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Bi-Level Unit Commitment Considering Virtual Power Plants and Demand Response Programs Using Information Gap Decision Theory

Y. Babaei Shahmars, J.Salehi, N. Taghizadegan Kalantari*

Department of Electrical Engineering, Azarbaijan Shahid Madani University, Tabriz, Iran

Abstract- *The integration of the distributed energy resources into a single entity can do with virtual power plants. VPP is a cluster of dispatchable and non- dispatchable resource with flexible loads which distributed in allover the grid that aggregated and acts as a unique power plant. Flexible load is able to change the consumption so demand response program is applied to use them to improvement of the power system performance. Virtual power plant generation has uncertainty and it make hard to schedule the VPP. To deal this matter Information gap decision theory hint us to optimal schedule of the VPP. To show the effects of VPP and DRP on power system operation cost a bi-level unit commitment with regard the VPPs and DRP is solved in modified IEEE 24 bus reliability test system. Results in presence of VPP and DRP in both IGDT strategies are compared with disregard VPP and DRP and effectiveness of the proposed model is reflected.***

Keyword: Virtual Power Plants, Demand Response Programms, Smart Grids, Unit Commitment, Bi-Level Programming, Information Gap Decision

NOMENCLATURE

b	bus indices
i	generator indices
j	point indices
k	bus which considered as a VPP indices
l	bus which includes load
Nb	set of the all grid buses
NL	set of the bus connectivity
NLoad	set of the load points
Np	set of the conventional power plants
Nvpp	set of the virtual power plants
ag, bg, cg	constant coefficient of the thermal units
B	line susceptance
es.t	elasticity in s and t time
I0	on/off status of unit 1 before unit commitment
Ls0/Prt0	load/price before DRP in s/t time
Pbjmax/min	maximum/minimum of the line power
Pmax/min	maximum/minimum of the unit
RU/RD	thermal units' ramp
SDc/SUc	shot-down/startup cost
U0/S0	on/off time duration
UT/DT	minimum up/down time
$\bar{u}$	uncertain variable
VOLL	load-shading cost €/MW
β	uncertainty tolerance
ΔPr	electricity changes of price after PBDR
θmax/min	maxi/min of voltage
Λ	VPPs maximum capacity
I	on/off status
Y	start-up time
Z	shot-down time
Cost-Emission	emission cost for thermal units
Cost (Lsh)	load-shading cost
Fc	fuel cost
LS	load-shading
Lt	load after demand response
P	units' generation power
Pbj	line power among b & j bus
Tcost	total cost
U	uncertain variable
vpp	VPP uncertain output
vppc	curtailment power of VPP
α	uncertainty radius
Δup/Δdown	up/down of VPP's output
θ	voltage angle of bus
λB	total cost of predicted VPPS l output
$\widetilde{vpp}$	actualized power of the VPP
$\overline{vpp}$	predicted power for VPP
CPP	conventional power plant
CVPP	commercial VPP
DER	distributed energy resource
DRP	demand response program
ED	economic dispatch
IGDT	information gap decision theory
ISO	independent system operator
KKT	karush-kuhn-tucker
MILP	mixed-integer linear programing
OS	opportunity-seeker
RA	risk-averse
RES	renewable energy source
TVPP	technical VPP
TEP	transmission expansion planning
UC	unit commitment
VPP	virtual power plant

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∗Corresponding author:
E-mail: j.salehi@azaruniv.ac.ir (J. Salehi)
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1. INTRODUCTION

In conventional power plants, crude oil, coal, and natural gas are used mainly as the energy sources. These fossil fuels have pollution and also are expensive. After industrial development and global energy crisis, requirements for energy was increased. Building a power plant is a long-term and costly recourse. Substantially increasing the electricity consumption in the past decades, is concerned people about traditional fossil fuel reserves depletion, growing up the pollution effects on human as well as on ecosystem, and the poor efficiency of existing power system [1]. This matter caused that researchers find another way to generate energy that inexpensive, low pollution and even applicable in short-term and meet the future demand increment.

Power systems around the world are undergoing significant change, driven particularly by the increasing availability of low-cost variable renewable energy, the deployment of distributed energy resources, advances in digitalization and growing opportunities for electrification [2]. DERs include controllable and interruptible loads, distributed storage, distributed generation such as wind turbine, PVs et. and smart switches with different capacities and characteristics. In many cases DGs like WT and PV have no cost for fuel, for this reason operation of the DERs has low marginal cost. Furthermore, these resources have low pollution and caused to save fossil fuels reserves for future. Scale up the DER utilization in the grid results the system fluctuations and volatility and many generating units, cannot modify their output in case of unpredicted fluctuations due to ramp rate restrictions [3]. On the other hand, in order to reduce the greenhouse gas emissions generated by fossil fuel based energy sources and expansion costs of transmission networks, renewable energy sources have considered as an appropriate alternative energy source. However, the investment costs of conventional power plants are lower than RESs, but the operating costs of energy and flexibility of power systems could be improved with a combination of RESs and fossil fuels based large scale power plants [4]. To integration of DERs, virtual power plants has been suggested. There is some definition for a VPP. In Ref. [5] defines VPP as a cluster of dispersed generator units, controllable loads and storage systems, aggregated to operate as a unique power plant. It enables integration of renewables and flexibility in demand in energy markets. A VPP structure is elaborated in Fig. 1. Actually, VPP includes dispatchable and non-dispatchable energy resources that distributed in power system. Dispatchable resource refers to the energy source can be turned on or off and adjust electricity power generation for example, thermal generation unit is a dispatchable energy resource because it can be turned on or off and it can increase or decrease output power in ramp rate range. The other type of energy resources is non-dispatchable resources. Unlike the dispatchable energy type, non-dispatchable resource which cannot adjust output power and just can only generate electricity while its energy flow is input on it. For example, wind power plant cannot increase or decrease output power because its generation depends on wind power and just it can be coupled or decoupled to grid.

Virtual power plants can operate in different forms. Based on pricing, VPPs can be a price-taker or price-maker one. In price-taker mode, VPP generation capacity is lower than specific capacity amount which independent system operator permit it to compete with other generation companies and activate in market since this VPP just can take price from other power generation companies. This condition is providing by ISO, because electricity power market is an oligopoly market. In an oligopoly market there is a few sellers and many buyers. So in other type of pricing if ISO rules permit to VPP, it can be a price-maker VPP.

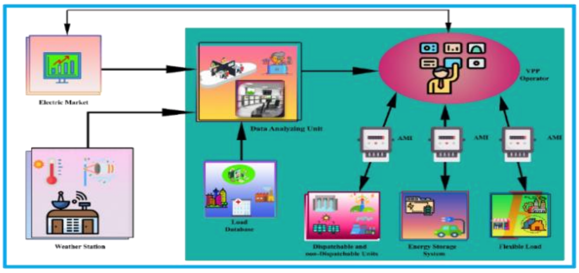

Fig. 1. Virtual power plant structure

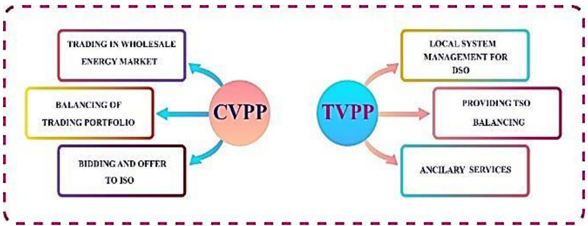

Fig. 2. Commercial and technical virtual power plant performance

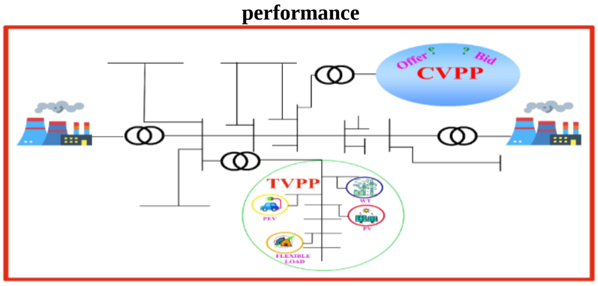

Fig. 3. Commercial and technical virtual power plant comparing

Virtual power plants based on considering distribution network are in commercial and technical categories. A commercial virtual power plant has an aggregated profile and output which represents the cost and operating characteristics for the DER portfolio. Distribution network impact is not covered in the aggregated CVPP profile. The operator of a CVPP can be any third party aggregator or a Balancing Responsible Party with market access; e.g. an energy supplier. The technical power plant consists of DER from the same geographic location. The TVPP includes the real-time influence of the local network on DER aggregated profile as well as representing the cost and operating characteristics of the portfolio. Services and functions from a TVPP and CVPP are compared in Fig. 2. The operator of a TVPP requires detailed information on the local network; typically, this will be the distribution system operator [6].

