response Planning in a System with High Penetration of Wind Power Generators

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Abstract

Integration of wind energy and other renewable energy resources in electrical systems create some challenges due to their uncertain and variable characteristics. In the quest for more flexibility of the electric systems, combination of these endogenous and renewable resources in accordance with strategies of Demand Response (DR) allows an increment/improvement of the demand potential, as well as a more secure, robust, sustainable and economically advantageous operation. This paper proposes a new model for integration of wind power and DR, thus optimizing supply and demand side operations through a price rule Time of Use (TOU), or incentive with Emergency DR Program (EDRP), as well as combining TOU and EDRP together. The problem is modelled using a stochastic Heuristic Multi-objective Multi-criteria decision making (HMM) method which aims to minimize operation costs and environmental emissions simultaneously, ensuring the security constraints through two-stage stochastic programming, considering various techno-economic indices such as load factor, electricity market prices, Energy Not Supplied (ENS) and Share Weighted Average Lerner Index (SWALI). Comprehensive numerical results indicate that the proposed model is entirely efficient in DR planning and power system operation.

Keywords: Demand response planning; multi-criteria; multi-objective; renewable energy; stochastic programming.

1. Nomenclature

1.1. Indexes

b	Index of system buses
i	Index of thermal units
j	Index for loads
l	Index of transmission lines
m	Segment index for the cost of thermal units
s	Index of wind scenarios
t	Index of hours
w	Index of wind unit

1.2. Parameters

a_t	Rate of incentive at hour t (\$/MWh)
c_{im}^{e}	Slope of segment m in linearized fuel cost curve of unit i (\$/MWh)
c_i^{ERU}/c_i^{ERD}	Offered energy of reserve up/down (\$/MWh)
c_i^{RU}/c_i^{RD}	Offered capacity of reserve up/down (\$/MW)
c_{wt}^{wind}	Cost of wind power producer

d_{jt}^0	Initial electricity demand of load *j* at hour *t*
dr^{max}	Maximum response potential
$e_{tt'}$	Elasticity of demand
$e_i^{SO_2}/e_i^{NO_x}$	Emission rate of SO_2 and NO_x (\$/kg)
mut_i/mdt_i	Minimum up/down time of generation unit *i*
nlc_i	No load cost of unit *i*
$p_w^{install}$	Installed capacity of wind farms (MW)
p_i^{min}/p_i^{max}	Minimum/Maximum generation limit (MW)
ru_i/rd_i	Ramp up/down of generation unit *i*
suc_i	Start-up cost of generation unit *i*
sur_i/sdr_i	Spinning up/down reserve of generation unit *i*
$voll_j$	Value of lost load in bus *j* (\$/MWh)
w_{wt}^{max}	Available wind power of wind unit *w* (MWh)
x_l	Reactance of line *l*
ρ_t^0	Initial electricity price at hour *t* (\$/MWh)
ρ_t	Electricity tariff at hour *t* (\$/MWh)
π_{cur}	Cost of wind spillage
ω_s	Probability of wind power scenario *s*

1.3. Variables

C_{it}^{ST}	Start-up cost of generation unit *i* in hour *t* (\$)
D_{jt}	Modified demand after implementing DRPs
F_{cost}	Total expected cost (\$)
$F_{emissions}$	Total emissions (kg)
F_{lts}	Power flow through line *l* (MVA)
I_{it}	Binary status indicator of generating unit *i*
L_{jt}	Load after implementing DRPs
L_t^{final}	Hourly load after implementing DRPs
LS_{jts}	Involuntary load shedding in load *j* (MW)
P_{itm}^e	Generation of segment *m* in linearized fuel cost curve of unit *i* (MWh)
P_{it}^{tot}	Total scheduled power of unit *i* (MW)
P_{its}^{tot}	Total deployed power of unit *i* (MW)
P_{wt}^{wind}	Scheduled wind power of wind unit *w* (MW)
SR_{its}^U/SR_{its}^D	Deployed up/down reserve of unit *i* (MW)
SR_{it}^U/SR_{it}^D	Scheduled up/down reserve of unit *i* (MW)
W_{wst}^{spil}	Wind power spillage of wind farm *w* (MW)
Y_{it}/Z_{it}	Binary start-up/shutdown indicator of unit *i*
δ_{bts}	Voltage angle at bus *b* in scenario *s* (rad)

2. Introduction

One of the challenging aspects of wind power units is the intermittent nature of this kind of energies. Because of the fluctuations in outage power of the wind units, integrating wind farms with Demand Response Programs (DRPs) can reduce this power unpredictability [1]. The current paper proposes the effective solution in this context.

2.1. Motivation

The challenging environmental targets set by governments and rising fossil fuel prices have affected increased production using renewable energy sources (wind, solar, mini-hydro) in electrical systems. It is possible to identify the benefits of renewable sources such as reducing emissions of pollutant gases, reducing energy imports and consequently reducing energy dependence, as well as increasing wealth and employment. Introducing and increasing exploitation of different renewable energies, a new challenge is faced in planning energy dispatch.

Renewable resources are characterized by variability; in general, predicting production amount is difficult, and renewable generation profile does not match with electric demand profile. Due to the above challenges and difficulties, variability, predictability and profile difference can cause energy deprivation in certain periods, and excess energy in other periods [2].

2.2. Literature Review

Increasing operational flexibility is considered as a key solution to mitigate the problems caused by intermittent nature of renewable sources, allowing safe operation of the electrical system [3]. To make electrical systems more flexible, networks should be evolved into smart grids by implementing innovative concepts such as DR programs [4], network reinforcement and existence of faster production groups in order to ensure continuity of energy supply [5], concept of vehicle-to-grid [6] and storing electricity [7].

Integrated demand response of multi-energy systems has been discussed in [8]. Some studies have focused on finding solutions for optimal operation of micro-grids with renewable resources utilizing DR. Optimal renewable resource planning in the presence of DR has been studied in [9]. Techno-economic optimization of a stand-alone micro-grid comprising hybrid PV/Wind generations and battery storage with DR implementation has been presented in [10].

A number of researchers have modelled some of the DRPs considering different market designs and have investigated impacts of these programs on various aspects of electricity market operations through decision-making models [3,11,12].

In [13], authors have analysed strategy of wind units considering intraday DR exchange. A DR market design has been proposed in [14] to expand renewable energy resources and reduce emissions using economic models. The latest data has been updated using decision-making process employed for wind units to offer in the energy market. In [11], the ability of DR to improve smart system performance is demonstrated. A stochastic multi-objective market equilibrium has been determined in [15] to evaluate uncertainties in DR programs. Assigning a strategic priority to the most effective DRP from ISO point of view is one of the most important issues. Multi-Criteria decision-making (MCDM) or Multi-Attribute Decision Making (MADM) is an appropriate approach to select the optimum DR program [16].

Some reports have employed multi-attribute decision-making methods for distribution system planning [17]. Reference [18] has solved a generation planning problem using MADM. An MCDM model has been developed to evaluate profits of residential energy programs [19]. All these studies have been conducted for distribution systems without considering renewable energy.

In this perspective, international experiments and results of DR have been analysed and it is observed that DRPs can be effectively recognized as possible solutions to obtain a more flexible electrical network [20]. Demand management is a concrete measure for energy economy, where consumers change electricity demand through energy price variations throughout the day or in response to incentives designed to reduce demand during peak periods [21].

On this basis, allowing customers' potential to be catalysed through DR programs, a new window of opportunities might be created to increase flexibility of the electric system in handling variability of wind potential or contingency events. The uncertainty of the wind potential has been incorporated into the Security Constrained Unit Commitment (SCUC) models in a number of recent publications [22]; DR strategies have also been proposed in the SCUC problem [23–25]. Although many reports have studied impact of DRPs, combination of Multi-Objective (MO) problem with MCDM has not been addressed in the literature. The outstanding results show that the proposed approach can be effectively employed as a valuable tool by system operators to recognize which strategy is more efficient.

2.3. Aims and Contributions

Many studies have been conducted to model the DRPs with unpredictable energy production resulting from injection of renewable units' generation in the power system. Nevertheless, none of them has considered such various aspects of modelling two-stage stochastic MO problem for providing a solution to ISO with MCDM simultaneously, to choose the most effective strategy.

Hence, this paper develops a new model employing a stochastic MO problem associated with an MCDM integrated with wind power and DR potential to minimize two objectives including operational costs and pollutant emissions. This new model allows dealing with uncertainty of wind energy represented by different possible scenarios through a two-stage stochastic problem.

In this problem, the operational reserve is requested in order to maintain a balance between production and consumption. In order to demonstrate the efficiency of DRPs and market power efficiency, several numerical indices such as load factor, marginal price, ENS and the Share Weighted Average Lerner Index (SWALI) are considered by the MCDM approach. The contributions of the paper can be summarized as follows:

- Developing a stochastic Heuristic Multi-Objective Multi-Criteria Decision Making (HMM) approach to design DR programs in power systems
- Modelling two-stage stochastic MO power system operation empowered by reliability and market power indices as a part of MCDM problem to integrate wind power and DR potential

2.4. Paper Organization

The paper is structured in five sections. In Section II, the different types of modelling the DR programs in this work are introduced, and their mathematical model is proposed. In Section III, the procedure of two-stage stochastic model and the HMM approach are formulated. Numerical results of the model are in Section IV, and the conclusion is in Section V.

3. The Proposed Model

In this paper, both categories of DRPs called priced-based and incentive-based are modeled. In the following the proposed Stochastic Multi-Objective formulation model, the relative constraints and HMM are discussed in detail.

3.1. Model of DR programs

First of all, an improved version of the economic model of responsive loads is presented based on the price elasticity concept and customers' behavior. DR can be defined as changes in behavior of final consumers related to normal electricity consumption. This change might be the result of electricity price variations over time, or imposing penalties or incentives designed to lower electricity consumption in periods where system reliability is at risk.

These programs can be divided into two groups: namely price-based DRPs (PBDRPs) and incentive-based DRPs (IBDRPs) [26]. In the PBDRPs, the programs are usually voluntary, Time of Use (TOU), Real Time Pricing (RTP) and Critical Peak Pricing (CPP) that provide variable rates in time. In this way, these programs induce end customers to reduce or change their demand through changes in electricity rates, i.e., if there are significant differences in electricity price between hours or periods of time, customers adapt their flexible loads according to lower prices. IBDRPs are classified into three subgroups including: voluntary, mandatory and market clearing programs. These programs motivate customers to change their typical demand, but in exchange for a specific payment, called an incentive [27].

