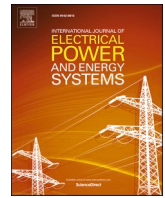


Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Capacity withholding assessment of power systems considering coordinated strategies of virtual power plants and generation companies

Mostafa Tabatabaei^a, Mehrdad Setayesh Nazar^a, Miadreza Shafie-khah^b, João P.S. Catalão^{c,*}^a Shahid Beheshti University, Tehran, Iran^b School of Technology and Innovations, University of Vaasa, 65200 Vaasa, Finland^c Faculty of Engineering of the University of Porto and INESC TEC, 4200-465 Porto, Portugal

ARTICLE INFO

Keywords:

Dynamic capacity withholding
 Generation company
 Optimization
 Arbitrage
 Market power

ABSTRACT

This paper presents a multi-level optimization framework for power system operators' joint electricity markets capacity-withholding assessment. The main contribution of this research is that three capacity-withholding indices are introduced for day-ahead, intra-day, and real-time scheduling of the system that detect the capacity withholding and arbitrage opportunities of Virtual Power Plants (VPPs) and non-utility fossil-fueled Generation Companies (GENCOs) in an ex-ante procedure. A three-level optimization process is used so that the system operator can estimate the coordinated bidding of VPPs/GENCOs in different energy and ancillary services markets to prevent the formation of withholding groups. The first level problem consists of two stages. The first stage estimates the optimal capacity withholding and arbitrage bidding strategy of VPPs/GENCOs, and the second stage determines the optimal system scheduling for the day-ahead horizon. A full competition algorithm is also carried out to evaluate the competition states of VPPs/GENCOs. The second and third level problems consist of two optimization stages for the intra-day and real-time optimization horizons. At the first stage of each level, the process estimates the coordinated bidding of VPPs/GENCOs, and at the second stage of each level, the system resources are optimally dispatched. The proposed method is applied to 30-bus and 118-bus IEEE test systems. The proposed algorithm reduced the maximum locational marginal prices of 30-bus and 118-bus test systems by about 57.04% and 44.73% compared to the normal and the worst-case contingency operating conditions, respectively. Furthermore, the proposed method reduced the average values of day-ahead, intra-day and real-time dynamic capacity withholding indices of the 118-bus test system by about 32.92%, 40.1%, and 46.85%, respectively.

1. Introduction

Distributed energy resource utilization is highly increased in the operational scheduling of electricity markets. The stochastic behavior of distributed energy resources leads to the complexity of dispatching the system's available energy resources, market power detection, and electricity and ancillary services prices volatility. The Virtual Power Plants (VPPs) and non-utility fossil-fueled Generation Companies (GENCOs) endeavor to maximize their profits, adopt coordinated capacity-withholding strategies, perform arbitrage of energy and ancillary services in different horizons markets, and impose market powers to increase the prices of the electricity markets. Further, VPPs can coordinate their bidding strategy with GENCOs and form multiple capacity withholding groups. They can withhold their generation capacity from

the market to lead the price reversal process in the energy and ancillary service markets and utilize the arbitrage strategy to gain more profit. The price reversal phenomenon occurs when the price of lower quality ancillary service is higher than that of higher quality ancillary service [1]. The arbitrage strategy of VPPs is defined as any activity in that they endeavor to purchase underpriced energy/ancillary services and sell a similar over-priced commodity. The arbitrage strategy of GENCOs/VPPs intensifies the price reversal phenomenon in electricity markets that decreases the system's social welfare and security margins [1]. The Independent System Operator (ISO) should detect multiple capacity withholding groups, prevent arbitrage strategy and price reversal, and penalize the GENCOs/VPPs that contribute to these procedures. The withholding assessment can be accomplished by employing ex-ante or ex-post methods.

The withholding process of GENCOs/VPPs can be categorized into

* Corresponding author.

E-mail address: catalao@fe.up.pt (J.P.S. Catalão).<https://doi.org/10.1016/j.ijepes.2022.108212>

Received 16 November 2021; Received in revised form 20 February 2022; Accepted 4 April 2022

Available online 9 April 2022

0142-0615/© 2022 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Nomenclature

Abbreviations

ARIMA Autoregressive Integrated Moving Average
 GENCO Non-utility Fossil-Fueled Generation Company
 ISO Independent System Operator
 JMCWI Joint Markets Capacity Withholding Index
 LMP Locational Marginal Price
 PHEV Plug-in Electric Vehicle
 VPP Virtual Power Plant

Sets

NVPPDAS Set of VPP day-ahead operating scenarios
 NVPPIDS Set of VPP intra-day operating scenarios
 NGENDAS Set of GENCO day-ahead operating scenarios
 NGENIDS Set of GENCO day-ahead operating scenarios
 NISODAS Set of independent system operator day-ahead operating scenarios
 NUOGB Number of utility owned generation bus
 NGB Number of generation bus
 NVPP Number of VPPs
 NGENCO Number of non-utility generation company
 NSCO Number of system contingencies
 NB Number of system buses
 NISOIDS Set of independent system operator intra-day operating scenarios
 NLB Number of load bus

Superscript

DA Day-ahead
 ID Intra-day
 RT Real-time

Index

t Time
 j Index of consumption bus

Parameters

ϖ^{NSR} The price of non-spinning reserve (MU/kW)
 ϖ^{SR} The price of spinning reserve (MU/kW)
 ϖ^{active} The price of active power (MU/kWh)
 $\varpi^{reactive}$ The price of reactive power (MU/kVArh)
 MC Marginal cost of utility-owned generation facility
 SU Start-up cost utility-owned generation facility
 SD Shot-down cost utility-owned generation facility
 β y-intercept of demand function (MW^{-1})
 α Slope of inverse demand function (MW^{-2})
 ϵ_1^{DA} Threshold of day-ahead joint markets capacity withholding index that the submitted biddings of VPPs/GENCOs are rejected
 ϵ_2^{DA} Threshold of day-ahead joint markets capacity withholding index that the submitted biddings of VPPs/GENCOs are accepted with penalties
 ϵ_1^{ID} Threshold of intra-day joint markets capacity withholding index that the submitted biddings of VPPs/GENCOs are rejected
 ϵ_2^{ID} Threshold of intra-day joint markets capacity withholding index that the submitted biddings of VPPs/GENCOs are accepted with penalties
 ϵ_1^{RT} Threshold of real-time joint markets capacity withholding index that the submitted biddings of VPPs/GENCOs are rejected
 ϵ_2^{RT} Threshold of real-time joint markets capacity withholding index that the submitted biddings of VPPs/GENCOs are accepted with penalties

CIC Customer interruption cost
 Prob Probability of scenario
 Y_{nm} Admittance of line between start bus n and end bus m

Variables

B_{VPP}^{DRP} VPP benefit of demand response programs (MU)
 B_{VPP}^{AR} VPP benefit of energy and ancillary services arbitrage (MU)
 B_{VPP}^{Sell} VPP benefit of energy and ancillary services sold to the system (MU)
 C_{VPP}^{IPG} Cost of VPP intermittent power generation facilities (MU)
 C_{VPP}^{PHEV} Cost of plug-in electric vehicle of VPP (MU)
 C_{VPP}^{DG} Cost of distributed generation of VPP (MU)
 C_{VPP}^{CHP} Cost of combined heat and power generation of VPP (MU)
 C_{VPP}^{ESS} Cost of energy storage system of VPP (MU)
 $C_{VPP}^{Purchase}$ Cost of electricity purchase of VPP (MU)
 $Penalty_{VPP}^{active}$ VPP active power mismatch and arbitrage penalties (MU)
 $Penalty_{VPP}^{reactive}$ VPP reactive power mismatch and arbitrage penalties (MU)
 $Penalty_{VPP}^{SR}$ VPP spinning reserve mismatch and arbitrage penalties (MU)
 $Penalty_{VPP}^{NSR}$ VPP non-spinning reserve mismatch and arbitrage penalties (MU)
 NSR_{VPP}^{Total} Non-spinning reserve that is provided by VPP (MW)
 SR_{VPP}^{Total} Spinning reserve that is provided by VPP (MW)
 P_{VPP}^{Total} Active power injection of VPP (MW)
 P_{VPP}^{DRP} Active power injection of demand response program (MW)
 P_{VPP}^{PHEV} Active power injection/withdrawal of PHEVs (MW)
 P_{VPP}^{IPG} Intermittent active power injection to the distribution system (MW)
 P_{VPP}^{DG} Distributed generation power generation active power injection to the distribution system (MW)
 P_{VPP}^{ESS} Active power injection/ withdrawal of energy storage (MW)
 P_{VPP}^{Load} Active power consumption of load (MW)
 P_{VPP}^{Loss} Active power loss in the VPP system (MW)
 Q_{VPP}^{Total} Reactive power injection of VPP (MVar)
 Q_{VPP}^{DRP} Demand response program reactive power injection (MVar)
 Q_{VPP}^{DG} Distributed generation power generation reactive power injection to the distribution system (MVar)
 Q_{VPP}^{PHEV} Reactive power injection/withdrawal of PHEV (MVar)
 Q_{VPP}^{Load} Reactive power withdrawal of load (MVar)
 Q_{VPP}^{Loss} Reactive power loss in the VPP system (MVar)
 $P_{VPP}^{Load Non-disp.}$ VPP non-dispatchable active load (MW)
 $P_{VPP}^{Load Disp.}$ VPP dispatchable active load (MW)
 $P_{VPP}^{Load Def.}$ VPP deferrable active load (MW)
 P_{VPP}^{DLC} VPP active load that is controlled by the direct load control process (MW)
 B_{GEN}^{AR} GENCO benefit of energy and ancillary services arbitrage (MU)
 B_{GEN}^{Sell} GENCO benefit of energy and ancillary services sold to the system (MU)
 C_{GEN}^{PP} Generation cost of GENCO (MU)
 $Penalty_{GEN}^{active}$ GENCO active power mismatch and arbitrage penalties (MU)
 $Penalty_{GEN}^{reactive}$ GENCO reactive power mismatch and arbitrage penalties (MU)
 $Penalty_{GEN}^{SR}$ GENCO spinning reserve mismatch and arbitrage penalties (MU)

ENSC	Energy not supplied cost (MU)	Z_{ID}^{VPP}	VPP objective function of intra-day optimization problem
P_{SPP}	Active power generation of utility-owned generation facility (MW)	Z_{ID}^{GENCO}	GENCO objective function of intra-day optimization problem
V	Voltage of bus (V)	Z_{ID}^{ISO}	ISO objective function of intra-day optimization problem
y	Demand (MW)	Z_{RT}^{VPP}	VPP objective function of real-time optimization problem
SR_{GEN}^{Total}	Spinning reserve that is provided by GENCO (MW)	Z_{RT}^{GENCO}	GENCO objective function of real-time optimization problem
P_{GENCO}^{Total}	Active power injection of GENCO (MW)	Z_{RT}^{ISO}	ISO objective function of real-time optimization problem
Q_{GENCO}^{Total}	Reactive power injection of GENCO (MW)	θ	Voltage angle (rad)
λ	Nodal price of bus (MU/MW)	JMCWI	Joint markets capacity withholding index
LMP	Locational marginal price (MUs/MWh)	I	Binary decision variable of commitment of utility-owned generation facility
Z_{DA}^{VPP}	VPP objective function of day-ahead optimization problem		
Z_{DA}^{GENCO}	GENCO objective function of day-ahead optimization problem		
Z_{DA}^{ISO}	ISO objective function of day-ahead optimization problem		

economic withholding and capacity withholding processes that are performed by increasing the bid prices and reducing the output of GENCOs/VPPs, respectively. The ISO can detect the economic withholding using marginal costs and the submitted bids. However, the capacity withholding detection is more complicated. Further, the withholding processes can be exercised for a single period or multi-period of the operational horizons, known as the static withholding process and dynamic withholding process, respectively.

The dynamic capacity withholding process can be categorized into implicit and explicit processes. In the implicit category, there is not any direct relationship between GENCOs/VPPs, whereas, in the explicit category, the market price is completely controlled by non-utility energy generation facilities [2]. The detection of the implicit dynamic capacity withholding process combined with the arbitrage strategy of GENCOs/VPPs is a very complicated procedure. Thus, more sophisticated dynamic capacity withholding procedures and indices are needed to analyze these combined strategies. As shown in Table 1, different papers assessed the static and dynamic capacity withholding process in recent years utilizing equilibrium models, economic or capacity-withholding indices, and simulation-based method processes.

Ref. [2] presented a bi-level optimization framework to detect thermal power plants' dynamic capacity withholding process considering renewable energy resources. The proposed model was recast as a mathematical problem with equilibrium constraints and formulated as mixed-integer linear programming. Ref. [3] presented an equilibrium model to consider the market power of prosumers that maximized their profit based on the Cournot game theory. The objective function of the system operator was considered, and the results showed that the prosumer exercised market power by proposing lower prices in the buyer mode of operation. Ref. [4] introduced a process to explore the strategic behavior of renewable electricity generation facilities in the day-ahead and real-time markets. The proposed algorithm utilized a three-level optimization procedure for the day-ahead market and two-level optimization processes for the real-time market. The method used the penalty of strategic capacity withholding process to mitigate the market power of variable renewable generation units. Refs. [2–4] did not consider the arbitrage strategy of generation companies and VPPs.

Ref. [5] presented a two-stage settlement process for reducing capacity withholding of Chinese GENCOs, and the model considered the system's dynamics. The method modeled the equilibrium point of the system and found the estimated values of GENCOs' bidding. The case study was performed for the Eastern China electricity market. Ref. [6] proposed a return on withholding capacity index for withholding assessment of GENCOs. The proposed index was used as a supplementary index for market power analysis that demonstrated the GENCOs incentives to withhold capacity from the market. There was not any GENCOs or ISO optimization process in the proposed framework. Ref. [7] introduced a framework for dynamic capacity withholding of

GENCOs using withholding indices. The method used a quadratic programming optimization process to formulate optimal power flow and detect the capacity withholding of GENCOs. However, the demand response processes or intermittent power generation facilities were not modeled. Refs. [5–7] did not assess the arbitrage strategy of GENCOs/VPPs in the day-ahead and real-time markets.

Ref. [8] presented a decomposition formulation of Locational Marginal Prices (LMPs) to detect the value of the economic withholding of GENCOs. The proposed method simulation was carried out for a 24-bus IEEE test system. Results showed that the method found the estimated values of capacity withholding of GENCOs considering the transmission system congestion. Ref. [9] introduced a Nash equilibrium model for analyzing the market power of hydrothermal electricity generation units in the electricity market. The supply function model was utilized to assess the bidding strategies of generation units in the electricity market. Refs. [8,9] did not model the arbitrage strategy of market entities in energy and ancillary services markets.

Ref. [10] developed a reinforcement-learning algorithm for renewable electricity generation units in the electricity market. The intermittent electricity generation facilities were considered as non-controllable energy resources. The model utilized the merit order optimization of agents, and the simulation was carried out for 10,000 households. The paper concluded that the capacity withholding was negligible for the simulated cases. Ref. [11] proposed a game theory model for static capacity withholding of GENCOs considering maintenance scheduling constraints. The proposed model considered the objective functions of the system operator, transmission operator, and GENCOs. Refs. [10,11] did not model the dynamic capacity withholding process and arbitrage opportunities of GENCOs/VPPs.

Ref. [12] presented an agent-based Nash equilibrium model for GENCOs capacity withholding in the electricity market. The proposed model utilized the LMP formulation to detect the capacity withholding of GENCOs. Different scenarios of pay-as-bid and uniform price simulations were carried out, and the results showed that the random rationing policy was more effective to prevent withholding procedure. Ref. [13] proposed a bi-level optimization framework for capacity withholding assessment of dominant GENCOs that imposed market power in the day-ahead electricity market. The financial virtual divestiture was utilized to mitigate the market power of dominant GENCOs, and the proposed algorithm used mathematical programming with equilibrium constraints and converted it into a mixed-integer linear programming problem. Ref. [14] presented a model for estimating the dynamic capacity withholding of GENCOs that was formulated based on the firm's size. Based on the proposed model, the GENCOs' capacity withholding was highly reduced when the market price was regulated. Refs. [12–14] did not model the arbitrage strategy of GENCOs/VPPs in the energy and ancillary services markets.

Ref. [15] presents a framework for analyzing the impact of demand

Table 1
Comparison of proposed DCW assessment with other approaches.

			2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	Proposed Method		
Withholding	Capacity	Static	x	x	✓	x	✓	x	x	✓	x	✓	✓	✓	x	✓	✓	x	x	x	✓	x	x	✓	x	✓	✓	x	✓	x	✓	x	x		
		Dynamic	✓	x	x	✓	x	✓	x	x	✓	x	x	x	✓	x	x	x	x	x	✓	x	x	✓	x	✓	x	x	x	x	✓	x	x	✓	
	Economic	Static	x	✓	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	✓	✓	x	x	✓	x	x	x	x	x	✓	x	x	x	x	x	
		Dynamic	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	
Game Theory			x	✓	x	x	x	x	x	✓	✓	✓	✓	✓	x	✓	✓	✓	x	x	✓	x	✓	x	✓	x	✓	x	x	✓	✓	✓	✓	x	
Agent Based			x	x	x	x	x	x	x	✓	x	✓	x	x	x	x	x	x	x	x	x	x	✓	✓	✓	x	x	x	x	✓	x	x	x		
Withholding Assessment	Ex-ante		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	
	Ex-post		✓	✓	✓	✓	✓	✓	✓	x	✓	x	✓	x	✓	✓	✓	✓	✓	✓	✓	x	✓	x	x	x	✓	✓	x	x	✓	x	x	x	
Withholding Index			x	x	x	x	✓	✓	x	x	x	✓	x	x	x	x	x	x	x	x	✓	x	x	x	x	✓	x	✓	x	x	x	x	x	✓	
Optimization	Nonlinear		x	x	x	✓	x	✓	x	✓	x	✓	x	✓	x	x	x	x	x	x	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	
	Linear		✓	✓	✓	x	x	x	x	x	x	✓	x	✓	x	✓	✓	✓	✓	x	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	
GENCO Optimization			✓	✓	✓	✓	x	✓	x	✓	✓	✓	✓	✓	x	✓	✓	✓	✓	x	x	✓	x	✓	✓	✓	x	✓	x	✓	✓	✓	✓	✓	
ISO Optimization			✓	✓	✓	x	x	✓	x	✓	✓	✓	x	✓	x	✓	✓	✓	✓	x	x	✓	x	✓	x	x	x	x	✓	✓	✓	✓	✓	✓	
GENCO Constraints			✓	✓	✓	✓	x	✓	x	✓	✓	✓	✓	✓	x	✓	✓	✓	✓	x	x	✓	x	✓	✓	✓	x	✓	x	✓	✓	✓	✓	✓	
Network Constraints			x	✓	✓	x	x	✓	x	✓	✓	✓	✓	✓	x	✓	✓	✓	✓	x	x	✓	x	✓	✓	✓	x	x	✓	✓	✓	✓	✓	✓	
Commodity	Active Power		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	Spinning Reserve		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	✓	
	Non-spinning Reserve		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	
	Reactive Power		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	
Intermittent DERs			x	x	✓	x	x	x	x	x	x	x	x	✓	x	x	x	✓	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	✓	
DRP			x	x	x	x	x	x	x	x	x	x	x	✓	x	x	✓	x	x	✓	x	x	x	✓	x	x	x	x	✓	x	x	x	✓		
Optimization	Deterministic		✓	✓	✓	✓	x	x	x	✓	✓	✓	✓	✓	x	✓	✓	✓	✓	x	x	✓	x	✓	✓	✓	x	✓	x	✓	✓	✓	x	x	
	Probabilistic		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x	
	Stochastic		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	
Arbitrage			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	
VPPs			x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	
Aggregators			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	
Day ahead			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Intra-day			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	
Real-time			x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	

response on the market equilibrium using Stackelberg game theory. The Oligopoly and full competition scenarios were analyzed, and it concluded that the demand response programs highly reduced the strategic behavior, and capacity withholding of GENCOs. Ref. [16] presented a binary Nash model to consider the market power of GENCOs in the electricity market. The trade-off between compensation payments and social welfare was modeled, and the Karush-Kuhn-Tucker optimality conditions were considered. The results showed that the method balanced the values of uplift payments and social welfare. Ref. [17] presented a game theory model for considering fossil-based thermal units' strategic behavior against wind farms. The authors concluded that the strategic behavior of rivals reduced the profit of renewable electricity generation units. Refs. [15–17] did not present the dynamic capacity withholding model and arbitrage opportunities of GENCOs/VPPs.

Ref. [18] developed a Cournot game model to detect the economic withholding of GENCOs in a non-competitive market. The results showed that the independent pricing strategies or mixed bundling led to a lower level of economic withholding. Ref. [19] developed a model for dynamic capacity withholding of GENCOs that was a function of demand, renewable electricity generations, market power, and network congestion. The model was assessed for the electricity market data of Italy, and it successfully detected the capacity withholding of GENCOs. Refs. [18–19] did not assess the dynamic capacity withholding process and the arbitrage strategy of market entities.

Ref. [20] proposed a static capacity-withholding index for analyzing GENCOs strategic behavior in the transmission-constrained system. The Oligopoly market model was developed using Cournot-Nash game theory, and the results were compared with the perfectly competitive market results. The model successfully determined the volume of capacity withholding of GENCOs in an Oligopoly market. Ref. [21] assessed the effects of forward contracts on static economic withholding. The model utilized the historical data of the electricity market, and the results showed that long-term contracts highly reduced the probability of economic withholding in the spot market. Ref. [22] introduced a Nash-equilibrium game theory model for detecting the dynamic capacity withholding of GENCOs in an ex-ante manner. The optimization algorithm utilized the projected subgradient optimization to find GENCOs strategic behavior. Refs. [20–22] did not consider the arbitrage strategy of GENCOs/VPPs in the energy and ancillary services markets.

Ref. [23] introduced an algorithm for analyzing of capacity withholding of market participants using an agent-based model. The proposed method concluded that the higher values of LMPs indicated the capacity withholding of GENCOs that led to higher values of their profits. Ref. [24] considered a repeated game model to analyze the dynamic capacity withholding of GENCOs. The algorithm utilized an optimal control process to maximize the GENCOs profit that led to disturbances in market prices. The paper concluded that the price cap regulation and regulatory intervention were essential to mitigate the market price volatility. Ref. [25] proposed a capacity-withholding index for transmission constrained networks that detected the market power of GENCOs using the pivotal supplier model. The model considered the must-run GENCOs and residual supply indices. The case study was carried out for the Australian electricity network. Refs. [23–25] did not model the arbitrage strategy of GENCOs/VPPs in the day-ahead and real-time electricity markets.

Ref. [26] introduced an implicit capacity withholding of GENCOs model that considered the GENCOs' profit margins, the elasticity of demand, and forward contracts. The algorithm used an evolutionary optimization process to find the best strategic behavior of GENCOs. Ref. [27] introduced a framework for the economic withholding assessment of GENCOs using withholding indices. The absolute and relative indices were utilized to analyze the economic withholding of GENCOs in the Chinese Zhejiang electricity market. Ref. [28] analyzed a resource adequacy model to assess the capacity credit market for GENCOs. The model optimized the social welfare of the system and utilized a penalty function for the strategic behavior of GENCOs. Refs. [26–28] did

not analyze the arbitrage strategies of GENCOs and VPPs in the electricity markets.

