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Optimal stochastic operation of technical virtual power plants in reconfigurable distribution networks considering contingencies

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ABSTRACT

Virtual Power Plants (VPPs) are one of the concepts introduced in modern power systems to handle the increasing number of the distributed generation (DG) units. Technical VPPs (TVPPs) consider both financial and technical perspectives of using DGs in the system. Besides, secure and reliable operation of the system is a priority. In this paper, optimal operation of technical virtual power plants in a reconfigurable network is formulated as an optimization problem to resolve the probable contingency problem in the lines of the system. The VPP is assumed to be a multi-carrier energy system including combined heat and power (CHP), renewable DGs and dispatchable DGs beside thermal and electrical storage systems and loads. The uncertainties of renewable based DGs and demand levels are handled using chance constrained programming (CCP). By using CCP in presence of uncertain parameters, the security of the system can be guaranteed in predefined level of probability. Finally, to evaluate the effectiveness, quality and applicability of the proposed methodology, the problem is structured as a mixed-integer nonlinear programming (MINLP) problem which is solved using General Algebraic Modeling System (GAMS) software via Baron solver.

1. Introduction

Rising energy consumption and concerns about global warming have prompted researchers to consider alternative ways to replace fossil fuels in energy systems. The use of renewable energy systems, including solar and wind systems, is one of these solutions. As declared in International Renewable Energy Agency (IRENA) report, by the end of 2016, at least 176 countries have had goals for renewable energy integration, and at least 150 countries have had policies for providing energy from renewable resources in power grids and at least 47 countries have used renewable resources for heating and cooling and finally, almost 41 countries have utilized renewable resources for transportation systems [1].

High penetration of such systems into distribution networks has caused many issues with operation of these systems. One way to overcome these challenges is emerging of Virtual Power Plants (VPP). VPP is a combination of various distributed generation (DG) units with multiple technologies in different sites that form a virtual energy network [2]. A typical VPP is shown in Fig. 1.

The VPPs can be divided into two different groups based on their structure: commercial VPPs (CVPP) and technical VPPs (TVPP). In the case of CVPP, the aggregated DER profile does not take into account the impact of the distribution network. By definition, CVPP is suitable for market integration and cannot provide services to the grid and the independent system operator (ISO). Unlike CVPP, TVPP considers the actual locations of DERs on the grid and incorporates grid operational constraints into its decision-making. The deployment of DERs to contribute to grid services such as congestion management and voltage regulation would be managed by TVPP. Based on such a definition, TVPP can consider the impact of contingency occurrences in the grid and design its bidding strategy to improve grid reliability [3].

In TVPPs, technical aspects alongside financial perspectives are considered simultaneously. This can be achieved with the cooperation of the VPP owner and ISO which is responsible for the technical management of the electrical power system [4]. Thus, it is assumed that TVPP is operated by the aid of ISO. Considering both financial and technical aspects could lead to a more reliable and efficient operation of the system which is desired by both the ISO and the TVPP owner. Operation of TVPPs can enhance the efficiency and reliability of the system and facilitate the higher penetration of DGs to distribution networks [5].

One of the most important issues in power systems is ensuring the security of the system. This could be whether in normal condition or

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Nomenclature

Abbreviations

DG	Distributed generation.
VPP	Virtual power plant.
$TVPP$	Technical virtual power plant.
CHP	Combined heat and power.
$MINLP$	Mixed-integer nonlinear programming.
CCP	Chance constrained programming.
PV	Photovoltaic.
TES	Thermal energy storage.

Indices

i, j, k	Indices for bus number.
t	Index for time.
dig	Subscript for diesel generator.
op	Superscript for operation.
max	Superscript for maximum value.
min	Superscript for minimum value.
chp	Subscript for CHP unit.
e	Subscript for electrical.
th	Subscript for thermal.
W	Subscript for wind generator.
R	Superscript for rated value.
$cutin$	Subscript for cut in velocity in wind turbine.
$cutout$	Subscript for cut out velocity in wind turbine.
PV	Subscript for PV unit.
std	Subscript for standard irradiation in PV.
cr	Subscript for certain irradiation in PV.
b	Subscript for battery.
cap	Superscript for converter/storage capacity in energy storage system.
ch	Superscript for charging in energy storage system.
dch	Superscript for discharging capacity in energy storage system.
int	Subscript for initial value.
fin	Subscript for final value.
TES	Subscript for thermal energy storage.
$loss$	Superscript for energy loss.
L	Subscript for load.
net	Superscript for net value.
gn	Subscript for generation.

Parameters

rmp	Ramp rate of the diesel generator.
C^{stup}	Start up cost.
a, b, c, d, e	Cost function coefficients.
η	Efficiency value.
μ	Mean value.
σ	Standard deviation.
r, x	Resistance and reactance of the lines of the system.
M	A large parameter in $big - M$ method.
ϵ	Reliability value in CCP.

Variables

P	Active power.
Q	Reactive power.
S	Apparent power.
τ	Binary variable indicating on/off status.
$Cost$	Cost amount.
ϕ	Binary variable indicating start up status.
H	Thermal power.
V	Wind velocity.
G	Solar irradiation.
ρ	Binary variable indicating charge/discharge status.
E	Energy level.
SoC	State of the charge of the battery system.
I	Current of the line.
U	Voltage of the bus.
ζ	Binary variable indicating a link between two specified buses.
θ	Auxiliary binary variable for indicating a link between two specified buses.

contingency condition. In contingency conditions, a failure could occur in system components which could disturb the power delivery and accordingly jeopardize the security of the network. The failure could lead to extreme violations of the operating constraints which can result in partial or total load shedding [6].

One of the convenient solutions for contingency problem, is optimal network reconfiguration. By using optimal switching in systems with contingencies, the problem of delivering power to the consumers and thus ensuring system reliability and security can be resolved [7]. ISO, as the agent in charge of technical aspects of the system, could perform switching actions to enhance the system's security. Cooperation of the TVPP and ISO in reconfigurable networks can lead to more resiliency and reliability besides the financial purposes [4].

Decisions with certainty are difficult to find due to some unknown future parameters existing in the problem. Conventional power systems are familiar with the concept of uncertainty because of the stochastic nature of demand levels. However, the power plants can handle these uncertainties. On the other hand, in modern power systems, renewable-based DGs e.g., solar and wind generation units, are becoming more popular. The output of these systems is uncertain which transforms the decision makings in such systems into stochastic ones. Stochastic programming is utilized for formulating and solving problems with uncertain parameters as random variables with known probability functions.

Various models for stochastic programming have been suggested by researchers e.g. scenario-based models, point estimation methods, chance-constrained programming, etc. By using scenario-based methods, numerous possible realizations of uncertainty should be considered which could increase the number of scenarios significantly, and thus, scenario reduction might be applied to the model [4]. Information gap decision theory (IGDT) is one of the most practical methods to deal with uncertainties. The IGDT has been introduced in the energy hub management to tackle the uncertainties as an efficient robust optimization tool with low complexity while ensuring the optimal operation of the system according to the priorities of the decision-maker entity [8]. The IGDT method generally provides the optimal solution considering all possible scenarios, which increases the overall cost of operation. In contrast, some of the scenarios would not happen in the real world. While the strategy behind the chance-constrained method is defined in

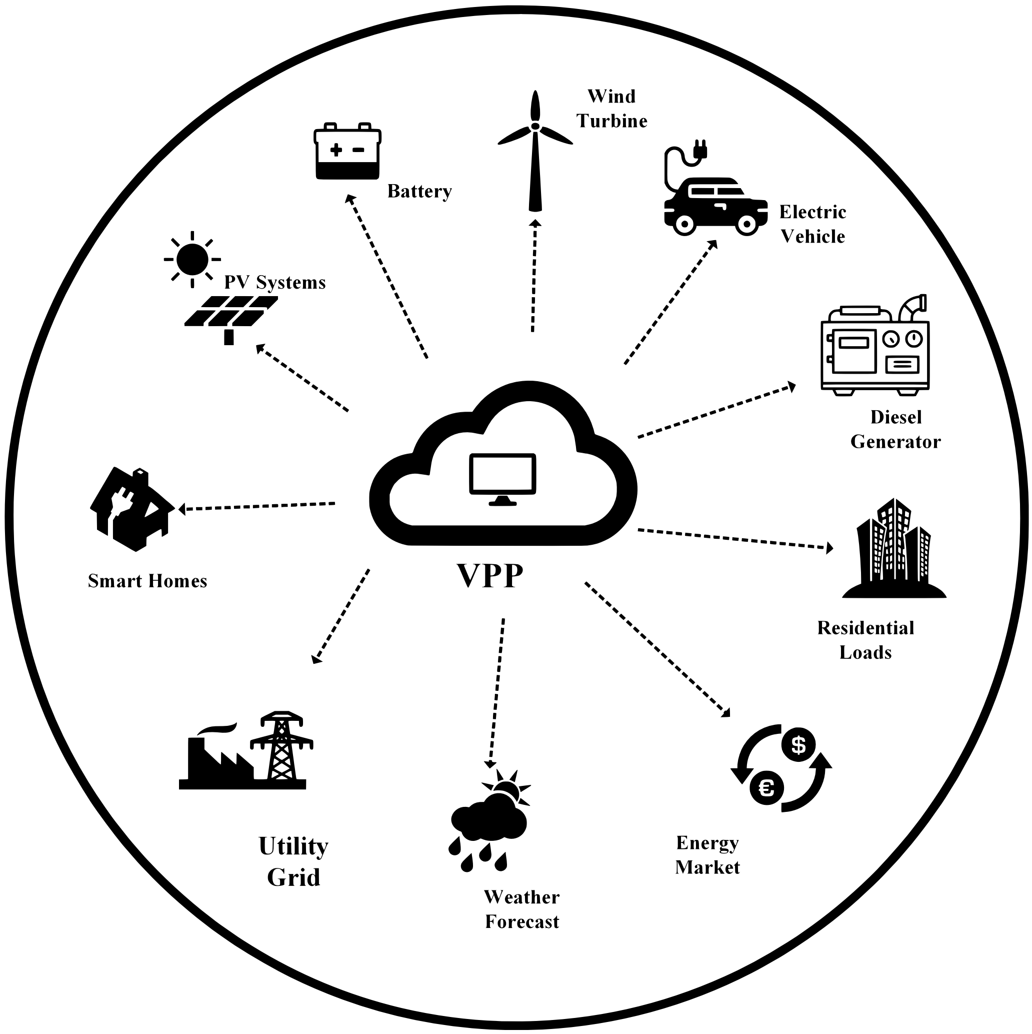

Fig. 1. A typical VPP system structure.

such a way as to solve the problem for the most probable scenarios with ignoring low-impact scenarios [9].

Although elimination of the scenarios might lighten the burden of calculations, it may jeopardize the security and stability of the system as a result of power imbalance in some of the unseen scenarios. Moreover, in most of the scenario-based models as recourse-based optimizations, the optimal solution is found through realizations of scenarios and making corrective actions, which might be infeasible. In the robust optimization, the worst-case scenario is assumed to happen, which could be a too conservative answer for daily scheduling problem and increase the costs. Another method for modeling the uncertainties is chance-constrained programming (CCP), which overcomes all the mentioned issues for stochastic programming. In CCP, some uncertain constraints are defined and the probability of violating certain constraints, which contain random variables, remains in a certain and small range [10] The optimization problems with CCP could be solved utilizing some approaches converting the chance-constraints into deterministic ones and facilitate the solution procedure [11]. Accordingly, CCP not only increases the stability and reliability of the system by keeping the probability of violating uncertain constraints at a desired level, but also by using deterministic equivalents, the calculations are reduced.

In modern energy systems, preparing a sustainable and efficient encounter for the increasing electric and heat demands is an important issue. Introducing combined heat and power (CHP) units has helped this issue where the thermal demand besides electrical demand could be provided simultaneously economically and efficiently. TVPPs could manage these systems in their network so that the likely operational issues associated with them could be reduced [12].

2. State of the art

2.1. Literature survey

The optimal operation of a VPP is done aiming at lowering the economic costs which is usually modeled as an optimization problem with an objective function to be optimized and respected operational constraints.

Heuristic methods are one of the optimization tools that can provide a good solution with a reasonable resolution time to the problem, but the optimality of the solution is under question. Various studies are done for optimal scheduling of VPPs via heuristic methods. Authors in [13] have applied particle swarm optimization (PSO) to an optimal scheduling model for a VPP participating in the day-ahead and real-time markets considering conditional value at risk to handle the risks associated with uncertainties in the system. Hadayeghparast et al. [14] have presented a stochastic model for day-ahead energy management of a VPP including PV systems, wind turbines, battery systems, CHP units, and heat-only units which is solved via PSO as a heuristic methodology. A stochastic decision-making tool for a VPP manager aiming at maximizing its profit by participating in both energy and balancing services markets is presented in [15] which is solved using genetic algorithm

(GA). Elgamal et al. [16] have investigated the planning and operation of VPPs in regulated markets based on profit maximization and using GA as the solution tool. In [17] a meta-heuristic method based on the big bang big crunch algorithm is used to find the minimum operational cost of a VPP in unbalanced distribution networks by managing the purchase of electricity from the utility and scheduling its units. Authors in [18] have applied imperialist competitive algorithm (ICA) aiming at minimizing the operational cost of a VPP.