Smart grids in power system provided conditions that increased interaction between generation and consumption side together. Since demand response program is a way that consumers can participate in load curve correction and emission mitigation. Demand response programs are some tariffs on energy price that encourage consumers to change their load in specific times or shift their loads to other times. Virtual power plant is a smart grid which equipped with interruptible load, distributed resources and Advance metering infrastructure. Virtual power plant operator with AMI can communicates with different part of grid. VPP operator can satisfy the consumers to decrease their loads by DRPs or increases the generation volume of the distributed generations; in the both cases, the result is the increase of the VPP output. In recently years many scholars introduce the VPP properties and effectiveness of the VPP in power system are verified. To ensure the profit margin, a bilateral contract was proposed. Transmission line in Ref. [7] was considered a local generation company. VPP was equipped with industrial loads and these loads were interruptible since a short-term scheduling of industrial VPP with suggesting the best demand response program was solved by mixed integer non-linear programming. In recent publication, VPP distributed renewable power generation have been incorporated into the internet of the energy. Deep reinforcement learning based artificial intelligence algorithm for realistic scenario generation to address VPP intermittence and non-convex economic dispatch represented in [8]. A comprehensive review on the Classic and new architecture of the VPP is discussed in Ref. [9]. Demand side management, different control and energy management strategies and ancillary services in different VPP architecture implementation were compared. Day-ahead framework, VPP scheduling is proposed in references [10] – [11]. A probabilistic scheduling for optimal operating thermal and electrical energy resources for DA is proposed in [10] . In Ref. [12] day-ahead VPP scheduling for joint energy and reserve market is highlighted. In [13] to close gaps between retailer and wholesale market in VPP framework, DERs bid/offer in DA and real time market a framework provided so that if predicted power was less than the real-time demand, we had to buy the extra power expensive than the real-time energy price and if predicted power was more than the real-time demand, we had to sell surplus power lower than the real-time energy price. This is a way to encourage to predict the demand with lowest error. Stochastic programming of VPP with plugged-in electric vehicle in DA with regard reserve market, decreasing the life time of PEV's battery was supposed in Ref. [11].

Among the optimization in two-stage form papers, we can be mentioned to references [14] – [15]. In [14] a smart grid which includes PEV, PV and WT to generation unit and attempted to minimize unbalanced transmission network by DRPs and optimal thermal power plants unit commitment also peak-shaving and valley-filling was done. A two stage mixed integer linear programming day-ahead unit commitment problem was solved with chance-constrained in Ref. [16]. Heuristic method was employed to convert uncertain chance-constrained to deterministic form. DA multi-objective scheduling of VPP with uncertainty of load and generation was provided in Ref. [17]. Different technology of generation like PV, WT, battery energy storage system and combined heat and power was intended. In reference [15] two-stage approach was taken account to management transmission line congestion by compressed air energy storage and wind power scheduling. To harness intermittence of the wind power, chance-constrained method was employed. In the first stage, social welfare was maximized. In order to local marginal price approach was applied to congestion alleviation by wind power. In the second stage stochastic security-constrained unit commitment model with DRP and CAES deployment, the operation cost was minimized.

A non-linear model for multi-coupling of gas and electrical and combined cooling, heat and power network was intended in reference [18]. All three network coordinal operated and effects of each network on the other one was investigated. Two-stage stochastic risk-constrained scheduling of the VPP with correlated demand response highlighted in Ref. [19]. First stage optimization was day-ahead unit commitment, scheduling and bidding management and second stage was real-time VPP energy management. In References [20]- [21] unit commitment problem is discussed. Ref. [20] focused on to integrate the CHP and only electric power generator unit in order to minimize greenhouse gas emission and also selling of the power in reserve market. A hybrid algorithm for unit commitment problem is discussed in Ref. [22]. Hybrid particle swarm optimization is a new form of the particle swarm optimization algorithm that reaching the successful is provided with low initial population. The mentioned paper, solved unit commitment problem with HPSO and compared results with other similar papers. Security-constrained unit commitment under demand response resource as virtual power plant was studied in Ref. [23]. Demand response programs was presented in two type; one type of this was assumed for only peak-shaving in peak times and the other one was presented to shift of the consume time for valley-filling and peak-shaving. Multi-stage robust unit commitment with affine policy for dispatch decision by Benders decomposition in large-scale polish 2736 bus-system under high dimensional uncertainty of the wind and solar farms carried out in Ref. [24]. Stochastic self-scheduling of hydro-thermal units with RES under various uncertainty elements is carried out in Ref. [21] and a profit- based structure for Genco's is represented. The advantage of Ref. [21] is improving the accuracy and achieving to realistic results and disadvantage of its is to select the filtering ratio. Multi-objective optimization of the virtual power plant was done in Ref. [25] and [26]. In aforementioned papers, object function was included the maximum profit of the virtual power plant and minimum of the CO_2 emission and minimum operation risk. Bi-level programming of virtual power plants was applied in references [27] - [28] and bi-level optimization was followed for a three stage programming in Ref. [29]. In Ref. [27] bi-level optimization for VPPs was carried out which in upper level, VPPs maximized their profit and in lower level, distribution company minimized the operation costs. In highlighted works, equilibrium problem with equilibrium constraints by Karush-Kuhn-Tucker conditions were became to non-linear single level problem. Three stage bi-level programming for VPP supply offer and demand bidding could be found in Ref. [29]. In the first stage variables were comprised the DA multi-stage VPP supply offer and load deceleration curves. At the second stage market-clearing process was done. Actually second stage was assumed that the lower-level. The third stage was regarded as upper-level of the bi-level problem and in this stage real-time energy profiles (production/consumption) were determined. Reference [30] Investigated daily unit commitment for hydro-thermal units under load uncertainty with information gap decision theory. Scheduling of renewable energy based a smart home under PV system output with IGDT for simulation of uncertainty was studied in reference [31]. Self-scheduling framework for demand response aggregators that applied market price and load uncertainty with IGDT which was solved with bi-level programming was mentioned in Ref. [32]. Reference [33] investigates the management of a smart home with IGDT in two risk-averse and opportunity-seeker strategy. Reference [34] Applied both strategy of IGDT for a UC problem with wind turbine output uncertainty. Results were shown that in RA strategy, by decreasing the share of WTs to compensate the portion of the wind power, CPPs' share was enhanced. As well as in OS strategy, by increasing the WTs share, contribution of the CPPs was decreased. In Ref. [35] based on Stackelberg equilibria to maximum profit of the micro-grid aggregators in retail market a game theory was modeled. To cope participation risk in retail market emergency demand response program in retail side was investigated. Due to drastic renewable energy resources and energy price ambiguity, RA strategy of the IGDT was set. In Reference [36] mixed integer linear bi-level programming was suggested for VPP bidding in DA and balancing oligopoly markets under bilateral contracts and financial transmission rights concept. At the upper level VPP aggregator profit was maximized and in the lower level social welfare of the system was maximized. The market severely stochastic nature, imposed to utilize IGDT methodology. Comprehensive reviews on demand response programs were conducted in references [37] - [38]. Reference [37] studied exclusively about strength, weakness opportunity and threats of the demand side management in Kuwait. Above study determined that if some demand response program was successful in a region it is not necessarily be useful in else country. Richness of the Kuwait economy and ample reserve of the fossil fuels caused that price-based demand response programs in Kuwait failed. In this regard informing the people about demand response programs benefits and incentive-based demand response schemes are very useful in this country. Reference [39] denoted the recent development of the DR system, load scheduling and several communication network technologies. Authors in Reference[39] believe that the available DR programs are unfair to existence of the some selfish consumers with high level consumption in residential district. These selfish consumers caused that energy price be expensive and all consumers be penalized. in this regard, recommendations include adaptive consumption-level pricing scheme to alleviation this affect. Reference [40] elaborated market-clearing process of Singapore wholesale market demand response programs. Mathematical relations in market-clearing model and demand response programs were demonstrated. Reference [41] explained how demand response programs were raised. In addition to classification of the demand response programs and demand response costs were discussed. Details of the meta-heuristic and mathematical optimization approaches on demand response problems were reviewed. A novel version of the demand response termed as integrated demand response was introduced in an energy-hub context that all energy users could be contribute in energy management by IDR. Value of the IDR analyzing and systematic literature were reviewed on the art station of the IDR. Developments, applications and implementation of the IDR in different countries all over the world in multi-energy system were described in Ref. [42]. Reference [38] reactive power planning is combined with transmission expansion planning considering demand response program. The price-based demand response program has good effect on cost and caused the cost of transmission expansion planning and reactive power planning be minimized. In mentioned literatures enough work done in unit commitment and VPPs output uncertainty with variable ways to simulation of uncertainty like fuzzy-logic, probabilistic functions, scenario-based and robust decision-making theories. As shown in table 1 most of the mentioned papers focused on probabilistic and scenario-based methods to quantify intermittence of the RES. Unit commitment problem in presence of the demand response programs are not taken accounted enough. Also bi-level unit commitment problem with VPP contribution is not examined more. In this regard seems the gap of aforementioned papers is unit commitment considering VPP and demand response program with another perspective. Beside to lack of the information about VPP output and existence of sever uncertainty in each time interval, IGDT is a useful object to analyze the VPP generation. Therefore, the main contributions of this paper are:

1. Unit commitment of CPPs with DRP, under output uncertainty VPP and network constraints is carried out.
2. IGDT for VPPs output uncertainty is discussed.

Table 1. Literature comparing

Reference	UC	UC considering VPP conception	Network constraints	Uncertainty model	DR	Bi-level
[14]	YES	NO	YES	NO	YES	NO
[15]	YES	NO	YES	STOCHASTIC	YES	NO
[16]	YES	NO	YES	STOCHASTIC	NO	NO
[19]	YES	NO	YES	STOCHASTIC	YES	NO
[20]	YES	NO	NO	NO	NO	NO
[22]	YES	NO	NO	NO	NO	NO
[23]	YES	YES	YES	NO	YES	NO
[24]	YES	NO	YES	ROBUST	NO	NO
[30]	YES	NO	NO	IGDT	NO	NO
[34]	YES	NO	YES	IGDT	YES	YES
Proposed study	YES	YES	YES	IGDT	YES	YES

3. Each IGDT RA and OS strategies solved with bi-level programming.
4. Results in DRP and VPPs presence is compared with lack of DRP and VPPs.

The rest of this paper is organized as follows: In section 3 system modeling and concept of the IGDT is presented. Mathematical formulation of the UC problem with demand response, network constraints and IGDT Uncertainty representation and the solution method are described. Input data and results discussing are carried out in section 4. Section 5 concludes the paper with some remarks for further study in this domain.

2. SYSTEM MODELING

2.1. Problem Description

The aim of this paper is present a generation allocation for CPPs to meet network constraints. Network constraints are modeled by DC-power flow equations. In modified IEEE 24 bus reliability test system, some buses are described as VPP. Existence of VPP in a grid have many benefits but creates challenges in power system. Optimal exploiting of the VPP in power system obviously helps operators to decrease operation costs and mitigates environment pollutions by utilizing cheap and clean energy sources and DRPs in VPP background but stochastic nature of the VPP output is one of the biggest challenges. To tackle severe lack of information about VPP output, IGDT model is suggested. In fact, this paper intends to do simultaneously cost-based unit commitment and economic dispatch to address the VPP and DRP effects on upstream network. IGDT has two RA and OS strategy and also has an uncertainty set that is called uncertainty radius. This set in both strategies based on the concept of the problem, has to be maximized or be minimized. Due this matter, object function and presence of the uncertainty set, optimization problem becomes to a bi-level problem. This bi-level problem cannot solve by solved by standard techniques and decomposition methods are required. For the mentioned problem, Benders-decomposition and performing Karush-Kuhn-Tucker conditions to convex and first order optimization are two common and useful techniques. BD has expensive processes for that reason we advise to use the KKT conditions to switch the bi-level problem to a single-level. In this situation the bi-level MILP optimization become to a single-level MINLP. This mathematical process are followed on Ref. [43] and Ref. [44]. To do this first, object function based on the predicted VPP outputs must be minimized. This value is an input for second stage and depend on the IGDT strategy, decision-variable gets the optimum value for uncertainty variable. More information about the IGDT and its strategies are represented in next sections.

2.2. Uncertainty Modeling

To deal with intermittence nature of phenomenon like RES energy generation in 24-hour horizon probabilistic, fuzzy-logic, robust and IGDT methods are suggested (Fig.4).

Probabilistic methods aim to actualize uncertain variables and decision-making by historical data and precise information like probability density function about uncertain variables. Scenario-based stochastic programing is based on scenario generation. To eliminate the extra process volume of the optimization, scenario reduction methods are taken account but nonetheless left scenarios are excess. Fuzzy-logic decision-making approach needs to have a membership function. This approach has to solve the problem for multiple values of α-cuts. Similar the stochastic approach, this one requires a significant information and process's is expensive. Robust optimization does not require a function to elaborate stochastic behavior but reliance to deterministic data which is called uncertainty sets. These sets impose a robust and optimal bound for decision-variable. Robust optimization due to deterministic sets, have slightly process. Based on Ref. [45] IGDT is a useful approach in sever uncertainty. IGDT does not require deterministic data or significant sets like robust optimization. It is note that all the intermittence phenomenon does not have PDF and one of the IGDT traits that distinguished against the other procedures is that IGDT could present substantially accurate information about ambiguity decision-variable without deterministic input data. IGDT to proceed this, only needs a prediction from uncertain decision-variable(s). IGDT expresses the sever lack of information in two pernicious and propitious prospects. Robustness function reflects the greatest value of the uncertainty until failure does not happen and minimal requirements be satisfied. While opportuneness function represents the least level of obscurity which entails the possibility of sweeping success. In fact, robustness is the degree of the resistance and immunity against the uncertainty whereas opportuneness is the immunity against windfall reward and indicates that attainment to great reward and success is possible in presence of little obscurity ambient. The first facet is called RA strategy and second slight to uncertainty is entitled OS strategy.

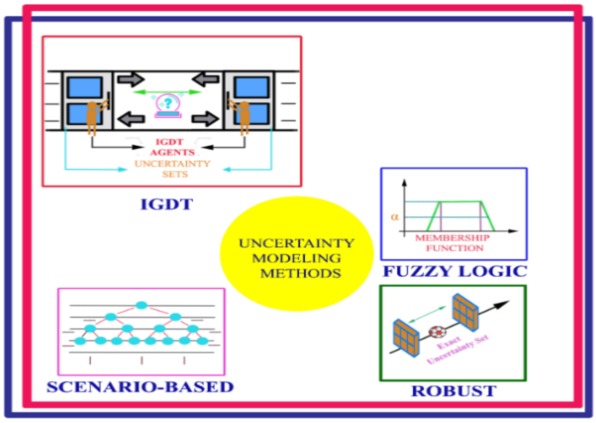

Fig. 4. Uncertainty models

If V be a decision-making vector, the RA and OS strategy can define as:

$$\hat{a}(V)=max\{\alpha\text{: minimal requirements are always satisfied}\} \quad (1)$$

$$\hat{o}(V)=min\{\alpha \text{ sweeping success is possible}\} \quad (2)$$

Let R (V, U) is a scalar reward function that includes V and U as decision vector and uncertainty vector respectively. The minimal requirement in R (V, U) is no less than a critical value r_c. in order to, R (V, U) to attain success in presence of the uncertainty is chosen greater than a specific value like r_w. as well as we express more explicitly robustness and opportuneness function:

$$\hat{a}(V.r_c) = max\{\ \alpha : (\min_{u\in U(\alpha.\bar{u})} R(V\ .U)) \geq r_c\} \quad (3)$$

$$\hat{o}(V.r_w) = min\{\ \alpha : (\max_{u\in U(\alpha.\bar{u})} R(V\ .U)) \geq r_w\} \quad (4)$$

â (V, r_c) is the greatest value of the uncertainty which is guaranteed that be no less than r_c and ô (V, rw) is the minimum level of the uncertainty that should be accepted to sweeping success (but no guarantee) as great as r_w. In some case the natural reward requirement is that R (V, U) must not exceed a particular level like r_c / r_w rather than to be less than r_c / r_w as in equations (3) and (4). In this situation robustness is the greatest value of the uncertainty that maximum reward is no greater than r_c. As in manner the opportuneness function is the minimum value of α that success can be occur as small as r_w. Through the addressed sentences, equations (3) and (4) can be modify as below:

$$\hat{a}(V.r_c) = max\{\ \alpha : (\max_{u\in U(\alpha.\bar{u})} R(V\ .U)) \leq r_c\} \quad (5)$$

$$\hat{o}(V.r_w) = min\{\ \alpha : (\min_{u\in U(\alpha.\bar{u})} R(V\ .U)) \leq r_w\} \quad (6)$$

According the mentioned explains about robustness and opportuneness, if we looking for concepts like minimum expected economic profit, we have to use equations (3) and (4) otherwise, if we looking for concepts like maximum expected economic cost, we have to use equations (5) and (6). IGDT optimization process components are described as below:

System Modeling: System model is the mathematical expressions of the system and according the concepts are chosen Eq. (3), (4) or Eq. (5), (6). If IGDT looks for the value that uncertainty to be greater than r_c or r_w equations (3) and (4) must be applied otherwise if IGDT looks for value that to be less than r_c or r_w equations (5) and (6) must be applied.