Ref. [29] introduced a repeated game model for capacity withholding analysis of GENCOs that considered the ISO and GENCOs optimization processes. The reinforcement-learning algorithm was used to model the behavior of GENCOs in the electricity market. The case study showed that the capacity withholding of GENCOs led to an increase in market price. Ref. [30] presented an optimization process that considered the objective functions of ISO and GENCOs. The algorithm used a Cournot model, and the distortion-withheld index was utilized to detect the capacity withholding of GENCOs. Ref. [31] evaluated a conditional value at risk model for strategic retailers' joint demand and virtual bidding. The optimization process compromised a bi-level optimization algorithm. The upper-level problem maximized the demand and virtual bidding profits and the lower level problem determined the market-clearing price. Refs. [29–31] did not consider the interactions of dynamic capacity withholding and arbitrage process of non-utility generation companies and virtual power plants in day-ahead, intra-day, and real-time energy and ancillary services markets. Further, Refs. [2–31] did not consider the impacts of stochastic bidding strategies of non-utility electricity generation facilities on the locational marginal prices and optimal operating scheduling of the system.

As shown in Table 1, different papers proposed different methods and indices to detect the withholding procedures in an ex-post manner and did not model the dynamic capacity withholding and arbitrage process in an ex-ante procedure. In this paper, for the first time, the ex-ante day-ahead, intra-day, and real-time dynamic capacity withholding assessment considering the arbitrage process of non-utility generation companies and virtual power plants based on three indices is proposed.

The main contributions of this paper are:

- The proposed framework explores the possible day-ahead, intra-day, and real-time dynamic capacity withholding group formation of non-utility generation companies and virtual power plants considering their arbitrage process,
- The proposed algorithm considered different sources of uncertainties consisting of VPP's intermittent electricity generations, VPP's PHEVs charge/discharge, demand response contributions, and electricity market price and load,
- The introduced method estimates the non-utility generation companies and virtual power plants bidding strategies in day-ahead, intra-day, and real-time markets and optimizes the system resources and switching of reactive compensation facilities considering the withholding and arbitrage strategies of non-utility energy resources,
- A three-level stochastic optimization process is proposed to optimize the system scheduling in day-ahead, intra-day, and real-time horizons considering the stochastic behavior of input parameters,
- Three capacity withholding detection indices are proposed to assess the arbitrage and withholding procedures and penalize the non-utility energy resources by the system operator.

The paper has been organized as follows: Section 2 presents the problem modeling and formulation. In Section 3, the solution algorithm is proposed. The simulation results are presented in Section 4. Finally, Section 5 presents the conclusions.

2. Problem modeling and formulation

2.1. Virtual power plant and non-utility generation company modeling

In this paper, the Technical VPP (TVPP) regarding the provision of energy and ancillary is considered. By increasing the penetration of distributed energy resources, two major problems were found in many electricity markets: a) many distributed energy resources were not visible for the independent system operator, and b) distributed energy

resources could not participate in energy and ancillary service markets [1]. It is assumed that the VPP aggregates and dispatches the distributed energy resources. However, the GENCO was directly dispatched by the ISO. Further, it was assumed that portfolio bidding was not allowed. The distributed energy resources based VPP may have Plug-in Electric Vehicles (PHEVs) parking lots, intermittent power generation facilities, and electrical energy storage.

Further, the VPP may contribute to demand response programs, and it may have fossil-fueled distributed generation and combined heat and power generation facilities. The VPP can submit its bids and transact active and reactive power with the power system in different buses. Furthermore, it can deliver energy and ancillary services to the system in different buses for the day-ahead, intra-day, and real-time markets.

The non-utility GENCO can submit its energy and ancillary services bids in day-ahead, intra-day, and real-time markets. The VPPs and GENCOs can coordinate their bidding in different markets to perform capacity withholding and arbitrage of energy and ancillary services and increase their benefits. These procedures may reduce the available energy resources of the system and increase the locational marginal prices of the system and expected energy not supplied costs.

2.2. The proposed framework

A three-level optimization method is presented, as shown in Fig. 1. The first stage of the first-level optimization problem maximizes the day-

ahead profit of non-utility generation companies and VPPs. At the second stage of the first level problem, the system operator optimizes the day-ahead scheduling of system resources considering the transmission system and security constraints. The system operator explores the strategic behavior and arbitrage opportunities of non-utility generation companies and VPPs that may lead to dynamic capacity withholding in normal and contingency conditions. At the second stage of the first level, the optimization process of non-utility generation companies and VPPs in the intra-day horizon is considered. At the second stage of the second level problem, the system operator optimizes the intra-ahead scheduling of system resources considering dynamic capacity withholding. At the first stage of the third-level, the real-time optimization of non-utility generation companies and VPPs is carried out. Finally, at the second stage of the third level, the system optimizes resource dispatch considering real-time operation constraints.

2.3. First level optimization problem

2.3.1. First stage of first level problem

At the first stage of the first level optimization process, the system operator simulates the non-utility generation companies and VPPs profit optimization process in the day-ahead horizon and explores their possible dynamic capacity withholding groups and arbitrage strategies. The objective function of this problem for VPPs can be presented as (1):

$$MaxZ_{DA}^{VPP} = \sum_{t=1}^{24} \sum_{NVPPDAS} Prob. (B_{VPP}^{DRPDA} + B_{VPP}^{ARDA} + B_{VPP}^{SellDA} - C_{VPP}^{IPGDA} - C_{VPP}^{PHEVDA} - C_{VPP}^{DGDA} - C_{VPP}^{CHPDA} - C_{VPP}^{ESSDA} - C_{VPP}^{PurchaseDA} - \sum Penalty_{VPP}^{activeDA} - \sum Penalty_{VPP}^{reactiveDA} - \sum Penalty_{VPP}^{SRDA} - \sum Penalty_{VPP}^{NSRDA}) \tag{1}$$

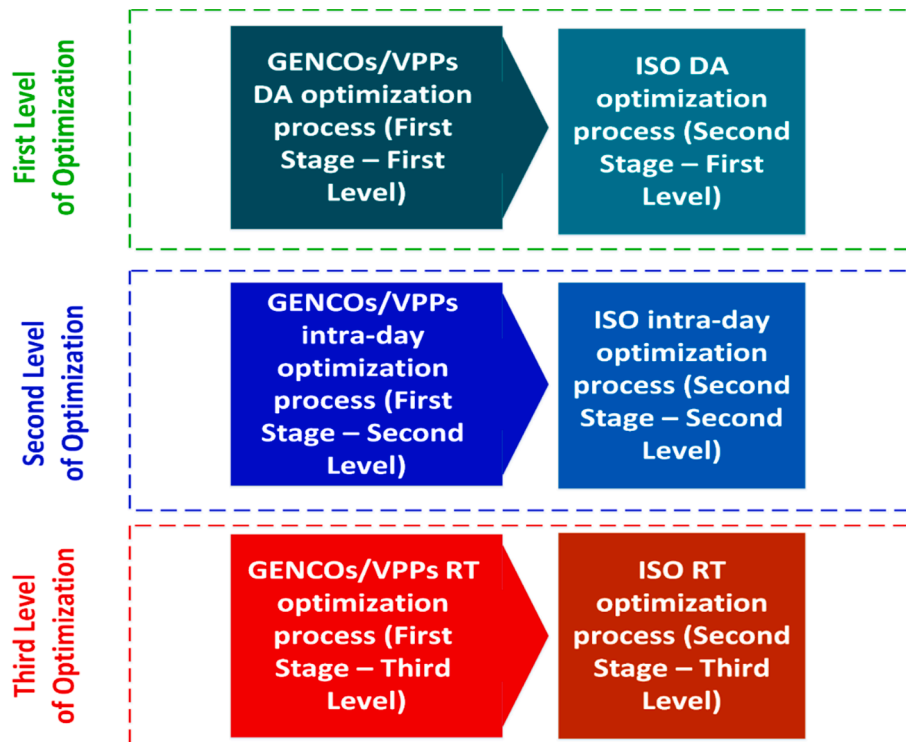


Fig. 1. The proposed three-level optimization method.

The objective function is divided into thirteen terms: 1) the VPP benefit of demand response programs ($B_{VPP}^{DRP\ DA}$); 2) the VPP benefit of energy and ancillary services arbitrage ($B_{SH}^{AR\ DA}$); 3) the VPP benefit of energy and ancillary services sold to the system ($B_{VPP}^{Sell\ DA}$); 4) the cost of VPP intermittent power generation facilities ($C_{VPP}^{IPG\ DA}$); 5) the cost of VPP PHEV ($C_{VPP}^{PHEV\ DA}$); 6) the cost of VPP fossil-fueled distributed generation ($C_{VPP}^{DG\ DA}$); 7) the cost of VPP combined heat and power generation facilities ($C_{VPP}^{CHP\ DA}$); 8) the cost of VPP energy storage system ($C_{VPP}^{ESS\ DA}$); 9) the VPP energy purchasing cost ($C_{VPP}^{Purchase\ DA}$); 10) the VPP active power mismatch and arbitrage penalties ($\sum Penalty_{VPP}^{active\ DA}$); 11) the VPP reactive power mismatch and arbitrage penalties ($\sum Penalty_{VPP}^{reactive\ DA}$); 12) the VPP spinning reserve mismatch and arbitrage penalties ($\sum Penalty_{VPP}^{SR\ DA}$) that is checked by system operator through the capacity tests process; 13) the VPP non-spinning reserve mismatch and arbitrage penalties ($\sum Penalty_{VPP}^{NSR\ DA}$) that is checked by system operator through the capacity tests process.

The VPP revenue in the day-ahead market can be written as (2):

$$B_{VPP}^{Sell\ DA} = \left(\sum \varpi^{NSR} \cdot NSR_{VPP}^{Total\ DA} + \sum \varpi^{SR} \cdot SR_{VPP}^{Total\ DA} + \sum \varpi^{active} \cdot P_{VPP}^{Total\ DA} + \sum \varpi^{reactive} \cdot Q_{VPP}^{Total\ DA} \right) \quad (2)$$

Eq. (2) decomposes into the following terms: the profit of VPP non-spinning reserve sold to the system in the day-ahead market ($\sum \varpi^{NSR} \cdot NSR_{VPP}^{Total\ DA}$), the profit of VPP spinning reserve sold to the system in the day-ahead market ($\sum \varpi^{SR} \cdot SR_{VPP}^{Total\ DA}$), the profit of VPP active power sold to the system for the day-ahead market ($\sum \varpi^{active} \cdot P_{VPP}^{Total\ DA}$), and the profit of VPP reactive power sold to the system in the day-ahead market ($\sum \varpi^{reactive} \cdot Q_{VPP}^{Total\ DA}$).

The VPP optimization objective function for the day-ahead horizon has the following constraints [32]:

$$Max_{Z_{DA}^{GENCO}} = \sum_{t=1}^{24} \sum_{NGENDAS} Prob \cdot (B_{GEN}^{ARDA} + B_{GEN}^{Sell\ DA} - C_{GEN}^{PPDA} - \sum Penalty_{GEN}^{active\ DA} - \sum Penalty_{GEN}^{reactive\ DA} - \sum Penalty_{GEN}^{SRDA}) \quad (9)$$

A. Electrical power balance constraint:

$$P_{VPP}^{Total} - (\sum P_{VPP}^{DRP} \pm \sum P_{VPP}^{PHEV} + \sum P_{VPP}^{IPG} + \sum P_{VPP}^{DG} \pm \sum P_{VPP}^{ESS} - \sum P_{VPP}^{Load} - \sum P_{VPP}^{Loss}) = 0 \quad (3)$$

Eq. (3) indicates the sum of the active power generation and consumptions equals zero. Eq. (3) terms are the active power injection/withdrawal to/from the point of common coupling (P_{VPP}^{Total}), the active power injection of demand response program ($\sum P_{VPP}^{DRP}$), the active power injection/withdrawal of PHEVs ($\sum P_{VPP}^{PHEV}$), the intermittent and distributed generation power generation active power injections to the distribution system ($\sum P_{VPP}^{IPG} + \sum P_{VPP}^{DG}$), the active power injection/withdrawal of energy storage ($\sum P_{VPP}^{ESS}$), the active power consumption of load ($\sum P_{VPP}^{Load}$), and active power loss in the VPP system ($\sum P_{VPP}^{Loss}$).

$$Q_{VPP}^{Total} - (\sum Q_{VPP}^{DRP} + \sum Q_{VPP}^{DG} \pm \sum Q_{VPP}^{PHEV} - \sum Q_{VPP}^{Load} - Q_{VPP}^{Loss}) = 0 \quad (4)$$

Eq. (4) indicates the sum of the reactive power generation and consumptions equals zero. Eq. (4) terms are the reactive power injection/withdrawal to/from the point of common coupling (Q_{VPP}^{Total}), the demand response program reactive power injection ($\sum Q_{VPP}^{DRP}$), the distributed generation power generation reactive power injection to the

distribution system ($\sum Q_{VPP}^{DG}$), the reactive power injection/withdrawal of PHEV ($\sum Q_{VPP}^{PHEV}$), the reactive power withdrawal of load ($\sum Q_{VPP}^{Load}$), and the reactive power loss in the VPP system (Q_{VPP}^{Loss}).

B. Demand response constraints:

The VPP loads consist of dispatchable, non-dispatchable, and deferrable loads that can be written as (5)–(8):

$$P_{VPP}^{Load} = P_{VPP}^{Load\ Non-disp.} + P_{VPP}^{Load\ Disp.} + P_{VPP}^{Load\ Def.} \quad (5)$$

$$\sum_{t=1}^T \Delta P_{VPP}^{Load\ Def.} = 0 \quad (6)$$

$$P_{VPP}^{DLC\ Max} = P_{VPP}^{Load\ Disp.} \quad (7)$$

$$P_{VPP}^{DRP} = P_{VPP}^{DLC} + P_{VPP}^{Load\ Def.} \quad (8)$$

Eq. (5) terms are the VPP non-dispatchable active load ($P_{VPP}^{Load\ Non-disp.}$), dispatchable active load ($P_{VPP}^{Load\ Disp.}$), and deferrable active load ($P_{VPP}^{Load\ Def.}$), respectively. Eq. (6) presents that deferrable load changes in loads should equal zero in the day-ahead horizon. Eq. (7) presents that the maximum value of direct load control is equal to dispatchable load. Eq. (8) terms are the sum of the direct load control and time-of-use active powers.

Further, the AC load flow for the VPP system, PHEV charging constraints, ramp rates of electricity generation facilities, and their maximum electricity generation constraints are considered in the first stage of the first level optimization problem [1,33]. The detailed commitment process of PHEVs, dispatchable loads, and other distributed energy resources are available in [33] and is not presented for the sake of space.

The objective function of the first stage of the first level problem for non-utility generation companies can be presented as (9):

The GENCO objective function for the day-ahead market is divided into six terms: 1) the generation company benefit of energy and ancillary services arbitrage (B_{GEN}^{ARDA}); 2) the generation company benefit of energy and ancillary services sold to the system ($B_{GEN}^{Sell\ DA}$) that is same as (2); 3) the cost of generation company power plant (C_{GEN}^{PPDA}); 4) the generation company active power mismatch and arbitrage penalties ($\sum Penalty_{GEN}^{active\ DA}$); 5) the generation company reactive power mismatch and arbitrage penalties ($\sum Penalty_{GEN}^{reactive\ DA}$); and 6) the generation company spinning reserve mismatch and arbitrage penalties ($\sum Penalty_{GEN}^{SRDA}$) that is checked by the system operator through the capacity test process.

The ramp rate constraints, the maximum and minimum limits of electricity generation constraints and the minimum on and off time constraints are considered in the optimization process.

2.3.2. Second stage of first level problem

At the second stage of the first level problem, the system operator optimizes the scheduling of its energy resources using the security-constrained unit commitment algorithm. The system operator should detect and reject the coordinated bidding strategies of non-utility generation companies and VPPs.

Thus, the day-ahead system control variables can be categorized into

the following groups:

- The day-ahead dispatching of the system energy resources, dispatchable and deferrable loads,
- Penalizing the non-utility generation companies and VPPs that utilize arbitrage strategy for the day-ahead horizon,
- Changing the time-of-use and direct load control fees for the day-ahead horizon,

It is assumed that the electricity consumption at bus j has the following inverse demand function [11]:

$$\lambda_j = -\alpha_j \cdot y_j + \beta_j \quad (10)$$

The objective function of the second stage of the first level problem is the weighted maximization of social welfare of the system for the day-ahead horizon, minimization of system locational marginal prices in the day-ahead horizon, and the expected system cost for the intra-day horizon:

$$\begin{aligned} & W_1 \cdot \left(-\sum_{NUGB} (MC \cdot P_{SPP} + SU + SD) \cdot I + \sum_{NVPP} (-B_{VPP}^{DRPDA} - B_{VPP}^{ARDA} - B_{VPP}^{SellDA} + \right. \\ & \quad \left. \sum Penalty_{VPP}^{activeDA} + \sum Penalty_{VPP}^{reactiveDA} + \sum Penalty_{VPP}^{SRDA}) + \right. \\ \text{Max } \mathbb{Z}_{ISO}^{DA} = & \sum_{i=1}^{24} \sum_{NISODAS} \text{Prob} \cdot \left(\sum_{NGENCO} (-B_{GEN}^{ARDA} - B_{GEN}^{SellDA} + \sum Penalty_{GEN}^{activeDA} + \right. \\ & \quad \left. \sum Penalty_{GEN}^{reactiveDA} + \sum Penalty_{GEN}^{SRDA}) + \sum_{NLB} (-0.5 \cdot \alpha \cdot y^2 + \beta \cdot y) \right) \\ & - W_2 \cdot \sum_{NSCO} ENSC + W_3 \cdot \sum_{NB} LMP + W_4 \cdot \sum_{NISODAS} \text{prob} \cdot \mathbb{Z}_{ISO}^{ID} \end{aligned} \quad (11)$$

The objective function is divided into eight groups: 1) the costs of utility-owned electricity generation facilities consist of marginal cost, start-up and start down costs ($\sum_{NUGB} (MC \cdot P_{SPP} + SU + SD)$); 2) the aggregated benefits of VPPs ($\sum_{NVPP} (-B_{VPP}^{DRPDA} - B_{VPP}^{ARDA} - B_{VPP}^{SellDA})$); 3) the aggregated penalties of VPPs ($\sum Penalty_{VPP}^{activeDA} + \sum Penalty_{VPP}^{reactiveDA} + \sum Penalty_{VPP}^{SRDA}$); 4) the aggregated benefits of non-utility generation companies ($\sum_{NGENCO} (-B_{GEN}^{ARDA} - B_{GEN}^{SellDA})$); 5) the aggregated penalties of generation companies ($\sum_{NGENCO} (-B_{GEN}^{ARDA} - B_{GEN}^{SellDA})$); 6) the aggregated surplus of loads; 7) the energy not supplied costs (ENSC); 8) the sum of the hourly locational marginal price of the system; 9) the expected objective function of the optimization process of the system in the intra-day horizon (second stage optimization objective function of the second level problem). The aggregated benefits of VPPs and GENCOs are considered in (11) to minimize the impacts of coordinated bidding strategies of VPPs/GENCOs that may lead to withholding and arbitrage strategies. The NISODAS parameter is the number of day-ahead operation scenarios of the system.

The problem constraints can be written as the following terms.

A. The supply-demand constraints:

$$\sum_{k=1}^{NGB} P_k - \sum_{l=1}^{NLB} |V_n| \cdot |V_m| \cdot |Y_{nm}| \cdot \cos(\theta_n - \theta_m) = 0 \quad (12)$$

$n : \text{startbusline}l, m : \text{endbusline}l$

$$\sum_{k=1}^{NGB} Q_k + \sum_{l=1}^{NLB} |V_n| \cdot |V_m| \cdot |Y_{nm}| \cdot \sin(\theta_n - \theta_m) = 0 \quad (13)$$

$n : \text{startbusline}l, m : \text{endbusline}l$

The optimization process should consider the voltage limit constraints, generation unit constraints, and AC power flow constraints. A Joint Markets Capacity Withholding Index (JMCWI) for the day-head operational planning is proposed as (14):

$$JMCWI^{DA} = \frac{|\mathbb{Z}_{ISO}^{DA FC} - \mathbb{Z}_{ISO}^{DA}|}{\mathbb{Z}_{ISO}^{DA FC}} \quad (14)$$

The \mathbb{Z}_{ISO}^{DA} is calculated in the second stage problem of the first level. The $\mathbb{Z}_{ISO}^{DA FC}$ is the objective function of full competition and no-arbitrage condition that is calculated by the system operator considering $B_{VPP}^{AR DA} = 0$ and $B_{GEN}^{AR DA} = 0$.

Thus, the system operator can detect the formation of capacity withholding groups of VPPs and non-utility generation companies and their arbitrage strategies using the proposed $JMCWI^{DA}$. The submitted

bidding of VPPs/GENCOs with $JMCWI^{DA} > \varepsilon_1^{DA}$ are rejected. ε_1^{DA} is the threshold of day-ahead joint markets capacity withholding index for the submitted biddings of VPPs/GENCOs performing arbitrage strategy and forming capacity withholding groups. The submitted biddings of VPPs/GENCOs with $JMCWI^{DA} > \varepsilon_2^{DA}$ are accepted with penalties. ε_2^{DA} is the threshold of day-ahead joint markets capacity withholding index for the submitted biddings of VPPs/GENCOs performing arbitrage strategy and forming capacity withholding groups.

2.4. Second level optimization problem

At the second level problem, the system operator optimizes the intra-day operational scheduling of system resources considering transmission system and security constraints. The system operator receives the intra-day bidding of active power, reactive power, and spinning reserve from fast-start non-utility electricity generation facilities and VPPs to compensate for any mismatches in generations and consumptions. Further, the system operator can utilize demand response programs to compensate for these mismatches. Thus, the second level problem is decomposed into two following problems.

2.4.1. First stage of second level problem

At the first stage of the second level optimization process, the system operator simulates the bidding scenarios of fast start non-utility generation companies and VPPs to assess their dynamic capacity withholding groups and arbitrage strategies in the intra-day horizon (next four hours). The objective function of this problem for VPPs can be presented as (15):

$$\begin{aligned}
 & B_{VPP}^{DRPID} + B_{VPP}^{ARID} + \sum \varpi^{SR} \cdot SR_{ID}^{VPP} + \sum \varpi^{active} \cdot P_{ID}^{VPP} + \sum \varpi^{reactive} \cdot Q_{ID}^{VPP} \\
 \text{Max } Z_{ID}^{VPP} = & \sum_{t=1}^{t+3} \sum_{NVPPIDS} \text{prob} \cdot (\quad - C_{VPP}^{IPGID} - C_{VPP}^{PHEVID} - C_{VPP}^{DGID} - C_{VPP}^{CHPID} - C_{VPP}^{ESSID} - C_{VPP}^{PurchaseID} \quad) \\
 & - \sum \text{Penalty}_{VPP}^{activeID} - \sum \text{Penalty}_{VPP}^{reactiveID} - \sum \text{Penalty}_{VPP}^{SRID} \quad) \quad (15)
 \end{aligned}$$

The objective function is calculated for the intra-day horizon, and its terms are the same as (1).

The (15) constraints for the intra-ahead horizon are the same as (3–8).