In order to avoid restating general model of economic loads based on demand price elasticity, the consumer's consumption after DR implementation has been derived directly from the model developed in [28] as can be seen in Eq. (1). The model is based on the customer's benefit function and the formulation procedure is explained step by step in [15].

$$D(t) = \mathrm{d}_0(t)\left\{1 + \sum_{t}\left[\frac{\left(e\,(t,t')\right).\left(a\,(t) + (\rho(t) - \rho^0(t))\right)}{\rho^0(t)}\right]\right\} \tag{1}$$

where $D(t)$ is consumer's consumption after DR implementation, $\mathrm{d}_0(t)$ is initial electricity demand of load at hour t, a (t) is rate of incentive at hour t ($/MWh), $\rho(t)\ and\ \rho^0(t)$ are respectively eelectricity tariff at hour t ($/MWh) and initial electricity price at hour t ($/MWh) and finally $e\,(t,t')$ is Elasticity of demand.

3.2. Stochastic Multi-Objective formulation

In this work, two approaches have been integrated into the proposed model: stochastic optimization method and augmented ε-constraint multi-objective method. The only stochastic parameter which is considered belongs to generation of wind farms, being modelled from scenarios that allow considering wind characteristic inconstancy.

The multi objective method augmented epsilon constraint allows simultaneous minimization of two functions with divergent objectives. In order to solve the proposed problem, two objective functions are considered including minimizing operational cost for ISO and minimizing emission rate of pollutant gases of the conventional units, which can be translated by Equation (2):

$$\text{Minimize } \{F_{cost}\ , F_{emissions}\ \} \tag{2}$$

where F_{cost} is the total expected cost ($) and $F_{emissions}$ is the total emissions (kg). Some electricity markets consider reducing Carbon Trading Scheme (CTS) or some sorts of renewable energy targets as an objective function. Carbon emission Trading Schemes are typically used at governmental stage based on international agreements to mitigate emissions and to meet obligations specified by Kyoto protocol.

Moreover, renewable energy expansion programs are in-line with emission reduction programs in most cases as these programs enable reducing carbon emissions produced by conventional fossil fuel-based power plants. However, some recent efforts have been devoted to reducing green-house gas emissions by defining a new role for Independent System Operators (ISOs) as independent entities to find new solutions to minimize emission produced by existing generating sources in electricity markets.

In 2014, U.S. Electric Reliability Coordinating Council (ERCC) expressed the fact that environmental dispatch can be done by RTOs/ISOs to meet emission reduction targets [29]. In 2017 regional energy outlook, ISO New England plans to refine systems and market rules to integrate renewable resources to reduce emissions from fossil-fuel-fired generators and to achieve a clean-energy future [30]. Moreover, California ISO suggests shifting to regional ISO to expand resource flexibility, grid reliability and emission reduction through a more local approach [31]. As such, this manuscript considers emission reduction as an objective function sub-part to be in compliance with the abovementioned market changes in real life scenarios.

Moreover, academic studies such as [32–36] consider emission reduction as an ISO objective function sub-part. In [32] an incentive-based model of demand, based on the concept of elasticity of demand and customer’s benefit function is proposed. A new linearized formulation of cost-emission associated with DRPs and moreover a new index called strategy success index (SSI) is determined to prioritize DRPs from the ISO perspective. Authors in [33] have considered the generated emission over the scheduling time zone as the second objective.

The models of load management are explored to reduce cost and emissions. A day-ahead self-optimizing load management with multiple communications between an ISO operator and customers [34]. A preventive maintenance scheduling of generators is addressed which is affected by IBDR programs. Indeed a new structure of cost-and-emission-based preventive maintenance problem is presented [35].

DR for industrial-case energy users in Midwest ISO associated with a dynamic programing approach to curtail energy use [36]. Firstly, it is necessary to present the formulation of each objective function. The operational cost for ISO is given in Equation (3):

$$F_{cost} = \sum_{t} \left\{ \begin{array}{c} \sum_{i} \left[\begin{array}{c} \left(nlc_i \,.\, \mathrm{Y}_{it} + suc_i + \sum_{m} \left(P_{it}^{e}(m) \,.\, c_i^{e}(m) \right) \right) \\ +(c_i^{RU} . SR_{it}^{U} + c_i^{RD} . SR_{it}^{D}) \end{array} \right] \\ + \sum_{w} \left(c_{wt}^{wind} . P_{wt}^{wind} \right) \end{array} \right\} + \sum_{s} \sum_{t} \omega_s \,. \left\{ \begin{array}{c} \sum_{i} [(c_i^{ERU} . SR_{its}^{U}) - (c_i^{ERD} . SR_{its}^{D})] \\ + \sum_{w} \left(\pi_{spil} . W_{wst}^{spil} \right) \\ + \sum_{j} \left(voll_j . \mathrm{LS}_{jts} \right) \end{array} \right\} \tag{3}$$

The cost function includes two stages. The first stage represents the decisions to be declared as hourly unit commitment statuses of conventional units, which do not depend on realizing of scenario (*s*). These variables do not change if there are variations in the production of renewable energy or electric demand.

Therefore, at this stage, the variables always have the same value regardless of any scenarios and correspond to day-ahead market costs. These decisions include the no load cost (nlc_i), binary start-up indicator of unit *i* ($Y_{i,t}$), start-up costs (suc_i), generation of segment m in linearized fuel cost curve of unit ($P_{it}^{e}(m)$) and the linearized fuel cost ($c_{it}^{e}(m)$). Here, is also considered the value of scheduled reserve up and down (SR_{it}^{U}, SR_{it}^{D}) and the respective costs (c_i^{RU}, c_i^{RD}) and the scheduled wind power (P_{wt}^{wind}) in each wind farm *w* and the cost of each wind producer (c_{wt}^{wind}).

The second stage is related to possible instances of wind generation that should be considered according to their probability (ω_s), that is, the value of the variables is different for each scenario according to wind intensity. These variables are equivalent to balancing market decisions made in real time.

Here is considered deployed up and down reserves ($sr_{its}^{U}, sr_{its}^{D}$) and their costs in scenario s (c_i^{ERU}, c_i^{ERD}), wind power spillage (W_{wst}^{spil}) and the cost of spillage (π_{spil}) and the value of lost load ($voll_j$) and involuntary load shedding cost (LS_{jts}). The objective function related to total emissions during planning period is calculated as follows:

$$F_{emission} = \sum_i \sum_t \left[P_{it}^{tot} . (e_i^{SO_2} + e_i^{NO_x})\right] \tag{4}$$

where P_{it}^{tot} is the total scheduled power of unit I (MW), $e_i^{SO_2}$ and $e_i^{NO_x}$ are emission rate of SO_2 and NO_x ($/kg), respectively.

3.3. Day-ahead Dispatch Constraints

Next, are presented the problem constraints related to day-ahead market, where the scenarios are not considered.

- *DR Constraints:*

$$\mathrm{D}_j(t) = dr^{max} . d_j^0(t) . \left(1 + \sum_t \left[\frac{\left(e\,(t,t')\right) . \left(a\,(t) + (\rho(t) - \rho^0(t))\right)}{\rho^0(t)}\right]\right) \tag{5}$$

$$\mathrm{L}_j(t) = \mathrm{D}_j(t) + (1 - dr^{max}) .\ d_j^0(t) \tag{6}$$

$$L^{final}(t) = \sum_j \mathrm{L}_j(t) \tag{7}$$

Equation (5) represents the demand for energy modified every hour after the implementation of DR programs. If it is an IBDRP the value of *a(t)* is equal to 1, however, if it is a PBDRP the value is equal to 0. dr^{max} is the maximum response potential or maximum participation level. In this paper, the maximum participation level in DR programs is considered 20%. It means that 80% of demand does not change due to price changes. On one hand, the unchangeable part of customers' demand is not larger than 80%. On the other hand, it does not mean that all 20% of demand is changed, but the potential of changes in the response to extreme price is 20%.

Indeed, the amount of changes depends on the elasticity. It should be noted that, the technical and behavioral constraints of customers are reflected in the elasticity, since the calculating methods of elasticity are based on analysis of real data and customers' surveys [37]. Equation (6) refers to $\mathrm{L}_j(t)$ the load after the DR implementation for each load j and for each hour t, while Equation (7) $L^{final}(t)$ presents the final load value after DR, for each hour.

- *Demand Balance Dispatch in Day-ahead:*

$$\sum_{i} P_{it}^{tot} + \sum_{w} P_{wt}^{wind} = \sum_{j} \mathrm{D}_j(t) \tag{8}$$

Equation (8) corresponds to the balancing equation for the day-ahead market, where P_{it}^{tot} the power set for all generators and P_{wt}^{wind} the scheduled wind power must be equal to $\mathrm{D}_j(t)$ the modified load demand after DR, that is, the production must be equal to the consumption.

- *Start-up Cost:*

$$0 \leq suc_i \leq C_{it}^{ST}(I_{it}\text{-}I_{i,t-1}) \tag{9}$$

The limit of the start-up costs for each generator is represented by equation (9). suc_i is start-up cost of generation unit *i*, C_{it}^{ST} is start-up cost of generation unit *i* in hour *t* ($) and I_{it} is binary status indicator of generating unit *i*.

- *Max Wind Scheduled in DA:*

$$P_{wt}^{wind} \leq w_{wt}^{max}.\, p_{w}^{install} \tag{10}$$

The value of wind energy scheduled in the day-ahead market (P_{wt}^{wind}) is expressed by equation (10). While w_{wt}^{max} is available wind power of wind unit w (MWh) and $p_{w}^{install}$ is installed capacity of wind farms (MW).

- *Maximum conventional scheduled power and reserve capacity:*

$$P_{it}^{tot} + SR_{it}^{U} \leq p_{i}^{max}.I_{it} \tag{11}$$

$$P_{it}^{tot} - SR_{it}^{D} \geq p_{i}^{min}.I_{it} \tag{12}$$

In order to deal with wind energy uncertainties and possible component failures, the scheduled up and down reserves SR_{it}^{U}/SR_{it}^{D} , are considered to ensure optimal system operation. Equations (11) and (12) express the capacity limits of both reserves added to power of the generators cannot exceed the maximum and minimum generation (P_{i}^{min}/P_{i}^{max}) limits of each generator. I_{it} is binary status indicator of generating unit *i*.

3.4. Balancing Stage Constraints

- *Demand Balance in RT:*

$$\sum_{i}(SR_{its}^{U}-SR_{its}^{D})+\sum_{j}LS_{jts}+\sum_{w}(p_{w}^{install}-P_{wt}^{wind}-w_{wst}^{spil})=\sum_{l}(F_{lts}) \tag{13}$$

$$F_{lts}=\frac{\delta_{bts}-\delta'_{b}ts}{x_l} \tag{14}$$

To ensure system security and load dispatch in each scenario, the power balance constraint for each bus must be satisfied. In this way, a power flow equation (TP) is applied, in equation (13). $SR_{its}^{U}/SR_{its}^{D}$ are deployed up/down reserve of unit *i* (MW), LS_{jts} is the involuntary load shedding in load j (MW), $p_{w}^{install}$ and P_{wt}^{wind} are the installed capacity of wind farms (MW) and scheduled wind power of wind unit *w* (MW) respectively. w_{wst}^{spil}, is Wind power spillage of wind farm *w* (MW) and F_{lts} is power flow through line *l* (MVA).