Uncertainty Modeling: Uncertainty model of the IGDT are several. In Ref. [45] three common models are such as:

Energy-bound model: this model is suitable for dynamic temporal and transient phenomenon which deviate from nominal value. u(t) indicates uncertainty variable and $\bar{u}(t)$ is the prior or certain information.

$$U(\alpha.\bar{u}) = \{u(t) \colon \int_0^\infty [u(t) - \bar{u}(t)]^2 dt \leq \alpha^2\} \quad \alpha \geq 0 \qquad (7)$$

Envelope-bound model: Similarly, the energy-bound, this model hedge the uncertainty deviation from nominal value to an expandable envelope. For a scalar function we have:

$$U(\alpha.\bar{u}) = \{u(t) \colon |u(t) - \bar{u}(t)| \leq \alpha\varepsilon(t)\}\ .\ \alpha \geq 0 \qquad (8)$$

Where ε(t) is the function that is known and it is referred to the shape of the envelope. Uncertainty radius (α) dedicates the size of envelope. In some cases, uncertainty deviation can be limit to special area by choosing ε(t)=1 for mentioned area and *ε(t)=0* to other. In other cases, *ε(t)* is used to represent the relative magnitude of variation. In this situation *ε(t)* has symmetrical relation with known information *(ε(t)* ∝ $\bar{u}(t)$*)* and envelope model in *Eq.(8)* becomes the set of functions *u(t)* whose fractional deviation from the nominal function $\bar{u}(t)$ is no greater than α:

$$U(\alpha.\bar{u}) = \left\{u(t) \colon \left|\frac{u(t)-\bar{u}(t)}{\bar{u}(t)}\right| \leq \alpha\right\}\ .\ \ \alpha \geq 0 \qquad (9)$$

Slope-bound model: Rate of the deviation can be constrained by uncertainty radius. In previous models, rate of variation has been not restricted in any of IGDT models. The envelope-bound concept can be applied to the slope rather than to the magnitude of the uncertain function. A simple slope-bound IGDT model for uncertain variations is:

$$U(\alpha.\bar{u}) = \left\{u(t) \colon \left|\frac{d[u(t)-\bar{u}(t)]}{dt}\right| \leq \alpha\zeta(t)\right\}\ .\ \alpha \geq 0 \qquad (10)$$

Where $\bar{u}(t)$ is the nominal value of the uncertainty and $\zeta(t)$ defines the envelope of uncertain variation of the slope. The other models like Minkowsky-norm, Fourier-bound and hybrid et. Models can found in Ref [45].

Proper Strategy: IGDT have two RA and OS strategy. RA strategy is in robustness manner and in this strategy, greatest value of the uncertainty in term which no failure happens. While OS strategy the minimum value of the uncertainty which entails the possibility of the reach to success.

2.3. Unit Commitment

Through this paper cost-based unit commitment problem is investigated with VPPs output uncertainty and price-based time of use demand response program. To calculate VPPs output, IGDT cause our problem to be a bi-level. The goal of the CBUC is to allocate the generation of each CPPs to match the demand for a specific study horizon so that cost is minimized.

2.3.1. Cost Function

In this section total cost function is presented as start-up and shot-down cost of the CPPs, fuel cost, greenhouse gas emission cost, load-shading cost. Non-linear fuel and emission cost function transform to piecewise-linear function in the first stage based on approach that is introduced in reference [46].

$$Tcost = \sum_{t=1}^{T}\sum_{i=1}^{N_p}(Fc(P(i.t)) \ + SUc(P(i.t)) + SDc(P(i.t)) + cost(emission)) + cost(lsh) \qquad (11)$$

2.3.2. Generation Cost

As mentioned in Ref. [47] maximum and minimum generation of the units in each time interval and their dependency of them to before and after time *t* and ram-rate are following below. If a unit should be off for the next hour, the power generated must be less than the shut-down limit this constraint is represented by Eq. (13). The shut-down ramp rate and ramp-down Limit are included in Eq. (14). Likewise, the above, the start-up ramp rate and ramp down limit are represented in Eq. (15). In this manner if a unit shot down or start-up at time *t*, start-up/shot-down ramp rate are added to ramp up/down rate respectively. Shot-down and start-up ramp rate are thermodynamic and nuclear limits and are forced power that must be generated for completing the chemical cycles.

$\forall\, t.s \in T\,.\forall\, i \in N_p(b.i).\forall\, b.j \in N_L(b.j)$:

$$P^{min}(i)I(i.t) \le P(i.t) \le P^{max}(i)I(i.t) \quad (12)$$

$$P(i.t) \le \mathrm{P}^{max}(\mathrm{i})\big(I(i.t) - Z(i.t+1)\big) + SD(i)Z(i.t+1) \quad (13)$$

$$P(i.t-1) - P(i.t) \le SD(i)Z(i.t) + RD(i) \quad (14)$$

$$P(i.t+1) - P(i.t) \le SU(i)Y(i.t) + RU(i) \quad (15)$$

2.3.3. Minimum Up and Minimum down Time Constraints

CPPs for thermodynamic and nuclear constraints cannot change their generations instantly for that reason minimum up/down time define as minimum time interval that a unit must be on/off to complete the chemical cycle. in this way, minimum up/down time constraints and on/off status of the units are as follow as:

$$\sum_{\mathrm{t=1}}^{\mathrm{B(i)}}\big(1 - \mathrm{I(i.t)}\big) = 0 \quad (16)$$

$$\sum_{\tau=t}^{T_1} I(i.\tau) \ge UT(i).Y(i.t)$$

$$\forall\, i\,.T_1 = t + UT(i).$$

$$\forall\, t = \ B(i) + 1. \dots .\vartheta - UT(i) + 1 \quad (17)$$

$$\sum_{\tau=t}^{\vartheta}\big(I(i.\tau) - Y(i.t)\big) \ge$$

$$\forall\, i\,.\forall\, t = \vartheta - UT(i) + 2. \dots .\vartheta \quad (18)$$

Equation (16) is a forced commitment limit for units that are not passed minimum up time. Equations (17) and (18) define that each unit which is on, it has to at least be keep on to start-up time frequencies. Similar to the Eq. (16) -(18) forced de-commitment for units that are not passed minimum down time, shot-down hours and frequency of the shot-down, limits satisfied by Eq. (19) – (21). Initial status of the units before scheduling time horizon is represented by Eq. (22) and (23). These equations determine that how many hours that a unit was on/off before scheduling respectively.