The objective function of the first stage of the second level problem for non-utility generation companies can be presented as (16):

$$\begin{aligned}
 \text{Max } Z_{ID}^{GENCO} = & \sum_{t=1}^{t+3} \sum_{NGENIDS} \text{prob} \cdot (\quad B_{GEN}^{ARID} + \sum \varpi^{SR} \cdot SR_{GEN}^{TotalID} + \sum \varpi^{active} \cdot P_{GEN}^{TotalID} + \sum \varpi^{reactive} \cdot Q_{GEN}^{TotalID} \\
 & - C_{GEN}^{PPID} - \sum \text{Penalty}_{GEN}^{activeID} - \sum \text{Penalty}_{GEN}^{reactiveID} - \sum \text{Penalty}_{GEN}^{SRID} \quad) \quad (16)
 \end{aligned}$$

The objective function terms are the same as (9). The ramp rate constraints, the maximum and minimum limits of electricity generation constraints, the minimum on and off time constraints are considered in this optimization process.

2.4.2. Second stage of second level problem

At the second stage of the second level problem, the system operator minimizes the mismatches of the scheduled energy resources dispatch and optimizes the intra-day scheduling of fast start non-utility electricity generation facilities and VPPs for the next four-hour horizon. Thus, the intra-day system control variables can be categorized into the following groups:

- The intra-day dispatching of the system energy resources, dispatchable and deferrable loads,
- Penalizing the fast electrical generation facilities and VPPs that utilize arbitrage strategy for this horizon,
- The commitment of direct load control for the intra-ahead horizon.

The objective function of the second stage of the second level problem is the weighted minimization of the second stage of the first level objective function, the mismatches of dispatchable energy resources, and the expected system costs for the real-day horizon.

$$\begin{aligned}
 \text{Min } Z_{ISO}^{ID} = & \sum_{t=1}^{t+3} \sum_{NISIDS} \text{prob} \cdot (\quad - \Delta Z_{ISO}^{DA} + W'_1 \cdot (\sum_{NGB} (MC \cdot P_{SPP} + SU + SD) \cdot I + \\
 & \sum_{NVPP} (\Delta B_{VPP}^{DRPID} + \Delta B_{VPP}^{ARID} + \Delta B_{VPP}^{SellID} - \sum \Delta \text{Penalty}_{VPP}^{activeID} \\
 & - \sum \Delta \text{Penalty}_{VPP}^{reactiveID} - \sum \Delta \text{Penalty}_{VPP}^{SRID}) + \\
 & \sum_{NGENCO} (\Delta B_{GEN}^{ARID} + \Delta B_{GEN}^{SellID} - \sum \Delta \text{Penalty}_{GEN}^{activeID} \\
 & - \sum \Delta \text{Penalty}_{GEN}^{reactiveID} - \sum \Delta \text{Penalty}_{GEN}^{SRID})) \quad) \quad (17) \\
 & + W'_2 \cdot \sum_{NSCO} ENSC + W'_3 \cdot \sum_{NB} LMP + W'_4 \cdot \sum_{NISORT} \text{prob} \cdot Z_{ISO}^{RT}
 \end{aligned}$$

Eq. (17) consists of the following terms: 1) The mismatches of (11); 2) the costs of utility-owned fast start electricity generation facilities consist of marginal cost, start-up and start down costs; 3) the mismatches of VPPs profits and penalties; 4) the mismatches of non-utility generation companies' profits and penalties; 5) the energy not supplied costs; 6) the sum of the hourly locational marginal price of the system; 7) the expected objective function of the optimization process of the system

in the real-time horizon (second stage optimization objective function of the third level problem).

Eq. (17) constraints are the same as (11) constraints.

The NISIDS parameter is the number of intra-day operation scenarios of the system.

The joint markets capacity-withholding index for intra-day operational planning is proposed as (18):

$$JMCWI^{ID} = \frac{| Z_{ISO}^{IDFC} - Z_{ISO}^{ID} |}{Z_{ISO}^{IDFC}} \quad (18)$$

The Z_{ISO}^{ID} is calculated in the second stage problem of the second level. The Z_{ISO}^{IDFC} is the objective function of full competition and no-arbitrage condition that is calculated by the system operator using (17) considering $B_{VPP}^{ARID} = 0$ and $B_{GEN}^{ARID} = 0$. It is assumed that the market is fully competitive for calculating Z_{ISO}^{IDFC} , and there are not any arbitrage opportunities for VPPs and non-utility generation companies in the intra-day horizon. Thus, the system operator can detect the formation of capacity withholding groups of VPPs and non-utility generation companies and their arbitrage strategies using the proposed $JMCWI^{ID}$.

The submitted bidding of VPPs/GENCOs with $JMCWI^{ID} > \epsilon_1^{ID}$ are rejected. ϵ_1^{ID} is the threshold of intra-day joint markets capacity withholding index for the submitted biddings of VPPs/GENCOs performing arbitrage strategy and forming capacity withholding groups. The sub-

mitted bidding of VPPs/GENCOS with $JMCWI^{ID} > \varepsilon_2^{ID}$ are accepted with penalties. ε_2^{ID} is the threshold of intra-day joint markets capacity withholding index for the submitted biddings of VPPs/GENCOS that are performing arbitrage strategy and forming capacity withholding groups.

2.5.2. Second stage of third level problem

At the second stage of the third level problem, the system operator minimizes the scheduled energy resources dispatch mismatches for the next 15 min horizon. The objective function of the second stage of the third level problem is proposed as (21) for the real-day horizon.

$$\begin{aligned} \text{Min } Z_{ISO}^{RT} = \sum_{k=1}^{k+1} & \left(-\Delta Z_{ISO}^{ID} + W_1 \sum_{NVPP} (\Delta B_{VPP}^{DRP}^{RT} + \Delta B_{VPP}^{ARRT} + \Delta B_{VPP}^{SellRT} - \sum \Delta \text{Penalty}_{VPP}^{activeRT} \right. \\ & \left. - \sum \Delta \text{Penalty}_{VPP}^{reactiveRT} - \sum \Delta \text{Penalty}_{VPP}^{SRRT}) + \right. \\ & \left. \sum_{NGENCO} (\Delta B_{GEN}^{ARRT} + \Delta B_{GEN}^{SellRT} - \sum \Delta \text{Penalty}_{GEN}^{activeRT} \right. \\ & \left. - \sum \Delta \text{Penalty}_{GEN}^{reactiveRT} - \sum \Delta \text{Penalty}_{GEN}^{SRRT}) \right) + \\ & W_2 \cdot \sum_{NSCONCU} P^{Load} \cdot CIC + W_3 \cdot \sum_{NB} LMP \end{aligned} \quad (21)$$

2.5. Third level optimization problem

2.5.1. First stage of third level problem

At the first stage of the third level optimization process, the system operator simulates the real-time VPPs and non-utility generation companies bidding scenarios to explore their dynamic capacity withholding groups and arbitrage strategies in the real-time horizon (next 15 min horizon). The VPP and non-utility generation companies can sell active and reactive powers in the real-time market. Thus, the objective function of this problem for VPPs can be presented as (19):

Eq. (21) consists of the following terms: 1) The mismatches of (17); 2) the mismatches of VPPs profits and penalties; 3) the mismatches of non-utility generation companies' profits and penalties; 4) the Customer Interruption Costs (CICs); 5) the sum of the real-time locational marginal price of the system. Eq. (21) constraints are the same as (11) constraints.

The joint markets capacity-withholding index for real-time operational planning is proposed as (22):

$$JMCWI^{RT} = \frac{|Z_{ISO}^{RTFC} - Z_{ISO}^{RT}|}{Z_{ISO}^{RTFC}} \quad (22)$$

$$\text{Max } Z_{RT}^{VPP} = \sum_{k=1}^{k+1} \left(\begin{aligned} & B_{VPP}^{DRP}^{RT} + B_{VPP}^{ARRT} + \sum \omega^{active} \cdot P_{RT}^{VPP} + \sum \omega^{reactive} \cdot Q_{RT}^{VPP} \\ & - C_{VPP}^{IPG}^{RT} - C_{VPP}^{PHEV}^{RT} - C_{VPP}^{DG}^{RT} - C_{VPP}^{CHP}^{RT} - C_{VPP}^{ESS}^{RT} - C_{VPP}^{Purchase}^{RT} \\ & - \sum \text{Penalty}_{VPP}^{activeRT} - \sum \text{Penalty}_{VPP}^{reactiveRT} \end{aligned} \right) \quad (19)$$

The objective function is calculated for the real-time horizon, and its terms are the same as (1). Further, its constraints are the same as (3–8).

The objective function of the first stage of the third level problem for non-utility generation companies can be presented as (20):

The Z_{ISO}^{RT} is calculated in the second stage problem of the third level. The Z_{ISO}^{RTFC} is the objective function of full competition and no-arbitrage condition that is calculated by the system operator using (21) considering $B_{VPP}^{ARRT} = 0$ and $B_{GEN}^{ARRT} = 0$. It is assumed that the market is fully

$$\text{Max } Z_{RT}^{GENCO} = \sum_{k=1}^{k+1} \left(\begin{aligned} & B_{GEN}^{ARRT} + \sum \omega^{SR} \cdot SR_{GEN}^{TotalRT} + \sum \omega^{active} \cdot P_{GEN}^{TotalRT} + \sum \omega^{reactive} \cdot Q_{GEN}^{TotalRT} \\ & - C_{GEN}^{PP}^{RT} - \sum \text{Penalty}_{GEN}^{activeRT} - \sum \text{Penalty}_{GEN}^{reactiveRT} - \sum \text{Penalty}_{GEN}^{SRRT} \end{aligned} \right) \quad (20)$$

The objective function terms are the same as (9). The AC load flow for the VPP system, ramp rate constraints, the maximum and minimum limits of electricity generation constraints, the minimum on and off time constraints are considered in the optimization process.

competitive for calculating Z_{ISO}^{RTFC} and there are not any arbitrage opportunities for VPPs and non-utility generation companies in the real-time horizon. Thus, the system operator can detect the formation of capacity withholding groups of VPPs and non-utility generation companies and their arbitrage strategies using the proposed $JMCWI^{RT}$.

The submitted bidding of VPPs/GENCOS with $JMCWI^{RT} > \varepsilon_1^{RT}$ are rejected. ε_1^{RT} is the threshold of real-time joint markets capacity withholding index for the submitted biddings of VPPs/GENCOS that are

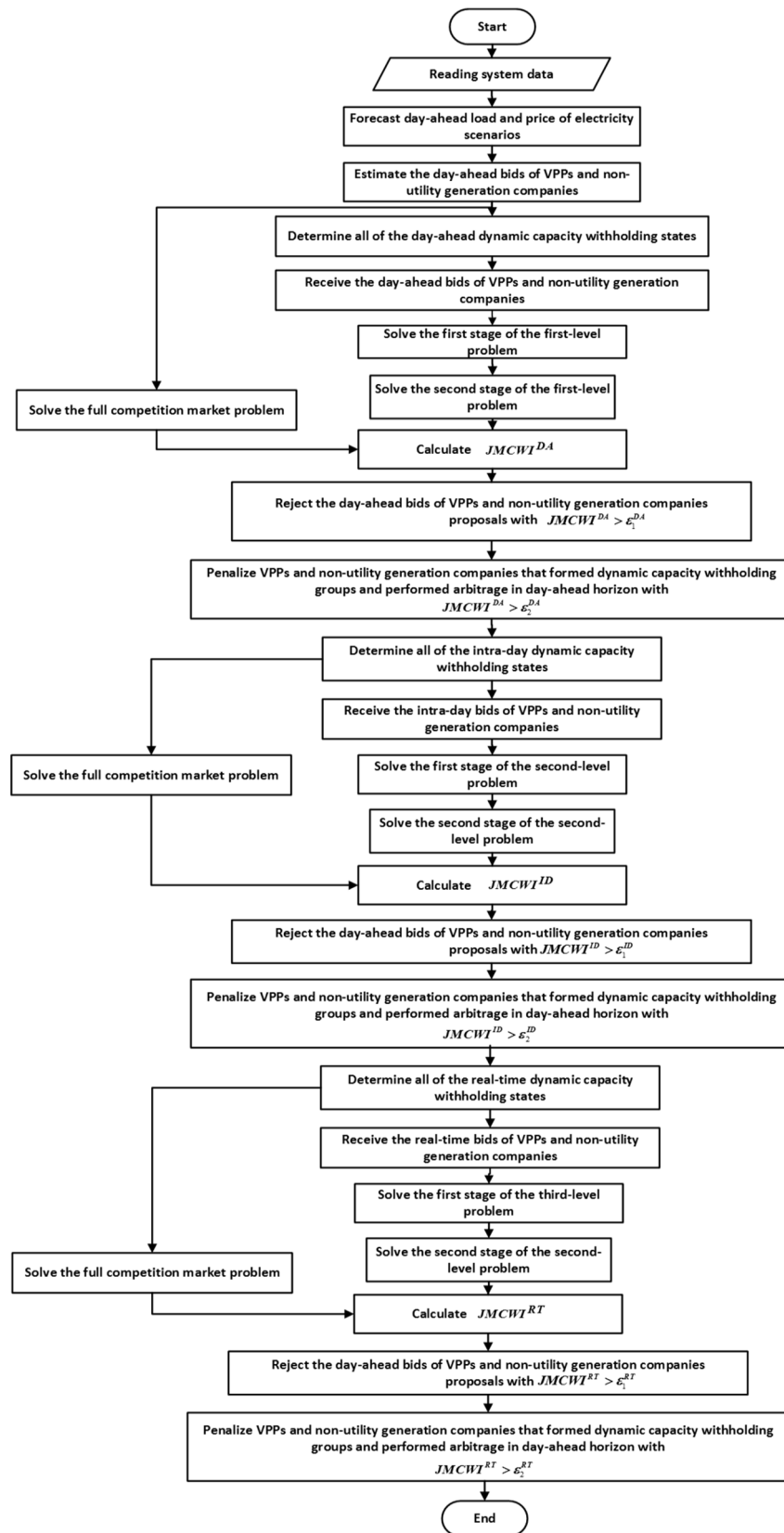


Fig. 2. Flowchart of the proposed algorithm.

performing arbitrage strategy and forming capacity withholding groups. The submitted bidding of VPPs/GENCOs with $JMCW^{RT} > \epsilon_2^{RT}$ are accepted with penalties. ϵ_2^{RT} is the threshold of real-time joint markets capacity withholding index for the submitted biddings of VPPs/GENCOs that are performing arbitrage strategy and forming capacity withholding groups.

3. Solution methodology

The proposed three-level optimization problem is a mixed-integer non-linear programming optimization (MINLP) problem with multiple discrete, non-linear decision variables. Namely:

- The Autoregressive Integrated Moving Average (ARIMA) forecasting algorithms were utilized to generate scenarios for loads and prices. Further, this technique was utilized to forecast VPP's intermittent electricity generations, VPP's PHEVs charge/discharge, and demand response contributions [33].
- Multiple scenarios were generated and reduced using the proposed method of [34].

- Weighting factors were calculated based on the weighted sum method that is available in [35] and is not presented for the sake of space.
- The proposed model is solved by the DICOPT solver of GAMS. The DICOPT solver utilizes CONOPT3 and CPLEX solvers for non-linear and mixed-integer programming problems, respectively [36]. The detailed process of the DICOPT solver is presented in [36] and is not presented for the sake of space.

The overall proposed procedure is presented in Fig. 2. The simulation was carried out on a PC (Intel Core i7-870 processor, 4*2.93 GHz, 8 GB RAM).

4. Simulation results

Two test systems, IEEE 30-bus and IEEE 118-bus, were considered to assess the proposed method. The data of the IEEE 30-bus and 118-bus test systems are available in [37].

4.1. 30-bus IEEE test system

Fig. 3 shows the IEEE 30-bus system topology and its virtual power

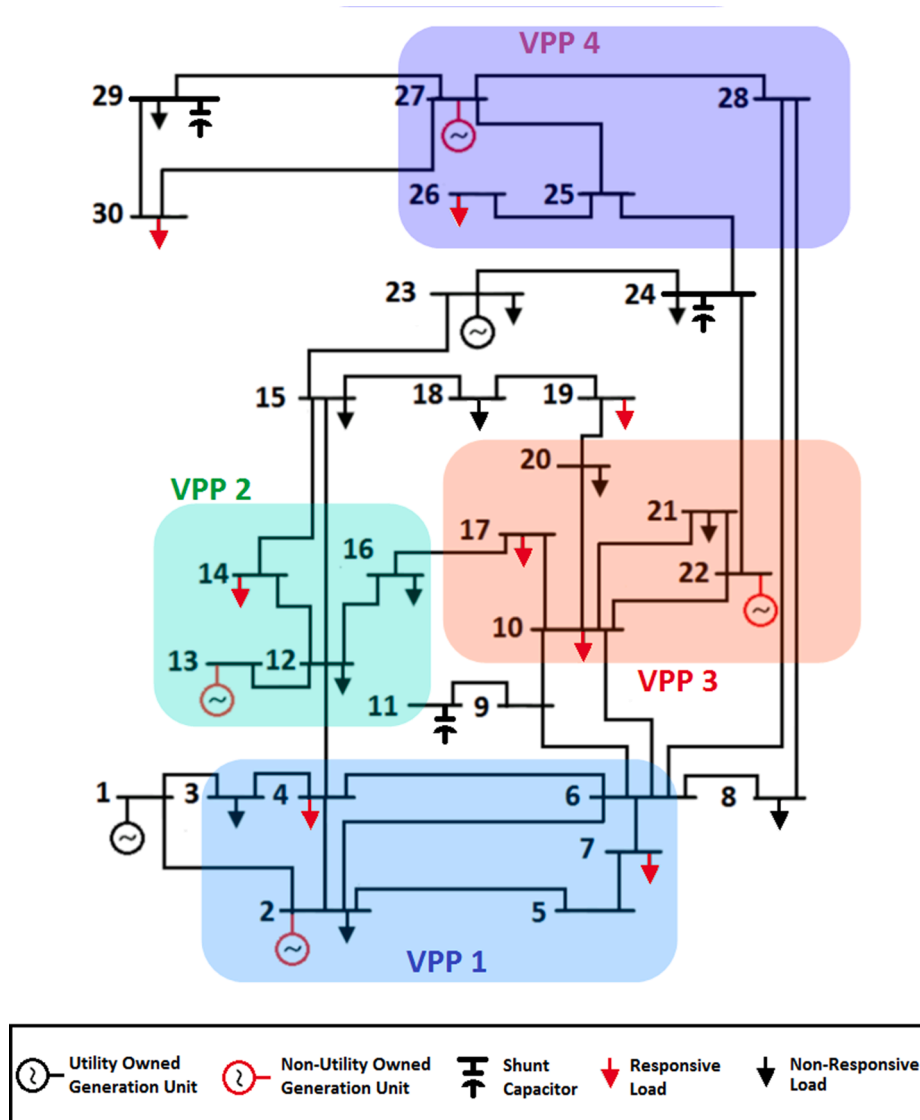


Fig. 3. The topology of 30-bus IEEE test system.

Table 2
The distributed energy resources of virtual power plants.

	Bus	Capacity (kW)	Aggregated Capacity (kW)
VPP 1			
Gas engine	2,4,5,6,7	3000,5000,4000,2000,6000	20,000
Electrical energy storage	2,4,6,7	2500,2000,2000,1500	8000
Photovoltaic system	2,4,6,7	1500,2000,2000,1500	7000
Wind turbine	2,4,6,7	800,600,1000,1000	3400
Parking lot	4,6,7	2500,3000,2500	8000
			46,400
VPP 2			
Gas engine	12,13,14,16	2000,4000,3000,3000	12,000
Electrical energy storage	12,13,14,16	1500,2000,1500,1500	6500
Photovoltaic system	12,13,16	1500,2000,1500	5000
Wind turbine	12,13	1000, 1000	2000
Parking lot	12,13,14	2000,3000,3000	8000
			33,500
VPP 3			
Gas engine	10,17,20,21,22	1000,4000,3000,2000,3000	13,000
Electrical energy storage	10,17,20,21,22	1500,1500,2000,1000,1000	7000
Photovoltaic system	10,17,20,21,22	1500,2000,1500,2000,2000	9000
Wind turbine	10, 20, 22	2000,3000, 2000	7000
Parking lot	10,17,21,22	300,3000,2000,3000	11,000
			47,000
VPP 4			
Gas engine	25,26,27,28	2000,4000,3000,4000	13,000
Electrical energy storage	25,26,27,28	3000,2000,3000,2000	10,000
Photovoltaic system	25,26,27,28	2000,3000,2000,3000	10,000
Wind turbine	25, 27,28	2000,2000,3000	7000
Parking lot	25,27	3000,2000	5000
			45,000

plants locations. The distributed energy resources parameters of virtual power plants are presented in Table 2. Fig. 4 presents the estimated values of system loads for the day-ahead horizon [38]. Fig. 5 depicts the estimated values of energy and ancillary services prices for the day-ahead horizon. For the IEEE 30-bus test system, it was assumed that the inverse demand function of each demand was $\lambda_j = -\alpha_j \cdot y_j + 46$. [11,38].

The slope of each inverse demand function was chosen in a way that $\lambda_j = 35.5$ \$/MW for the given value of y_j in [37]. The parameters of

network congestion are available in [37,11].

The system operator optimized the first level of the proposed algorithm. At the first stage of the first level, ISO estimated the optimal day-ahead bids of virtual power plants and non-utility generation companies. The estimated values of optimal day-ahead bids of virtual power plants for the active power market are presented in Fig. 6. The virtual power plants consumed energy for off-peak hours and delivered energy for peak hours. The aggregated accepted energy generation of virtual power plants was 463.21 MWh. The maximum value of virtual power

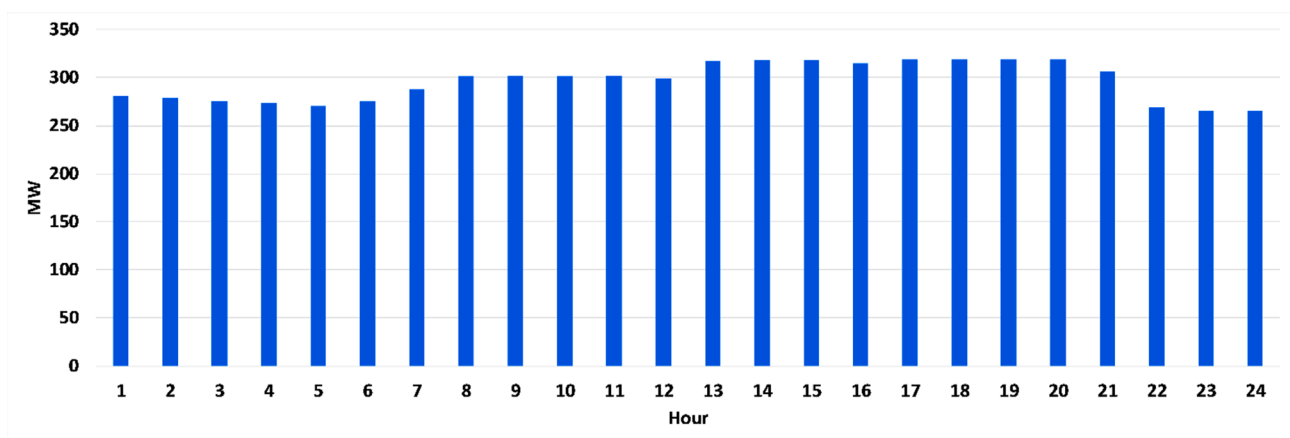


Fig. 4. The day-ahead load forecasting for the 30-bus test system.