- *Load Shedding and Wind Spillage:*

$$LS_{jts} \leq L_j(t) \tag{15}$$

$$W_{wst}^{spli} \leq P_{wt}^{wind}.p_{w}^{install} \tag{16}$$

The limits of the load shedding and the value of wind spillage are represented in equation (15) and (16). LS_{jts} is involuntary load shedding in load j (MW), $\mathrm{L}_j(t)$ the load after the DR implementation for each load j and for each hour *t*, $p_{w}^{install}$ and P_{wt}^{wind} are the installed capacity of wind farms (MW) and scheduled wind power of the wind unit *w* (MW), respectively. W_{wst}^{spli} is the wind power spillage of wind farm *w* (MW)

- *Reserve Constraints of Conventional Power Plants*

$$SR_{its}^{U} \leq SR_{it}^{U} \tag{17}$$

$$SR_{its}^{D} \leq SR_{it}^{D} \tag{18}$$

Equations (17) and (18) correspond to the constraints for $SR_{its}^{U}/SR_{its}^{D}$ deployed up and down reserves that should be lower than SR_{it}^{U}/SR_{it}^{D} the values of scheduled up/down reserves made before.

- *Constraints for Reserve Limitations:*

$$P_{its}^{tot} = P_{it}^{tot} + SR_{its}^{U} \text{ - } SR_{its}^{D} \tag{19}$$

$$P_{its}^{tot} \leq p_i^{max}.I_{it} \tag{20}$$

$$P_{its}^{tot} \geq p_i^{min}.I_{it} \tag{21}$$

The value of the real-time power (P_{its}^{tot}) depends on the previously scheduled power (P_{it}^{tot}) and the reserves that are employed, equation (19) where $SR_{its}^{U}/SR_{its}^{D}$ deployed up and down reserves. The limitations of real power (P_{its}^{tot}) are presented in equations (20) and (21), where (P_i^{min}/P_i^{max}), are Minimum/Maximum generation limit (MW), respectively. After having the formulation for the two objective functions and the constraints for the system, now it is possible to make the model for the MO function. Compared to problems with only one objective function, MO problems are more difficult to solve since there is more than one solution. Rather, there is a set of acceptable solutions within a range of values.

This set is called the Pareto front. The most desired solution for the decision maker is chosen from Pareto front. Creating Pareto front allows the decision maker to make a more informed choice by looking at a wide range of solutions. In this way, this feature becomes very useful and provides a better understanding of the system [38]. In order to obtain the curve of Pareto, augmented ε-constraint method is used. First, the payoff table has to be established, which is presented in this work as Table 1.

This table refers to values of the individual optimization of each objective function, considering all constraints of the problem. After calculating the payoff table, one of the objective functions is considered as the main function, in this case, is F_{cost}, where the range of *K-1* values of each objective function will be used as a constraint ($F_{emissions}$). The range of values of $F_{emissions}$ is divided into *q* ranges, varying the value of ε_2^k [39].

Table 1. Definition of Payoff Table

	$\boldsymbol{F^{Cost}}$($)	$\boldsymbol{F^{Emissions}}$ (kg)
Min $\boldsymbol{F^{Cost}}$	F_{min}^{Cost}	$F_{max}^{Emission}$
Min $\boldsymbol{F^{Emissions}}$	F_{max}^{Cost}	$F_{min}^{Emission}$

The augmented ε-constraint method is formulated as:

$$Min\left(F_{cost} - \delta \times \left(\frac{S_2}{r_2}\right)\right) \tag{22}$$

$subject\ to: F_{emissions} + S_2 \;=\; \varepsilon_2^k, S_2 \in R^+$, where

$$\varepsilon_2^k = F_{max}^{Emission} - \left(\frac{F_{max}^{Emission} - F_{min}^{Emission}}{q_2}\right) \times \mathrm{k}, \mathrm{k} = 0, 1, \dots, q_2 \tag{23}$$

where δ is a scaling factor, and S_2 is a slack variable. $F_{max}^{Emission}$ and $F_{min}^{Emission}$, represent the maximum and minimum values of the emission objective function, based on the payoff table, respectively. ε_2^k , is the k-th range of $F_{emissions}$. r_2 and q_2 are the range of the total air pollutants emission and the number of the equal parts, respectively. More details of generation units are presented in Table 2.

One of the great benefits of this method is the possibility to control the problem density through variable q. Comparing to the simple epsilon-constraint method, the objective function is incremented by the sum of variable S_2. In order to avoid dimensioning problems, the variable S_2 is replaced in the second term of the objective function $\delta \times (S_2/r_2)$. This mechanism prevents the production of inefficient solutions.

Table 2. Generation unit energy offering information

Unit no.	Piece wise linearization parameters (MW)				Energy bidding data				Start-up cost ($)	Emission rates (Kg/MWh)	
	p_i^{min}	$P_{it}^e(1)$	$P_{it}^e(2)$	p_i^{max}	$c_{it}^e(1)$	$c_{it}^e(2)$	$c_{it}^e(3)$	$c_{it}^e(4)$	C_{it}^{ST}	$e_i^{NO_x}$	$e_i^{SO_2}$
1-5	2.4	6	9.6	12	23.41	23.78	26.84	30.4	87.4	1.14	0.456
6-9	15.8	16	19.8	20	29.58	30.42	42.82	43.28	15	0.832	0.333
10-13	15.2	38	60.8	76	11.46	11.96	13.89	15.97	715.2	3.125	1.25
14-16	2.4	6	9.6	12	23.41	23.78	26.84	30.4	575	1.85	0.74
17-20	54.25	93	124	155	9.92	10.25	10.68	11.26	312	2.602	1.041
21-23	68.95	118.2	157.6	197	19.2	20.32	21.22	22.13	1018.9	3.26	1.304
24	140	227.5	280	350	10.08	10.66	11.09	11.72	2298	8.333	3.333
25-26	54.25	93	124	155	9.92	10.25	10.68	11.26	0	0	0

3.5. Heuristic Multi- Objective Multi-Criteria decision-making (HMM)

Different DRPs have various influences on the energy market efficiency. In this context, it is crucial for the market regulator to select and implement a proper DR program which stabilizes and mitigates market power. In order to choose the most effective DRP as an optimal solution, a DR portfolio is employed by the Geometric Average Utility Function (GAUF) as one of the Goal Programming (GP) methods [40]. GP method is extensively used by decision makers for deriving a single objective problem from multiple objectives.

The GP approach is preferable compared to other solutions such as weighting method [41]. Two terms called the Strategy Index (SI) and Strategy Success Index (SSI) are employed in following equations (24) and (25) [40].

$$SI_m = \sum_{t=1}^{24}\left\{\left(St_1(t)\right)^{w_1}\left(St_2(t)\right)^{w_2}\cdots\left(St_k(t)\right)^{w_k}\right\} \tag{24}$$

$$SSI_m = SI_m / SI_{\max} \times 100 \tag{25}$$

In Eq. (24), $St_k(t)$ depicts performance value of k^{th} criteria for each option at the t^{th} hour, and W_k shows weight of k^{th} criteria and its importance which can be changed from ISO's point of view depending on market's conditions and priorities. The SSI term formulated by equation (25) is the normalized value of SI factor. In brief, the successful implementation of a DR program increases SSI. According to this factor, the decision maker can prioritize various DRPs based on criteria's weight of market efficiency and potential occurrence of market power.

To solve this stochastic multi-objective MCDM, one of the effective solutions, producing the Pareto-optimal collection that follows the min-max clustering principle is required. The goals and priorities between multiple attributes in the MCDM decision process are considered through GP. As described previously, in the MO method, augmented ε -constraint is the main function which generates the Pareto front and selects the best possible solutions. In order to select the best compromising solution, it is assumed that the system operator is responsible for decision-making. To this end, three indices are considered as the criteria to analyse effectiveness of DR programs. These indices are as follows:

- Load Factor: $LF = \frac{Average\ Load}{Maximum\ demand} \times 100$;
- Expected Energy Not Supplied: $EENS = \sum_j \sum_t \sum_s (LS_{jts})$;
- $SWALI_t = \sum_i \sum_s s_i \frac{Price_t - Marginal\ cost_{it}}{Price_t}$

where s_i is the generation share of unit i and can be calculated by (26).

$$s_i = \frac{p_i^{\max}}{\sum_i p_i^{\max}} \tag{26}$$

These criteria, i.e., *SWALI*, *EENS*, and *LF* are considered with the same weights equal to 0.33. Also, a sensitivity analysis is performed to indicate the impact of weights on the optimal option and system operation. Fig. 1 shows the flowchart of the HMM procedure, depicting the process accurately.