Although numerous studies have been conducted for VPP scheduling using heuristic methods, these approaches fail to present a guaranteed optimum. On the other hand, some studies contain modeling of the problem as mathematical programming, i.e., mixed-integer linear/nonlinear programming (MIP/MINLP) methods. AC optimal power flow (ACOPF) is one of the most important sub-problems of the VPP optimal operation planning and it is a non-convex and non-linear optimization problem. However, this problem can be linearized in such a way as to reduce the computational burden. Several works have presented the linearized ACOPF problem in the literature. There are some discussions on the preciseness and scalability of the linearized ACOPF problems [19]. The decentralized ACOPF problem based on the alternating direction method of multipliers (ADMM) has been developed by the authors in [20] for peer-to-peer heat and power transactions in the distribution networks, however, the topology of the network is supposed to be fixed during the operational planning problem. The authors in [21] implemented McCormick envelopes in the linearization of the ACOPF problem and the obtained results are satisfactory for the quadratically constrained problem and the proposed methodology can be applied to the operational planning problems. It should be noted that the computational burden of the multi-temporal ACOPF is considerable for large-scale distribution networks, even for the linearized ACOPF methods.

Li et al. [22] have proposed a robust MIP optimization model to obtain parameters of the VPP in a way that they become independent from the information of day-ahead energy markets, e.g. ramp rates and time-varying power bounds. A multi-stage stochastic programming approach for optimization of the bidding strategy of a VPP operating on the Spanish spot market for electricity has been proposed in [23]. Alahyari et al. [24] have proposed a linear formulation for the scheduling strategy of a VPP that aggregates the EVs and wind generation units to participate in electricity markets, as well as day-ahead energy and reserve markets. In [25], a two-stage stochastic problem for energy resource scheduling in a VPP as an MILP formulation has been presented aiming at minimizing the expected operational cost of the system. Jafari and Foroud [26] have presented an MILP model for VPPs scheduling based on auction theory to participate in the day-ahead market. An offering strategy of a VPP that participates in the energy and reserve electricity markets using a stochastic bi-level model is proposed in [27]. In [28], an MINLP bi-level scheduling model for VPPs with flexible loads and RES has been proposed to reduce the net exchange power deviation caused by the forecast error of RES. Furthermore, in [29] an MINLP-based framework for optimized bidding strategy of a VPP to maximize the profit on day-ahead and real-time bases has been introduced. Gougheri et al. [30] have proposed an optimal bidding strategy for VPPs to participate in energy and spinning reserve markets considering the uncertainty of load demand, electricity prices, and wind speed. In [31] the aim is to analyze the feasibility of VPP using local RES construction and the update of high efficiency appliances located in electricity customers. Authors in [32], have investigated the energy management problem of a VPP in energy markets considering contingencies of its own units which has been formulated as a stochastic robust optimization model.

The ancillary services market is designed to guarantee the security and reliability of the electrical grid which is done by balancing the generation and demand. Participation of VPPs in such markets is growing and accordingly, some researches have been conducted in this area. Authors in [33], have proposed a new framework for the system frequency response of a VPP which is done through the optimal reserve scheduling to obtain the best frequency response in the frequency recovery as in the ancillary services market. A day-ahead scheduling framework for VPP is proposed in [34] for participation in energy, regulation, and reserve markets as ancillary services. Shafiekhani et al. [35] have represented a framework for the strategic bidding strategy of a VPP in a joint energy and regulation market using a bi-level mathematical model. Likewise, Authors in [36] have proposed a real-time cooperation scheme for VPPs to find an optimal bidding strategy to participate in joint energy and regulation markets, considering battery cycle life. The optimal offering strategy problem of a VPP as a price-maker player in the day-ahead frequency market as an ancillary service is presented in [37]. The problem is modeled as a bi-level optimization problem. In [38] the design of a feedback controller for VPPs has been addressed which aims at meeting energy market and tertiary reserve targets. It has mostly focused on control system design rather than economic aspects of the operation of the VPPs.

In the above reviewed sources, in the operation of the VPPs the technical constraints of the network, such as power flow, voltage profile of the buses, congestion in the lines, power losses experienced by the system, contingencies in the lines, etc., have not been considered. These constraints show the influence of units of the VPP on the physical distribution grid [5]. However, few studies have tried to take the technical perspectives of the operation of the network, which leads to the formation of Technical VPPs (TVPPs). Sadeghian et al. [39], have proposed maintenance management of a VPP for scheduling the planned outage of units, trying to increase their lifespan using a risk-based optimization and considering the uncertainty in price. Also, the proposed framework contains minimizing power loss in the grid, operational constraints of units, and power flow constraints. Likewise, in [40] scheduling framework for VPPs is proposed considering the operational and security constraints of the network. The studied VPP contains PV systems, wind turbines, electric vehicles, energy storage units, and diesel generators. In [41], an MILP model for simultaneous scheduling of energy and reserve in a TVPP considering the uncertainties of market prices, electrical demand and renewable power generation has been proposed. In [42], the control and bidding problem of a TVPP, containing RES and inelastic demand has been investigated using stochastic bi-level optimization programming and avoiding generation/demand mismatch and frequency instability. The technical aspects of the network operation have been addressed as well as the commercial aspects of the VPP. An optimization model for the TVPP is proposed in [43] which has taken network constraints into account. Hu et al. [44] have considered network congestion, which is an important technical issue, in the energy management framework of TVPP aiming at minimizing the amount of congestion in the network. The objective of the [5] was to develop an operational model for TVPP to obtain optimal scheduling in a day-ahead energy market, considering grid management constraints.

2.2. Contributions and paper structure

High penetration of DGs into distribution networks has caused operational problems which can be handled by introducing the notion of VPPs. Considering technical aspects of operation leads to the genesis of TVPPs. Furthermore, one of the important issues in the way of secure and reliable operation of the systems is the contingency problem. One important and possible solution for this, is optimal network reconfiguration. Besides, by using renewable-based DGs, significant uncertain parameters appear in the power system which require convenient modeling for the uncertainties. Also, the need for an efficient energy supply has encouraged the system owners to utilize CHP units.

According to the previous subsection, it is deduced that significant research has been carried out on the concept of financial aspects of VPPs and participation in various markets, however, limited studies are conducted on TVPPs. Table 1 illustrates the findings of this study

Table 1
Comparison of the proposed method with different studies.

Reference	Uncertainties			Uncertainty modeling	Technical VPP	Power loss	Contingencies
	Load	PV	Wind				
[13]	✓	–	✓	Scenarios-based Expected Value Optimization	–	–	–
[15]	–	✓	✓	Scenarios-based Expected Value Optimization	–	–	–
[22]	–	✓	✓	Robust Optimization	–	–	–
[25]	✓	✓	✓	Scenarios-based Expected Value Optimization	–	–	–
[30]	✓	–	✓	Machine Learning	–	–	–
[34]	–	–	✓	PEM	–	–	–
[35]	–	–	✓	Scenarios-based Expected Value Optimization	–	–	–
[41]	✓	✓	✓	PEM	✓	–	–
[42]	✓	–	✓	Scenarios-based Expected Value Optimization	✓	–	–
[43]	–	–	–	–	✓	–	–
[5]	✓	✓	✓	Scenarios-based Expected Value Optimization	✓	✓	–
Proposed	✓	✓	✓	**CCP**	✓	✓	✓

in comparison with others and to the best knowledge of the authors, the contingency issue in presence of TVPPs has not been addressed before. In this study, the optimal operation of TVPP for resolving contingency problem in reconfigurable distribution networks will be investigated. The objective contains not only minimum operational cost for the entities of the TVPP but also minimum switching actions for contingency management and minimizing the loss, which results in a reduction of load shedding. Most of the reviewed literature have used scenario-based methods for handling the uncertainties which can bring a high calculation burden or loss of information to the modeling. However, in this study, uncertainty modeling is done by employing the CCP method which could improve the reliability and security of the system in presence of unknown parameters, in comparison with other methods of uncertainty modeling. To sum up, the contributions of the paper could be categorized as follows:

• Proposing an optimal scheduling method for TVPP aiming at resolving contingency problem in the network.

• The case study is a VPP containing variety of energy systems e.g. diesel generators, CHPs, renewable power sources, electrical and thermal storages, etc.

• Using CCP for modeling the uncertainties associated with the system.

The rest of the article is sectioned as follows: System modeling and problem formulation for the optimal scheduling in presence of contingencies is introduced in Section 3. Section 4 demonstrates the simulation results and discussions about the effectiveness of the proposed method and finally in the last section the conclusion is conducted.

3. System modeling and problem formulation

This section contains system modeling and problem formulation for optimal operation of TVPPs in presence of contingencies. Modeling of various units would be presented and the procedure of optimal resolving of the contingency problem will be illustrated. The process of handling uncertainties would be defined.

3.1. Diesel generator

Diesel generators are one of the controllable DGs which are very popular for their durability and versatility. The following equations illustrate the relative constraints and cost function of the operation.

$$0 \leq P_{dig,t} \leq \tau_{dig,t} \cdot P_{dig}^{max} \quad \tau_{dig,t} \in \{0,1\} \tag{1}$$

$$\left|P_{dig,t} - P_{dig,t-1}\right| \leq rmp_{dig} \cdot P_{dig}^{max} \tag{2}$$

$$P_{dig,t}^2 + Q_{dig,t}^2 \leq \tau_{dig,t} \cdot S_{dig,t}^2 \tag{3}$$

A quadratic function is usually used to model the cost function of these generators. Also, a start up cost is also considered for them.

$$Cost_{dig,t}^{op} = a \cdot P_{dig,t}^2 + b \cdot P_{dig,t} + c \tag{4}$$

$$Cost_{dig,t}^{stup} = \phi_{dig,t} \cdot C_{dig}^{stup} \tag{5}$$

$$\phi_{dig,t} = max[(\tau_{dig,t} - \tau_{dig,t-1}), 0] \tag{6}$$

$$Cost_{dig,t} = Cost_{dig,t}^{op} + Cost_{dig,t}^{stup} \tag{7}$$

Eqs. (1)–(3) stand for technical operational constraints of the diesel generator while Eqs. (4)–(7) demonstrate the cost for operating the system.

3.2. Combined Heat and Power Unit

CHPs are becoming more popular because of their capability of providing both thermal and electrical energy. In this subsection modeling of a back-pressure type of CHP units will be presented. The back-pressure CHPs consist of diesel generator and chiller [12,45].

Eqs. (8)–(10) show the electrical power constraints of the CHP unit which is a diesel generator. The cost function for its operation is defined via Eqs. (11)–(14). The relation between electrical and thermal output of the back-pressure type CHP is shown in terms of Eq. (15) and finally Eqs. (16) and (17) stand for the thermal constraints of the system.

$$0 \leq P_{chp,t} \leq \tau_{chp,t} \cdot P_{chp}^{max} \quad \tau_{chp,t} \in \{0,1\} \tag{8}$$

$$\left|P_{chp,t} - P_{chp,t-1}\right| \leq rmp_{chp,e} \cdot P_{chp}^{max} \tag{9}$$

$$P_{chp,t}^2 + Q_{chp,t}^2 \leq \tau_{chp,t} \cdot S_{chp,t}^2 \tag{10}$$

$$Cost_{chp,t}^{op} = a \cdot P_{chp,t}^2 + b \cdot P_{chp,t} + c \cdot H_{chp,t}^2 + d \cdot H_{chp,t} + e \tag{11}$$

$$Cost_{chp,t}^{stup} = \phi_{chp,t} \cdot C_{chp}^{stup} \tag{12}$$

$$\phi_{chp,t} = max[(\tau_{chp,t} - \tau_{chp,t-1}), 0] \tag{13}$$

$$Cost_{chp,t} = Cost_{chp,t}^{op} + Cost_{chp,t}^{stup} \tag{14}$$

$$H_{chp,t} = P_{chp,t} \frac{(1 - \eta_{chp,dig} - \eta_{chp,hl})}{\eta_{chp,dig}} \tag{15}$$

$$0 \leq H_{chp,t} \leq \tau_{chp,t} \cdot H_{chp}^{max} \tag{16}$$

$$\left|H_{chp,t} - H_{chp,t-1}\right| \leq rmp_{chp,th} \cdot H_{chp}^{max} \tag{17}$$

3.3. Wind turbines

Wind turbines are used widely in modern power systems as renewable-based generation systems. They extract electrical power from the kinetic energy of the air and accordingly, their output energy is varied based on the wind speed. The wind speed is a stochastic phenomenon that is generally modeled as a Weibull probability distribution function.