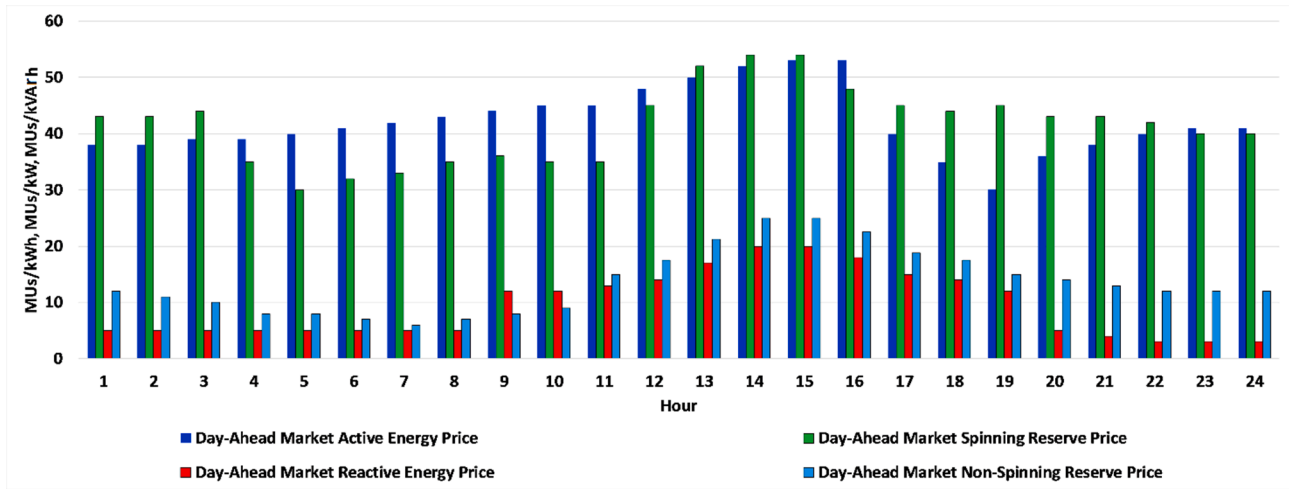


Fig. 5. The forecasted day-ahead active power and ancillary services prices.

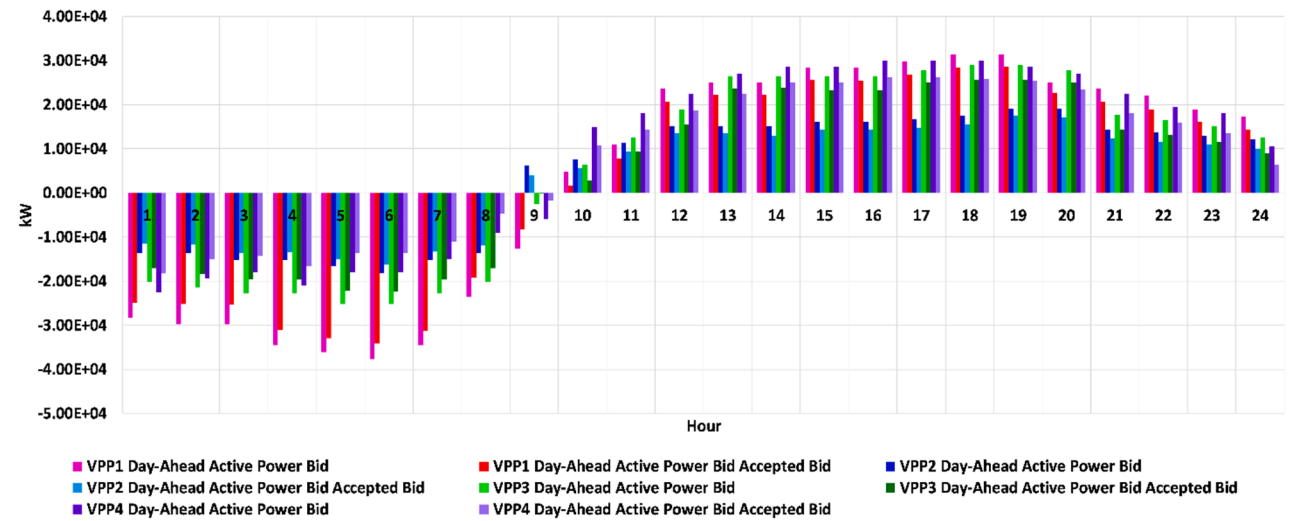


Fig. 6. The estimated values of optimal day-ahead bids of virtual power plants for the active power market.

plant bids was 28.5 MW for the day-ahead horizon.

Fig. 7 (a), (b), (c) depict the estimated values of virtual power plants bids for spinning reserve, non-spinning reserve, and reactive power markets for the day-ahead horizon. The aggregated accepted reactive power generation of virtual power plants was 152 MVarh. The average values of VPP1 and VPP2 day-ahead spinning reserve accepted bids were 13981.48 kW and 9136.57 kW, respectively. Further, the average values of VPP1 and VPP2 day-ahead reactive power accepted bids were 952.92 kVar and 1239.40 kVar, respectively. The average values of VPP3 and VPP4 day-ahead spinning reserve accepted bids were 12547.22 kW and 13777.31 kW, respectively. Further, the average values of VPP3 and VPP4 day-ahead reactive power accepted bids were 1572.07 kVar and 2579.01 kVar, respectively. Finally, the average values of VPP1, VPP2, VPP3, and VPP4 day-ahead non-spinning reserve accepted bids were 6629.55 kW, 6108.95 kW, 8788.11 kW, and 7072.01 kW, respectively.

At the second stage of the first level, the system operator conducted the optimization process to find the optimal dispatch of its energy

generation resources for the day-ahead horizon. Fig. 8 (a), (b) present the day-ahead non-utility generation companies bids and the energy generation schedule of generation companies, respectively. The aggregated generated energy of non-utility generation companies and utility-owned generation companies were 3494 MWh and 3095.71 MWh, respectively. The accepted day-ahead active power bids concerning the submitted values of G2, G3, G4, and G6 GENCOs took on values 93.14%, 74.11%, 77.71%, and 73.13%, respectively.

Fig. 9 (a), (b) show the non-utility generation companies day-ahead reactive power bids and spinning reserve bids, respectively. The aggregated reactive power generation of non-utility generation companies and utility-owned generation companies were 1147.779 MVarh and 1030 MVarh, respectively. The average value of the day-ahead spinning reserve bids was about 14.85 kW.

The system operator determined the probable dynamic capacity withholding groups and calculated the $JMCW^{DA}$ for the day-ahead horizon. Table 3 presents the probable combination of capacity

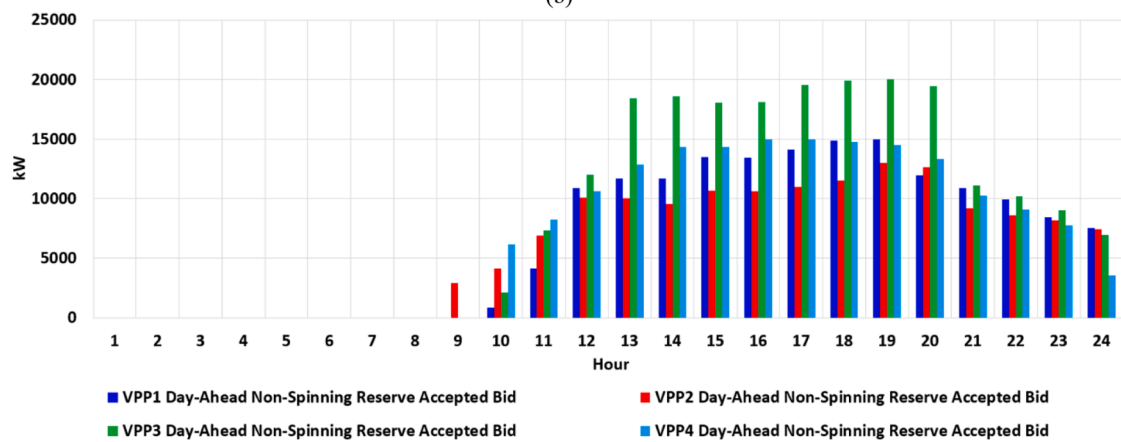
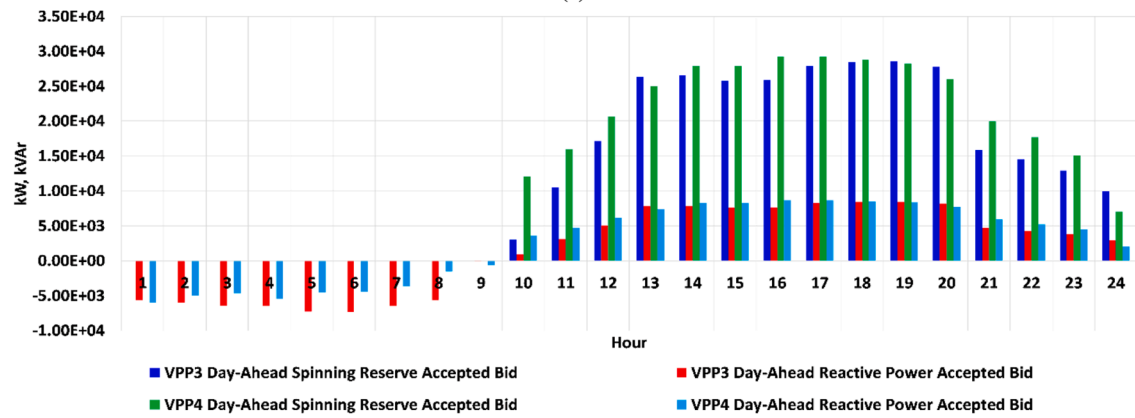
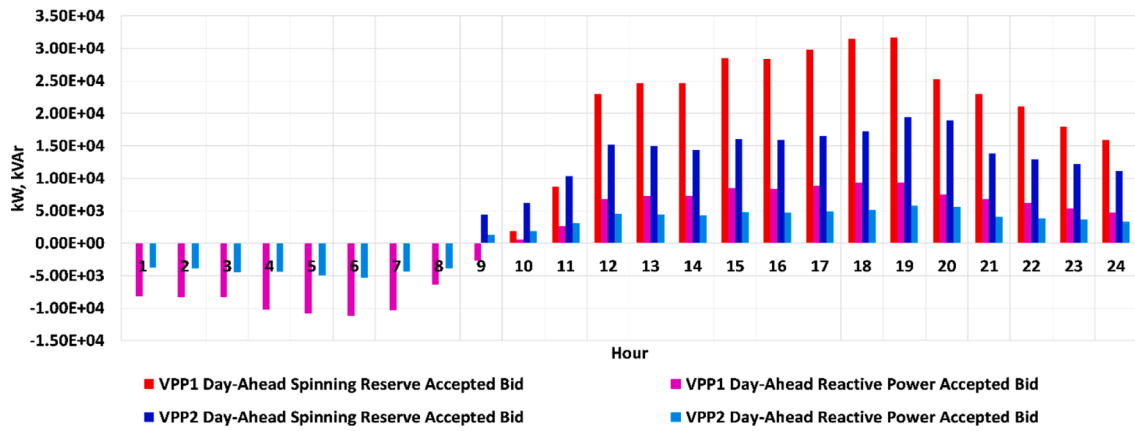


Fig. 7. (a) The estimated values of VPP1 and VPP2 bids for spinning reserve and reactive power markets for the day-ahead horizon. (b) The estimated values of VPP3 and VPP4 bids for spinning reserve and reactive power markets for the day-ahead horizon. (c) The estimated values of VPP1-VPP4 bids for non-spinning reserve markets for the day-ahead horizon.

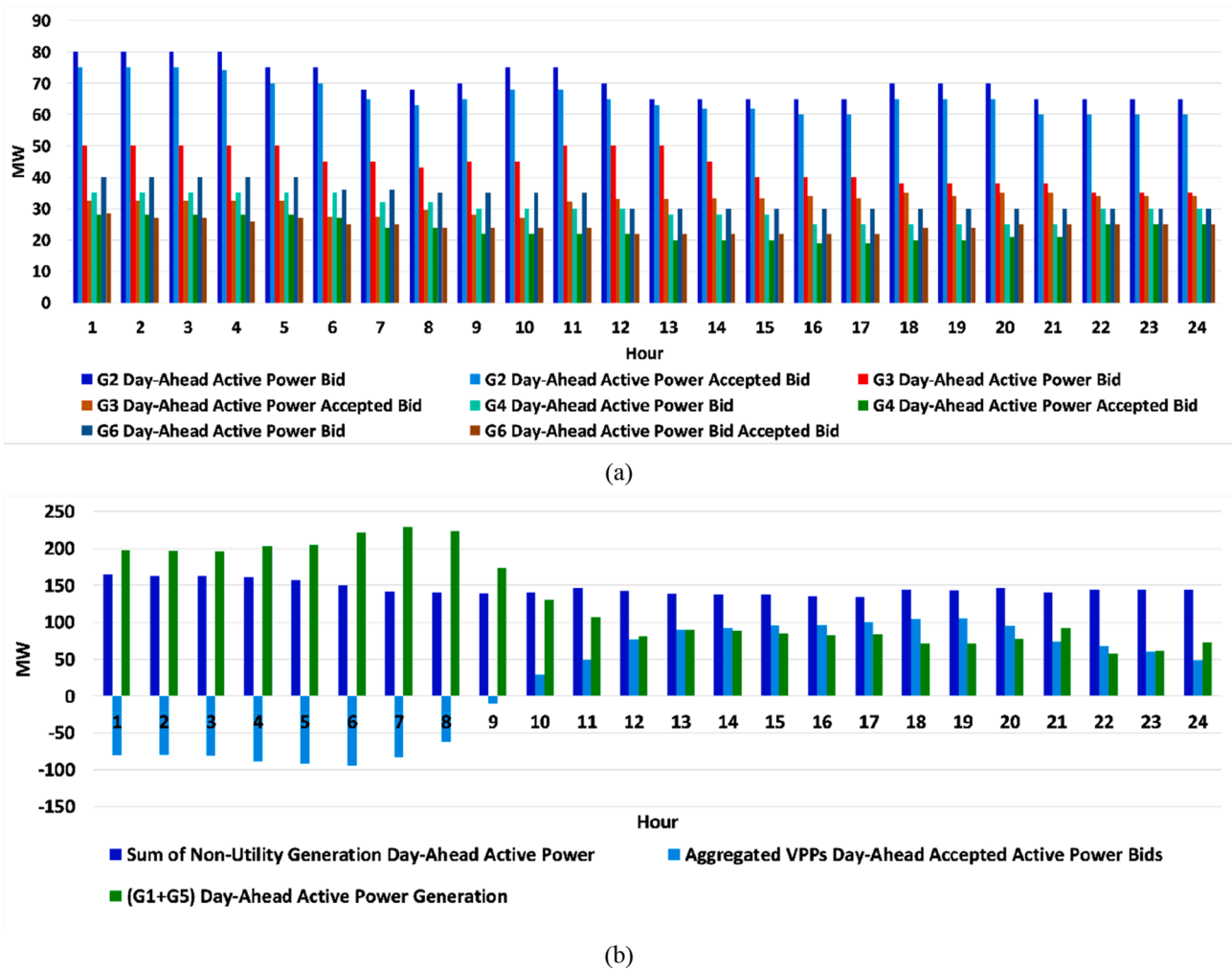


Fig. 8. (a) The day-ahead non-utility generation companies bids. (b) The day-ahead energy generation schedule of generation companies.

withholding groups and their corresponding identification number. Fig. 10 depicts the estimated values of $JMCWI^{DA}$ for the day-ahead horizon. It was assumed that $\epsilon_1^{DA} = 0.25, \epsilon_1^{ID} = 0.25, \epsilon_1^{RT} = 0.25$ and $\epsilon_1^{DA} = 0.05, \epsilon_1^{ID} = 0.05, \epsilon_1^{RT} = 0.05$.

As shown in Fig. 10, the average and maximum values of $JMCWI^{DA}$ were 0.2426 and 0.64, respectively. The 167th dynamic capacity-withholding group corresponded to the coordinated bidding of all virtual power plants and non-utility generation companies for the day-ahead horizon that led to these entities' maximum capacity withholding and arbitrage benefit. At this condition, the second stage of the first level objective function reached its lowest value (36% of full competition objective function).

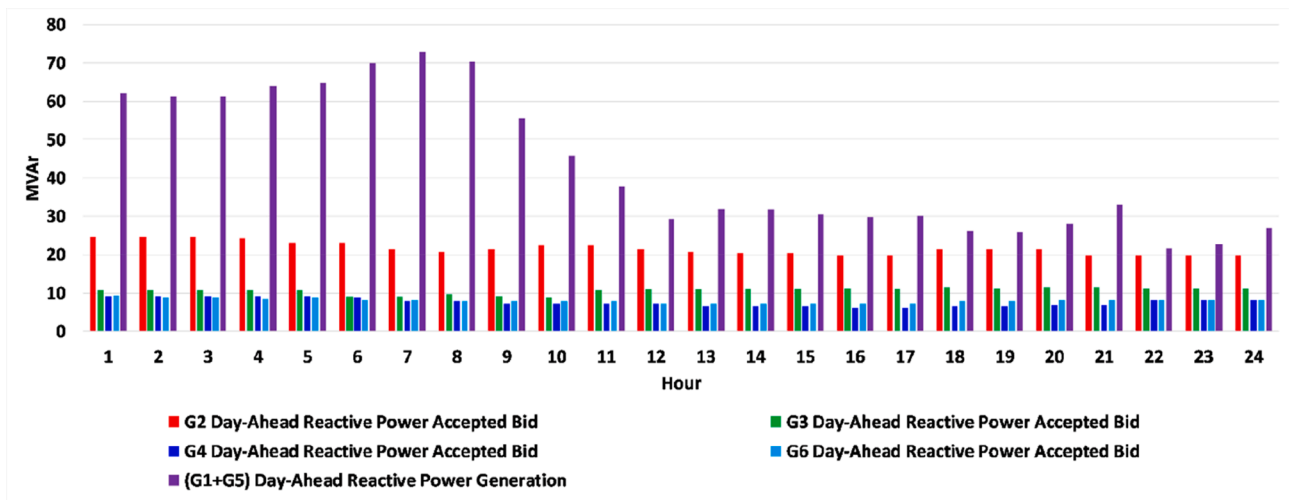
Fig. 11 (a) presents the expected values of system costs for the conditions that the system operator did not utilize the proposed algorithm. The sum of system costs was 623.1492 MMUs. Fig. 11 (b) shows the expected values of benefits of virtual power plants and non-utility generation companies and their aggregated penalties for the conditions that the system operator did not perform the proposed algorithm. The sum of benefits of virtual power plants and non-utility generation

companies was 623.1492 MMUs.

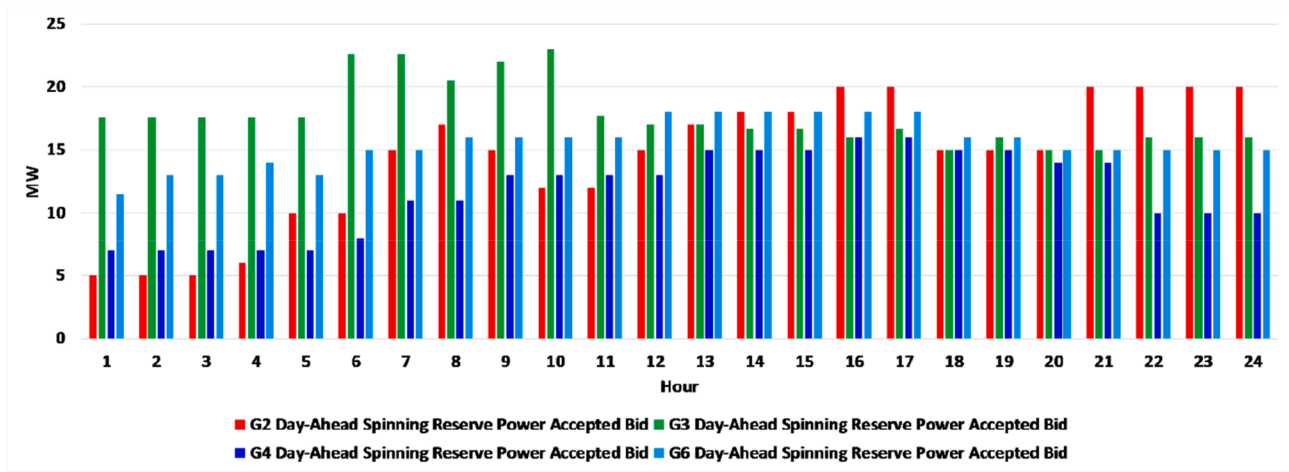
Fig. 12 (a) presents the expected values of system costs for the conditions that the system operator utilized the proposed algorithm. The sum of system costs was 439.8712 MMUs. Fig. 12 (b) shows the expected benefits of virtual power plants and non-utility generation companies and their aggregated penalties for the conditions that the system operator performed the proposed algorithm. The sum of benefits of virtual power plants and non-utility generation companies was 41.4802 MMUs.

By comparing the values of Fig. 11 and Fig. 12, it can be concluded that the proposed algorithm reduced the system costs and arbitrage benefits for day-ahead operational scheduling by about 29.41% and 75.46% concerning their base case, respectively.

Then, the system operator optimized the second level problem for the intra-day horizon. Fig. 13 and Fig. 14 present the estimated values of optimal intra-day bids of virtual power plants for the active power and ancillary services markets, respectively. As shown in Fig. 13, the aggregated value of energy generation of virtual power plants was 41.4 MWh for the intra-day horizon. Further, the aggregated value of reactive power generation of virtual power plants was 13.6 MVarh for the intra-



(a)



(b)

Fig. 9. (a) The non-utility generation companies reactive power bids for the day-ahead horizon. (b) The non-utility generation companies spinning reserve bids for the day-ahead horizon.

day horizon.

Fig. 15 depicts the estimated values of $JMCWI^D$ for the intra-day horizon. As shown in Fig. 15, the average and maximum values of $JMCWI^D$ were 0.3698 and 0.8223, respectively. The maximum value of capacity withholding index for intra-day horizon increased by about 28.48% concerning the day-ahead index based on the fact that the virtual power plants and non-utility generation companies had more opportunities for arbitrage and capacity withholding in the intra-day horizon when the scarcity of energy resources was increased concerning day-ahead scheduling.

At the third level of optimization, the system operator performed the price and load forecasting process. Fig. 16 and Fig. 17 present the estimated values of price and load forecasting for the real-time horizon, respectively. Then, the system operator performed the first and second stages of the third level optimization process. The maximum active and reactive power mismatches values were 14.85 MW and 4.88 MVar,

respectively. The minimum active and reactive power mismatches values were -3.89 MW and -1.27 MVar, respectively.

Fig. 18 depicts the estimated values of $JMCWI^{RT}$ for the real-time horizon. As shown in Fig. 18, the average and maximum values of $JMCWI^{RT}$ were 0.4651 and 0.9727, respectively. The maximum value of the capacity-withholding index for real-time horizon increased by about 51.99% concerning the day-ahead index based on the fact that the virtual power plants and non-utility generation companies had more opportunities for arbitrage and capacity withholding in the real-time horizon.

Fig. 19 presents the average and maximum values of locational marginal price with and without the proposed algorithm. The average and maximum values of locational marginal prices for normal operating conditions considering the proposed algorithm were 50.70 MUs and 63.03 MUs, respectively. Further, the average and maximum values of locational marginal prices for the worst-case contingency operating

Table 3

The probable combination of capacity withholding groups and their corresponding identification number.