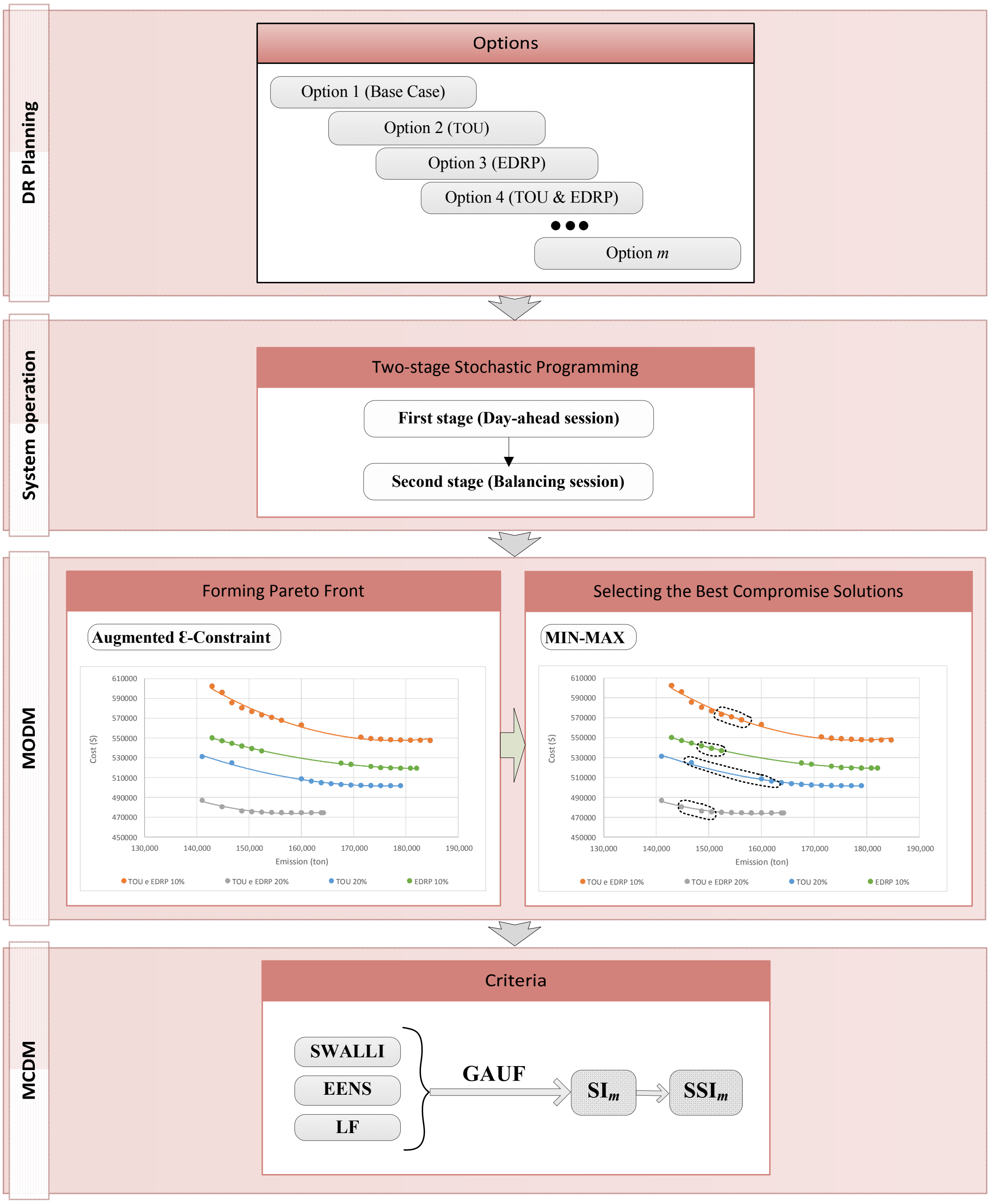


Fig. 1. Flowchart of the HMM procedure.

4. Numerical Study

In order to indicate the impact of DR programs in this model, the IEEE 24-bus test system is employed. This test system has 26 generators, 24 buses, 6 wind farms, 5 transformers and 17 loads, described in Fig. 2. In relation to the wind farms included in the network, these were introduced in buses 1, 4, 6, 18, 21 and 22 [42]. Each of these wind farms produces 150 MW, with 900 MW total installed wind power capacity. In order to model wind generation, a Weibull distribution is considered for wind speed and a similar procedure is followed to obtain the corresponding wind energy.

In order to be able to represent the inconstancy of this type of production, different scenarios, are considered based on a technique called Roulette Wheel Mechanism (RWM) based on the wind speed data in the state of South Australia [43]. The wind speed scenarios are reduced to ten scenarios for each wind farm using K-means clustering technique [44] and then transformed into power scenarios considering the Vestas 3 MW turbine model. Of all generated scenarios, only 10 are used in order to reduce the computational complexity. The various scenarios used are shown in Fig. 3. The probability of each scenario is 10%. The cost of wind spillage is 40$/MWh.

For this model, it is assumed that the generating units present their offerings in three linearized segments between minimum and maximum values which can be produced. The power of each generator, the linearized cost of fossil fuel, the start-up cost, and the emissions rate of pollutant gases for the 26 generators are presented in Table 2.

The Value of Lost Load (VOLL) is considered 100$/MWh for each load, this means that for each loss of 1 MWh the system operator pays 100$ to the affected consumer. The workstation employed has Intel (R) XEON (R) CPU E5-2687W0 (2 processors, with 16 layers each), @ 3.10 GHz with 192 GB of memory and 64-Bit operating system.

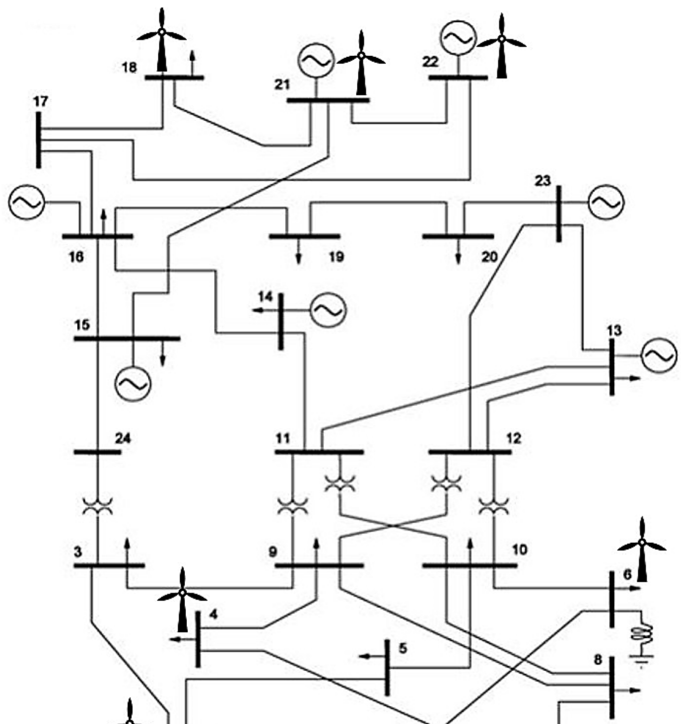


Fig. 2. Modified single line diagram of the IEEE RTS

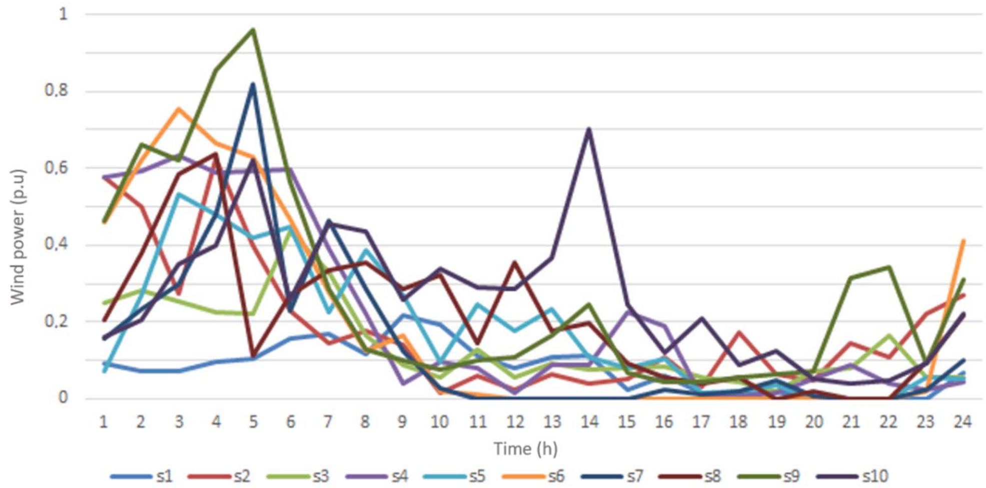


Fig. 3. Considered wind power generation scenarios

4.1. Case studies

In order to investigate the effectiveness of DR programs in the proposed model, the implementation of TOU program and the EDRP program were considered, as well as the implementation of the combination of both programs simultaneously. The electric tariffs of the programs are presented in Table 3. For this model, the initial value of the electricity $\rho^0(t)$ is equal to 15 \$/MWh, calculated through the average market price before the implementation of DR programs.

Therefore, seven different cases were defined, Table 4. Case 1 corresponds to resolution of the algorithm without any DRP, where the electric tariff is fixed for all periods. In case 2, TOU program is implemented with 10% of consumers participation while in case 3, 20% of consumers participate in the TOU program. In case 4 and case 5, the EDRP program is used, again with different levels of costumer's participation, 10%, and 20% respectively. The TOU and EDRP programs are used simultaneously to test efficiency of the two programs simultaneously, with 10% and 20% DR potential.

For the augmented ε-constraint, the number of iterations was 65, and the values for Payoff Table were obtained by the optimization of each objective function individually, Table 5.

Table 3. Tariffs/incentives of considered DRP's (\$/MWh)

Case	Valley (t1 to t8)	Off-peak (t9 to t16)	Peak (t17 to t24)
Base case	15	15	15
TOU	7.5	15	30
EDRP	15	15	Tariff: 15; Inc: 15
TOU and EDRP	7.5	15	Tariff: 30; Inc: 15

Table 4. Cases in study

Case	DRP	Maximum response potential (%)
1	Base case – without DR	0
2	TOU	10%
3	TOU	20%
4	EDRP	10%
5	EDRP	20%
6	TOU and EDRP	10%
7	TOU and EDRP	20%

Table 5. Payoff Table

	$\boldsymbol{F^{Cost}}$(\$)	$\boldsymbol{F^{Emissions}}$ (kg)
Min $\boldsymbol{F^{Cost}}$	447661.3	264350.3
Min $\boldsymbol{F^{Emissions}}$	2992686.2	141033.4

4.2. Cases 1, 2 and 3

In this section, the first three cases are analysed, the base case and the TOU program with 10% and 20% of customers' participation. Once the Pareto curve is obtained, the best solution is selected for each case from system operator's point of view. In order to select this point, the restriction established for pollutant emissions less than 150 tons must be respected. After this, points which verify the restriction are verified and point with smallest value is selected.

The Pareto curves are shown in Fig. 4, and the selected optimal points are identified in red. For the base case, the chosen point has the values of 148622.1 kg and 580538.5$, for case 2 of 148622.1 kg and 545864.8$, and for case 3 the coordinates of the optimum point are 146724.9 kg and 524873.34$. It can be concluded that cost decreases about 6% in the base case. Increasing the clients' participation in, case 3, cost decreases even more, about 10%. Regarding value of the pollutant emissions, the value decreases slightly in case 3.

In Fig. 5, the system load profile for 24 hours for the 3 cases is represented. It can be verified that increasing electric tariff (15 $/MWh to 30 $/MWh), during peak period from 17h to 24h in the base case, reduces electric demand. On the other hand, electric demand increases in the valley (1h to 8h), where the electric tariffs are lower. With 20% customers' participation, these changes become more pronounced and demand is even lower at peak periods and higher in the valley.

Regarding load factor, it is desired that the value is as higher as possible since it proves reducing maximum value of load to a value closer to the average. Therefore, load factor is calculated for the 3 cases, being 82.9%, 89.23% and 87.34% for cases 1, 2 and 3, respectively. It is verified that with different levels of the TOU program, value of load factor of the base case increases since there is no such a peak value of the load any longer.