The Weibull function has two parameters known as the scale (γ) and the shape (k) factors as shown below:

$$f(V) = (\frac{k}{\gamma})(\frac{V}{\gamma})^{k-1} e^{-(\frac{V}{\gamma})^k} \quad 0 \leq V \leq \infty \tag{18}$$

It is assumed that output power of the wind turbine is a function of the wind speed as illustrated in Eq. (19):

$$P_{W,t} = \begin{cases} 0 & V_t \leq V_{cutin}, \quad V_t \geq V_{cutout} \\ \frac{V_t - V_{cutin}}{V^R - V_{cutin}} \times P_W^R & V_{cutin} \leq V_t \leq V^R \\ P_W^R & V^R \leq V_t \leq V_{cutout} \end{cases} \tag{19}$$

3.4. Photovoltaic systems

PV units are one of the most popular and easiest ways of producing clean energy. The lower cost and smaller size in comparison with wind units have caused a tendency of using them in households. The produced energy of PVs depends on the weather circumstances i.e. solar irradiance and temperature which is stochastic in nature. The irradiance is usually modeled by the lognormal function which is shown in Eq. (20):

$$f(G) = \frac{1}{G \cdot \sigma \cdot \sqrt{2\pi}} exp[\frac{-(\ln G - \mu)^2}{2\sigma^2}] \quad G \geq 0 \tag{20}$$

The relationship between the output electrical energy of the PV unit and the solar irradiance is as follows:

$$P_{PV,t} = \begin{cases} P_{PV}^R \times (\frac{G_t^2}{G_{std} \cdot G_{cr}}) & G_t \leq G_{cr} \\ P_{PV}^R \times (\frac{G_t^2}{G_{std}}) & G_{cr} \leq G_t \end{cases} \tag{21}$$

3.5. Electrical energy storage system

Electrical energy storage systems are one of the indisputable parts of modern power systems. They are responsible for the compensation of power fluctuations caused by renewable sources. Lithium-ion batteries are one of the most popular energy storage systems in the world. This is due to their reliability and accessibility which leads to the production of large-scale storage systems. They might be the most expensive technology among the others, however, they have a low cost per cycle of charging which makes them perfect for renewable energy storage. In this subsection technical constraints used for modeling the batteries inside a VPP will be presented [46].

Charging and discharging power capacity constraints of a battery storage system are shown via Eqs. (22) and (23). Simultaneous charging and discharging are avoided using Eq. (24). The changes in the energy level of the battery are shown by the state of charge (SoC) which is calculated using Eqs. (25)–(28). Finally, Eq. (29) illustrates the amount of battery power which in negative values indicates discharging and in positive values shows charging mode.

$$0 \leq P_{b,t}^{ch} \leq \rho_{b,t}^{ch} P_b^{cap} \tag{22}$$

$$0 \leq P_{b,t}^{dch} \leq \rho_{b,t}^{dch} P_b^{cap} \tag{23}$$

$$\rho_{b,t}^{ch} + \rho_{b,t}^{dch} \leq 1 \quad \rho_{b,t}^{ch}, \rho_{b,t}^{dch} \in \{0,1\} \tag{24}$$

$$SoC_t = SoC_{t-1} - \frac{1}{E_b^{cap}}(P_{b,t}^{dch} - P_{b,t}^{ch}) \cdot \Delta t \tag{25}$$

$$0 \leq SoC_t \leq 1 \tag{26}$$

$$SoC_{t_0} = SoC_{int} \tag{27}$$

$$SoC_{t_f} = SoC_{fin} \tag{28}$$

$$P_{b,t} = P_{b,t}^{ch} - P_{b,t}^{dch} \tag{29}$$

3.6. Thermal energy storage system

Thermal energy storage (TES) system is integrated with the CHP to increase heat efficiency. The operational constraints of the TES system are presented in terms of Eqs. (30)–(37). Eqs (30) and (31) stand for the charging and discharging capacity of the TES. To avoid simultaneous charging and discharging Eq. (32) is utilized. The changes in the energy level of the TES are calculated via Eqs. (33)–(36). Finally, in (29) the amount of thermal power of the system is shown which in negative values indicates discharging and in positive values shows charging mode.

$$0 \leq H_{tes,t}^{ch} \leq \rho_{tes,t}^{ch} \cdot H_{tes}^{cap} \tag{30}$$

$$0 \leq H_{tes,t}^{dch} \leq \rho_{tes,t}^{dch} \cdot H_{tes}^{cap} \tag{31}$$

$$\rho_{tes,t}^{dis} + \rho_{tes,t}^{ch} \leq 1 \quad \rho_{tes,t}^{dis}, \rho_{tes,t}^{ch} \in \{0,1\} \tag{32}$$

$$E_t = E_{t-1}(1 - \eta_{tes}^{loss}) + (H_{tes,t}^{ch} - H_{tes,t}^{dis} \eta_i^{ch}) \cdot \Delta t \tag{33}$$

$$E^{min} \leq E_t \leq E^{max} \tag{34}$$

$$E_{t_0} = E_{int} \tag{35}$$

$$E_{t_f} = E_{fin} \tag{36}$$

$$H_{tes,t} = H_{tes,t}^{ch} - H_{tes,t}^{dch} \tag{37}$$

3.7. Thermal power balance

Thermal power balance stands for thermal energy balancing in the VPP. It contains generated thermal power from CHPs, TES systems, and thermal load besides the heat loss. The following shows the thermal power balance in the system.

$$H_{chp,t} + H_{utility,t} = H_{tes,t} + H_{L,t} + H_t^{loss} \tag{38}$$

3.8. Loads

Another source of uncertainty in this study is assumed to be the loads. The demand level is modeled via normal distribution function as shown below:

$$f(L) = \frac{1}{\sigma \cdot \sqrt{2\pi}} \cdot e^{\frac{-(L-\mu)^2}{2\sigma^2}} \quad L \geq 0 \tag{39}$$

3.9. Power flow modeling

VPPs are usually located in distribution systems which are usually radial networks. It is assumed that the first bus is connected to the utility grid and has a flexible power injection with a voltage of 1 $p.u.$

The following equations show the convex power flow formulation in such networks. Eq. (40) shows the net apparent power that exits each bus which is calculated by the difference between generation and consumption. The total generated power in each bus is defined via Eq. (41). Eqs. (42)–(45) demonstrated the power flow constraints for calculating voltage of buses which is obtained by Kirchhoff's laws and final equations stand for voltage, current and active and reactive power limitations of the respective buses and lines. $\mathfrak{T}$ is the set of buses connected to a specific bus and are ahead of that in the radial formation.

$$S_{k,t}^{net} = S_{k,b,t} + S_{k,L,t} - S_{k,gn,t} \tag{40}$$

$$S_{k,gn,t} = S_{k,dig,t} + S_{k,W,t} + S_{k,PV,t} + S_{k,chp,t} \tag{41}$$

$$S^{net}_{k,t} = P^{net}_{k,t} + j \cdot Q^{net}_{k,t} \tag{42}$$

$$P^{net}_{k,t} = P_{ik,t} - r_{ik} I^2_{ik,t} - \sum_{j\in\mathfrak{T}} P_{kj,t} \tag{43}$$

$$Q^{net}_{k,t} = Q_{ik,t} - x_{ik} I^2_{ik,t} - \sum_{j\in\mathfrak{T}} Q_{kj,t} \tag{44}$$

$$U^2_{k,t} = U^2_{i,t}(t) - 2(r_{ik} P_{ik,t} + x_{ik} Q_{ik,t}) + (r^2_{ik} + x^2_{ik}) \cdot I^2_{ik,t} \tag{45}$$

$$U^{min}_i \le U_{i,t} \le U^{max}_i \tag{46}$$

$$S^2_{ik,t} \ge P^2_{ik,t} + Q^2_{ik,t} \tag{47}$$

$$I^2_{ik,t} = \frac{S^2_{ik,t}}{U^2_{i,t}} \tag{48}$$

$$-I^{max}_{ik} \le I_{ik,t} \le I^{max}_{ik} \tag{49}$$

$$-P^{max}_{ik} \le P_{ik,t} \le P^{max}_{ik} \tag{50}$$

$$-Q^{max}_{ik} \le Q_{ik,t} \le Q^{max}_{ik} \tag{51}$$

3.10. Reconfigurable network modeling

Reconfiguration could help the safe and secure operation of the system in emergency situations such as contingency in lines. The model presented in the previous subsection is used for fixed radial networks. In reconfigurable networks, some modifications should be applied to the above modeling to deal with the switching actions that change the shape of the network. Thus power flow should be adopted to the new topology. For this purpose, binary variable $\zeta_{i,k}$ is defined which equals 1 in the case of a connection between buses i and k. To model this, the big M method is applied to the problem formulation. In this case, if there is a connection between buses i and k, $\zeta_{i,k}$ becomes 1, and accordingly, Eqs. (55) and (56), Eqs. (57) and (58), and Eqs. (59) and (60), transforms into equality constraints as in Eqs. (43), (44) and (45), respectively.

$$S^{net}_{k,t} = S_{k,b,t} + S_{k,L,t} - S_{k,gn,t} \tag{52}$$

$$S_{k,gn,t} = S_{k,dig,t} + S_{k,W,t} + S_{k,PV,t} + S_{k,chp,t} \tag{53}$$

$$S^{net}_{k,t} = P^{net}_{k,t} + j \cdot Q^{net}_{k,t} \tag{54}$$

$$P^{net}_{k,t} \ge [P_{ik,t} - r_{ik} I^2_{ik,t} - \sum_{j\in\mathfrak{T}} P_{kj,t}] - [1-\zeta_{ik,t}] \cdot M \tag{55}$$

$$P^{net}_{k,t} \le [P_{ik,t} - r_{ik} I^2_{ik,t} - \sum_{j\in\mathfrak{T}} P_{kj,t}] + [1-\zeta_{ik,t}] \cdot M \tag{56}$$

$$Q^{net}_{k,t} \ge [Q_{ik,t} - x_{ik} I^2_{ik,t} - \sum_{j\in\mathfrak{T}} Q_{kj,t}] - [1-\zeta_{ik,t}] \cdot M \tag{57}$$

$$Q^{net}_{k,t} \le [Q_{ik,t} - x_{ik} I^2_{ik,t} - \sum_{j\in\mathfrak{T}} Q_{kj,t}] + [1-\zeta_{ik,t}] \cdot M \tag{58}$$

$$U^2_{k,t} - U^2_{i,t}(t) \ge [-2(r_{ik} P_{ik,t} + x_{ik} Q_{ik,t}) + (r^2_{ik} + x^2_{ik}) \cdot I^2_{ik,t}] - [1-\zeta_{ik,t}] \cdot M \tag{59}$$

$$U^2_{k,t} - U^2_{i,t}(t) \le [-2(r_{ik} P_{ik,t} + x_{ik} Q_{ik,t}) + (r^2_{ik} + x^2_{ik}) \cdot I^2_{ik,t}] + [1-\zeta_{ik,t}] \cdot M \tag{60}$$

$$U^{min}_i \le U_{i,t} \le U^{max}_i \tag{61}$$

$$S^2_{ik,t} \ge P^2_{ik,t} + Q^2_{ik,t} \tag{62}$$

$$I^2_{ik,t} = \frac{S^2_{ik,t}}{U^2_{i,t}} \tag{63}$$

$$-\zeta_{ik,t} \cdot I^{max}_{ik} \le I_{ik,t} \le \zeta_{ik,t} \cdot I^{max}_{ik} \tag{64}$$

$$-\zeta_{ik,t} \cdot P^{max}_{ik} \le P_{ik,t} \le \zeta_{ik,t} \cdot P^{max}_{ik} \tag{65}$$

$$-\zeta_{ik,t} \cdot Q^{max}_{ik} \le Q_{ik,t} \le \zeta_{ik,t} \cdot Q^{max}_{ik} \tag{66}$$

3.11. Network radiality modeling

With the possibility of reconfiguration in the network, multiple topologies can occur for the network. However, in distribution networks, the operation should be in radial form at all times. So, the ISO should check the radiality of the network. The spanning tree approach is selected for this goal which can be expressed in terms of the following equations [47]:

$$\theta_{ik,t} + \theta_{ki,t} = \zeta_{ik,t} \tag{67}$$

$$\sum_k \theta_{k0,t} = 0 \tag{68}$$

$$\sum_k \theta_{ki,t} \le 1 \tag{69}$$

In this method, each node has only one parent node and the first bus has no parent. Eq. (67) illustrates that if the jth node is the parent of the ith node or vice versa, accordingly there is a connection between these two buses which is shown by binary variable ζ_{ik}. To avoid multiple parents for the first bus, Eq. (68) is applied and finally, Eq. (69) stands for forcing each bus to have one parent bus.