#Group	CWGs	#Group	CWGs	#Group	CWGs	#Group	CWGs	#Group	CWGs
1	VPP1 G2	35	VPP3 G2 G3	69	VPP3 VPP4 G4	103	VPP1 VPP4 G2 G4	137	VPP1 VPP4 G4 G6 G2
2	VPP1 G3	36	VPP3 G2 G4	70	VPP3 VPP4 G6	104	VPP1 VPP4 G3 G6	138	VPP1 VPP4 G6 G2 G3
3	VPP1 G4	37	VPP3 G2 G6	71	VPP1 G2 G3 G4	105	VPP2 VPP3 G2 G3	139	VPP2 VPP3 G2 G3 G4
4	VPP1 G6	38	VPP3 G3 G4	72	VPP1 G2 G4 G6	106	VPP2 VPP3 G3 G4	140	VPP2 VPP3 G3 G4 G6
5	VPP2 G2	39	VPP3 G3 G6	73	VPP1 G2 G6 G3	107	VPP2 VPP3 G4 G6	141	VPP2 VPP3 G4 G6 G2
6	VPP2 G3	40	VPP3 G4 G6	74	VPP1 G3 G4 G6	108	VPP2 VPP3 G6 G2	142	VPP2 VPP3 G6 G2 G3
7	VPP2 G4	41	VPP4 G2 G3	75	VPP2 G2 G3 G4	109	VPP2 VPP4 G2 G3	143	VPP2 VPP4 G2 G3 G4
8	VPP2 G6	42	VPP4 G2 G4	76	VPP2 G2 G4 G6	110	VPP2 VPP4 G3 G4	144	VPP2 VPP4 G3 G4 G6
9	VPP3 G2	43	VPP4 G2 G6	77	VPP2 G2 G6 G3	111	VPP2 VPP4 G4 G6	145	VPP2 VPP4 G4 G6 G2
10	VPP3 G3	44	VPP4 G3 G4	78	VPP2 G3 G4 G6	112	VPP2 VPP4 G6 G2	146	VPP2 VPP4 G6 G2 G3
11	VPP3 G4	45	VPP4 G3 G6	79	VPP3 G2 G3 G4	113	VPP2 VPP3 G2 G4	147	VPP3 VPP4 G2 G3 G4
12	VPP3 G6	46	VPP4 G4 G6	80	VPP3 G2 G4 G6	114	VPP2 VPP3 G3 G6	148	VPP3 VPP4 G3 G4 G6
13	VPP4 G2	47	VPP1 VPP2 G2	81	VPP3 G2 G6 G3	115	VPP2 VPP4 G2 G4	149	VPP3 VPP4 G4 G6 G2
14	VPP4 G3	48	VPP1 VPP2 G3	82	VPP3 G3 G4 G6	116	VPP2 VPP4 G3 G6	150	VPP3 VPP4 G6 G2 G3
15	VPP4 G4	49	VPP1 VPP2 G4	83	VPP4 G2 G3 G4	117	VPP3 VPP4 G2 G3	151	VPP1 G2 G3 G4 G6 VPP2
16	VPP4 G6	50	VPP1 VPP2 G6	84	VPP4 G2 G4 G6	118	VPP3 VPP4 G3 G4	152	VPP1 G2 G3 G4 G6 VPP3
17	VPP1 VPP2	51	VPP1 VPP3 G2	85	VPP4 G2 G6 G3	119	VPP3 VPP4 G4 G6	153	VPP1 G2 G3 G4 G6 VPP4
18	VPP1 VPP3	52	VPP1 VPP3 G3	86	VPP4 G3 G4 G6	120	VPP3 VPP4 G6 G2	154	VPP2 G2 G3 G4 G6 VPP3
19	VPP1 VPP4	53	VPP1 VPP3 G4	87	VPP1 VPP2 G2 G3	121	VPP3 VPP4 G2 G4	155	VPP2 G2 G3 G4 G6 VPP4
20	VPP2 VPP3	54	VPP1 VPP3 G6	88	VPP1 VPP2 G3 G4	122	VPP3 VPP4 G3 G6	156	VPP3 G2 G3 G4 G6 VPP4
21	VPP2 VPP4	55	VPP1 VPP4 G2	89	VPP1 VPP2 G4 G6	123	VPP1 G2 G3 G4 G6	157	VPP1 VPP2 G2 G3 G4 G6
22	VPP3 VPP4	56	VPP1 VPP4 G3	90	VPP1 VPP2 G6 G2	124	VPP2 G2 G3 G4 G6	158	VPP1 VPP3 G2 G3 G4 G6
23	VPP1 G2 G3	57	VPP1 VPP4 G4	91	VPP1 VPP3 G2 G3	125	VPP3 G2 G3 G4 G6	159	VPP1 VPP4 G2 G3 G4 G6
24	VPP1 G2 G4	58	VPP1 VPP4 G6	92	VPP1 VPP3 G3 G4	126	VPP4 G2 G3 G4 G6	160	VPP2 VPP3 G2 G3 G4 G6
25	VPP1 G2 G6	59	VPP2 VPP3 G2	93	VPP1 VPP3 G4 G6	127	VPP1 VPP2 G2 G3 G4	161	VPP2 VPP4 G2 G3 G4 G6
26	VPP1 G3 G4	60	VPP2 VPP3 G3	94	VPP1 VPP3 G6 G2	128	VPP1 VPP2 G3 G4 G6	162	VPP3 VPP4 G2 G3 G4 G6
27	VPP1 G3 G6	61	VPP2 VPP3 G4	95	VPP1 VPP4 G2 G3	129	VPP1 VPP2 G4 G6 G2	163	VPP1 G2 G3 G4 G6 VPP2 VPP3
28	VPP1 G4 G6	62	VPP2 VPP3 G6	96	VPP1 VPP4 G3 G4	130	VPP1 VPP2 G6 G2 G3	164	VPP1 G2 G3 G4 G6 VPP2 VPP4
29	VPP2 G2 G3	63	VPP2 VPP4 G2	97	VPP1 VPP4 G4 G6	131	VPP1 VPP3 G2 G3 G4	165	VPP1 G2 G3 G4 G6 VPP3 VPP4
30	VPP2 G2 G4	64	VPP2 VPP4 G3	98	VPP1 VPP4 G6 G2	132	VPP1 VPP3 G3 G4 G6	166	VPP2 G2 G3 G4 G6 VPP3 VPP4
31	VPP2 G2 G6	65	VPP2 VPP4 G4	99	VPP1 VPP2 G2 G4	133	VPP1 VPP3 G4 G6 G2	167	VPP1 G2 G3 G4 G6 VPP2 VPP3 VPP4
32	VPP2 G3 G4	66	VPP2 VPP4 G6	100	VPP1 VPP2 G3 G6	134	VPP1 VPP3 G6 G2 G3		
33	VPP2 G3 G6	67	VPP3 VPP4 G2	101	VPP1 VPP3 G2 G4	135	VPP1 VPP4 G2 G3 G4		
34	VPP2 G4 G6	68	VPP3 VPP4 G3	102	VPP1 VPP3 G3 G6	136	VPP1 VPP4 G3 G4 G6		

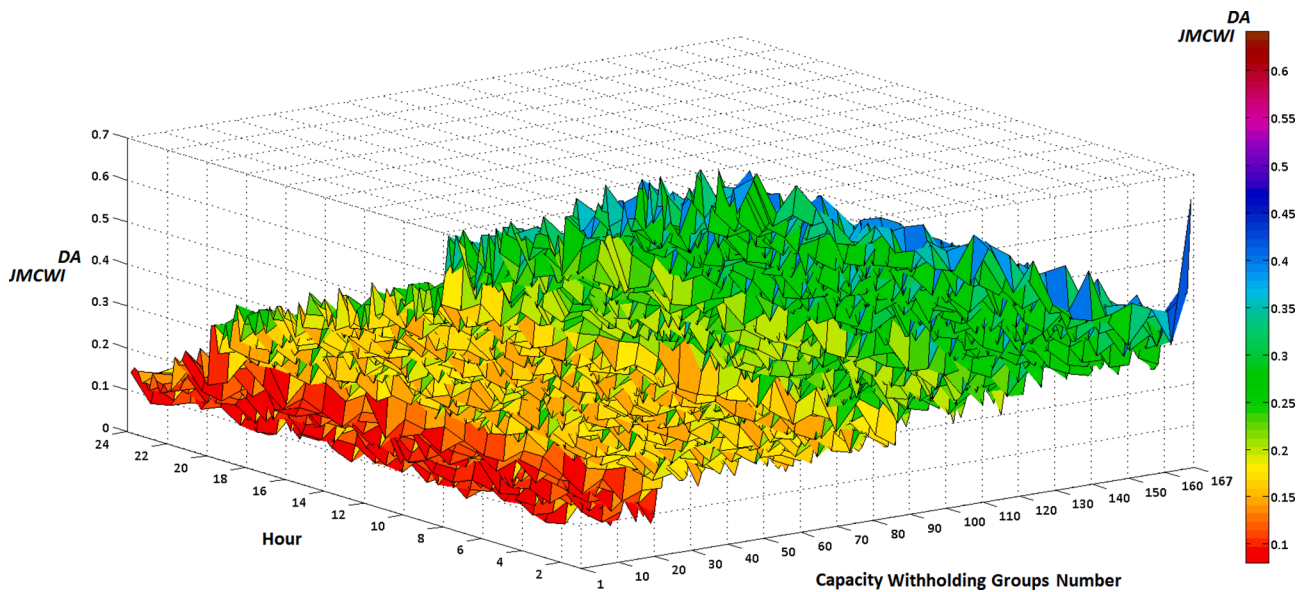
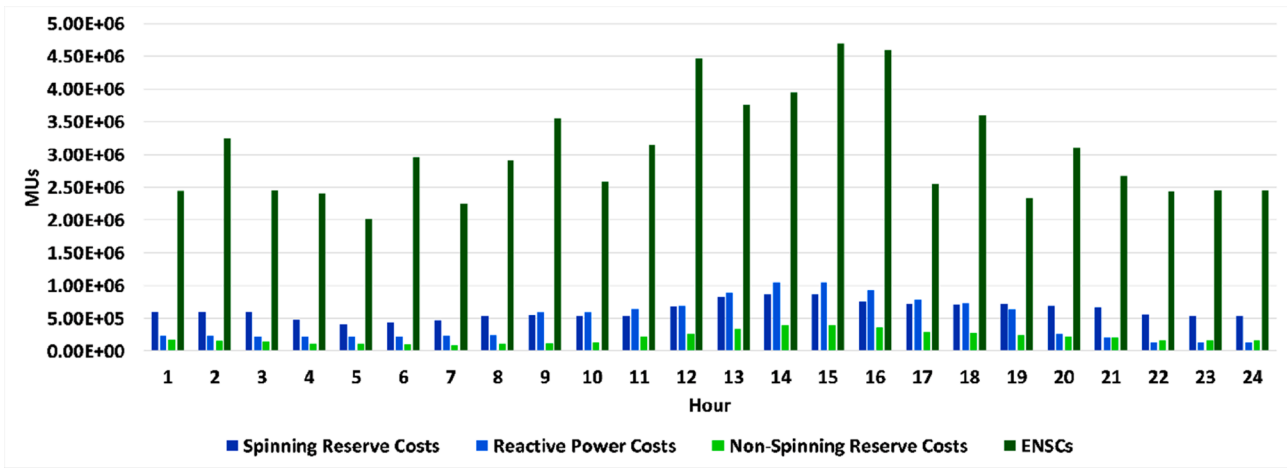
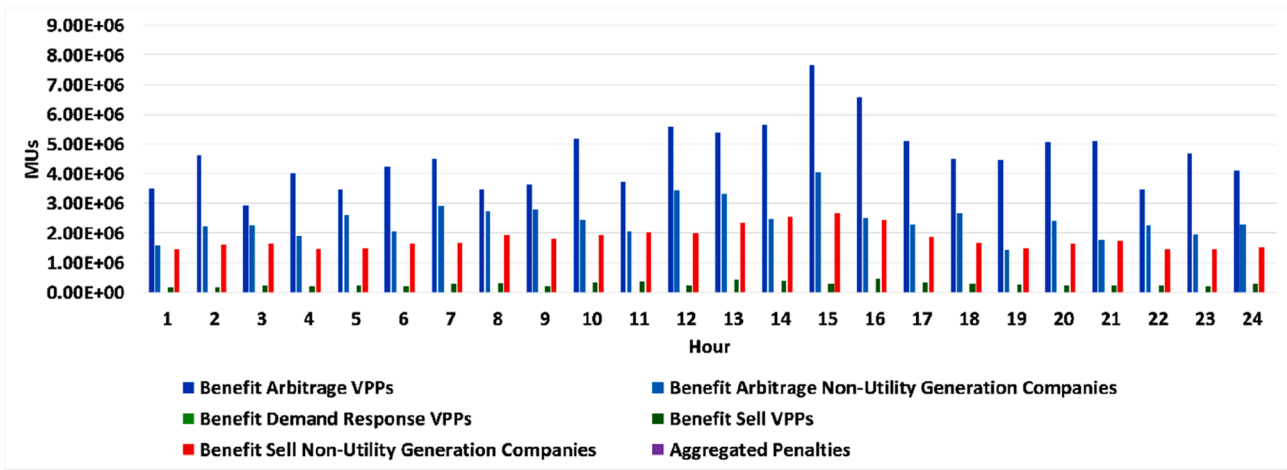


Fig. 10. The estimated values of $JMCW^{DA}$ for the day-ahead horizon.



(a)



(b)

Fig. 11. (a) The expected values of system costs for the conditions that the system operator did not utilize the proposed algorithm. (b) The expected values of benefits of virtual power plants and non-utility generation companies and their aggregated penalties for the conditions that the system operator did not utilize the proposed algorithm.

condition considering the proposed algorithm were 67.07 MUs and 80.91 MUs, respectively. The maximum values of locational marginal prices for normal and the worst-case contingency operating conditions (without the proposed method) were 113.81 MUs and 188.33 MUs, respectively. The proposed algorithm reduced the maximum values of locational marginal prices by about 44.61% and 57.04% concerning the normal and the worst-case contingency operating conditions, respectively.

Fig. 20 presents the average values of $JMCWI^{DA}$, $JMCWI^{ID}$, and $JMCWI^{RT}$ with and without the proposed algorithm for the 30-bus test system. The average values of $JMCWI^{DA}$, $JMCWI^{ID}$, and $JMCWI^{RT}$ indices without the proposed algorithm were 0.5324, 0.5907, and 0.6582, respectively. However, the average values of $JMCWI^{DA}$, $JMCWI^{ID}$, and $JMCWI^{RT}$ indices with the proposed algorithm were 0.3571, 0.3538, and 0.3498, respectively. The proposed method reduced the average values of $JMCWI^{DA}$, $JMCWI^{ID}$, and $JMCWI^{RT}$ indices by about 32.92%, 40.1%,

and 46.85%, respectively. The proposed algorithm solved the day-ahead, intra-day, and real-time problems in 97, 34, and 9 s, respectively.

4.2. 118-bus IEEE test system

The simulation of the three-level optimization algorithm was performed for the IEEE 118-bus system. Fig. 21 shows the IEEE 118-bus system topology. Fig. 22 presents the day ahead load curve of the system. The distributed energy resources parameters of virtual power plants are presented in Table 4.

For the IEEE 118-bus test system, it was assumed that the inverse demand function of each demand was $\lambda_j = -a_j \cdot y_j + 46$. [11]. The slope of each inverse demand function was chosen in a way that $\lambda_j = 30$ \$/MW for the given value of y_j in [37]. The estimated values of optimal day-ahead bids of virtual power plants for the active power market are presented in Fig. 23 (a), (b). The aggregated accepted energy generation

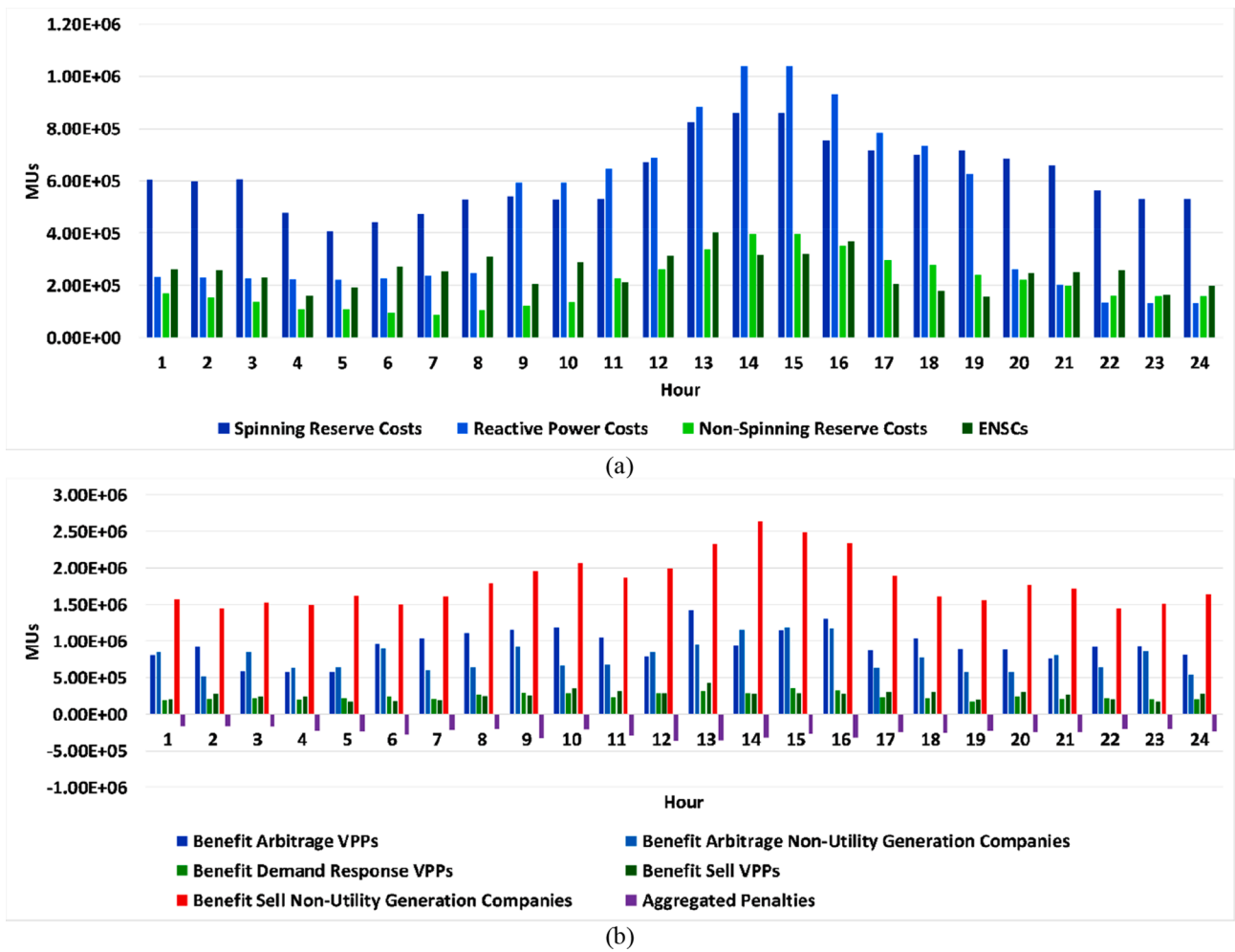


Fig. 12. (a) The expected values of system costs for the conditions that the system operator utilized the proposed algorithm. (b) The expected values of benefits of virtual power plants and non-utility generation companies and their aggregated penalties for the conditions that the system operator performed the proposed algorithm.

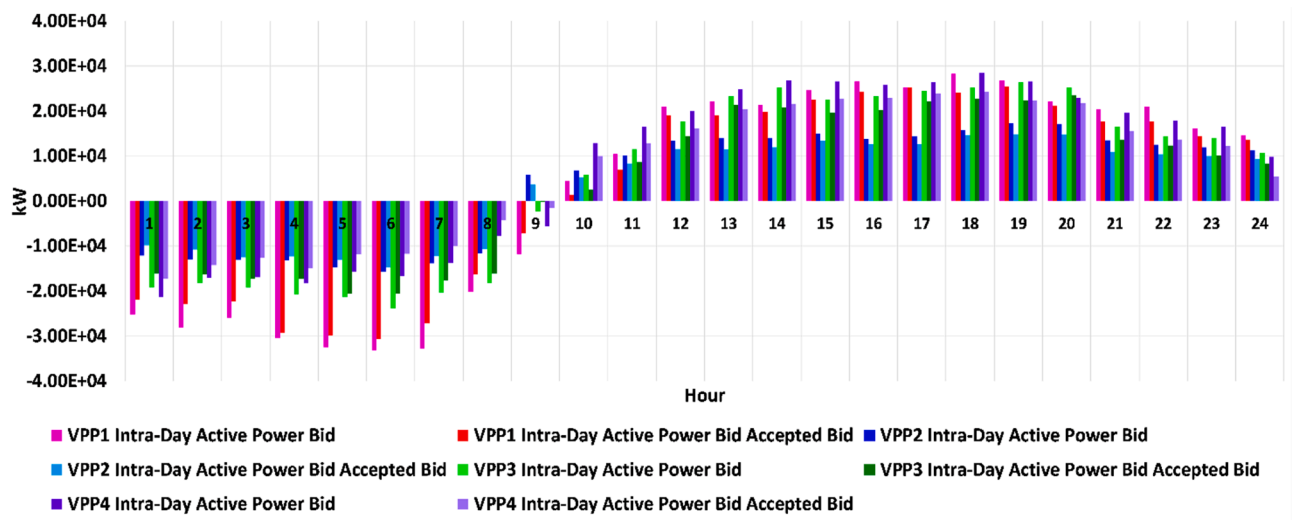


Fig. 13. The estimated values of optimal intra-day bids of virtual power plants for the active power market.

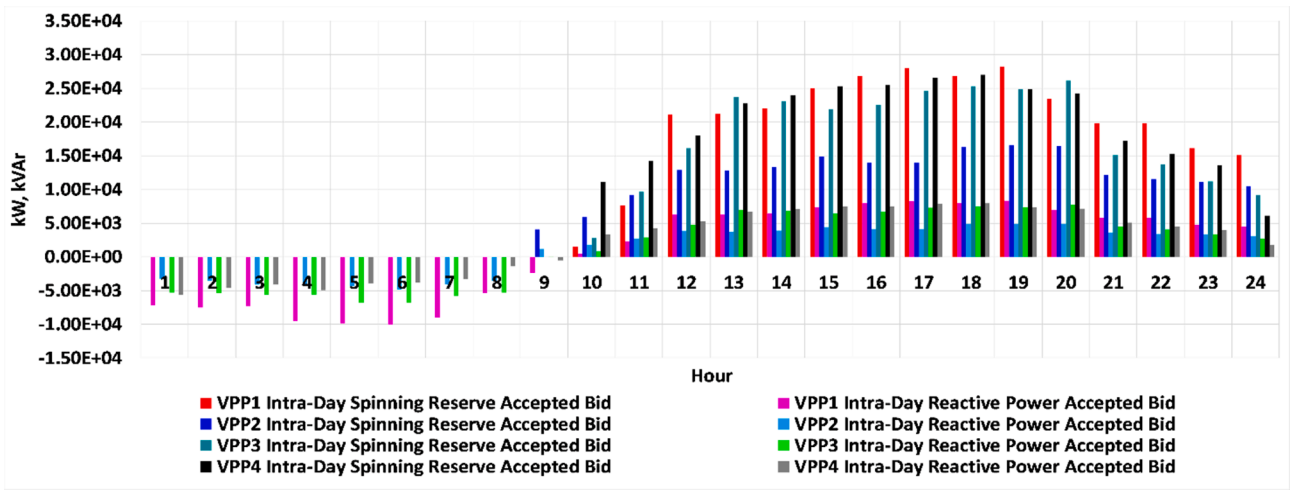


Fig. 14. The estimated values of optimal intra-day bids of virtual power plants for the ancillary services market.