$$\sum_{t=1}^{C(i)} I(i.t) = 0 \quad (19)$$

$$\sum_{\tau=t}^{T_2} 1 - I(i.\tau) \ge DT(i).Z(i.t)$$

$$\forall\, i\,.T_2 = t + DT(i) - 1\,.$$

$$\forall\, t = C(i) + 1. \dots .\vartheta - DT(i) + 1 \quad (20)$$

$$\sum_{\tau=t}^{\vartheta}\big(1 - I(i.\tau) - Z(i.t)\big) \ge 0$$

$$\forall\, i\,.\forall\, t = \vartheta - DT_i + 2. \dots .\vartheta \quad (21)$$

$$B(i) = min\{\vartheta.\big(UT(i) - UT^0(i)\big)I^0(i)\} \quad (22)$$

$$C(i) = min\{\vartheta.(DT(i) - S^0(i))(1 - I^0(i))\} \quad (23)$$

2.3.4. Logical State of Commitment

To prevent interference of the units on/off status and interaction of binary variables, below equations are provided for each unit:

$$\mathrm{Y(i.t) - Z(i.t) = I(i.t) - I(i.t-1)} \quad (24)$$

$$\mathrm{Y(i.t) + Z(i.t) \le 1} \quad (25)$$

2.3.5. Cost Constraints

Fuel, load-shading and greenhouse gas emission costs and constraint can be obtained byEqns. (26) – (29):

$$\mathrm{Fc(i.t) = a_g^2P(i.t) + b_gP(i.t) + c_g} \quad (26)$$

$$\mathrm{Cost(LSh)} = \sum_{\mathrm{b \in N_b}}\sum_{\mathrm{t}}^{\mathrm{T}} \mathrm{VOLL \times LS(b.t)} \quad (27)$$

$$\mathrm{LS^{min} < LS(b.t) < LS^{max}} \quad (28)$$

$$\mathrm{Emission\ cost\ = a_e^2P(i.t) + b_eP(i.t) + c_e} \quad (29)$$

2.3.6. Demand Response Limits

Price-based demand response programs are type of schemes that by changing the energy price, costumer behavior changes. Time of use is one type of PBDR programs. Performance of the TOU is such as performing tariffs on some hours caused costumers transfer their loads to valley-load time. Usually for TOU demand response program, three-time interval is assumed. In each time interval, energy price has significant value. off course energy price must have highest price in peak-times. It is worth nothing that all loads like illuminating loads is not able to transfer the off-peak time. Furthermore, extra tariffs on energy price has not same effects on costumer behavior. Some consumers are selfish or rich and it is not important to them how much is the energy price be expensive. Contrary the rich people, there is some consumers that energy price has significant impact on their lifestyle. To this end elasticity concept provided by demand price as Eq. (30). If price be changed in diverse period, consumers can transfer loads to off-peak time or otherwise only on or off; in the case that some loads have not capable to transfer to other period and loads have sensitivity in a single-period call self-elasticity and always have negative value. the other action which capable to move other time intervals is called multi-period sensitivity and evaluate by cross-elasticity. Cross-elasticity always have positive value. TOU demand response program for loads participation in unit commitment problem constraints are followed by [48]. Equation (30) determines the elasticity of each load in 24h time horizon. Eq. (31) calculates the load level changing after TOU demand response program. maximum allowable participation in DRP and load change rate are in Eq. (32) and (33) respectively. Also Eq. (33) describes that, the sum of all load changing in 24-h time horizon must be lower than maximum amount of load changing:

$$e(s.t) = \frac{\Delta L(s)/L^0(s)}{\Delta Pr(t)/Pr^0(t)} \quad \begin{cases} e(s.t) \le 0 & \text{if } s = t \\ e(s.t) \ge 0 & \text{if } s \ne t \end{cases} \quad (30)$$

$$L(t) = L^0(t) \times [1 + e(t.t) \times \frac{[Pr(t) - Pr^0(t)]}{Pr^0(t)} + \sum_{\substack{s=1 \\ s\ne t}}^{24} e(s.t) \times \frac{[Pr(s) - Pr^0(s)]}{Pr^0(s)}] \quad (31)$$

$$|\Delta L(s)| \le \Delta L^{max} \quad (32)$$

$$\Delta \underline{L} \le \Delta L(s) - \Delta L(s-1) \le \Delta \overline{L} \quad (33)$$

$$\sum_1^{24} \Delta L(s) \le \Delta L^{max} \quad (34)$$

2.3.7. Network Constraints

In this study a linear DC power flow is embedded and network constraints are mentioned in Eqns. (35) -(37). Eq. (35) is the line power; Eq. (36) is the line power limits and Eq. (37) taken account the power balance in grid and ensures that generation and demand are balanced during all time intervals.

$$P_{bj}(b.j.t) = B(b.j) * \left(\theta(b.t) - \theta(j.t)\right) \quad (35)$$

$$P_{bj}^{min} \le P_{bj}(b.j.t) \le P_{bj}^{max} \quad (36)$$

$$LS(b.t) + \sum_{i\in N_P} P(i.t) + \overline{vpp}(k.t) - Lt(l.t) = \sum_{b.j\in N_L} P_{bj}(b.j.t)$$

$$k \in N_{vpp}(b). l \in N_{Load}(b) \quad (37)$$

3. PROPOSED ALGORITHM

3.1. First Stage of Optimization

In the first stage, is assumed that VPPs output are exactly equal to predicted amount. So the total cost of the operation is minimized:

$$\lambda_B = \min_X Tcost \quad \text{, Subject to Eqns. (11–37)} \quad (38)$$

3.2. IGDT Implementation

In IGDT the only information that have to be known, is a predict of the uncertainty decision-making variable. IGDT also has advantages over robust model. In robust model, uncertainty sets are deterministic, but in IGDT these sets have even uncertainty. In RA strategy uncertainty is an undesired phenomenon and decision-variable tries to increase robustness of the object function so in this case as a result, the value of α is maximized. In OS strategy uncertainty is a desired phenomenon and decision-variable tries to search an optimum value in minimum uncertainty radius. in this case uncertainty radius is minimized. Envelope model of uncertainty is proposed for this study. For $k \in N_{vpp}(b)$ we have:

$$\mathbb{u}(\alpha.\overline{vpp}(k.t)) = vpp(k.t): |vpp(k.t) - \overline{vpp}(k.t)| \le \alpha * \overline{vpp}(k.t) \quad (39)$$

$$vpp(k.t) = \widehat{vpp}(k.t) + vpp^c(k.t) \quad (40)$$

3.2.1. VPP Output Limits

$$0 \le vpp^c(k.t) \le vpp(k.t) \le \Lambda(k) \quad (41)$$

$$0 \le \widehat{vpp}(k.t) \le vpp(k.t) \le \Lambda(k) \quad (42)$$

$\overline{vpp}$ is a predict of the VPPs output and $\widehat{vpp}$ is actualized VPPs output. Also vpp is uncertain output of each one. Eq. (39) represents the envelope IGDT model. To avoid power fluctuation, it has to VPP be curtailed, this fact is modeled by Eq. (40). In Eq. (41) and (42) VPP maximum and minimum values are determined in each curtailment, uncertain and actualized amount.

$$vpp(k.t) = \overline{vpp}(k.t) + \Delta up(k.t) - \Delta down(k.t) \quad (43)$$

$$\Delta up(k.t). \Delta down(k.t) \ge 0 \quad (44)$$

$$\Delta up(k.t) * \Delta down(k.t) = 0 \quad (45)$$

$$\Delta up(k.t) \le \alpha * \overline{vpp}(k.t) \quad (46)$$

$$\Delta down(k.t) \le \alpha * \overline{vpp}(k.t) \quad (47)$$

$$\Delta up(k.t) \le \Lambda(k) - \overline{vpp}(k.t) \quad (48)$$

Equation (43) recognizes the uncertain VPP output. Equation (44) - (48) settle the minimum and maximum value of the output deviation in order to increase and decrease cannot occur in same time; this fact is assigned by Eq. (45). For RA strategy upper-level object function is maximizing of the α in relevant β and Eq. (49) describes the upper level object function. The lower-level object function is Eq. (50). Also lower-level constraints are Eqns. (11) - (36) and (39) – (48) and (51). Eq. (51) introduces the power balance in all lines.

$$R_{RA} = \max_{\mathbb{x}} \hat{\alpha}(\mathbb{x}.\overline{vpp}(k.t)) \quad (49)$$

$$\hat{\alpha}(\mathbb{x}.\overline{vpp}(k.t) = \max_{vpp(k.t)\in\mathbb{u}(\alpha.\overline{vpp}(k.t))} Tcost \le (1+\beta_c)\lambda_B \quad (50)$$

$$Lsh(b.t) + \sum_{i\in N_P} P(b.t) + (1-\hat{\alpha}) * \overline{vpp}(k.t) - Lt(l.t) = \sum_{b.j\in N_L} P_{bj}(b.j.t), \quad k \in N_{vpp}(b). l \in N_{Load}(b) \quad (51)$$