Fig. 6 shows the average marginal price of every hour. Implementing the TOU program, the marginal market price is much lower than the marginal price of the base case. It is concluded that the TOU program allows the marginal price to be reduced with high impact in most hours. Participation percentage of the customers, increases in certain hours, the increase of the price in the periods of low-load, once the demand becomes higher.

Regarding the ENS, the value corresponds to sum of load shedding, so lower value is expected. For the base case the value for ENS is 21.2MWh, and for the TOU program with 10% and 20% the ENS is lower, 12.2MWh and 18.2MWh, respectively. Once again, effectiveness of DR programs that allow reducing the involuntary load shedding is proved.

An hourly average of Lerner index of all generators is presented in Fig. 7. It can be verified that in base case, the value of the index decreases considerably and the most competitive generators are 21, 22 and 23, with values close to zero. It can also be concluded that with TOU 20%, some of the generators are not needed. Then, TOU program increases market power and its efficiency. Fig. 8 shows the hourly SWALI in cases 1-3. As it can be seen, TOU programs can decrease the SWALI in all hours.

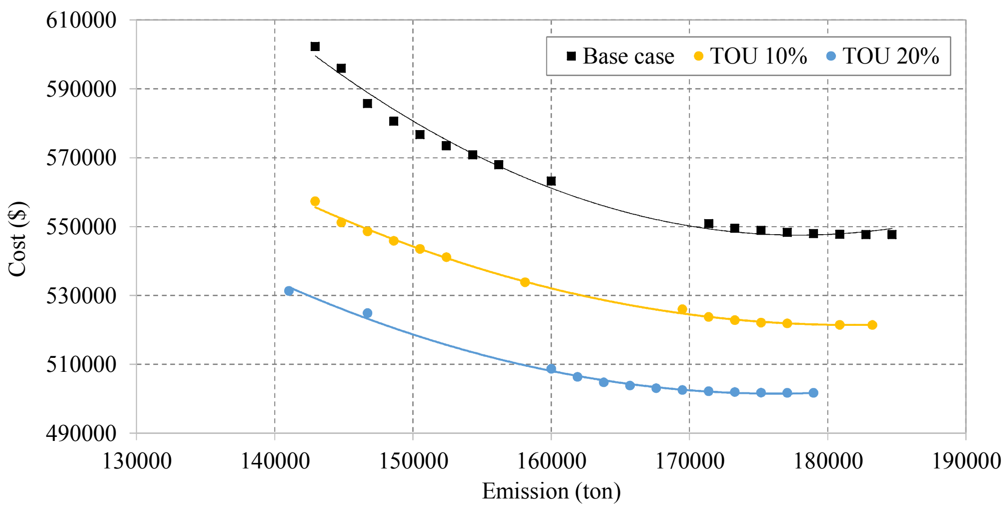


Fig. 4. Pareto front in cases 1, 2 and 3

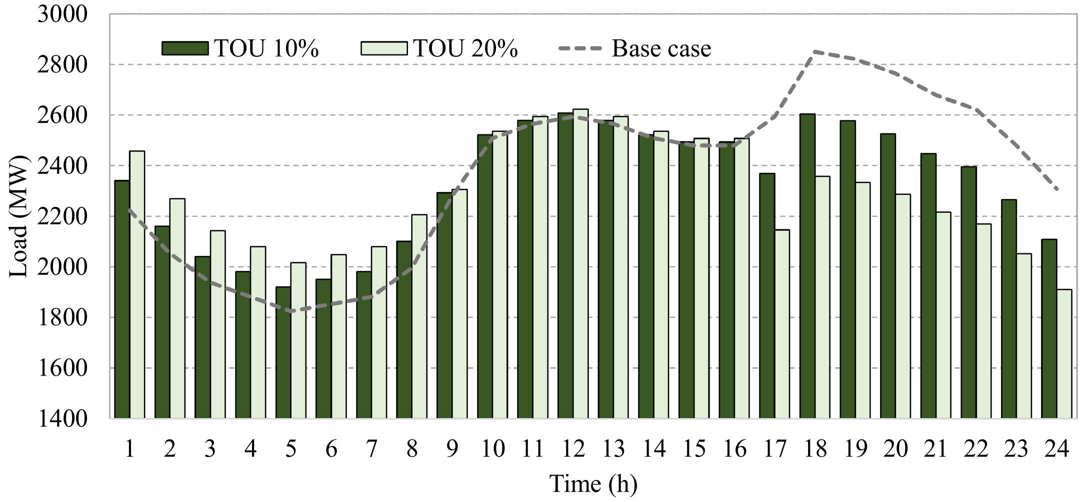


Fig. 5. Load profile for cases 1, 2 and 3

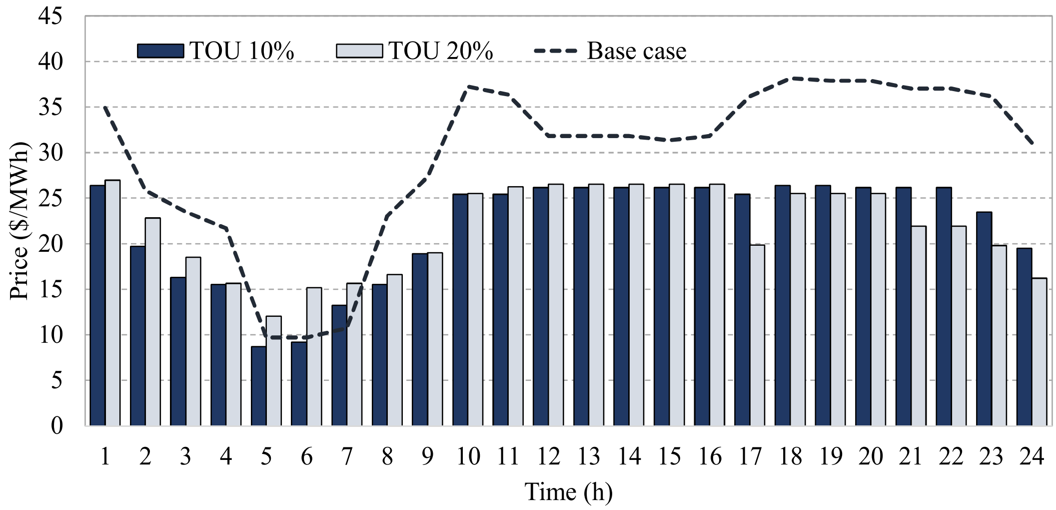


Fig. 6. Marginal prices for cases 1, 2 and 3

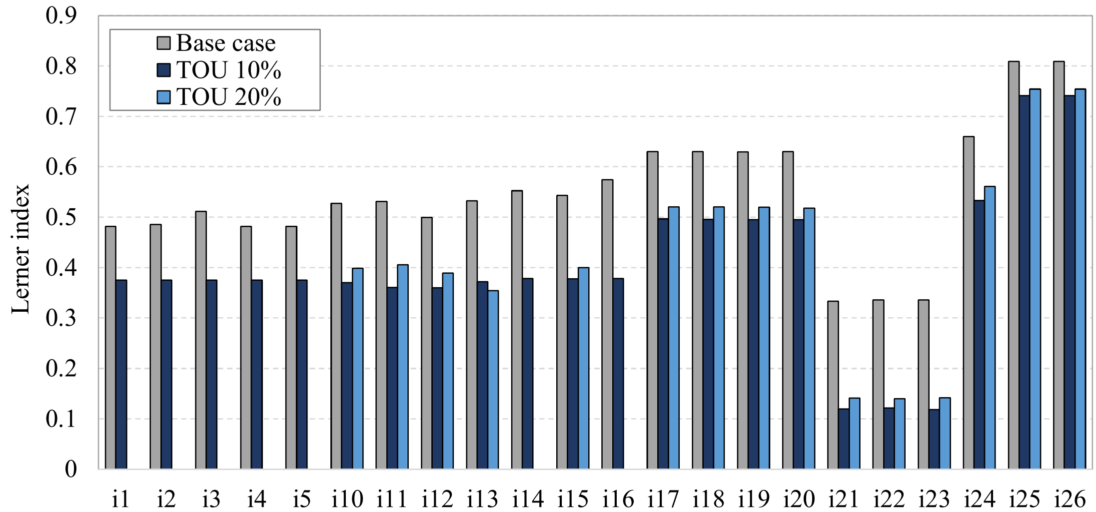


Fig. 7. Lerner index for all the generators in cases 1, 2 and 3

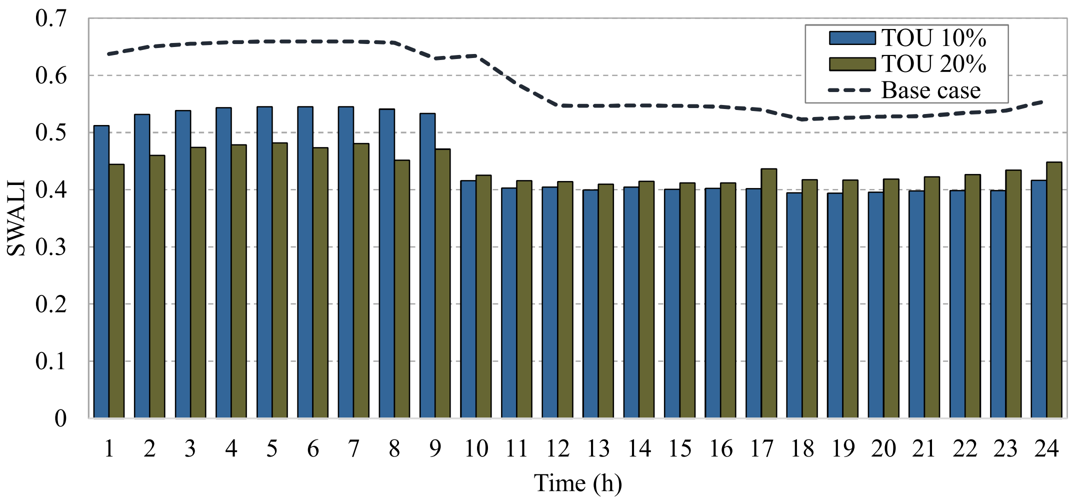


Fig. 8. Hourly SWALI for cases 1, 2 and 3

4.3. Cases 1, 4 and 5

In this section, indices for the EDRP program are analysed, with the same rate as the base case (15$/MWh), however, an incentive equal to the tariff is applied in the case of a reduction in the peak period.

To evaluate the indices, it is necessary to choose the optimum point from the Pareto curves shown in Fig. 9, for all cases. Value of the emissions is the same for the 3 cases, 148622.1 kg, since it corresponds to the first point to verify that restriction of emissions are less than 150 tons. Regarding the cost, with a 10% participation in the EDRP, value is 541891.7$, a 7% decrease in the base case. In the EDRP program 20% of the cost value drops to 515218.6$, about 11 % in regard to base case cost.