3.12. Uncertainty modeling

In modern power systems, uncertainty in power generation is an inseparable issue. Many approaches have been utilized by researchers to deal with uncertainties. CCP is one of them which contains constraints with uncertain parameters and it is required that the probability of violating these constraints remains in a predefined range.

A general formulation for CCP is shown in terms of the below equations which is known as $P - Model$ [48]:

$$min\,\{f(x) : x \in \Omega, \mathcal{P}[x \in \chi(\psi)] \ge 1-\epsilon\} \tag{70}$$

where x and ψ are decision vector stochastic variables, and Ω and χ are respective sets for deterministic and probabilistic constraints.

In optimal scheduling of the VPP, wind units, PV units, and demand levels are assumed to be the uncertainty source. Eqs. (52) and (53) contain the mentioned variables and accordingly, they can be transformed into a chance constraint in each bus as follows:

$$\mathcal{P}[\bigcap_{k=1}^{n_{bus}} (S_{k,t} - S_{k,b,t} \ge S_{k,L,t} - [S_{k,dig,t} + S_{k,W,t} + S_{k,PV,t} + S_{k,chp,t}])] \ge 1-\epsilon \tag{71}$$

The above formulation stands for joint CCP which could impart severe nonconvexities and make the optimization problem difficult to solve. Thus, a deterministic equivalent for this formulation is proposed in [49] which is also applied in this study that makes the joint CCP into separate CCP:

$$\mathcal{P}[S_{k,t} - S_{k,b,t} + S_{k,dig,t} + S_{k,chp,t} \ge S_{k,L,t} - S_{k,W,t} - S_{k,PV,t}] \ge 1 - \frac{\epsilon}{n_{bus}} \tag{72}$$

The right hand-side of the above relation can be encountered as a random variable with cumulative distribution function, $\mathcal{F}$ and thus Eq. (72) can be written as a deterministic formulation as follows:

$$\mathcal{F}[S_{k,t} - S_{k,b,t} + S_{k,dig,t} + S_{k,chp,t}] \ge 1 - \frac{\epsilon}{n_{bus}} \tag{73}$$

$$S_{k,t} - S_{k,b,t} + S_{k,dig,t} + S_{k,chp,t} \ge \mathcal{F}^{-1}(1 - \frac{\epsilon}{n_{bus}}) \tag{74}$$

Inverse cumulative distribution function can be calculated using numerical and iterative methods and the one applied in this study has been proposed in [50] that is shown in Alg. 1.

Eqs. (52) and (53) can be replaced by (74) to make the problem as a deterministic equivalent for the CCP modeling of the problem.

Algorithm 1 Calculating $\mathcal{F}^{-1}$

procedure START
  Predetermine a value for $\mathcal{F}^{-1}$ *as* ϱ
  loop:
  Generate load/generation samples using Monte Carlo simulations and find probability for $\mathcal{P}[\varrho \geq S_{k,L,t} - S_{k,W,t} - S_{k,PV,t}]$
  if $|\mathcal{P} - [1 - \frac{\epsilon}{n_{bus}}]| \geq \epsilon$ **then**
    if $\mathcal{P} \geq 1 - \frac{\epsilon}{n_{bus}}$ **then**
      Increase ϱ.
      Update ϱ.
      goto *loop*.
    else
      Decrease ϱ.
      Update ϱ.
      goto *loop*.
  else
    close;
  Print ϱ as $\mathcal{F}^{-1}$.

3.13. Optimal operation of TVPP for contingency problem

As mentioned earlier, contingencies can jeopardize the security of the system which can result in load shedding and dissatisfaction. One solution is operation of a TVPP in a reconfigurable network. The optimization model for the operation of TVPP is formulated as an MINLP problem. The objective function includes revenue obtained from selling energy to the consumers, the cost of operation of diesel generators and CHP units, the cost of switching actions for avoiding multiple switchings, and finally to obtain an optimal topology from the power loss perspective, a power loss cost is also contemplated in the objective function. The costs for buying energy from the utility grid are also contemplated in the objective function. In this regard, with negative values of utility grid power, the VPP can sell its excessive power to the upper grid. Eq. (76) shows the contingent line and Γ shows the set of lines with outages. It is assumed that there are enough tie lines to supply all the buses in the case of contingencies in the system lines. Power transfer to the upstream grid has not been considered. This optimization problem is shown in terms of the below equations.

$$o.f. = \max \sum_t \{\lambda_{elec} \cdot \sum_L P_{L,t} + \lambda_{therm} \cdot \sum_L H_{L,t} - \sum_{NO} \zeta_{ik,t} \cdot C_{sw} - \sum_{NC} (1-\zeta_{ik,t}) \cdot C_{sw} - \sum_{dig} Cost_{dig,t} - \lambda_{elec,t} \cdot P_{utility,t} - \lambda_{therm,t} \cdot H_{utility,t} - \sum_{chp} Cost_{chp,t} - \sum \lambda_{loss} \cdot (r_{ik} I^2_{ik,t} \zeta_{ik,t})\} \tag{75}$$

$$subject\ to: \quad Eqs.\ (1)\text{–}(17),\ (22)\text{–}(37),\ (38),\ (54)\text{–}(66),\ (67)\text{–}(69),\ (74) \quad \forall t$$

$$\zeta_{ik,t} = 0 \qquad ik \in \Gamma \tag{76}$$

4. Simulation results

In this section, simulations on a test system are presented to illustrate the applicability and effectiveness of the proposed framework. Baron solver via GAMS software is chosen for performing the simulations which are done using a system with a Core i7 CPU and 8 GB of RAM. Baron solver is chosen to handle the presented MINLP model, which has shown a great effectiveness and preciseness and the research has shown that it can solve the most benchmark problems and require the least amount of time per problem.

The test system is a VPP located in the IEEE 33-bus distribution network. The VPP contains diesel generators, CHPs, a photovoltaic unit, a wind generation unit, and electrical and thermal energy storage systems. The system structure is shown in Fig. 2. Also Tables 2 and 3 present the characteristics of the units. The network has the capability of reconfiguration which can be done by optimal switching actions. The switching cost is selected as 4$ per action. The scheduling is done for the day-ahead horizon with a one-hour time resolution. The energy exchange price during the scheduling period is shown in Fig. 3. Besides, it is assumed that the voltage variations are allowed between 0.9 and 1.1 $p.u.$ and the first bus will have a 1 $p.u.$ voltage value.

Case studies are as follows:

- *Case I.* There is a contingency in line 3–23 between hours 13 to 15 and the CCP parameter is assumed to be 0.95.
- *Case II.* There is a contingency in line 6–26 between hours 18 to 21 and the CCP parameter is assumed to be 0.9.
- *Case III.* The system is assumed to be non-reconfigurable and there is a contingency in line 3–23 between hours 13 to 15 and the CCP parameter is assumed to be 0.95.
- *Case IV.* The system is assumed to be non-reconfigurable and there is a contingency in line 6–26 between hours 18 to 21 and the CCP parameter is assumed to be 0.9.
- *Case V.* There is a contingency in line 3–23 between hours 13 to 15 and the CCP parameter is assumed to be 0.95. Furthermore, the loads on buses #24, #25, #26, and #27 are flexible and there are extra ESSs and extra capacities for the existing ones.

In the first case, it is assumed that there is a contingency in the line connecting buses 3 and 23 between hours 13 to 15. The system has the capability to perform a reconfiguration and accordingly, the event can be handled. The CCP parameter is assumed to be 0.95. In the second case study, the contingency is assumed to occur on a line that separates parts of the VPP from the rest of the system. Case studies 3 and 4 are selected on a non-reconfigurable system to see the effect of the reconfiguration on the output of the problem. Finally, the 5th case study is the same as the first one with additional storage systems and flexible loads to evaluate the effect of these facilities in the operation of VPP. Thus, the system is capable of handling contingencies and the reliability level in CCP is the same as in the first case study.

4.1. Case I

In this case, the response of the process for the contingency in the line between buses 3 and 23 is investigated. The CCP parameter is considered as 0.95. The results of the scheduling are shown in Figs. 4–6 and the objective value for the 24 h planning is 1083$. Diesel power generation, electrical and thermal outputs of the CHP, transactions with upper grid, battery and TES charging and discharging power, and status, are shown in these figures. The TVPP tries to minimize its operational cost and gain benefit by selling power to the utility grid in periods with higher energy prices, whilst attempts to purchase from the utility in the times with lower prices which can be seen in the power curves of DGs and energy storage devices. For instance at night, when the energy price is high, the DGs are working with higher output and the amount of power sold to the utility grid is high. On the other hand, in the early morning hours with lower energy prices, the amount of power bought from the grid is high and the DGs are working in low ratings. Also, the energy storage devices are storing energy at lower price times and selling at higher price times. This justification also applies to the thermal system. The voltage of buses during the scheduling is depicted in Fig. 7. The voltage is varied in a range between 0.975 to 1.015 $p.u.$.

The switching actions are shown in Table 4. It can be seen that by proper switching, the effect of contingency in the system has been reduced and all the demands are supplied. By outage of line 3–23, line 25–29, takes its place and the demands on the buses #23, #24, and #25 are supplied.

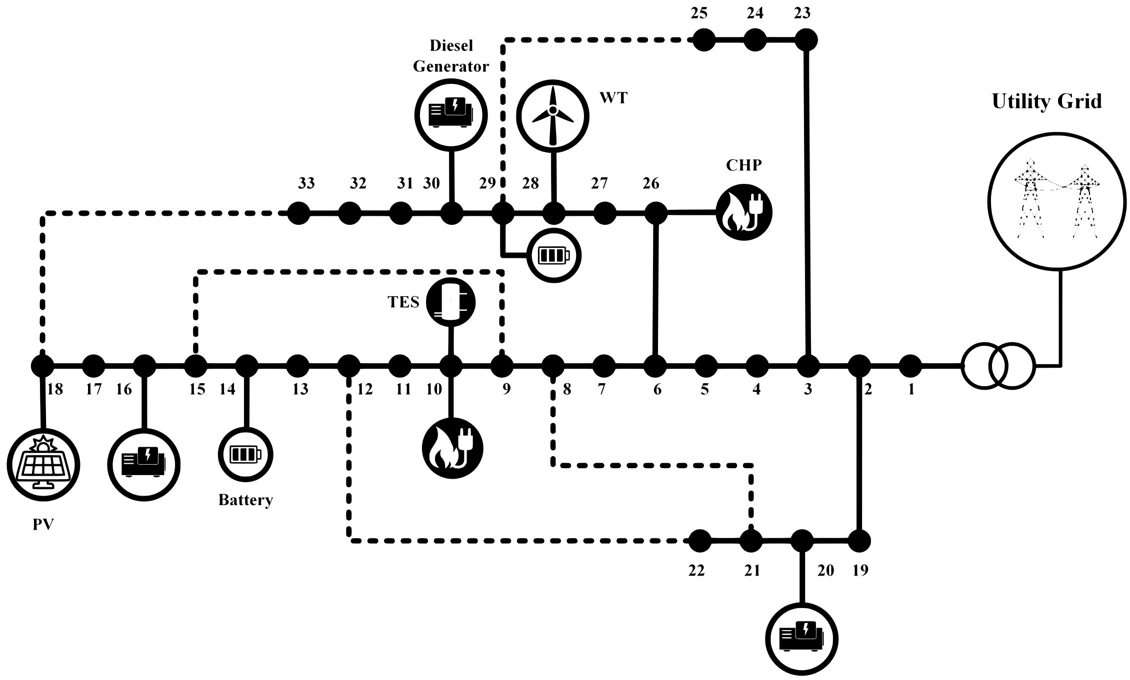

Fig. 2. Test system structure.

Table 2
Characteristics of DGs.

Bus #	DG type	P^{min} (MW)	P^{max} (MW)	Ramp rate (MW/h)	H^{min} (MW)	H^{max} (MW)	a (\$/MW^2)	b (\$/MW)	c (\$/MW^2)	d (\$/MW)	e (\$)	C^{stup} (\$)
10	CHP	0	0.8	0.5	0	0.6	0.0435	28	0.027	4.6	0	10
16	Diesel Generator	0	0.6	0.6	0	0	0.045	18	0	0	0	10
18	Photovoltaic	0	1.2	1.2	0	0	0	0	0	0	0	0
20	Diesel Generator	0	0.6	0.6	0	0	0.06	24	0	0	0	5
26	CHP	0	1	0.8	0	0.8	0.055	19.5	0.03	6.2	0	9
28	Wind Turbine	0	1.2	1.2	0	0	0	0	0	0	0	0
30	Diesel Generator	0	0.6	0.6	0	0	0.05	19	0	0	0	8

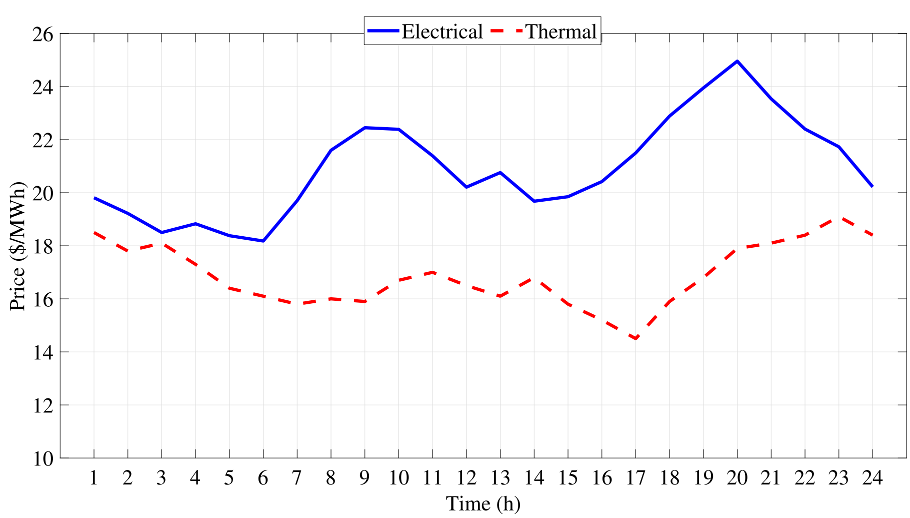

Fig. 3. Energy price during scheduling period.