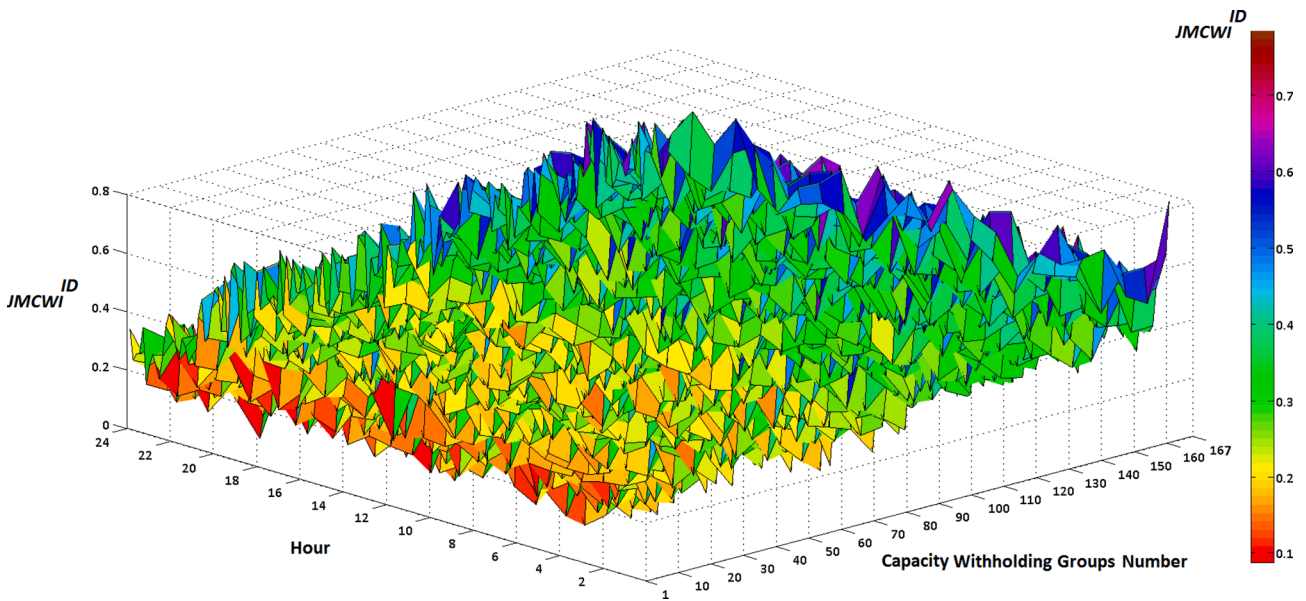


Fig. 15. The estimated values of $JMCWI^{ID}$ for the intra-day horizon.

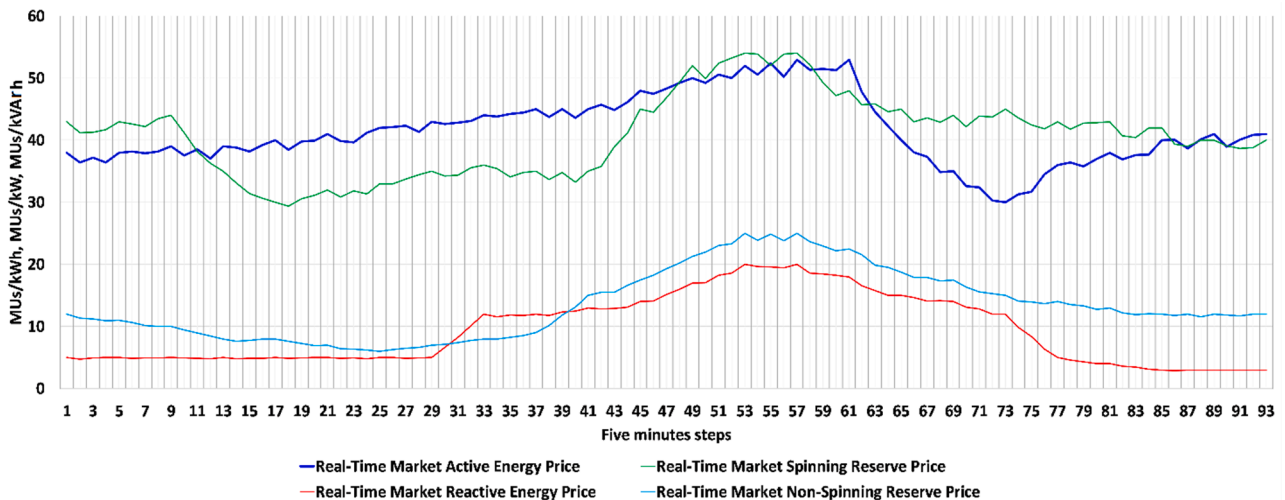


Fig. 16. The estimated values of price forecasting for the real-time horizon.

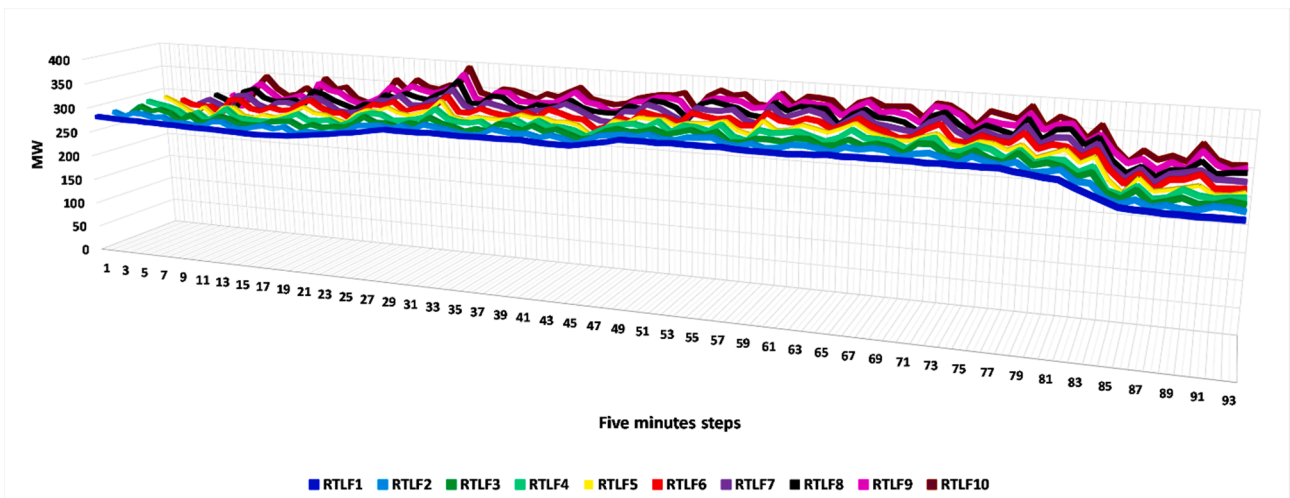


Fig. 17. The estimated values of load forecasting for the real-time horizon.

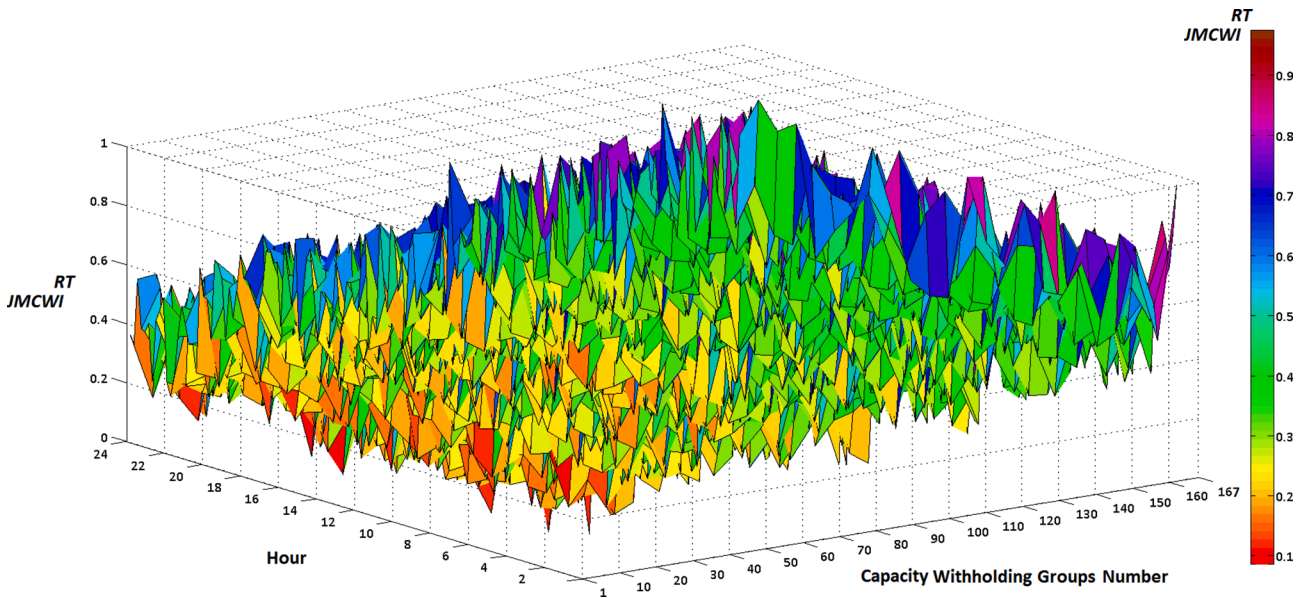


Fig. 18. The estimated values of $JMCWI^{RT}$ for the real-time horizon.

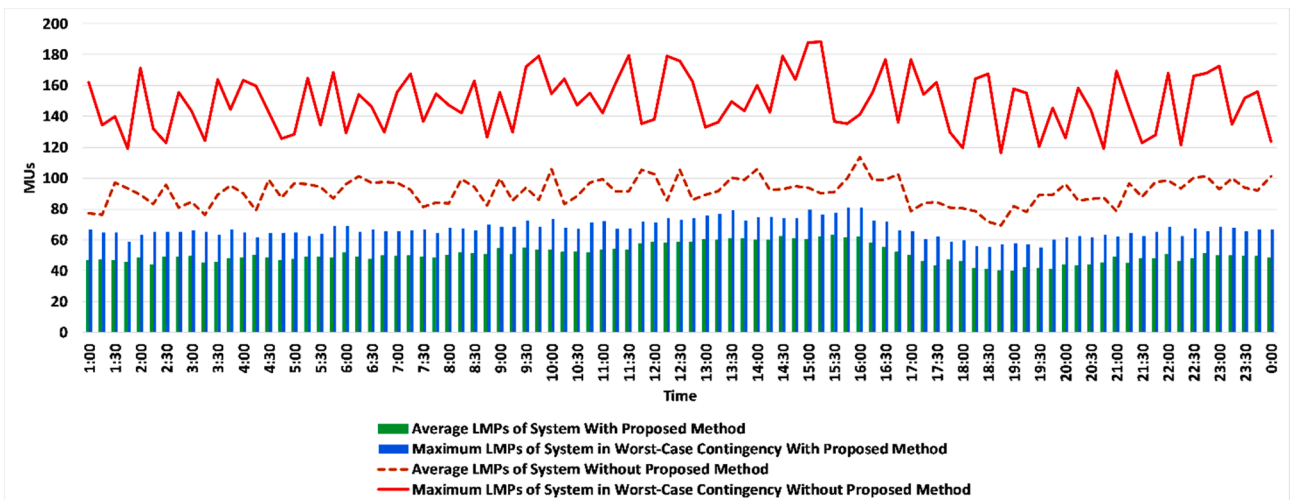


Fig. 19. The average and maximum values of locational marginal price with and without the proposed algorithm.

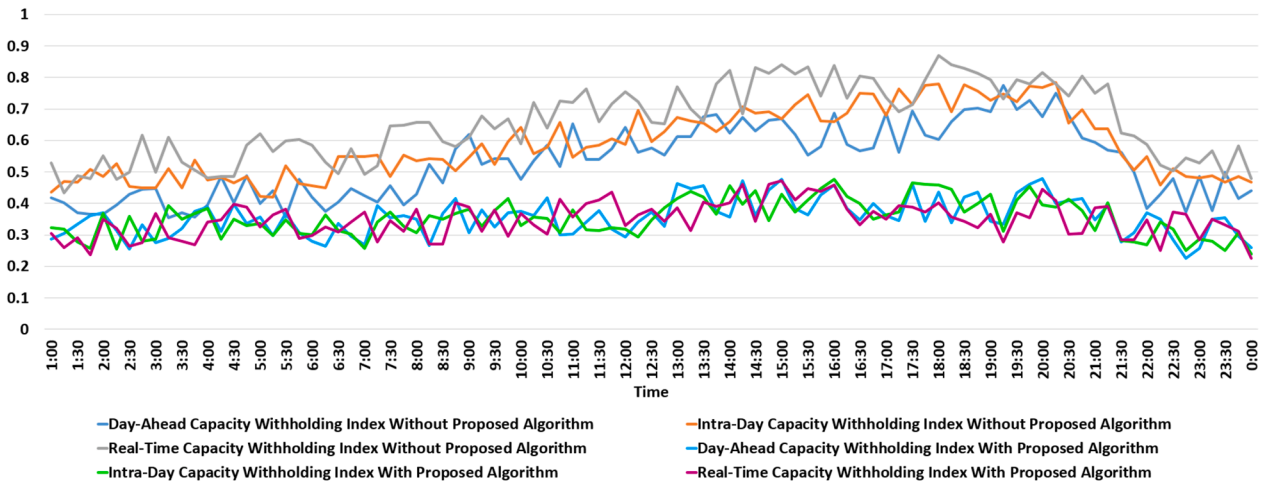


Fig. 20. The average values of $JMCWI^{DA}$, $JMCWI^{ID}$, and $JMCWI^{RT}$ with and without the proposed algorithm for the 30-bus test system.

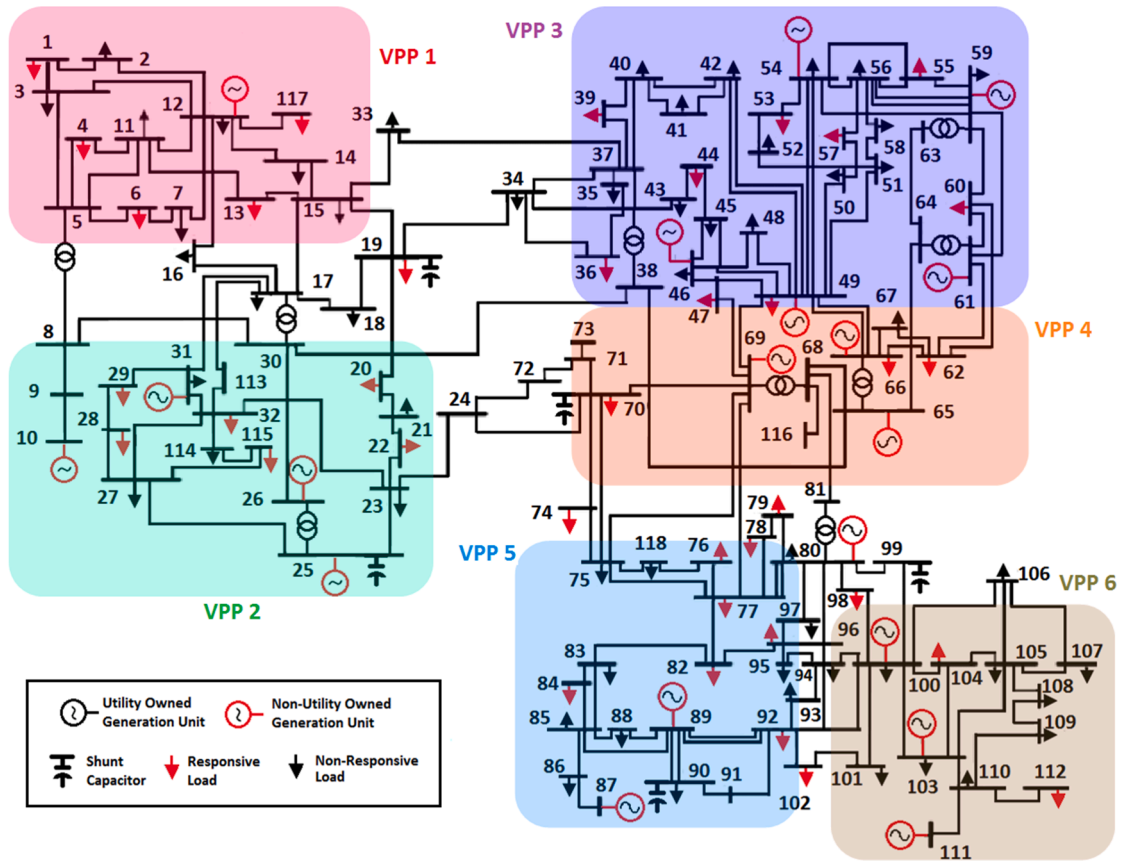


Fig. 21. The topology of the 118-bus IEEE test system.

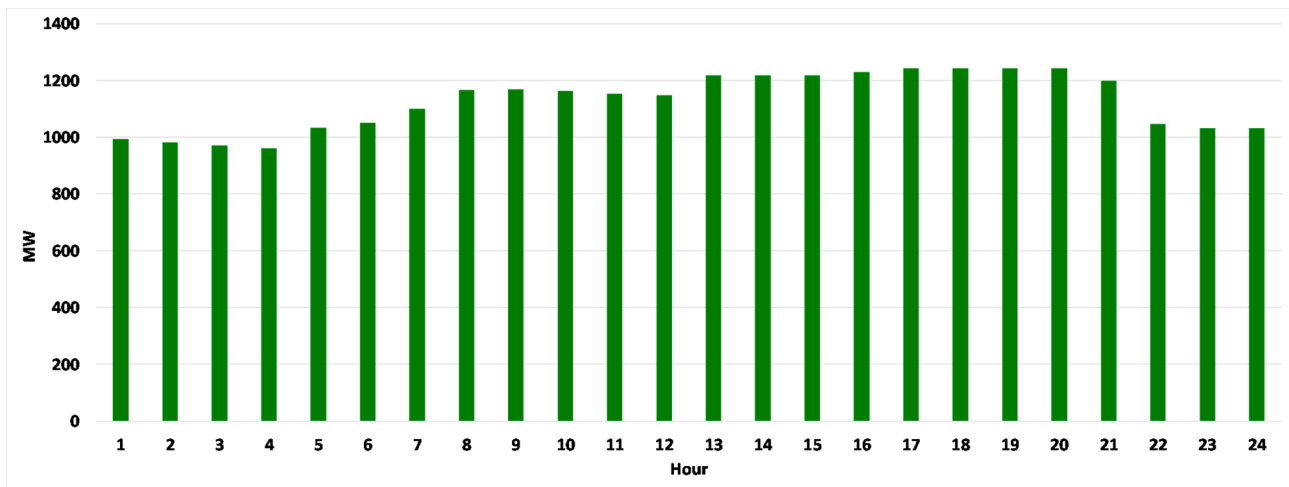
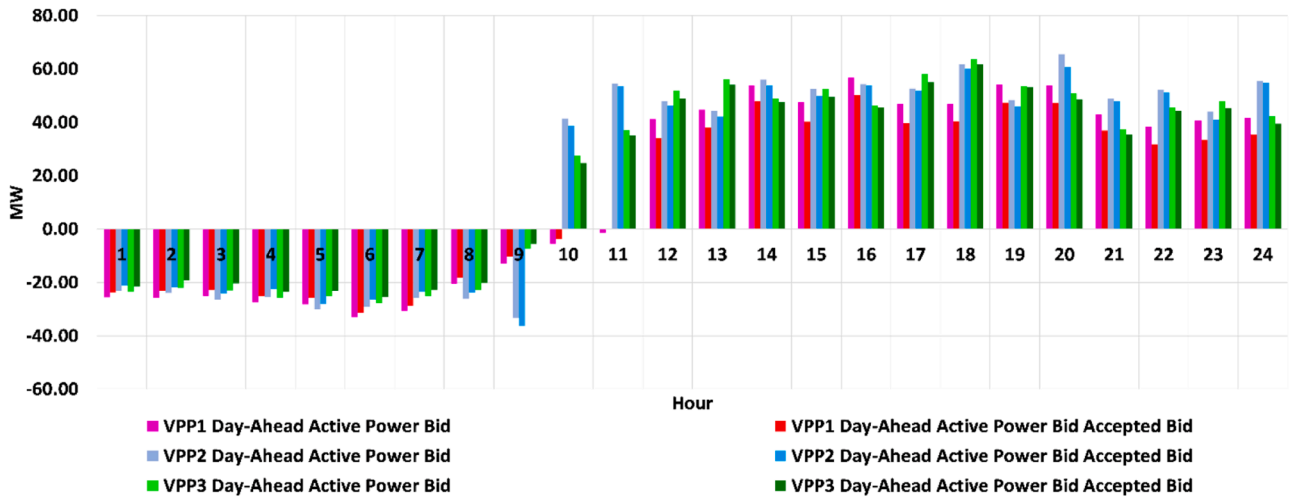


Fig. 22. The day-ahead load forecasting for the 118-bus test system.

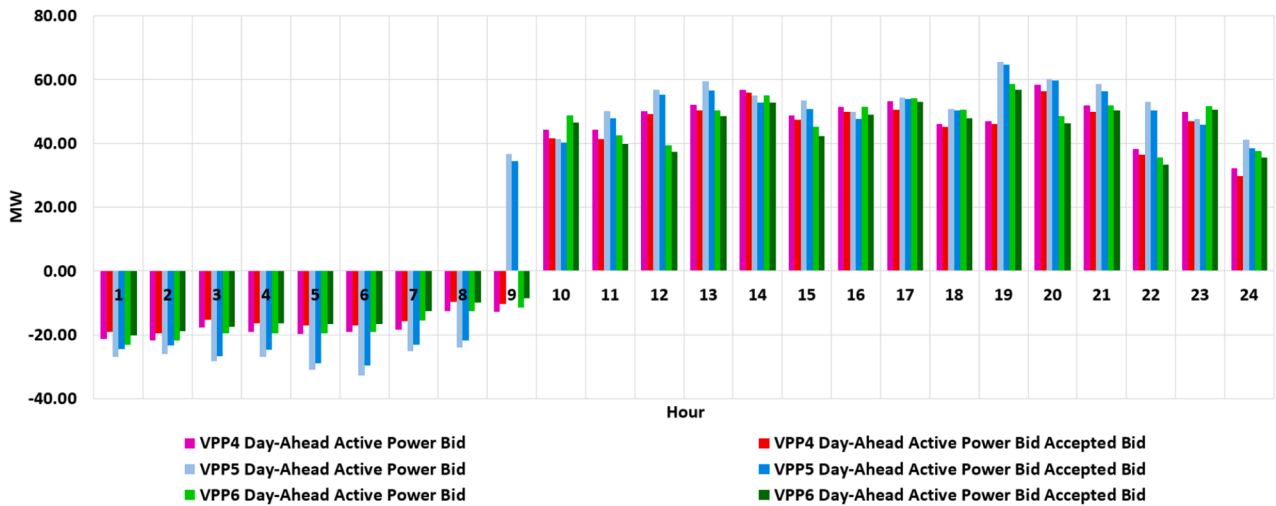
Table 4

The distributed energy resources of virtual power plants.