Observing Fig. 10, is possible to analyse the changes in load profile with the ERDP program. There is a decrease in electric demand in the peak period from the incentive paid by the system operator and increases load slightly during low load and off-peak periods. Reducing load and recovery for other periods is more evident in the TOU program due to the tariff difference that does not occur for the EDRP. The load factor is 88.1% for case 4 and 85.4% for case 5, values higher than the base case (82.9%) which indicate that these two cases make the load profile more balanced.

The average marginal price is demonstrated for all hours. Peak price is reduced with different levels of the EDRP program, with the market price being lower than the base case for all hours, Fig. 11.

Regarding the ENS, as seen before, the value is 21.2 MWh for the base case. With 10% EDRP, a lower value is observed for the ENS, 18.2 MWh. Using EDRP with 20% participation load shedding occurs in different wind scenarios with a total value of ENS equal to 53 MWh.

With regard to the Lerner index, analysis of Fig. 12 shows that implementing the EDRP program with fewer generators are used than in the base case, since demand decreases in peak periods. Consequently, there is a greater level of competitiveness in the market compared to the base case, making it more efficient.

Fig. 13 indicates the impact of EDRP on SWALI. As it can be observed, similar to TOU programs, EDRP can reduce the SWALI in all hours of the day. In addition, higher DR participation level decreases the SWALI in the valley hours and increases it, in the peak period.

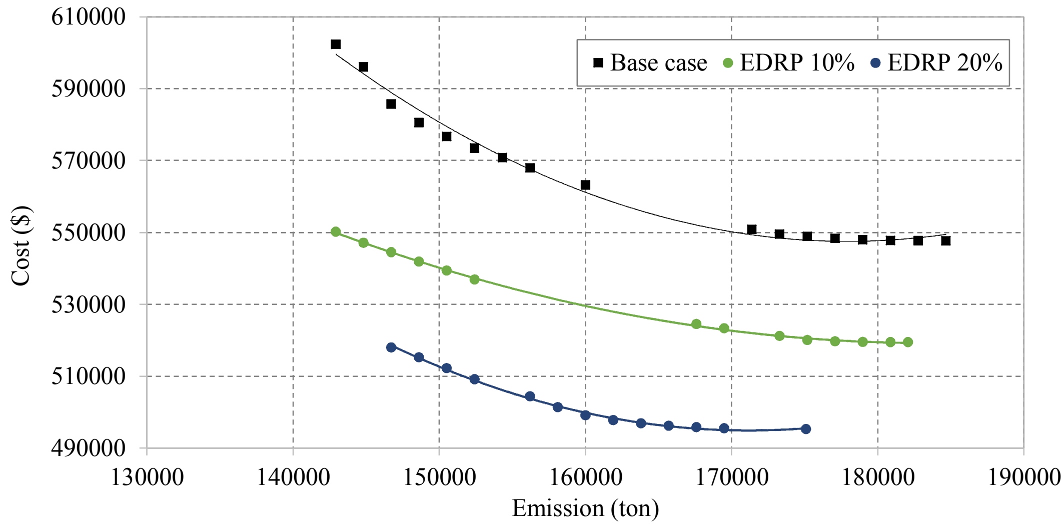


Fig. 9. Pareto front in cases 1, 4 and 5

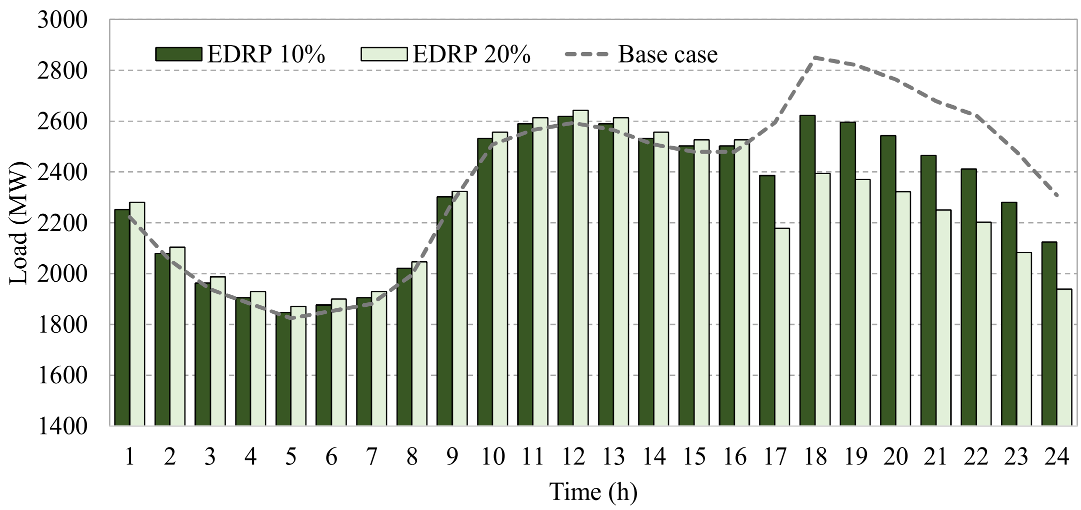


Fig. 10. Load profile for cases 1, 4 and 5

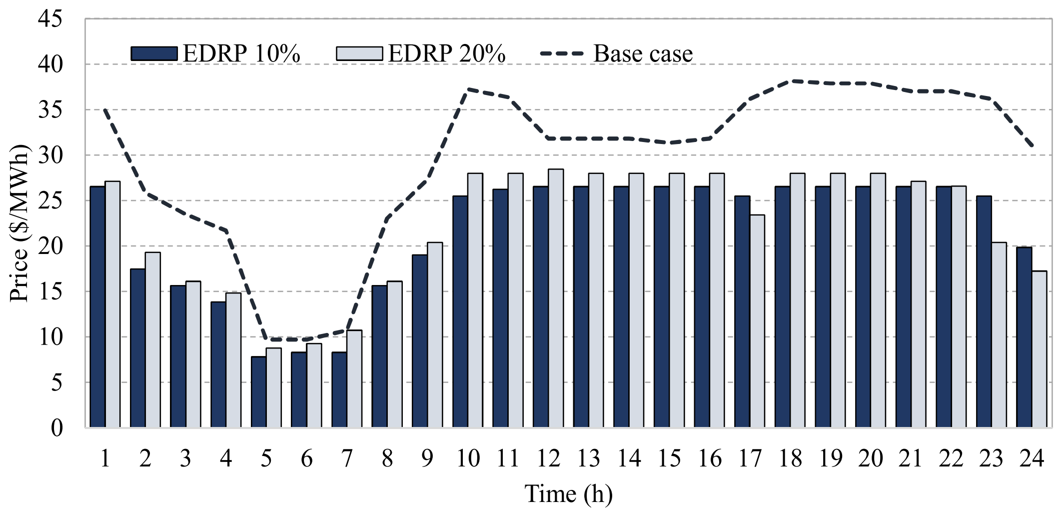


Fig. 11. Marginal prices for cases 1, 4 and 5

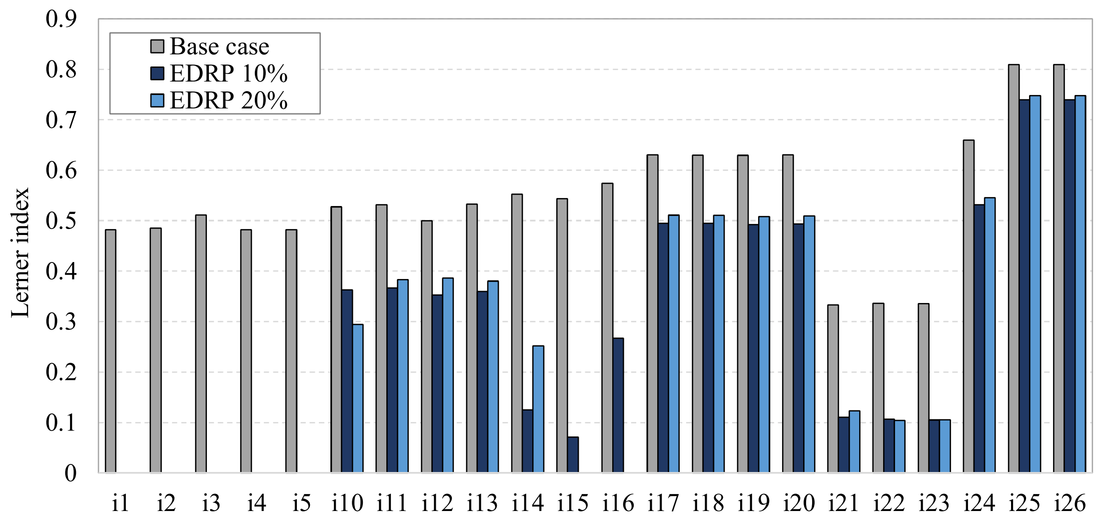


Fig. 12. Lerner index for all the generators for cases 1, 4 and 5

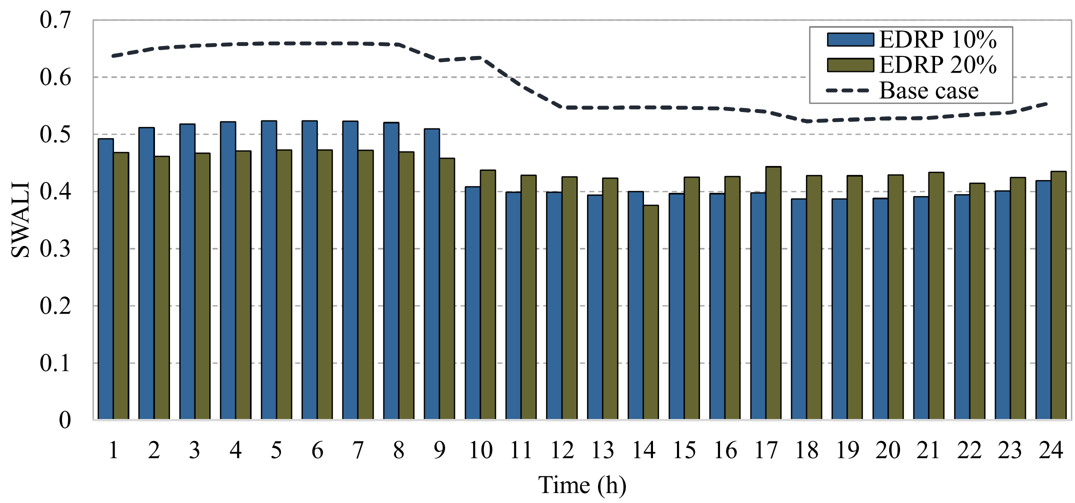


Fig. 13. Hourly SWALI for cases 1, 4 and 5

4.4. Cases 1, 6 and 7

Finally, combination of the two programs is evaluated simultaneously, TOU and EDRP. Here customers are encouraged to change their electricity demand, by price variations from the TOU program and by incentives from the EDRP.