4.2. Case II

In this case, the response of the process for the contingency in the line between buses 6 and 26 will be investigated. The reliability level in the CCP has been reduced to 0.9. Due to reconfiguration capability, the TVPP can be operated with no limitations in comparison with a non-contingent system. The switching actions are perfectly done to compensate for the contingency and the results are shown in Table 5. The results of the scheduling are shown in Figs. 4–6 and the operational cost for the 24 h planning is 1275\$. The voltage of buses during the scheduling is depicted in Fig. 7. It can be seen that by decreasing the reliability level, the operational cost has been reduced and the benefit has increased. This is due to more dependency on renewables as photovoltaic and wind generation units which are considered to have

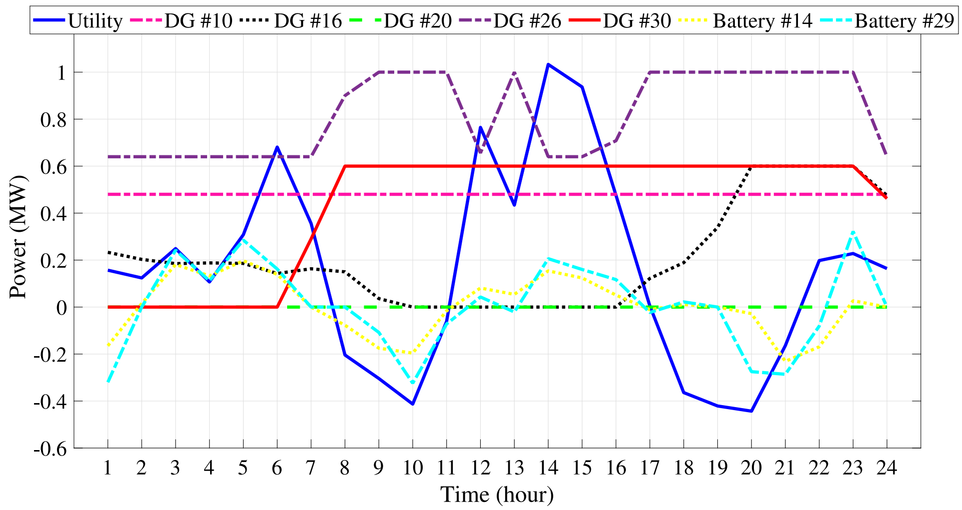

Fig. 4. Optimal DG output in *case I*.

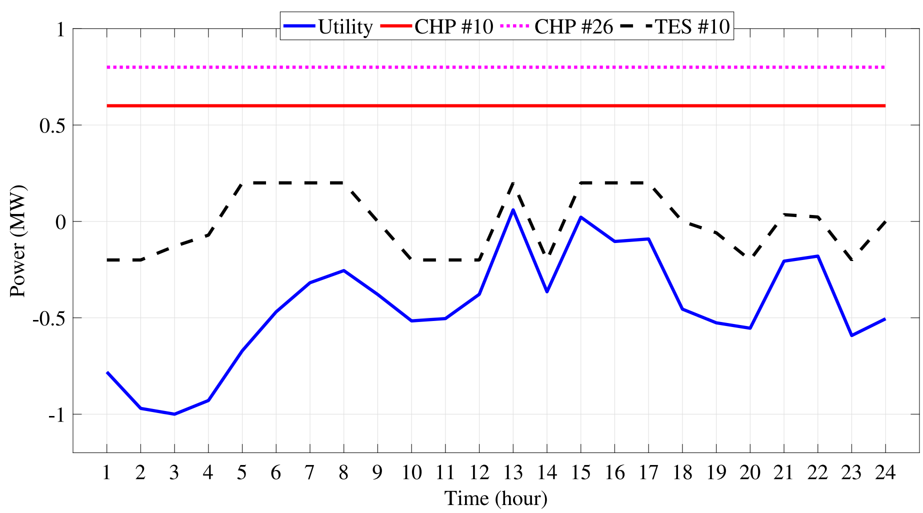

Fig. 5. Optimal operation of thermal units in *case I*.

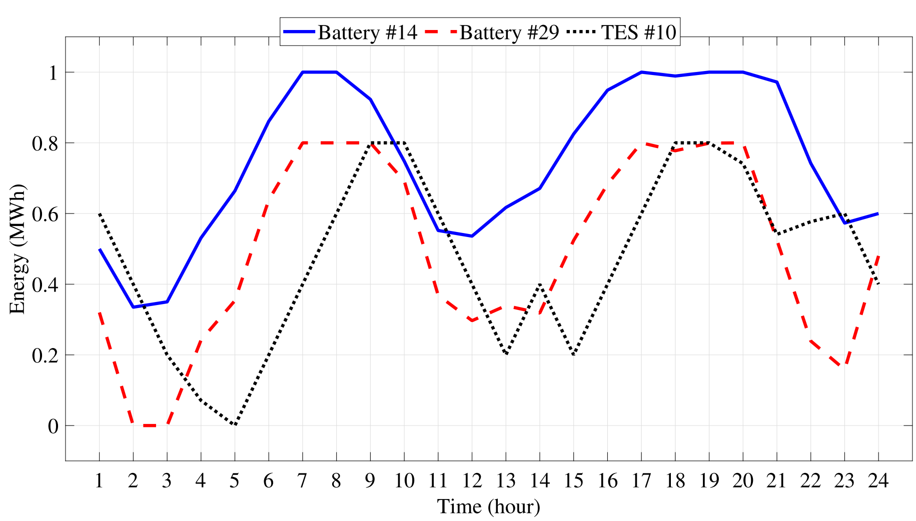

Fig. 6. Optimal energy level of energy storage devices in *case I*.

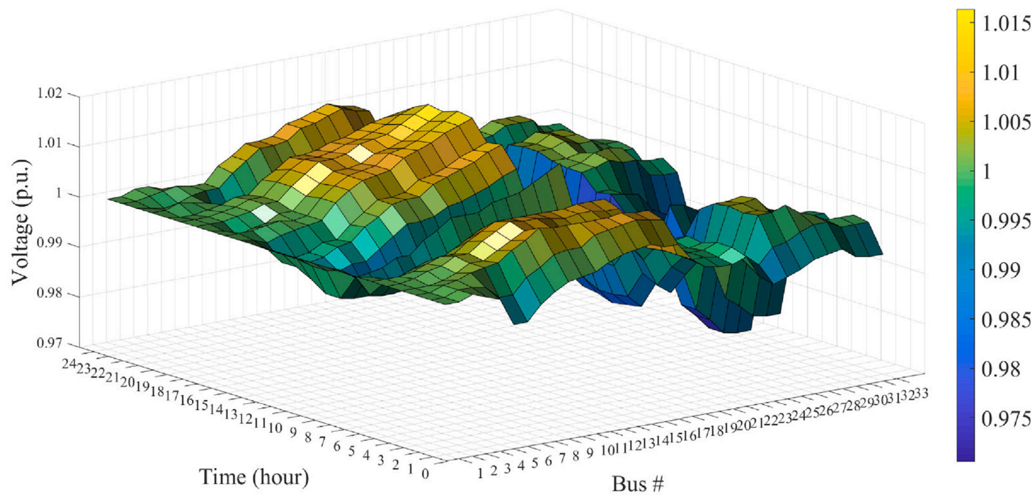

Fig. 7. Bus voltage values in *case I*.

Table 3
Characteristics of energy storage systems.

Bus #	Storage type	Initial energy (MWh)	Final energy (MWh)	Capacity (MWh)	P^{max} (MW)
10	TES	0.6	0.4	0.8	0.2
14	Battery	0.5	0.6	1	0.5
29	Battery	0.32	0.48	0.8	0.4

Table 4
Switching actions during scheduling horizon in *case I*.

Time	Open switches	Time	Open switches
1	12–22, 9–15, 8–21, 18–33, 25–29	13	8–9, 9–15, 8–21, 18–33, 3–23
2	2–3, 9–15, 8–21, 18–33, 25–29	14	8–9, 9–15, 8–21, 18–33, 3–23
3	2–3, 9–15, 8–21, 18–33, 25–29	15	8–9, 9–15, 8–21, 18–33, 3–23
4	2–3, 9–15, 8–21, 18–33, 25–29	16	8–9, 14–15, 26–27, 8–21, 25–29
5	2–3, 9–15, 8–21, 18–33, 25–29	17	8–9, 14–15, 26–27, 8–21, 25–29
6	2-3, 9–15, 8–21, 18–33, 25–29	18	8–9, 14–15, 26–27, 8–21, 25–29
7	2–3, 9–15, 8–21, 18–33, 25–29	19	8–9, 14–15, 26–27, 8–21, 25–29
8	8–9, 9–15, 8–21, 18–33, 25–29	20	8–9, 14–15, 26–27, 8–21, 25–29
9	8–9, 9–15, 8–21, 18–33, 25–29	21	8–9, 14–15, 26–27, 8–21, 25–29
10	8–9, 9–15, 8–21, 18–33, 25–29	22	8–9, 14–15, 26–27, 8–21, 25–29
11	8–9, 9–15, 8–21, 18–33, 25–29	23	8–9, 14–15, 26–27, 8–21, 25–29
12	8–9, 9–15, 8–21, 18–33, 25–29	24	8–9, 14–15, 26–27, 8–21, 25–29

zero operational cost. Consequently, the amount of buying energy from the upper grid has also been reduced and the amount sold to the upper grid has been increased. For instance in comparison with the previous case, at hour 9, the power sold to the utility grid, has reached from 300 kw in the previous case to 500 kw. It can be deduced from this result that the system operator has more dependency on PV and wind systems as stochastic RESs when the price of electricity is almost high. Also, more usage of energy storage systems is visible, which again is a result of relying more on renewables(see Figs. 8–11). .

4.3. Case III

In this case, the system is assumed to be incapable of performing reconfiguration. The system is the same as *case I* and the contingency occurs in line 3–23 between hours 13 to 15. The contingency in this line only affects the loads and no DG is isolated from the system. The CCP parameter has been selected as 0.95. This case is selected to see the effect of reconfiguration on resolving contingency problems. The results of the scheduling are shown in Figs. 12–14 and the objective function for the 24 h planning is 1063$. In comparison with the first case, although the first case had a switching cost, in this case, the benefit has been reduced. This is because of load shedding that has occurred in

Table 5
Switching actions during scheduling horizon in *case II*.

Time	Open switches	Time	Open switches
1	12–22, 9–15, 8–21, 18–3, 25–29	13	8–9, 9–15, 8–21, 18–3, 25–29
2	2–3, 9–15, 8–21, 18–3, 25–29	14	8–9, 14–15, 27–28, 8–21, 25–29
3	2–3, 9–15, 8–21, 18–3, 25–29	15	8–9, 14–15, 26–27, 8–21, 25–29
4	2–3, 9–15, 8–21, 18–3, 25–29	16	8–9, 14–15, 26–27, 8–21, 25–29
5	2–3, 9–15, 8–21, 18–3, 25–29	17	8–9, 14–15, 26–27, 8–21, 25–29
6	2–3, 9–15, 8–21, 18–3, 25–29	18	5–6, 14–15, 6–26, 8–21, 25–29
7	2–3, 9–15, 8–21, 18–3, 25–29	19	5–6, 14–15, 6–26, 8–21, 25–29
8	8–9, 9–15, 8–21, 18–3, 25–29	20	5–6, 14–15, 6–26, 3–23, 8–21
9	8–9, 9–15, 8–21, 18–3, 25–29	21	5–6, 14–15, 6–26, 3–23, 8–21
10	8–9, 9–15, 8–21, 18–3, 25–29	22	8–9, 14–15, 26–27, 8–21, 25–29
11	8–9, 9–15, 8–21, 18–3, 25–29	23	8–9, 14–15, 26–27, 8–21, 25–29
12	8–9, 9–15, 8–21, 18–3, 25–29	24	8–9, 14–15, 26–27, 8–21, 25–29

buses #23, #24, and #25 and consequently reducing the amount of sold energy to the consumers. The voltage of buses during the scheduling is depicted in Fig. 15. In this figure, the voltages of various buses are shown, however, due to contingency in the system some part of the network has been isolated, and accordingly, a load shedding and zero voltage in the buses in a specific period of the scheduling is visible which did not appear in previous case studies.