	Bus	Capacity (MW)	Aggregated Capacity (MW)
VPP 1			
Gas engine	2,3,6,13	10,10,10,10	40
Electrical energy storage	4,5,7,13,15,14	10,12,5,10,5,5	47
Photovoltaic system	1,3,7	10,10,10	30
Wind turbine	3,4,13	10,10,10	30
Parking lot	2,3,4,5,7	10,10,5,5,10	40
VPP 2			
Gas engine	8,10,22,34	10,15,10,10	45
Electrical energy storage	8,9,23,25,115	10,15,5,5,5	40
Photovoltaic system	10,20,26	10,15,15	40
Wind turbine	9,20,115	15,10,10	35
Parking lot	8,9,32,114,115	5,15,15,5,5	45
VPP 3			
Gas engine	35,41,52,63,64	10,10,10,10,10	50
Electrical energy storage	35,40,41,42,57	10,12,15,10,15	62
Photovoltaic system	37,39,63	10,12,10	32
Wind turbine	35,37,57	10,10,12	32
Parking lot	35,40,42,58	10,15,10,13	48
VPP 4			
Gas engine	68,71,73,116	10,15,10,10	45
Electrical energy storage	71,73,116	10,15,15	40
Photovoltaic system	62,66, 116	10,10,10	30
Wind turbine	62,68,71	10,10,10	30
Parking lot	62,65,70	10,15,15	40
VPP 5			
Gas engine	75,76,91	10,10,10	30
Electrical energy storage	76,83,86,88	10, 5, 5,5	25
Photovoltaic system	75,77,95	10,12,15	37
Wind turbine	75,77	15,10	25
Parking lot	75,77	10,15	25
VPP 6			
Gas engine	101,103,112	15, 5,10	30
Electrical energy storage	100,103,109	10,10,10	30
Photovoltaic system	100,112	10, 15	25
Wind turbine	101,112	10,20	30
Parking lot	100,107,109	10,15,15	40



(a)



(b)

Fig. 23. (a) The estimated values of optimal day-ahead bids of VPP1-VPP3 for the active power market. (b) The estimated values of optimal day-ahead bids of VPP4-VPP6 for the active power market.

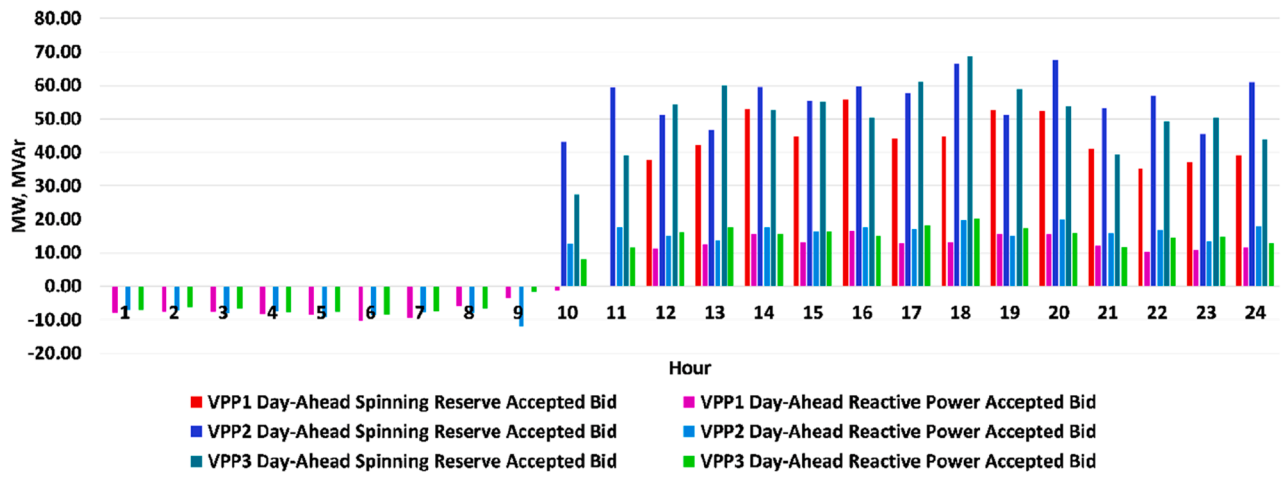
of virtual power plants was 3063.97 MWh. The maximum value of virtual power plant bids was 64.73 MW for the day-ahead horizon. The average values of VPP1, VPP2, and VPP3 day-ahead active power accepted bids were 12.87 MW, 21.83 MW, and 21.12 MW, respectively. Further, the average values of VPP4, VPP5, and VPP6 day-ahead active power accepted bids were 23.23 MW, 25.15 MW, and 23.03 MW, respectively.

Fig. 24 (a) depicts the estimated values of VPP1-VPP3 day-ahead bids for the spinning reserve and reactive power market. The average values of VPP1, VPP2, and VPP3 day-ahead reactive power accepted bids were 4.23 MVar, 7.17 MVar, and 6.94 MVar, respectively.

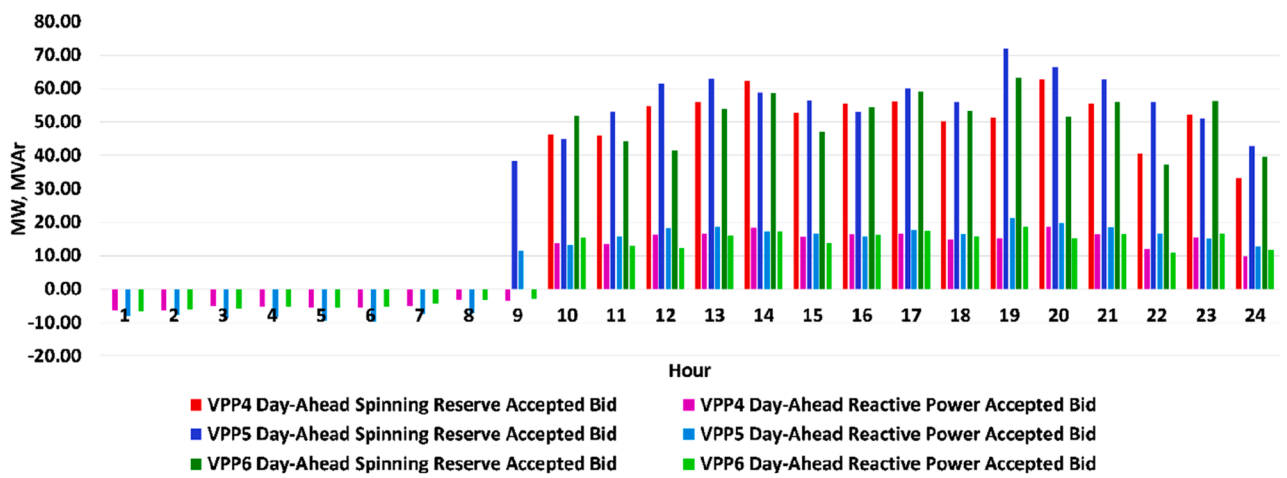
Fig. 24 (b) shows the estimated values of VPP4-VPP6 day-ahead bids for spinning reserve and reactive power market. The aggregated

accepted reactive power generation of virtual power plants was 1003.17 MVarh. The average values of VPP4, VPP5, and VPP6 day-ahead reactive power accepted bids were 7.63 MVar, 8.26 MVar, and 7.57 MVar, respectively. Fig. 24 (c) presents the estimated values of VPP1-VPP6 bids for the non-spinning reserve market for the day-ahead horizon. The average values of VPP1, VPP2, and VPP3 day-ahead non-spinning reserve accepted bids were 11.45 MW, 23.27 MW, and 22.31 MW, respectively. Further, the average values of VPP4, VPP5, and VPP6 day-ahead non-spinning reserve accepted bids were 16.57 MW, 17.67 MW, and 15.13 MW, respectively.

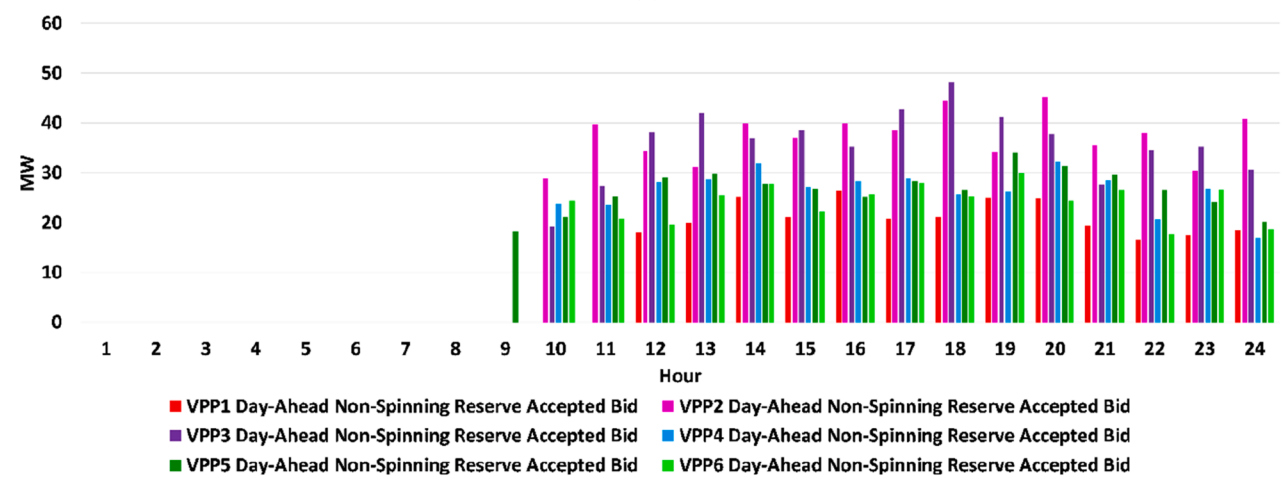
Fig. 25 presents the sum of non-utility generation companies' active power generation for the day-ahead horizon. The aggregated active power generation of non-utility generation companies was 24533.6



(a)



(b)



(c)

Fig. 24. (a) The estimated values of VPP1-VPP3 bids for spinning reserve and reactive power markets for the day-ahead horizon. (b) The estimated values of VPP4-VPP6 bids for spinning reserve and reactive power markets for the day-ahead horizon. (c) The estimated values of VPP1-VPP6 bids for the non-spinning reserve market for the day-ahead horizon.

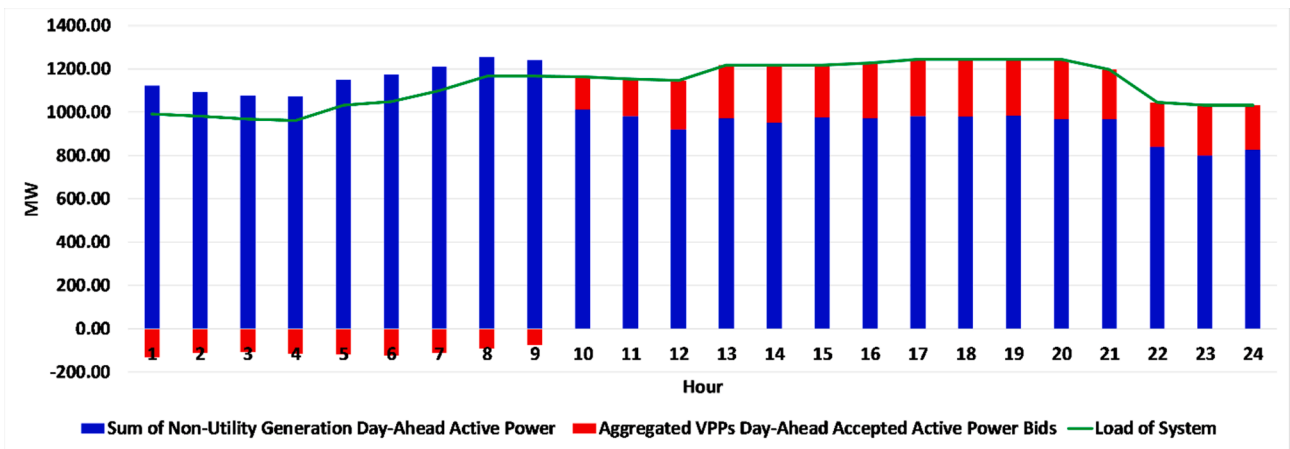


Fig. 25. The sum of non-utility generation companies' active power generation for the day-ahead horizon.

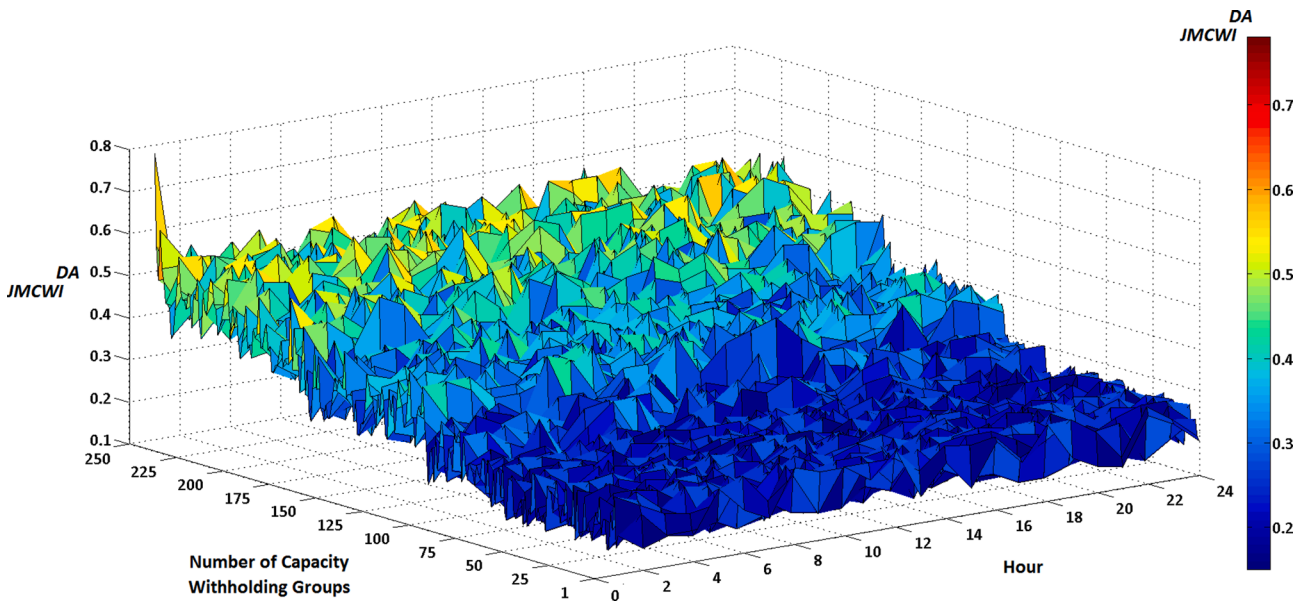


Fig. 26. The estimated values of $JMCWI^{DA}$ for the day-ahead horizon.

MWh.

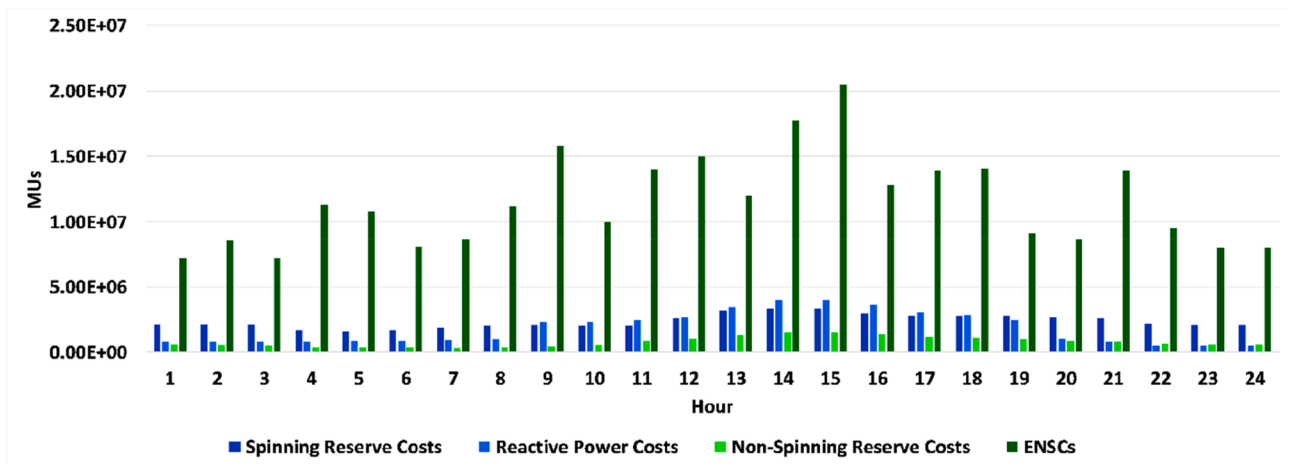
It was assumed that $\epsilon_1^{DA} = 0.25, \epsilon_1^{ID} = 0.25, \epsilon_1^{RT} = 0.25$ and $\epsilon_1^{DA} = 0.05, \epsilon_1^{ID} = 0.05, \epsilon_1^{RT} = 0.05$.

The 250th most important probable combinations of capacity withholding groups were considered for the 118-bus test system. Fig. 26 depicts the estimated values of $JMCWI^{DA}$ for the day-ahead horizon.

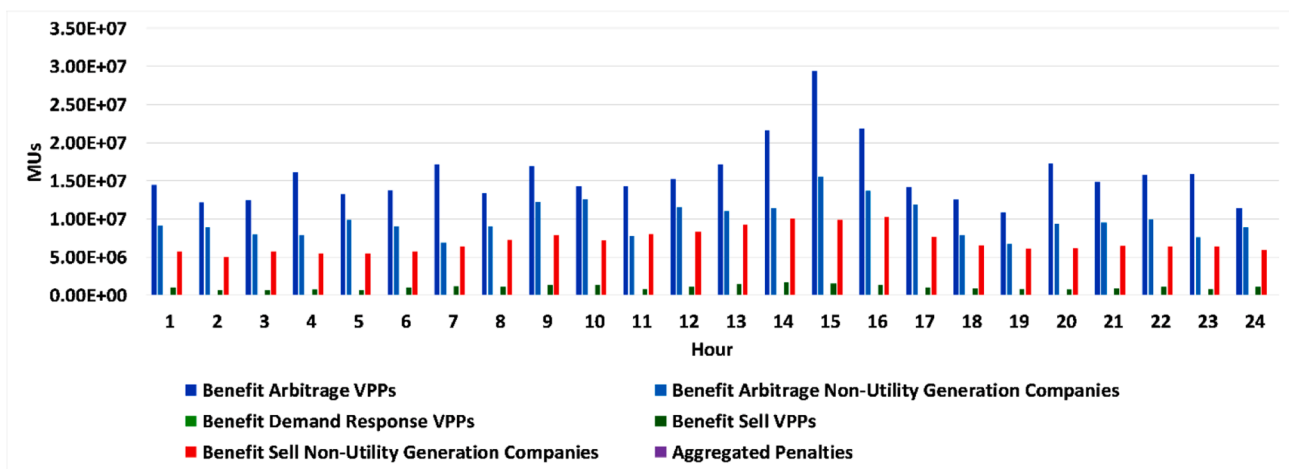
As shown in Fig. 26, the average and maximum values of $JMCWI^{DA}$ were 0.3208 and 0.7801, respectively. The 250th dynamic capacity-withholding group corresponded to the coordinated bidding of all virtual power plants and non-utility generation companies for the day-ahead horizon that led to maximum capacity withholding and arbitrage benefit of these entities. At this condition, the second stage of the first level objective function reached its lowest value (21.99% of full competition objective function).

Fig. 27 (a) presents the expected values of system costs for the conditions that the system operator did not utilize the proposed algorithm. The sum of system costs was 2344.58 MMUs. Fig. 27 (b) shows the expected values of benefits of virtual power plants and non-utility generation companies and their aggregated penalties for the conditions that the system operator did not perform the proposed algorithm. The sum of benefits of virtual power plants and non-utility generation companies was 613.12 MMUs.

Fig. 28 (a) presents the expected values of system costs for the conditions that the system operator did not utilize the proposed algorithm. The sum of system costs was 1740.38 MMUs. Fig. 28 (b) shows the expected values of benefits of virtual power plants and non-utility generation companies and their aggregated penalties for the conditions that the system operator did not perform the proposed algorithm. The



(a)



(b)

Fig. 27. (a) The expected values of system costs for the conditions that the system operator did not utilize the proposed algorithm. (b) The expected values of benefits of virtual power plants and non-utility generation companies and their aggregated penalties for the conditions that the system operator did not perform the proposed algorithm.

benefits of virtual power plants and non-utility generation companies were 164.37 MMUs. By comparing the values of Fig. 27 and Fig. 28, it can be concluded that the proposed algorithm reduced the system costs and arbitrage benefits for day-ahead operational scheduling by about 25.77% and 73.19% concerning their base case, respectively.

Fig. 29 depicts the estimated values of $JMCW^{ID}$ for the intra-day horizon. As shown in Fig. 32, the average and maximum values of $JMCW^{ID}$ were 0.4102 and 0.8554, respectively. The maximum value of the capacity withholding index for intra-day horizon increased by about 9.6526% concerning the day-ahead index based on the fact that the virtual power plants and non-utility generation companies had more opportunities for arbitrage and capacity withholding in the intra-day horizon.

Fig. 30 presents the estimated values of load forecasting for the real-time horizon.

Fig. 31 depicts the estimated values of $JMCW^{RT}$ for the real-time horizon. As shown in Fig. 31, the average and maximum values of $JMCW^{RT}$ were 0.4720 and 0.9145, respectively. The maximum value of the capacity-withholding index for real-time horizon increased by about 17.22% concerning the day-ahead index based on the fact that the virtual power plants and non-utility generation companies had more opportunities for arbitrage and capacity withholding in the real-time horizon.