Subject to Eqns. (11)- (36) and (39) – (48) and (51) as lower-level constraints. For opportunity-seeker strategy uncertainty radius (α) should be minimized in relevant β and Eq. (52) describes the upper level object function. The lower-level object function is Eq. (53) and lower-level constraints are included Eqns. (11) - (36) and (39) – (48) and (54).

$$R_{OS} = \min_{\mathbb{x}} \breve{\alpha}(\mathbb{x}.\overline{vpp}(k.t)) \quad (52)$$

$$\breve{\alpha}(\mathbb{x}.\overline{vpp}(k.t) = \min_{vpp(k.t)\in\mathbb{u}(\alpha.\overline{vpp}(k.t))} Tcost \le (1-\beta_o)\lambda_b \quad (53)$$

$$Lsh(b.t) + \sum_{i\in N_P} P(i.t) + (1+\breve{\alpha}) * \overline{vpp}(k.t) - Lt(l.t) = \sum_{b.j\in N_L} P_{bj}(b.j.t) \quad k \in N_{vpp}(b). l \in N_{Load}(b) \quad (54)$$

The variable and parameter vectors are represented as $\mathbb{x}$ and:

$$\mathbb{x} = \begin{Bmatrix} P_i(t).\,\mathrm{vpp}(b.t).\,\widetilde{\mathrm{vpp}}(b.t).\,\mathrm{vpp}^c(b.t) \\ P_{bj}(b.t).\,\theta(b.t).\,\Delta\mathrm{up}(b.t).\,\Delta\mathrm{down}(b.t).\,\lambda_B.\,\alpha \end{Bmatrix} \quad (55)$$

$$\mathbb{u} = \left\{\beta_{c/o}.\,\Lambda.\,\overline{\mathrm{vpp}}.\,P_i^{max/min}.\,\mathrm{RU}.\,\mathrm{RD}.\,B_{b,j}.\,P_{b,j}^{max/min}\right\} \quad (56)$$

Flowchart of RA and OS strategies are depicted in Fig. 5 and Fig. 6 respectively.

4. SIMULATION RESULTS

4.1. Data

A simultaneous generation allocation and economic dispatch in presence of VPPs and DR program is simulated in this study. To show simulation results, modified IEEE 24 bus reliability test system in Fig. 7 is supposed. This transmission network consists of 12 units. The units 8 and 9 are assumed as nuclear units and unit 10 is supposed a hydro unit. To this end units 8,9 and 10 are must-run units. These mentioned units have no start-up and shot-down cost. It is worth nothing that, similar the thermal units, nuclear and hydro units have start-up and shot-down ramp rate. These features calculation is complex but like the many cases, these parameters can be approximated. For that reason, to simplify the problem start-up and shot-down ramp rate in test system is assigned as constant power. Before begin of the scheduling, maybe some units were online or offline therefore status of each unit are inserted in table 2. Table3 shows the technical data of generation units, costs and initial state of generating units. Other data of the network and thermal units like load data and transmission line data are elaborated in references [49] and [50].

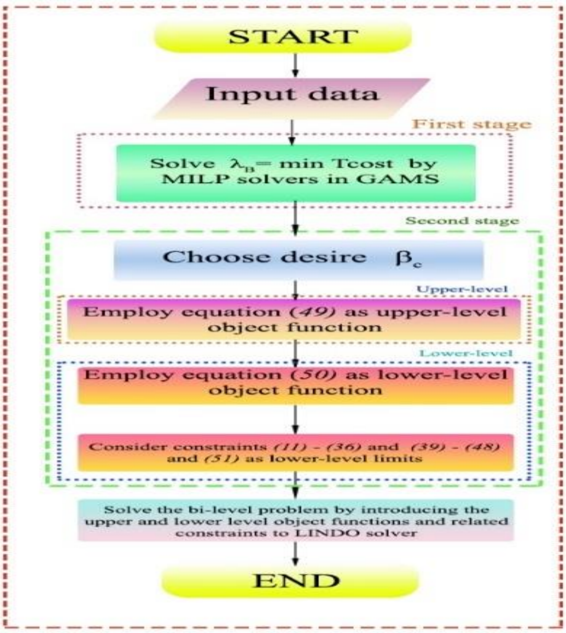

Fig. 5. Flowchart of RA strategy

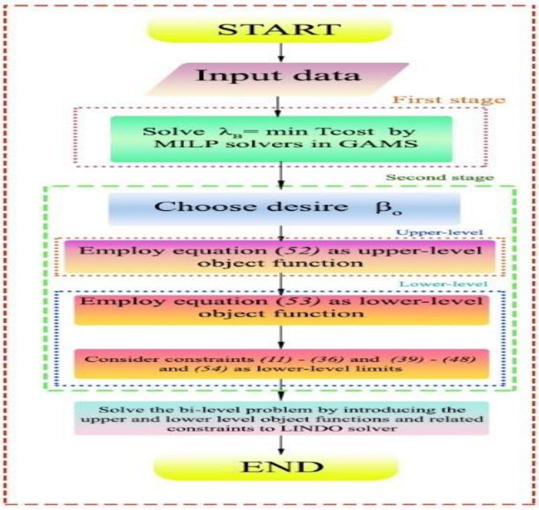

Fig. 6. Flowchart of OS strategy

Table 2. Technical data of generation units

Unit	Pmax (MW)	Pmin (MW)	Start-up ramp rate (MW)	Shot-down ramp rate (MW)	Ramp up (MW)	Ramp down (MW)	Minimum up time (h)	Minimum down time (h)
1	152	30.4	152	152	120	120	8	4
2	152	30.4	152	152	120	120	8	4
3	350	75	300	300	350	350	8	8
4	591	206.85	540	540	240	240	12	10
5	60	12	60	60	60	60	4	2
6	155	54.25	155	155	155	155	8	8
7	155	54.25	155	155	155	155	8	8
8	400	100	400	400	280	280	1	1
9	400	100	400	400	280	280	1	1
10	300	300	300	300	300	300	0	0
11	310	108.5	310	310	180	180	8	8
12	350	140	240	240	240	240	8	8

Table 3. Cost and initial state of generation units

Unit	Start-up cost (€)	Shot-down cost (€)	$P_{initial}$ (MW)	Initial status	Initial online time (h)	Initial offline time (h)
1	1430.4	1430.4	76	1	22	0
2	1430.4	1430.4	76	1	22	0
3	1725	1725	0	0	0	2
4	3056.7	3056.7	0	0	0	1
5	437	437	0	0	0	1
6	312	312	0	0	0	2
7	312	312	124	1	10	0
8	0	0	240	1	50	0
9	0	0	240	1	16	0
10	0	0	240	1	24	0
11	624	624	248	1	10	0
12	2298	2298	280	1	50	0

Table 4. Total demand in 24-h time horizon

Hour	System Demand (MW)	Hour	System Demand (MW)	Hour	System Demand (MW)
1	1775.835	9	2517.975	17	2623.995
2	1669.815	10	2544.48	18	2650.5
3	1590.3	11	2544.48	19	2650.5
4	1563.795	12	2517.975	20	2544.48
5	1563.795	13	2517.975	21	2411.955
6	1590.3	14	2517.975	22	2199.915
7	1961.37	15	2464.965	23	1934.865
8	2279.43	16	2464.965	24	1669.815

Table5 Node location and distribution of the total system demand

Node	% of system load	Node	% of system load	Node	% of system load
1	3.8	7	4.4	15	11.1
2	3.4	8	6	16	3.5
3	6.3	9	6.1	18	11.7
4	2.6	10	6.8	19	6.4
5	2.5	13	9.3	20	4.5
6	4.8	14	6.8		

Please note that load forecasting problem is outside of the scope of this paper. Buses number 19,8,14 and 9 supposed as virtual power plants; VPPs capacities are 36,198,200 and 252 MW respectively. It is assumed that all buses in transmission system participated in demand response program. Simulations are processed in two cases; in the case I, UC problem is solved only with network constraints, without VPPs and DRP presence by GAMS [51] software using CPLEX solver in MILP model; non-linear constraints like fuel and emission costs are linearized. In the case II, UC problem is solved with bi-level model under VPPs, DRP and network constraints presence by GAMS using LINDO solver. Simulations are processed with Intel® core(TM) i7-8550U CPU @ 1.80 GHz PC RAM 16 GB laptop system. It is worth nothing that for the first stage optimization a MILP model is proceeded by CPLEX solver. The computation time in the without presents of DRP and VPP case is 12s and in the both strategies of the case II, computation time is about 530s. The difference computation time is driven to the β variation in both cases. Bus number 13 is slack bus and peak load of the network is 2650.5 MW in 24-hour time horizon. For all nodes, hourly load calculated according the table4 and table5. in table4 hourly load for all transmission system is demonstrated and in table5 node location and distribution of the total System demand is inserted.