4.4. Case IV

Like the previous case, the system is assumed to be incapable of performing reconfiguration. The system is the same as *case II* and the contingency occurs in line 6–26 between hours 18 to 21. The contingency in this line not only affects the loads but also, DGs in that part are isolated from the system. The CCP parameter has been selected as 0.9 so the results can be comparable with *case II*. This case is selected to see the effect of reconfiguration on resolving contingency problems which can affect both loads and DGs of the VPP. The results of the scheduling are shown in Figs. 16–18 and the objective function for the 24 h planning is 1213$. In comparison with the *case II*, in this case, the benefit has been reduced which is due to contingency in line 6–26 between hours 18 to 21. This is not only because of load interruption but also as a result of the outage of VPP's units located in buses 26 to 33. In the second case, only load interruptions had occurred and the units could work on their maximum ratings in a condition that the network constraints were satisfied. The increment in the benefit in comparison with *case III* can be justified by reliability reduction in the CCP algorithm. The voltage of buses during the scheduling is depicted in Fig. 19. Like the previous case study a hole as a result of contingency is shown in this figure in the period of contingency in the lines.

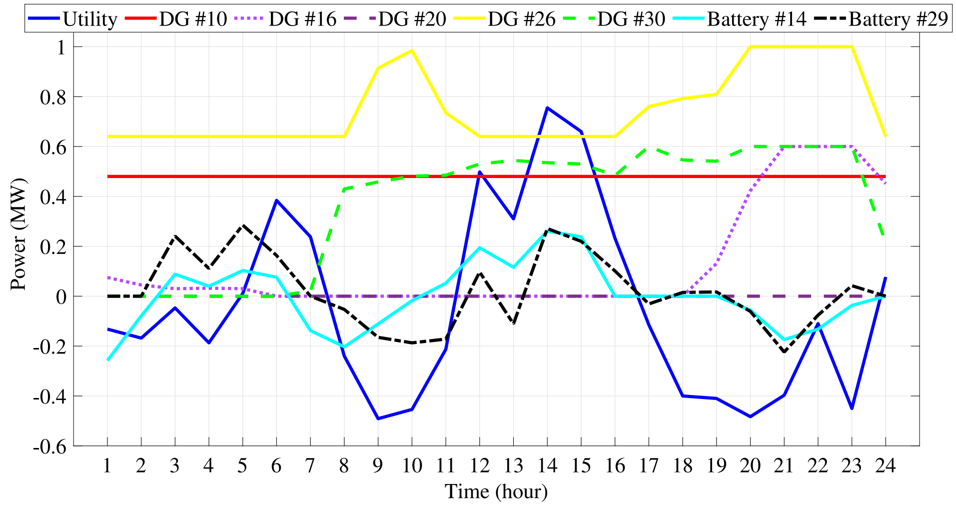

Fig. 8. Optimal DG output in *case II*.

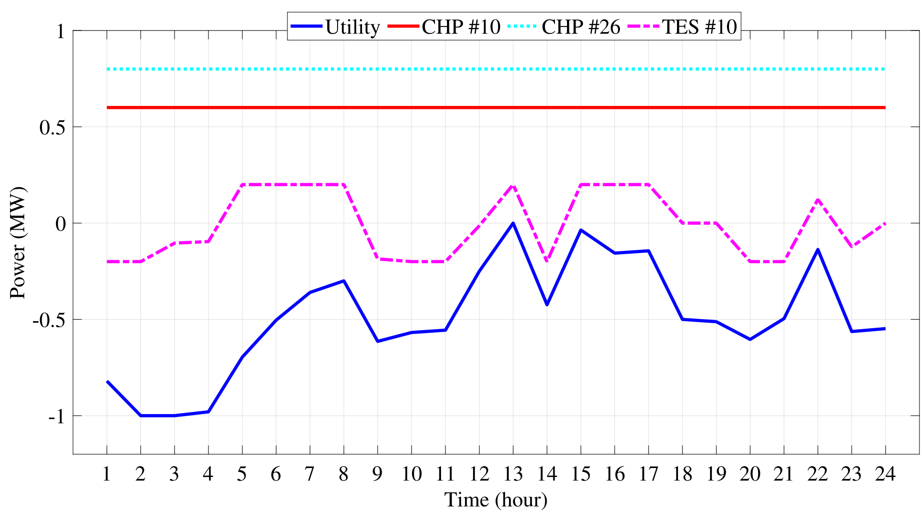

Fig. 9. Optimal operation of thermal units in *case II*.

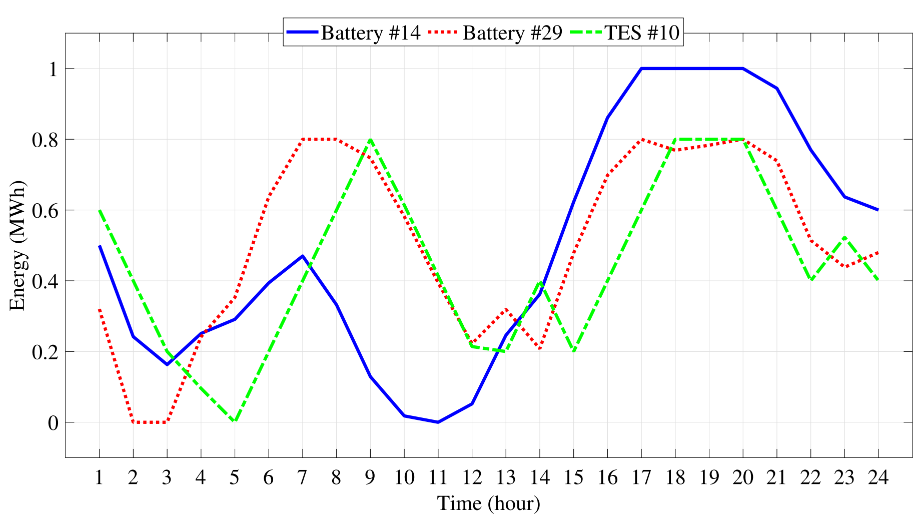

Fig. 10. Optimal energy level of energy storage devices in *case II*.

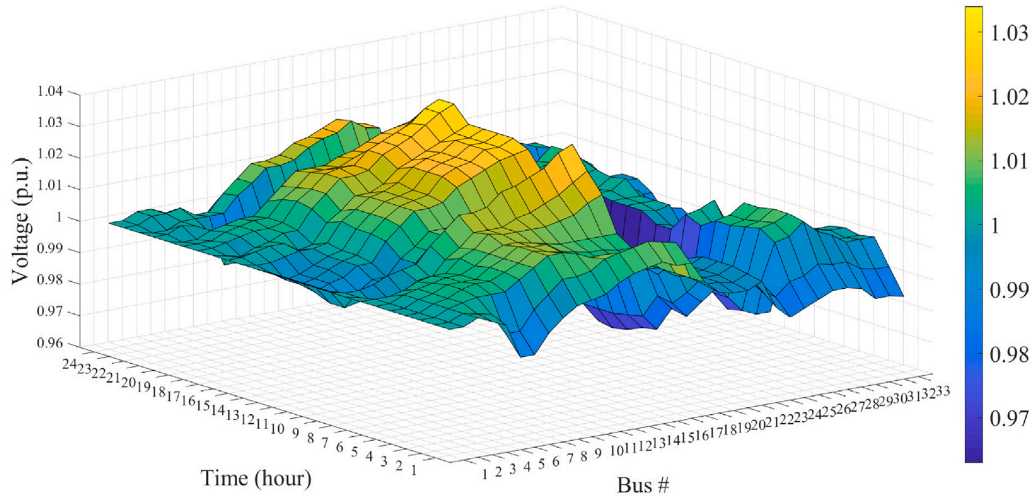

Fig. 11. Bus voltage values in *case II*.

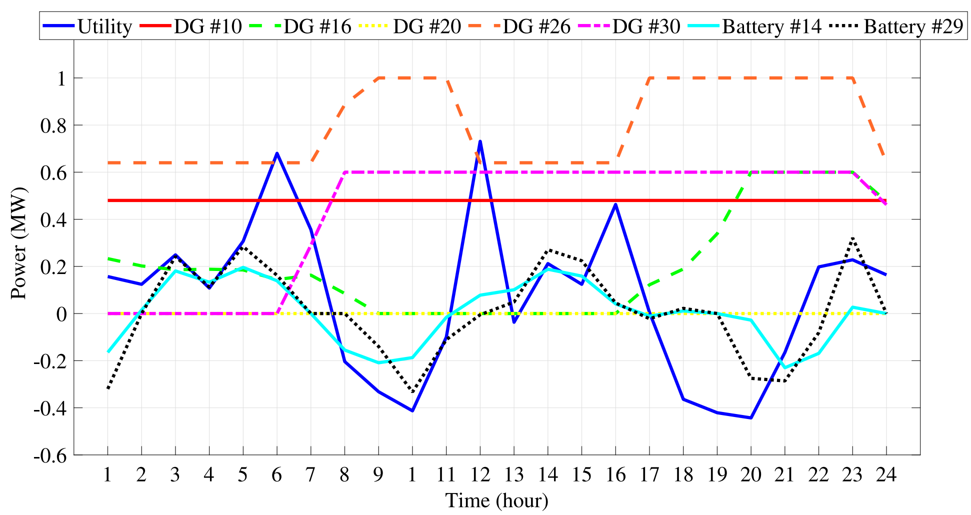

Fig. 12. Optimal DG output in *case III*.

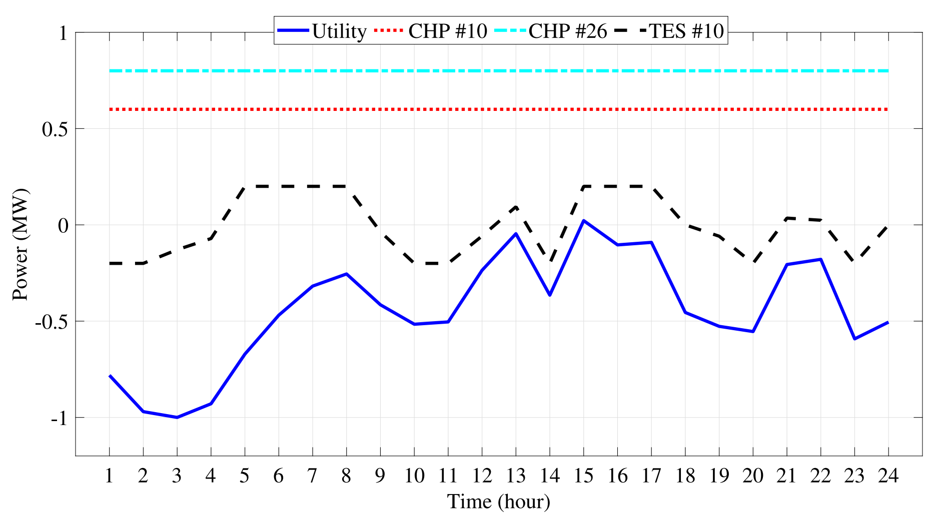

Fig. 13. Optimal operation of thermal units in *case III*.

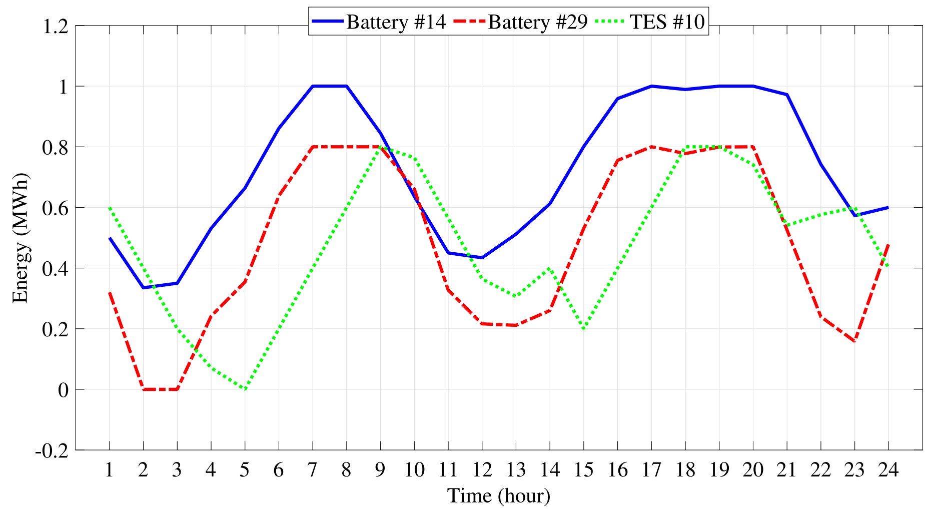

Fig. 14. Optimal energy level of energy storage devices in *case III*.