The obtained results from MO are represented in Pareto front, Fig. 14. Once again, the optimal points for each case must be determined. The optimal point for case 6 corresponds to 146724.9 kg for the emissions and 516304.7$ for the cost, while for case 7 the emission and cost values are 148622.1 kg and 476160.8$. This combination of programs allows a great reduction in the cost for the system operator, about 11% for case 6 and about 18% for case 7.

Analysis of Fig. 15 shows there is a high decrease in the electric demand in the peak periods in regard to base case, due to high TOU tariffs for peak period and the incentive from EDRP. On the other hand, the electric demand increases periods of low-load and of off-load.

Load factor in case 6 is 86.3% and in case 7, it is 81.7%. Comparing the load factor in base case (82.9%) with the load factor in case 6, an increase is seen, the load profile becomes more balanced throughout the day. However, case 7 has a lower load factor compared to the base case which can be explained by the very sharp reduction which occurs in the peak period.

As in previous cases, marginal market prices in some cases are lower than the price established in the base case. The price reduction is more noticeable at peak periods since demand has decreased. However, at certain times, prices increase due to increased demand at the same times, Fig. 16.

In relation to the ENS, the values obtained were 18.22 MWh and 21.24 MWh for cases 6 and 7, respectively. Case 6 provides a lower load loss than the base case (21.24 MWh). However, for case 7 the value remained the same. Again, it can be seen in Fig. 17 that while analysing the Lerner index of each generator, the value has decreased considerably and some of the generators are not needed while using the DR programs.

In Fig. 18, the impact of combined TOU and EDRP on the SWALI is illustrated. Based on Fig. 19, these combined programs can decrease SWALI in all hours. However, by increasing the DR participation level, these DR programs can decrease SWALI in peak hours more significantly, due to the considerable reduction of demand in peak period in case 7.

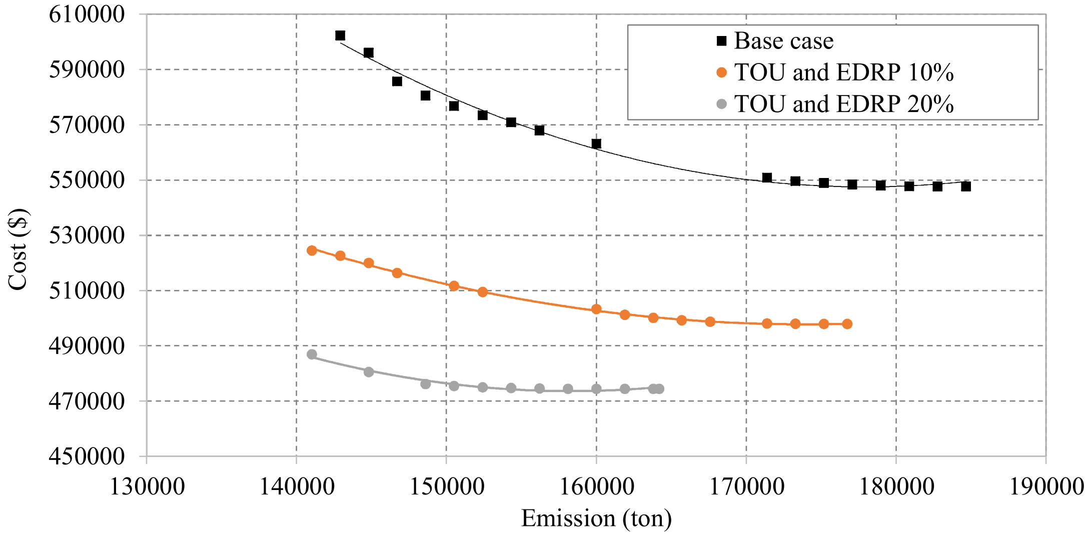


Fig. 14. Pareto front in cases 1, 6 and 7

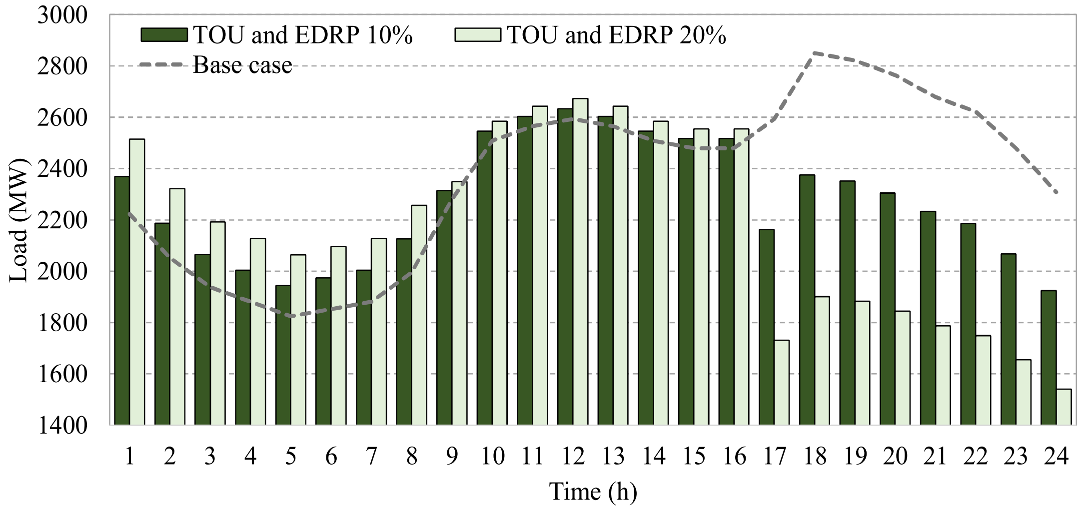


Fig. 15. Load profile for cases 1, 6 and 7

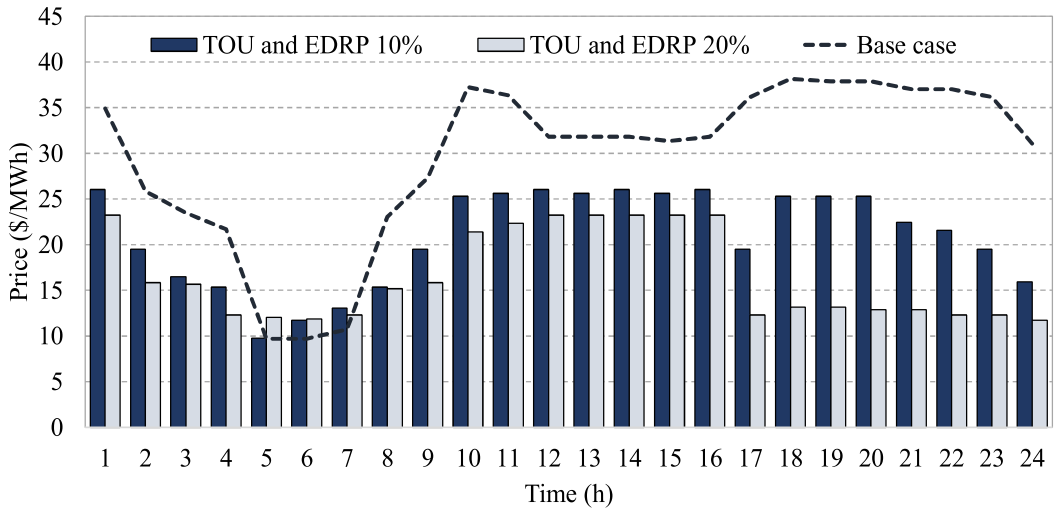


Fig. 16. Marginal prices for cases 1, 6 and 7

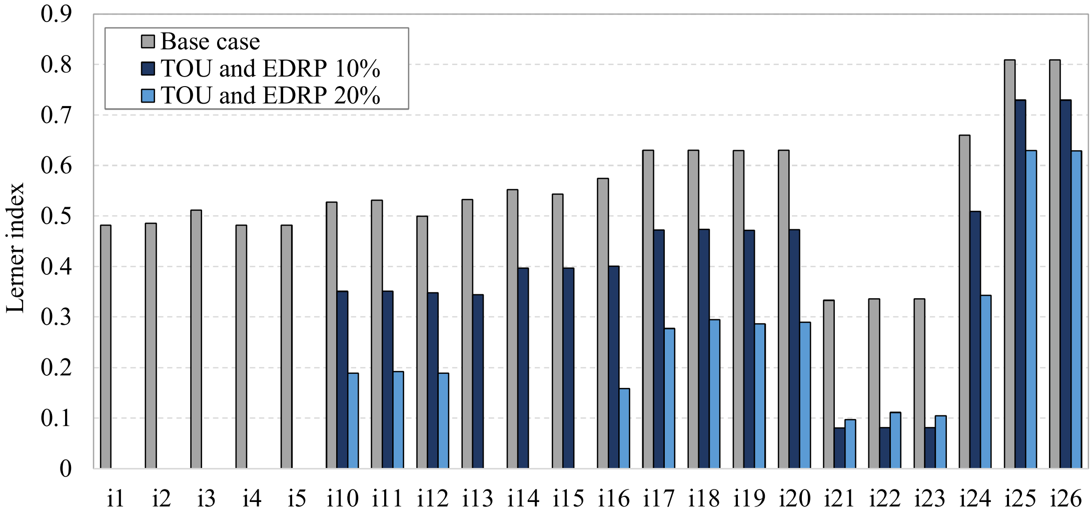


Fig. 17. Lerner index for all the generators for cases 1, 6 and 7

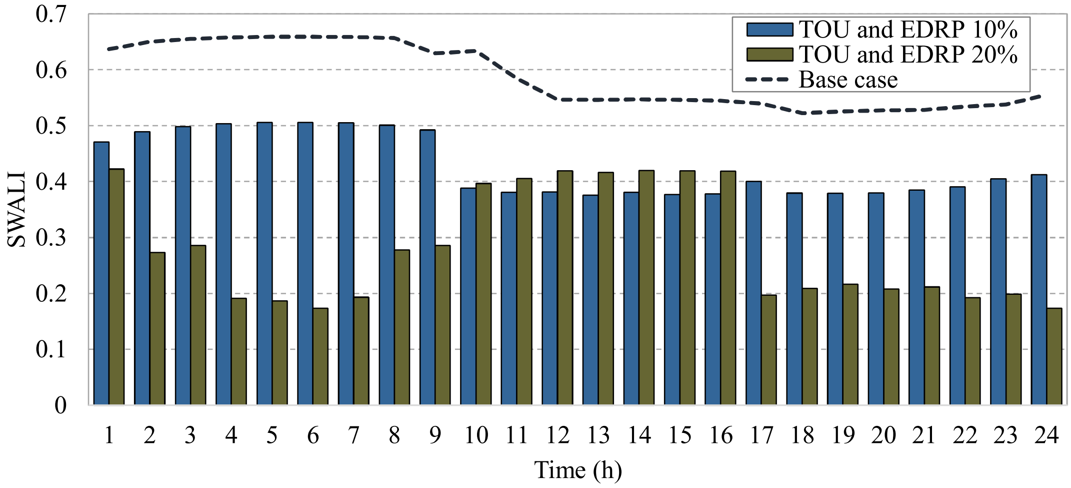


Fig. 18. Hourly SWALI for cases 1, 6 and 7

4.5. HMM Results

One of the main goals of ISO is to implement the most effective DRP. Therefore, the SSI coefficient is utilized to obtain the most effective DRP tariff which can be profitable for the market operator to mitigate the market power, balance the demand-supply market equations and increase flexibility of the electricity market. To this end, the predetermined DRPs are prioritized as illustrated in Fig. 19, the weight of each criterion is considered 0.33.