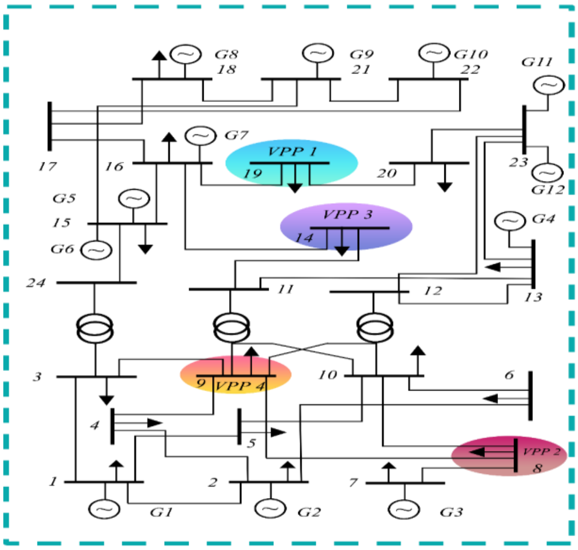

Fig. 7. IEEE reliability test system modified 24 bus

4.2. Numerical Results

4.2.1. Results without VPPs and DRP

In this case total cost includes fuel cost, start-up and shot-down cost, emission cost and load-shading cost. Fuel cost and start-up, shot-down cost are together supposed as generation cost. For each load point 1000 €/MW penalty is intended to loss of load so 11300 € for load-shading is spent. Generation cost and emission cost are 1360462.058 €, 275783.519 € respectively. Total cost is equal to 1647545.5770 €. Load-shading in 24h for each bus is as follows as the table 6.

4.2.2. Results with VPPs and DRP

Unit commitment problem in presence of the VPPs and DRP is solved with IGDT. So for both strategies we need to have a prediction of the VPPs output. DRP is analyzed for both strategies and we have to note that it has same results in both strategies because energy consumption is determined in both strategies.

In figure 8 energy price based on Ref. [52] in real-time and after TOU demand response implementation are compared. According the figure 8, before of the DR program performing, there is a peak time that energy price has the highest value between 8 to 19-time interval. Price in TOU demand response program is in three portion. In the valley times, energy price is in low level; valley time is [1,7]-time interval and in this portion, price is 30 € / MWh. In peak time energy price is expensive than the other hours; peak time is 8-19 hours and price equals to 55 € / MWh. In the end, between 21 to 24 hours, energy price is lower than the peak time and higher than the valley time. In light time, electricity price equals to 40 € / MWh. Load curve with and without DRP are depicted in figure 9. According the figure 9 peak of the demand is in two portion. One of the peak is hour 9 to16 and the other one is hour 16 to 20. It seen that in figure 9 the curve which is considered DRP, is under the curve that is in base case in hour 9 to 20. Because in mentioned interval, energy price for consumers that are participated in TOU demand response program, is higher than real-time and consumers try to manage their loads and decline their consumption. In the other hand Fig. 9 shows that DR supposed curve is in top of the base case in hour 1 to 8 and 21-24. In these interval TOU energy price is lower than real-time price regarding this fact, consumers shifted portion of their loads to these time intervals. This compare turns out that consumers transferred their interruptible loads from peak time to off-peak hours. In fact, TOU demand response program caused that customer behavior is changed. In action, peak-shaving and valley-filling is done with consumers' participation in TOU demand response program and load curve become smoother than base case. Our prediction for VPPs output is illustrated in figure 10. Total cost for first stage is equal to 992022.711 €.

Table 6. Load-shading for load points in 24 h

Bus	Load-shading(MW)	Bus	Load-shading(MW)	Bus	Load-shading(MW)	Bus	Load-shading(MW)
1	0.604	6	0.763	13	0	19	1.018
2	0.541	7	0.700	14	0	20	0
3	1.002	8	0.954	15	1.765		
4	0.413	9	0.970	16	0.557		
5	0.152	10	0	18	1.861		

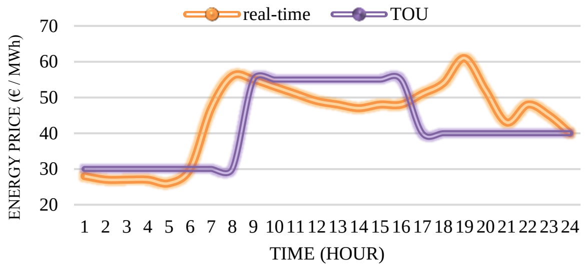

Fig. 8. Hourly energy price

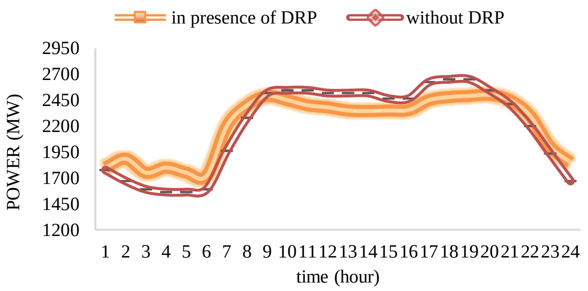

Fig. 9. Load curve in presence of DRP and without DRP

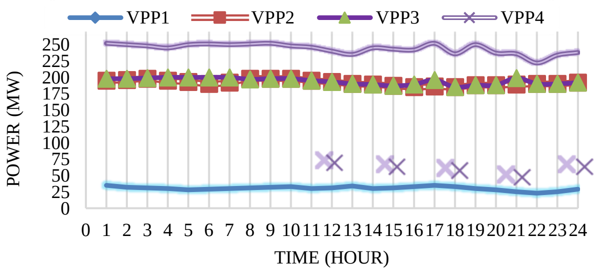

Fig. 10. Hourly VPP output prediction

RA Strategy in this strategy decision-variable select the optimum value in the way that robustness of the object function is ensured versus a specified β and uncertainty is an undesired phenomenon. For 5% tolerance of uncertainty (β=0.05) total cost is equal 1041623.847 € (1.05*992022.711=1041623.846). Generation cost and emission cost are 904370.545 €, 137253.302 € respectively. Load-shading in this case is zero. α is without dimension variable. In 5% tolerance uncertainty radius is 0.0807. this means that if uncertainty tolerance be 5%, the maximum immunity of the object function against the uncertainty is equal to 0.0807. Low value for uncertainty radius, means that object function is vulnerable against uncertainty for that reason, great α is resulted the more robustness and immunity. Of course too great robustness causes that total cost value be enhanced in this way must be a tradeoff between robustness and minimum total cost. The VPPs output in RA strategy are displayed in Fig.11. In RA strategy, when tolerance is increasing, robustness of the total cost is increasing simultaneously and value of the total cost grows up respectively. This fact is depicted in Fig.12 because in RA strategy, by increasing the tolerance, to immunity of the object function it is entails that robustness of the object function must be enhanced. Now a question arises that which one of these values for total cost is better. For this question we have to say, all of these values are optimal but which one of them has great α its robustness is more than the others. for the RA strategy it is better that the uncertainty radius has great value. great value in RA strategy means that immunity of the object function is improved. Uncertainty radius has symmetric relation with immunity and robustness of the object function.

OS Strategy: In OS strategy uncertainty is a desired phenomenon and decision variable search another optimum point that condition's is better than predicted value. In this study OS strategy tries to find an optimum point that value's is lower than the predicted one. In tolerance of the 5% total cost is 942421.575 €. The 833809.143 € of the total cost is related to generation cost and 108612.432 € is share of the emission cost. Similar the RA strategy, load-shading is zero. Uncertainty radius in OS strategy in β=0.05 is equal to 0.157. This means that if uncertainty tolerance be 5% the 0.157 is the minimum uncertainty radius that should be accepted that to sweep the success.