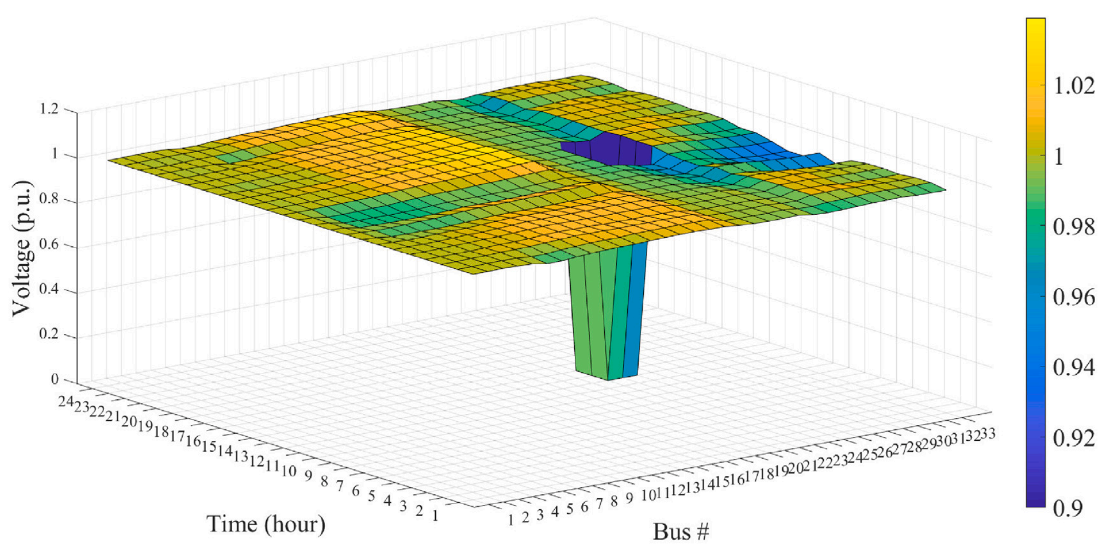

Fig. 15. Bus voltage values in *case III*.

As mentioned earlier, Fig. 20 illustrates total sold energy in various case studies which may affect the total revenue of TVPP. As shown, in the reconfigurable system, whether there is a contingency or not, the most energy is sold in comparison with the cases with contingencies. In addition, if the system is incapable of handling contingencies, the amount of sold energy is reduced which depends on the location of the contingency. This can emphasize the effect of considering a TVPP with the capability of contingency management.

4.5. Case V

In this case, the system is assumed to be capable of performing reconfiguration. Likewise the first case, a contingency occurs in line 6–26 between hours 18 to 21. The CCP parameter has been selected as 0.95 so the results can be comparable with *case I*. There are flexible loads on buses #24, #25, #26, and #27 and extra electrical storage at buses #4 and #8 and thermal storage ate bus #26, besides the existing ones, and increased capacity of energy and power in comparison with the previous case studies. Table 6 shows the characteristics of energy storage systems utilized in this case study instead of the ones illustrated in Table 3.

Table 6
Characteristics of energy storage systems in *Case V*.

Bus #	Storage type	Initial energy (MWh)	Final energy (MWh)	Capacity (MWh)	P^{max} (MW)
4	Battery	1.6	0.8	2	1
8	Battery	1.6	0.8	2	1
10	TES	0.6	0.4	1.8	0.6
14	Battery	1.2	1.2	2	1
26	TES	1	0.8	2	0.5
29	Battery	0.96	0.64	1.6	0.8

The results of the scheduling are shown in Figs. 21–24 and the objective value for the 24 h planning is 1135$. In comparison with the first case study, this shows a rise in the revenue of the TVPP. This can be justified with higher capacities of energy storage units and also executing demand response on flexible loads. The electrical output power of diesel units, electrical and thermal outputs of the CHPs, transactions with the utility grid, the battery and TES charging and discharging power and status, besides the changes of flexible loads during scheduling horizon, are shown in these figures.

In the higher price periods, the TVPP owner schedules its units in a way to gain benefit by selling power to the utility grid and tries to purchase from the utility in the times with lower prices which can be seen in the power curves of DGs and energy storage devices.

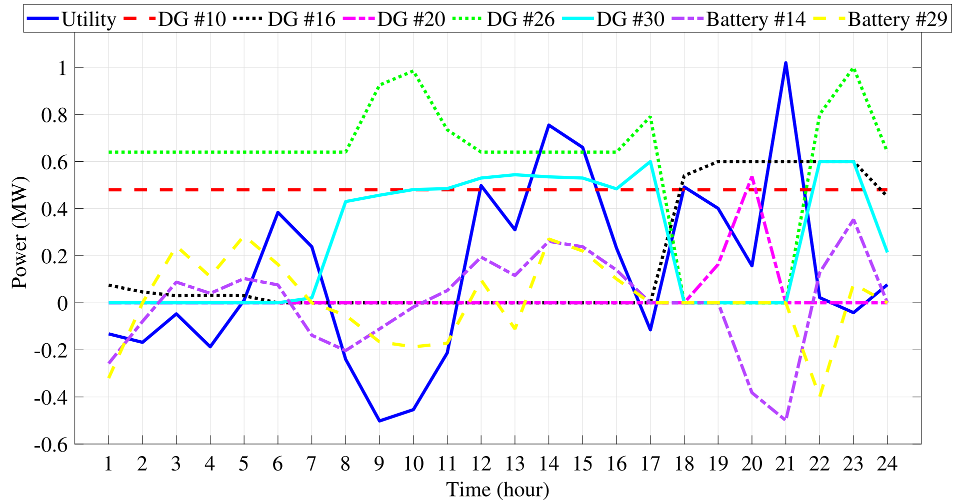

Fig. 16. Optimal DG output in *case IV*.

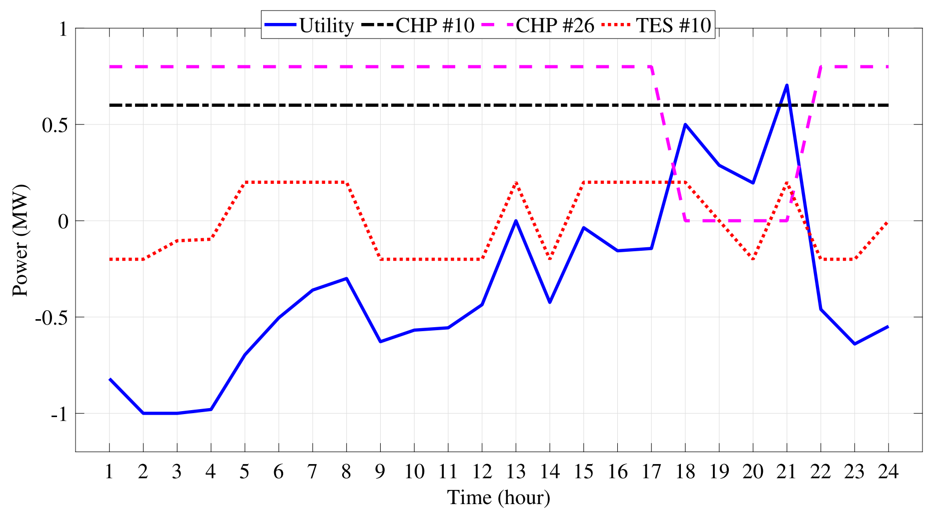

Fig. 17. Optimal operation of thermal units in *case IV*.

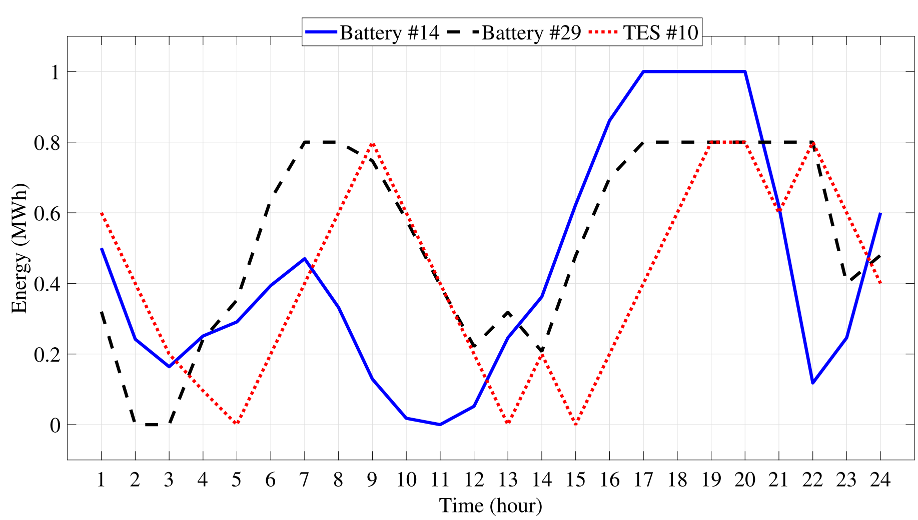

Fig. 18. Optimal energy level of energy storage devices in *case IV*.

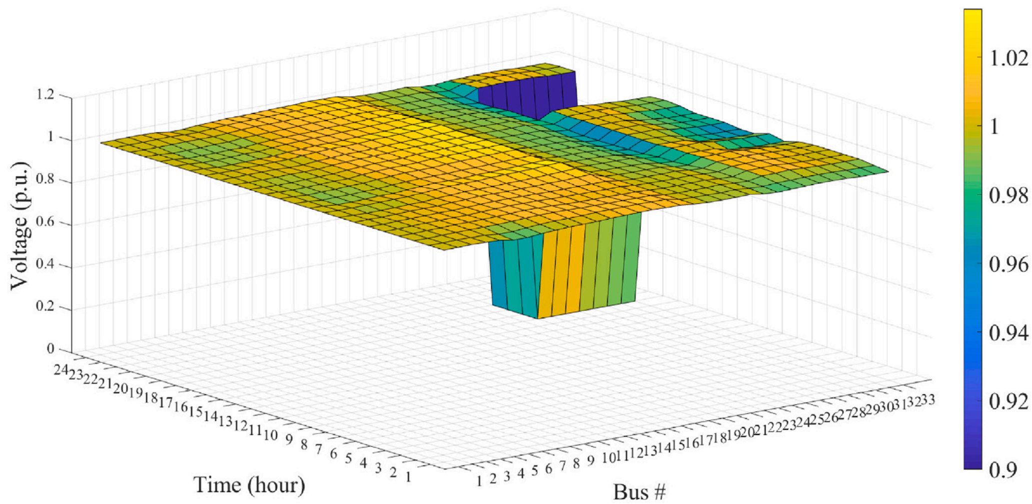

Fig. 19. Bus voltage values in *case IV*.

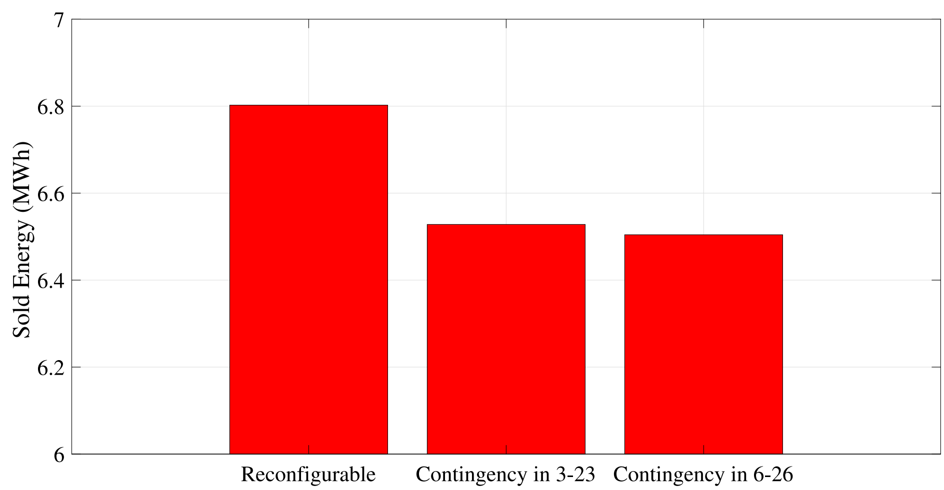

Fig. 20. Sold energy to the loads in reconfigurable, contingency in 3–23 and contingency in 6–26.