Fig. 20 investigates the impact of weights of these criteria in different cases. It is noteworthy that in case of TOU 10%, decreasing weight of ENS results in higher SSI, while in case of TOU-EDRP 20%, decreasing the weight of SWALI results in higher SSI. It should be noted that in Fig. 20, SSI is presented only based on weights of ENS and SWALI. The sum of weights of ENS, SWALI and LF is 1.

Fig. 21 illustrates the impact of the number of scenarios on the performance of the model. The values of objective functions and solution time have been calculated by using different scenarios applied on the case with TOU 10%. The generated number of scenarios by RWM is 1000. Then, by using K-means, the number of scenario is reduced to 10.

With reducing the number of scenarios, the number of variables in the model decreases, and consequently the solution time decreases. As can be seen in Fig. 21, by reducing the number of scenarios, the value of objective function (i.e., the average of operation cost in the compromise solutions of case 2) varies less than 0.7%, while the computation time dramatically decreases. In should be noted that in order to better illustration, the y-axis of computation time is logarithmic.

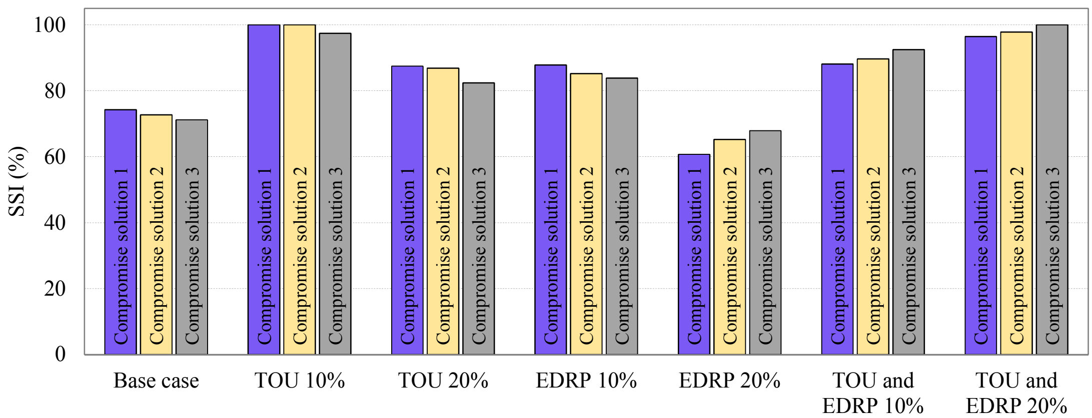
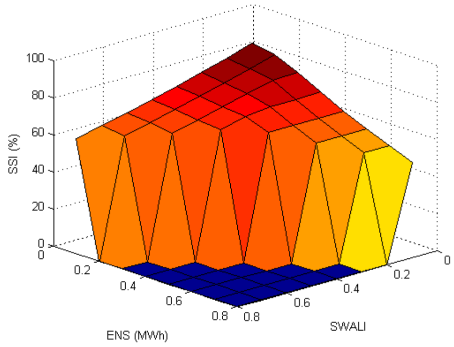
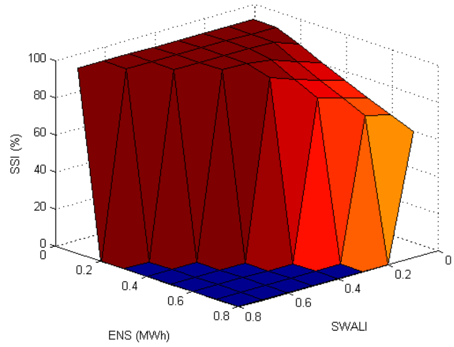


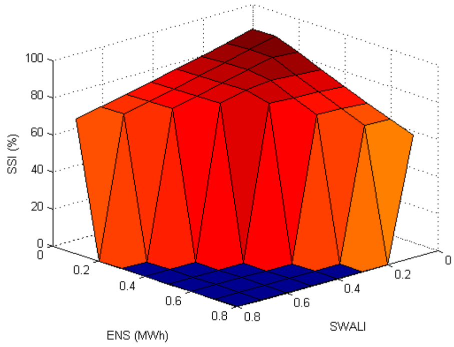
Fig. 19. Prioritizing of DRPs in different selected compromise solutions



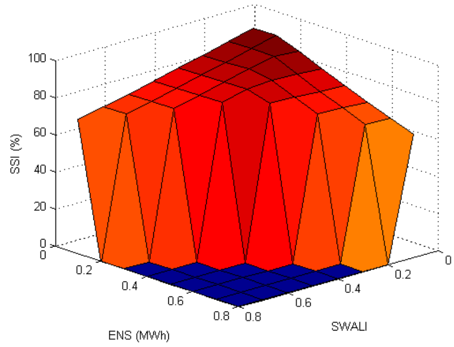
a) Base case



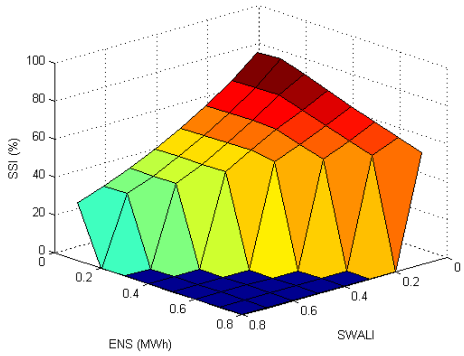
b) TOU 10%



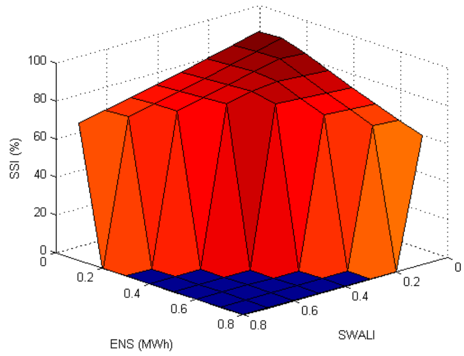
c) TOU 20%



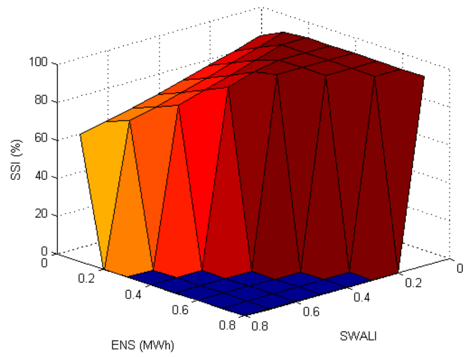
d) EDRP 10%



e) EDRP 20%



f) TOU and EDRP 10%



g) TOU and EDRP 20%

Fig. 20. Sensitivity analysis of different criteria on the SSI of DRPs

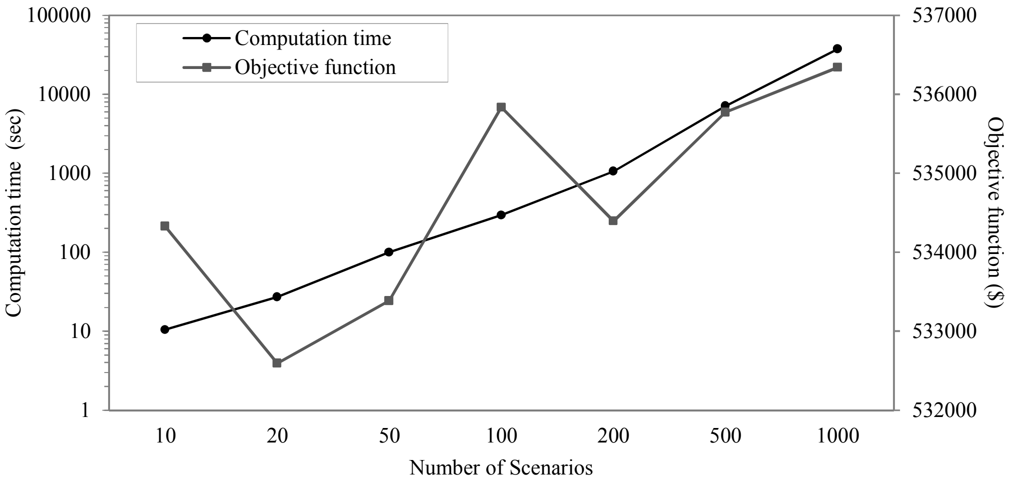


Fig. 21. Impact of the number of scenarios on the objective function and computation time

5. Conclusions

A stochastic Heuristic Multi-Objective Multi-Criteria Decision Making model was developed for integrating wind power and DR. This model considers different options of DR programs, different system operation points, and uncertainties of renewable energies. Several criteria including load factor, ENS, Lerner index and SWALI were analysed in order to demonstrate the efficiency of DRPs and market power. Two types of DRPs, TOU and EDRP and their combination were implemented, with different costumers' participation level. It was verified that reducing electric demand occurs in the peak periods with recovering low-load and off-load periods, contributing to balance the load profile. Increasing the participation level, decreasing the peak periods and increasing low demand hours, has a greater impact. In comparison with the base case, it was verified that the load factor increases in all studied cases, which proves the efficacy of these programs in reducing the peak electric demand. For TOU and EDRP with 20%, the load factor has decreased since the peak period has passed to another time. One of the benefits of this model is reducing marginal price by changing the electric demand for periods of less demand (lower prices) and reducing electric demand during high price periods. Another benefit is decreasing ENS, which leads to a greater service continuity, with fewer interruptions. Improvements are also observed in terms of market power, since the Lerner index and SWALI obtained for the different studied cases were close to zero, which indicates a more competitive market.

Acknowledgement

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