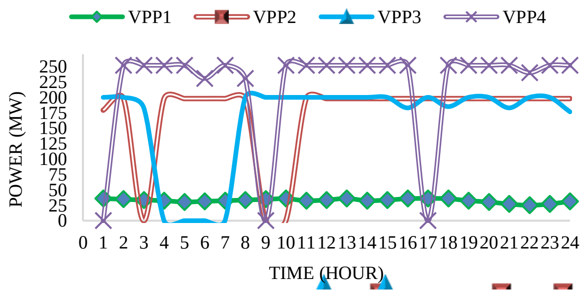

Fig. 11. Hourly VPP output in RA strategy

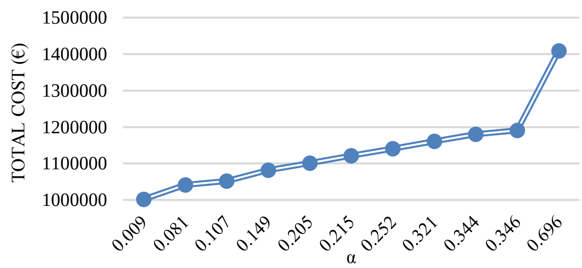

Fig. 12. Total cost in various uncertainty radius in RA strategy

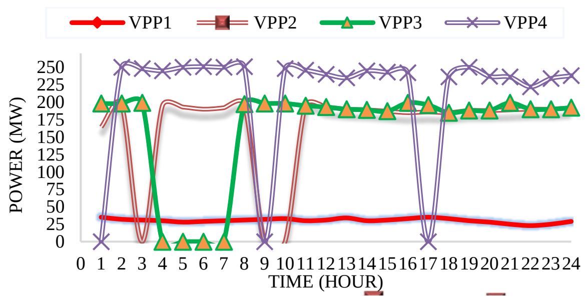

Fig. 13. Hourly VPP output in OS strategy

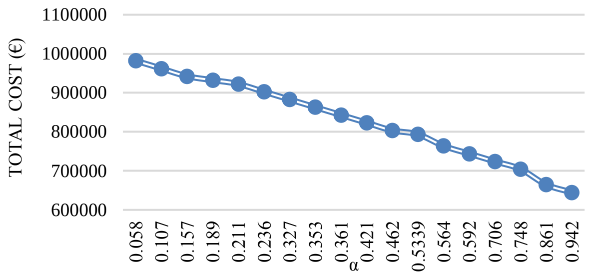

Fig. 14. Total cost in OS strategy in various uncertainty radius

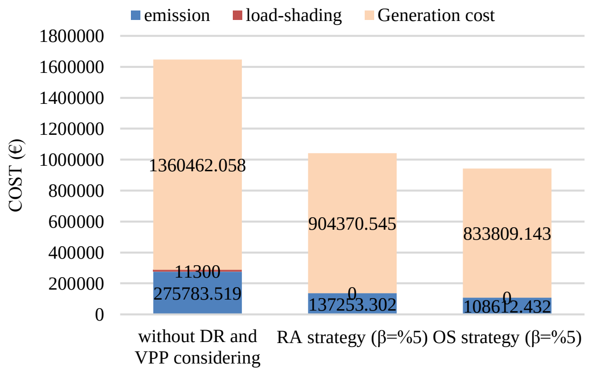

Fig. 15. Compare cost in different case studie

Success is the all constraints be satisfied and object function be lower than 0.95 of the predicted value. This strategy in versus of the RA, does not perform with immunity of object function. OS strategy wants to reach success in minimum uncertainty radius but is not guaranteed the value. In OS strategy low value for uncertainty radius means that decision-variable sweep the success in minimum uncertainty tolerance. According the above, in OS strategy, uncertainty radius has anti-symmetric relationship with the opportuneness. Low uncertainty radius results the more opportuneness. The VPP generation in 24-h are illustrated in Fig.13.

Like the RA strategy when the uncertainty tolerance is increased, uncertainty radius is increased and total cost is declined. This fact is declared in Fig.14. If uncertainty tolerance is increased the space for sweeping the success is enhanced and decision-variable can search lower value for total cost. In the OS strategy decision variable aims to sweep the success in minimum uncertainty tolerance this means that good opportuneness is gain in low α. Maximum amount of the uncertainty tolerance that problem is feasible is 35% and total cost in this tolerance equals to 644814.762 €. A comparison between generation, emission and load-shading cost in two case is illustrated in Fig.15 this figure displays this fact that total cost in presence of VPP and DRP is lower than the base case also other features of the proposed model have good condition against the case I. By observation of the Fig.15 it is brightly seen that the proposed model has lower load-shading and emission cost and effectiveness of the VPP and DRP is proofed.

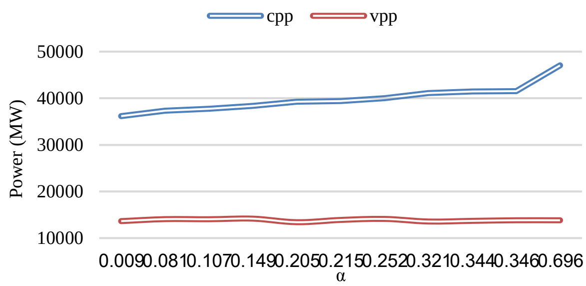

Fig. 16. Share of CPP and VPP in RA strategy

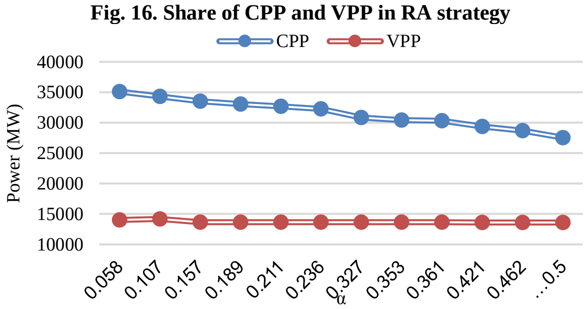

Fig. 17. Share of CPP and VPP in OS strategy

4.3. Comparison

In this section a comparison between this paper and other similar paper is proposed. It should note that, in last published papers, there is no a paper which exactly done unit commitment in presence of the VPP under generation uncertainty and DRP but in Ref [53] a similar work is done. In mentioned reference, UC problem is solved in IEEE 118 bus test system and wind power plants have uncertainty. A flexible DRP is proposed. In Ref [53] in each strategy, share of the wind power plants are changed. In RA strategy, by growing up the β share of the wind power plants are decreased and to compensation of generation balance, share of thermal units are increased. Contrary in OS strategy, by increasing the tolerance of uncertainty (β), share of wind farm participation are increased and share of the CPPs are decreased. DRP in reference [53] has good influence on cost function in both strategies and caused to be reduced the total cost. In this paper UC problem under VPPs output uncertainty considering price-based demand response program in IEEE 24 bus reliability test system is solved. DR program has good effect on total cost reducing in both strategies.

In each paper, UC and DRP setting, effect on cost function in both strategies. There is difference in obtained results by changing the uncertainty tolerance in both paper. Unlike the comprised paper, in this work it can't see tangible impact by changing uncertainty tolerance in both strategies on share of VPPs output. This fact can see in figure16 and figure17. in RA strategy by increasing the cost function, generation of the CPP is increased and in OS strategy by decreasing the cost function, generation of the CPP is reduced but in both strategies, share of the VPP almost is constant.

5. CONCLUSION

This paper presented UC problem in presence of the network constraints, VPPs and DRP under IGDT uncertainty modeling. VPP concept and difference of the technical and commercial virtual power plant and difference between dispatchable and non-dispatchable energy resource were discussed. In context of the VPPs, DRP could be implemented in electrical networks. A TOU, price-based demand response program for all buses of the modified IEEE 24 bus reliability test system and presence of 4 VPPs in four buses was studied. Outputs of the VPPs were not deterministic, to tackle the uncertainty, IGDT was represented. IGDT helped us to actualize the amount of VPP's generation. In RA strategy by growing up the tolerance, total cost increased and robustness of the object function became better but more robustness resulted the great total cost in this way, a tradeoff should be adopted between robustness and minimum total cost. Contrary in OS strategy uncertainty was a desired phenomenon and by growing up the tolerance, total cost decreased. Briefly in RA strategy, big α was better and α had symmetrical relation with robustness contrary in OS strategy α had anti-symmetrical relationship with opportuneness and low α was better in OS strategy.

For the future works, we suggest to consider the hot and cold start-up cost for CPPs. If placement of the VPPs and cost of the hydro and nuclear separately be calculate it can be very helpful and can be reach the more real results.

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