Transactions with the utility network in both thermal and electrical systems have seen a change compared to *case I*. More power is sold to the utility grid in higher price hours which is a result of more capacities of the storage units. This can show how important is the size of energy storage units. Furthermore, flexible loads are scheduled in a way that they are shifted from higher price periods to lower price hours. For instance in the early hours of the night, when the energy price is high, these demands are shifted down and in the early morning hours with a lower energy price, the amount of the demands are shifted up as shown in Fig. 24. Also, the energy storage devices are storing energy in lower price times and selling in higher price times. This has more effect on the output of the units in comparison with the first case study. This justification also applies to the thermal system. The voltage of buses during the scheduling is depicted in Fig. 25. The voltage is varied in a range between 0.95 to 1.03 *p.u.*

Also, in Table 7 open switches during the scheduling are shown which handle the contingencies in the system and all the demands are supplied. Like case 1, the contingencies are handled perfectly by proper switching, and both ISO and VPP owner has taken advantage of this cooperation.

Table 7
Switching actions during scheduling horizon in *case V*.

Time	Open switches	Time	Open switches
1	12–22, 9–15, 8–21, 18–33, 25–29	13	8–9, 9–15, 8–21, 18–33, 3–23
2	2–3, 9–15, 8–21, 18–33, 25–29	14	8–9, 9–15, 8–21, 18–33, 3–23
3	2–3, 9–15, 8–21, 18–33, 25–29	15	8–9, 9–15, 8–21, 18–33, 3–23
4	2–3, 9–15, 8–21, 18–33, 25–29	16	8–9, 14–15, 26–27, 8–21, 25–29
5	2–3, 9–15, 8–21, 18–33, 25–29	17	8–9, 14–15, 26–27, 8–21, 25-29
6	2–3, 9–15, 8–21, 18–33, 25–29	18	8–9, 14–15, 26–27, 8–21, 25–29
7	2–3, 9–15, 8–21, 18–33, 25–29	19	8–9, 14–15, 26–27, 8–21, 25–29
8	8–9, 9–15, 8–21, 18–33, 25–29	20	8–9, 14–15, 26–27, 8–21, 25–29
9	8–9, 9–15, 8–21, 18–33, 25–29	21	8–9, 14–15, 26–27, 8–21, 25–29
10	8–9, 9–15, 8–21, 18–33, 25–29	22	8–9, 14–15, 26–27, 8–21, 25–29
11	8–9, 9–15, 8–21, 18–33, 25–29	23	8–9, 14–15, 26–27, 8–21, 25–29
12	8–9, 9–15, 8–21, 18–33, 25–29	24	8–9, 14–15, 26–27, 8–21, 25–29

5. Conclusion

Virtual Power Plants (VPP) are one of the emerging concepts in modern smart grids due to the increasing number of DGs which usually focus on financial aspects. In technical VPPs (TVPPs) both financial and technical perspectives of the utilization of DGs in the system are contemplated. One of the important issues in power systems is contingencies in the components of the system. In this regard, the optimal operation of TVPPs in a reconfigurable network has been formulated to handle the contingencies. To avoid multiple switching actions and achieve the best network structure, power loss and switching cost has been considered. The studied structure, contained CHPs, renewable DGs, and dispatchable DGs beside thermal and electrical

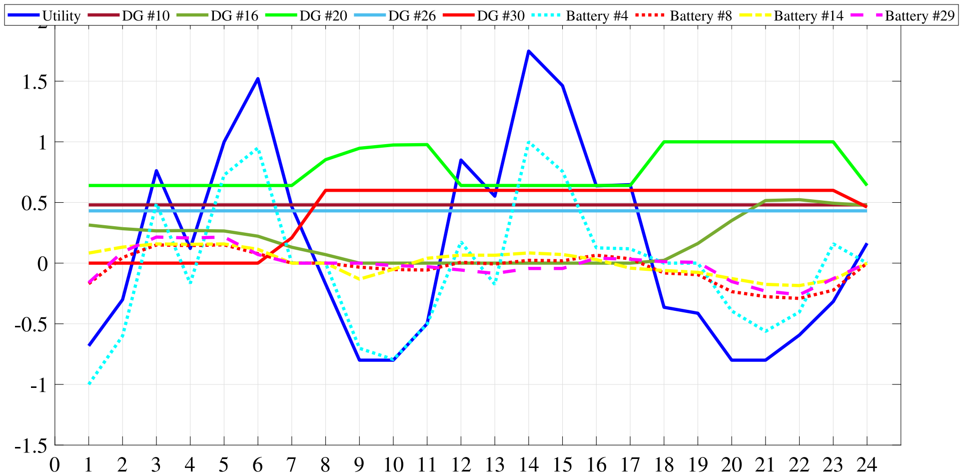

Fig. 21. Optimal DG output in *case V*.

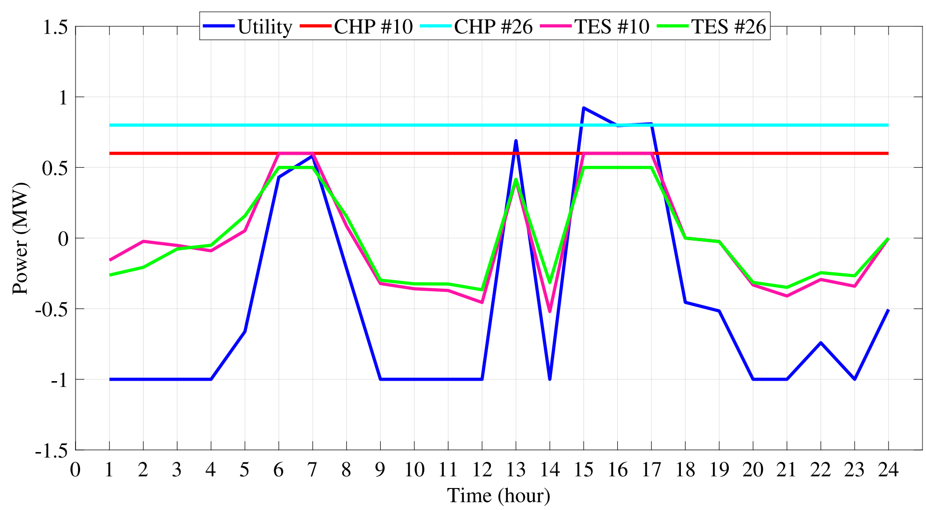

Fig. 22. Optimal operation of thermal units in *case V*.

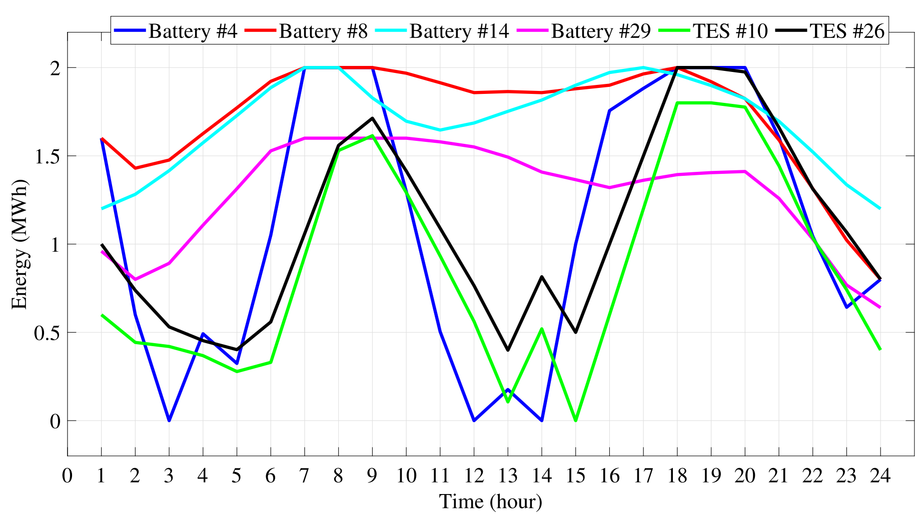

Fig. 23. Optimal energy level of energy storage devices in *case V*.

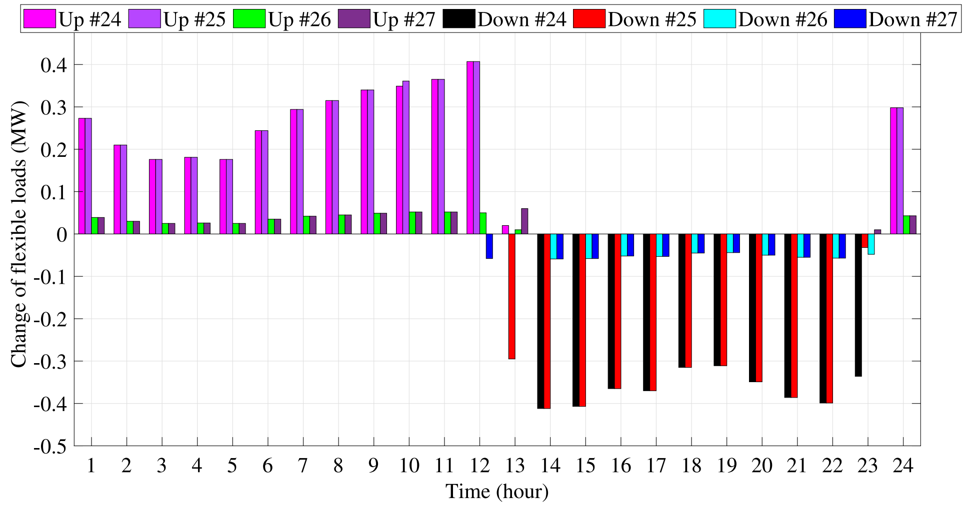

Fig. 24. Changes of flexible loads in *case V*.

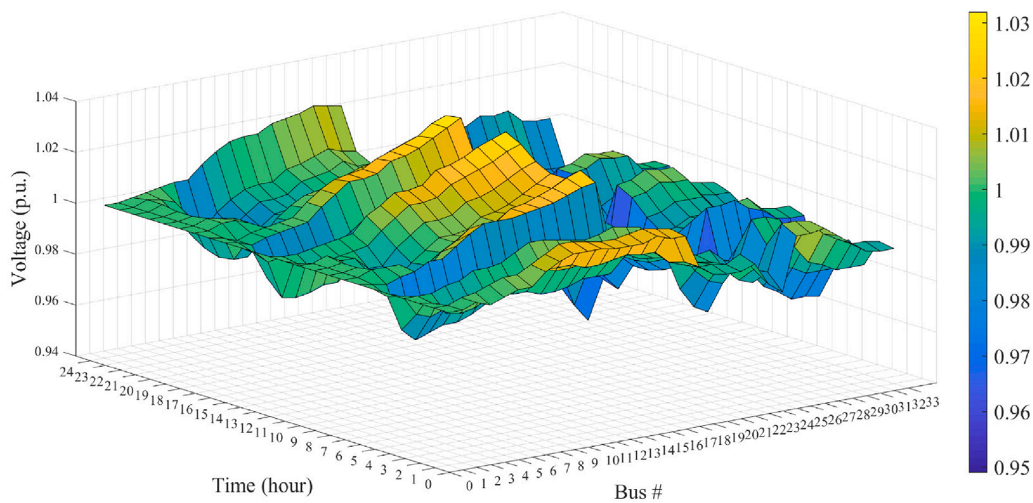

Fig. 25. Bus voltage values in *case V*.

storage systems and loads. CCP has been applied to the problem to handle the uncertainties. Five different case studies have been selected to investigate the effectiveness of the solution procedure. Two cases were in a reconfigurable network with different CCP reliability levels. By decreasing the reliability level, the benefit of the TVPP has been increased. In particular, by decreasing the reliability level from 0.95 to 0.9, the benefit of the TVPP has increased from 1083$ to 1275$ which shows a 17.73% increase. In both scenarios, the contingencies in different lines and different hours have been handled perfectly and the optimal scheduling of the TVPP has not been affected by the event. In the next two case studies, the network is assumed to be non-reconfigurable. Although switching actions may charge costs to the TVPP, however, incapability of the system for handling contingencies has caused decrement in the benefit of the TVPP which is due to load shedding and DG isolation from the system. Considering demand dissatisfaction cost could decrease the benefit even more. In the final case, the effect of higher capacities for the energy storage units and performing demand response programs on the output program of TVPP has been investigated. The results showed that higher capacities for energy storage units and executing demand response programs could increase the revenue of the TVPP. However, optimal sizing of the units for a TVPP can be considered for future studies. To sum up, the results showed the benefits that a reconfiguration in a TVPP can bring to a distribution grid, including contingency management, loss reduction, and technical constraints in the operation of the system. For future works, a linearized model to obtain a global optima and prevent challenges of the nonlinear programming is suggested.

CRediT authorship contribution statement

Farid Hamzeh Aghdam: Methodology, Data curation, Software, Writing – original draft, Writing – review & editing. **Mohammad Sadegh Javadi:** Investigation, Review & editing, Supervision, Conceptualization. **João P.S. Catalão:** Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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