Fig. 32 presents the average and maximum values of locational marginal price with and without the proposed algorithm. The average and maximum values of locational marginal prices considering the proposed algorithm and for normal operating conditions were 62.59 MUs and 75.71 MUs, respectively. Further, the average and maximum values of locational marginal prices for the worst-case contingency operating condition considering the proposed algorithm were 91.21

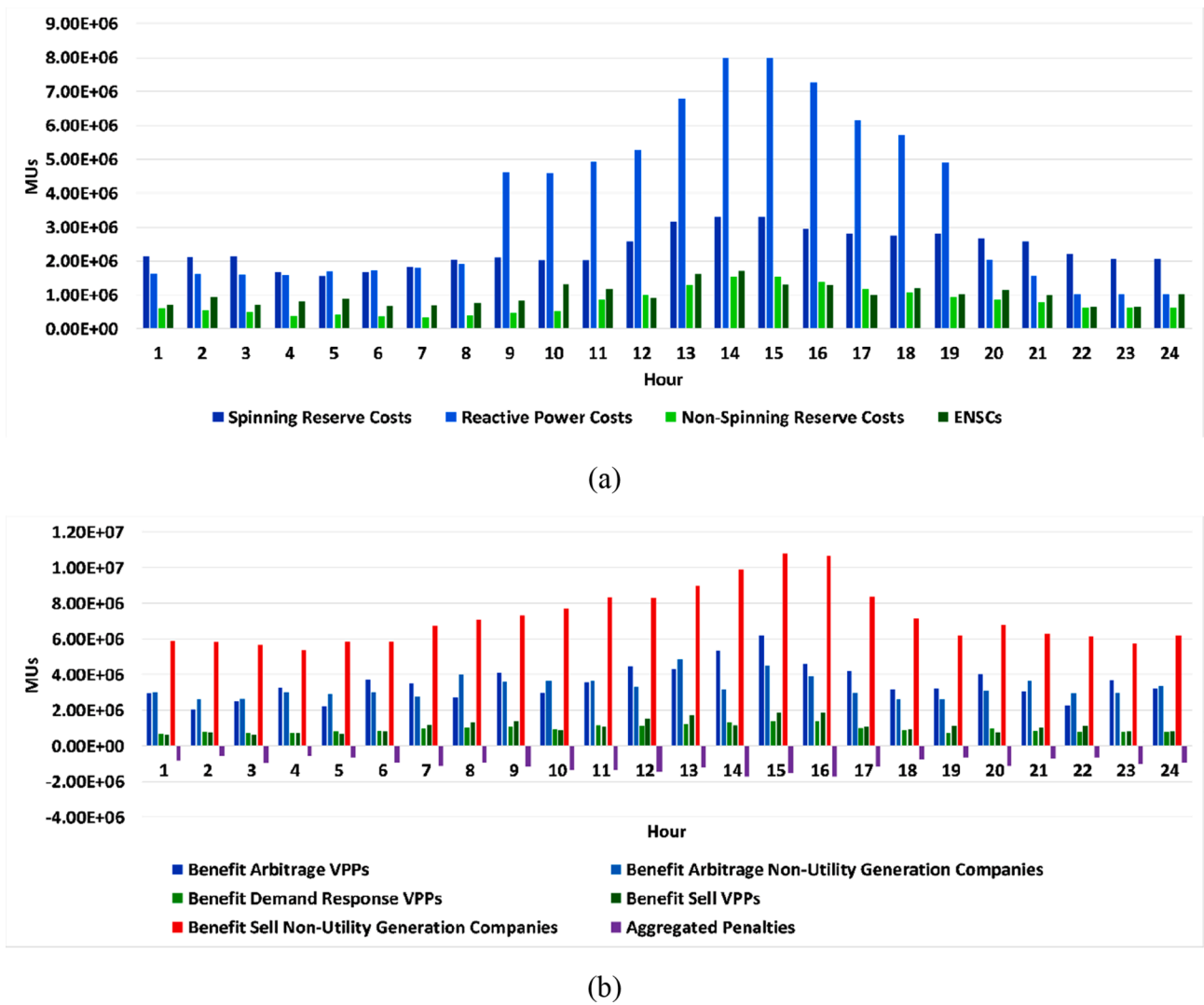


Fig. 28. (a) The expected values of system costs for the conditions that the system operator performed the proposed algorithm. (b) The expected values of benefits of virtual power plants and non-utility generation companies and their aggregated penalties for the conditions that the system operator did not perform the proposed algorithm.

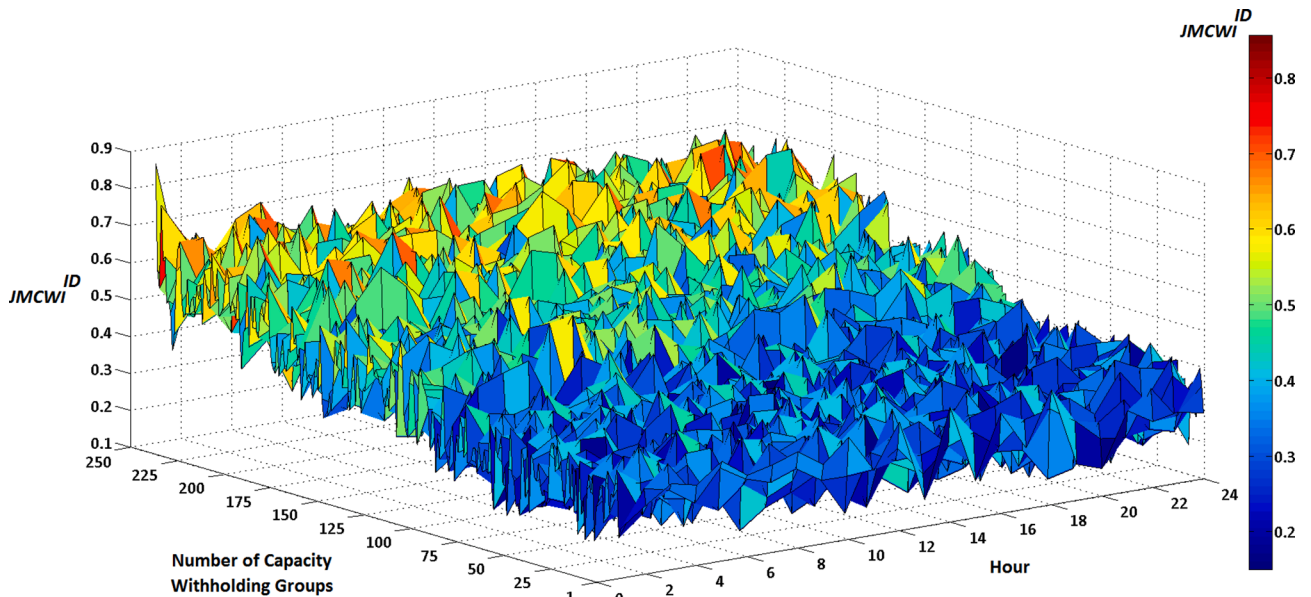


Fig. 29. The estimated values of $JMCWI^{ID}$ for the intra-day horizon.

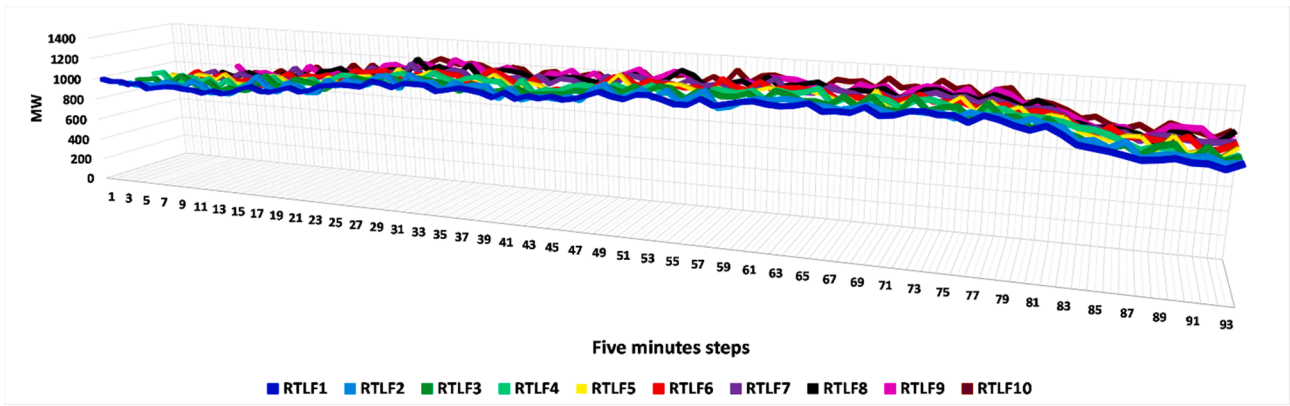


Fig. 30. The estimated real-time load forecasting of the 118-bus IEEE tests system.

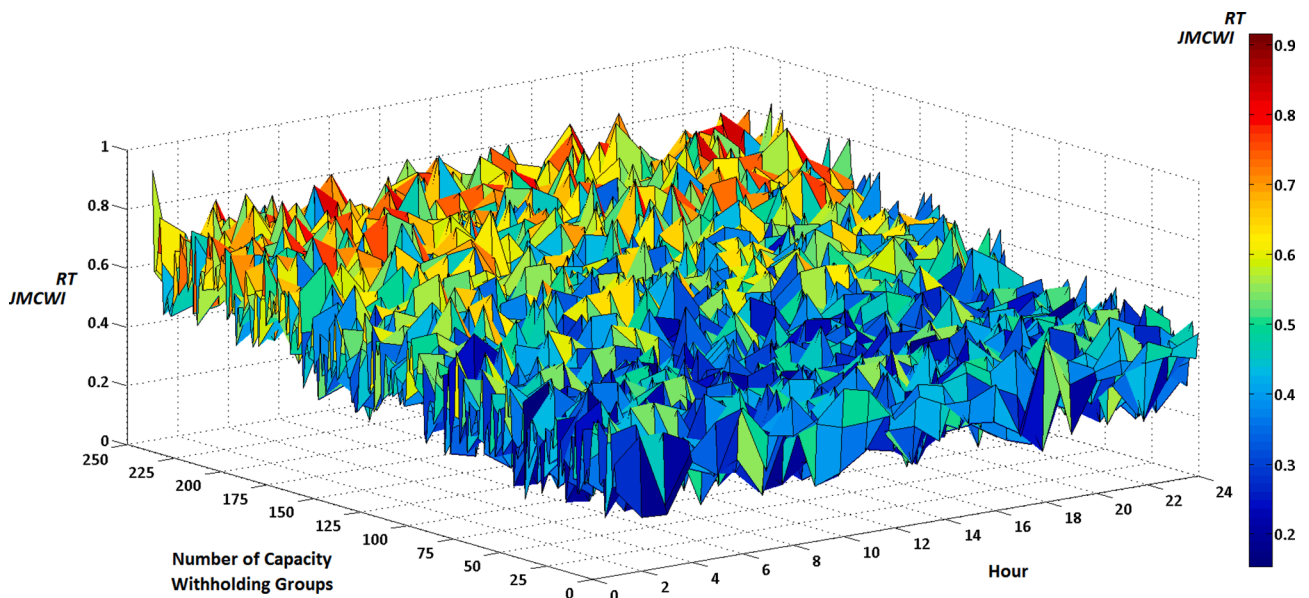


Fig. 31. The estimated values of $JMCW^{RT}$ for the real-time horizon.

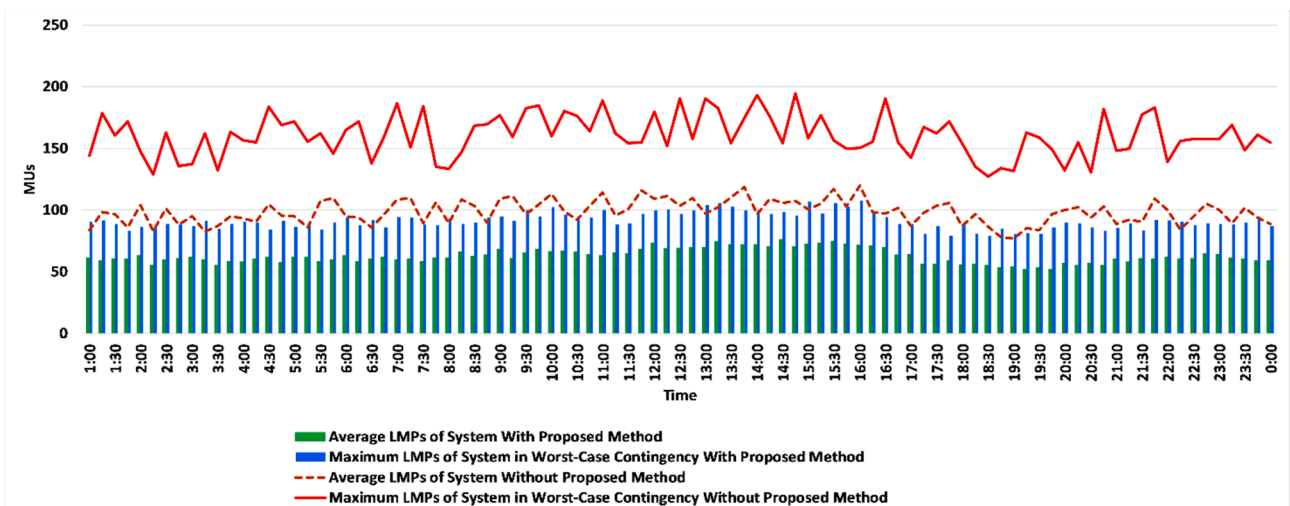


Fig. 32. The average and maximum values of locational marginal price with and without the proposed algorithm.

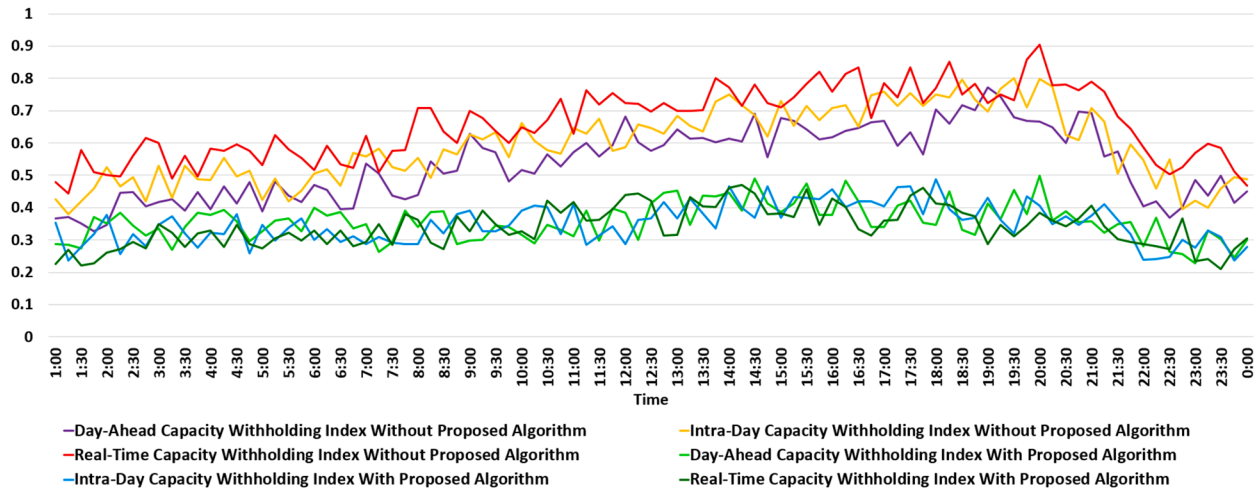


Fig. 33. The average values of $JMCW^{DA}$, $JMCW^{ID}$, and $JMCW^{RT}$ with and without the proposed algorithm.

MUs and 107.31 MUs, respectively. The maximum values of locational marginal prices for normal and the worst-case contingency operating conditions (without the proposed algorithm) were 119.6 MUs and 194.14 MUs, respectively. The proposed algorithm reduced the maximum values of locational marginal prices by about 36.69% and 44.73% concerning the normal and the worst-case contingency operating conditions, respectively.

Fig. 33 presents the average values of $JMCW^{DA}$, $JMCW^{ID}$, and $JMCW^{RT}$ with and without the proposed algorithm. The average values of $JMCW^{DA}$, $JMCW^{ID}$, and $JMCW^{RT}$ indices without the proposed algorithm were 0.5394, 0.5955, and 0.6621, respectively. However, the average values of $JMCW^{DA}$, $JMCW^{ID}$, and $JMCW^{RT}$ indices with the proposed algorithm were 0.3584, 0.3511, and 0.3417, respectively. The proposed method reduced the average values of $JMCW^{DA}$, $JMCW^{ID}$, and $JMCW^{RT}$ indices by about 33.55%, 41.04%, and 0.4839%, respectively. The proposed algorithm solved the day-ahead, intra-day, and real-time problems in 256, 89, and 36 s, respectively.

5. Conclusion

This paper introduced a mixed-integer non-linear optimization algorithm for day-ahead, intra-day, and real-time optimal scheduling of virtual power plants, utility-owned and non-utility owned generation companies. The proposed method explored the formation of dynamic capacity withholding groups and their impacts on the locational marginal prices. Further, the method considered the arbitrage of energy and ancillary services in different electricity markets. A three-level optimization algorithm was proposed. The proposed method was applied to 30-bus and 118-bus IEEE test systems. The proposed algorithm reduced the maximum values of locational marginal prices of 30-bus and 118-bus test systems by about 57.04% and 44.73% concerning the normal and the worst-case contingency operating conditions, respectively. Further, the proposed method reduced the average values of day-ahead, intra-day and real-time dynamic capacity withholding indices of the 118-bus test system by about 32.92%, 40.1%, and 46.85%, respectively. In conclusion, the adoption of the proposed capacity withholding assessment method can detect the possible formation of groups that should be prevented in an ex-ante manner by the system operator. In future research works, virtual bidding [39] and financial transmission right [40] might also be further included and studied.

CRedit authorship contribution statement

Mostafa Tabatabaei: Investigation, Data curation, Writing –

original draft. Mehrdad Setayesh Nazar: Conceptualization, Methodology, Supervision. Miadreza Shafie-khah: Formal analysis, Validation. João P.S. Catalão: Visualization, Writing – review & editing.

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.

Acknowledgment

J.P.S. Catalão acknowledges the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under POCI-01-0145-FEDER-029803 (02/SAICT/2017).

References

- [1] Nezamabadi H, Mehrdad Setayesh Nazar, Arbitrage strategy of virtual power plants in energy, spinning reserve and reactive power markets. IET Gener Transm Distrib 2016;10:750–63.
- [2] Fang X, Guo H, Zhang DA, Chen Q. Cost recovery and investment barriers for renewables under market manipulation of thermal collusion. Appl Energy 2021; 285:116487.
- [3] Ramyar S, Liu AL, Chen Y. A Power Market Model in Presence of Strategic Prosumers. IEEE Trans Power Syst 2020;35:898–908.
- [4] Guo H, Chen Q, Fang X, Liu K, Xia Q, Kang C. Efficiency loss for variable renewable energy incurred by competition in electricity markets. IEEE Trans Sustain Energy 2020;11:1951–64.
- [5] Huang C, Yan Z, Chen S, Yang L, Li X. Two-stage market clearing approach to mitigate generator collusion in Eastern China electricity market via system dynamics method. IET Gener Transm Distrib 2019;13:3346–53.
- [6] Bataille M, Bodnar O, Steinmetz A, Thorwarth S. Screening instruments for monitoring market power — The Return on Withholding Capacity Index (RWC). Energy Econ 2019;81:227–37.
- [7] Samadi M, Hajiabadi Mohammad Ebrahim. Assessment of the collusion possibility and profitability in the electricity market: A new analytical approach. Int J Electr Power Energy Syst 2019;112:381–92.
- [8] Hajiabadi Mohammad Ebrahim, Samadi Mahdi. Locational marginal price share: a new structural market power index. J Mod Power Syst Clean Energy 2019;7: 1709–20.
- [9] Löschenbrand M, Korpås M. Multiple Nash equilibria in electricity markets with price-making hydrothermal producers. IEEE Trans Power Syst 2019;34:422–31.
- [10] Staudt Philipp, Gärtner Johannes, Weinhardt Christof. Assessment of market power in local electricity markets with regards to competition and tacit collusion. Tagungsband Multikonferenz Wirtschaftsinformatik 2018:912–23.
- [11] Salarkheili S, Nazar Mehrdad Setayesh. Capacity withholding assessment in the presence of integrated generation and transmission maintenance scheduling. IET Gener Transm Distrib 2017;11:3903–11.
- [12] Aliabadi Danial Esmaeili, Kaya Murat, Şahin Güvenç. An agent-based simulation of power generation company behavior in electricity markets under different market-clearing mechanisms. Energy Policy 2017;100:191–205.

- [13] Ameri M, Rahimiyan M, Latify Mohammad Amin. Capacity withholding constrained by operational limits of generation under financial virtual divestiture in a day-ahead market. *IEEE Trans Power Sys* 2018;33:771–80.
- [14] Dijkstra P, Haan MA, Mulder M. Industry structure and collusion with uniform yardstick competition: theory and experiments. *Int J Industrial Organization* 2017; 50:1–33.
- [15] Yoo T-H, Ko W, Rhee C-H, Park J-K. The incentive announcement effect of demand response on market power mitigation in the electricity market. *Renew Sustain Energy Rev* 2017;76:545–54.
- [16] Huppmann Daniel, Siddiqui Sauleh. An exact solution method for binary equilibrium problems with compensation and the power market uplift problem. *Eur J Oper Res* 2018;226:622–8.
- [17] Shafie-khah M, Siano P, Fitiwi DZ, Santos SF, Catalão JP, E. Heydarian-Forushani. Regulatory, support of wind power producers against strategic and collusive behavior of conventional thermal units. In: *International Conference on the European Energy Market*; 2016. p. 1–5.
- [18] Baranes Edmond, Podesta Marion, Poudou Jean-Christophe. Mixed bundling may hinder collusion. *Res Econ* 2016;70:638–58.
- [19] Sapio A, Spagnolo N. Price regimes in an energy island: Tacit collusion vs. cost and network explanations. *Energy Econ* 2016;55:157–72.
- [20] Salarkheili S, Nazar Mehrdad Setayesh. Capacity withholding analysis in transmission-constrained electricity markets. *IET Gener Transm Distrib* 2016;10: 487–95.
- [21] Schubert J. The impact of forward contracting on tacit collusion: Experimental evidence. *J Econ Behav Organiz* 2015;119:109–23.
- [22] Moiseeva E, Hesamzadeh MR, Dimoulkas I. Tacit collusion with imperfect information: Ex-ante detection. In: *IEEE PES General Meeting Conference & Exposition*; 2014. p. 1–5.
- [23] Li H, Tesfatsion L. ISO net surplus collection and allocation in wholesale power markets under LMP. *IEEE Trans Power Syst* 2011;26:627–41.
- [24] Mohtavipour SS, Haghifam MR, Sheikh-El-Eslami MK. Emergence of capacity withholding: an agent-based simulation of a double price cap electricity market. *IET Gener Transm Distrib* 2012;6:69–78.
- [25] Hesamzadeh MR, Biggar DR, Hosseinzadeh N. The TC-PSI indicator for forecasting the potential for market power in wholesale electricity markets. *Energy Policy* 2011;39(10):5588–98.
- [26] Anderson EJ, Cau TD. Implicit collusion and individual market power in electricity markets. *European J Oper Res* 2011;211:403–14.
- [27] Zhou H, Chen B, Han ZX, Zhang FQ. Study on economic withholding in electricity market of Zhejiang Province, China. *Commun Nonlinear Sci Numer Simulat* 2009; 14:2495–501.
- [28] Frezzi P, Garcés F, Haubrich H-J. Analysis of short-term bidding strategies in power markets. *IEEE Lausanne Power Tech* 2007:971–6.
- [29] Tellidou AC, Bakirtzis AG. Agent-based analysis of capacity withholding and tacit collusion in electricity markets. *IEEE Trans Power Syst* 2007;22:1735–42.
- [30] Salarkheili, Setayesh Nazar M. New indices of capacity withholding in power markets. *Int Trans Electr Energy Syst* 2015;25:180–96.
- [31] Xiao D, Prado Josue Camposdo, Qiao Wei. Optimal joint demand and virtual bidding for a strategic retailer in the short term electricity market". *Elect Power Syst Res* 2021;190:106855.
- [32] Dai T, Qiao W. Finding equilibria in the pool-based electricity market with strategic wind power producers and network constraints. *IEEE Trans Power Syst* 2016;32(1):389–99.
- [33] Aboutalebi M, Setayesh Nazar M, Shafie-khah M, Catalão JPS. Optimal scheduling of self-healing distribution systems considering distributed energy resource capacity withholding strategies. *Int J Electr Power Energy Syst* 2022;136:107662.
- [34] Heitsch H, Romisch W. Scenario reduction algorithms in stochastic programming. *Comput Optim Appl* 2003;24:187–206.
- [35] Lobato FS, Steffen Jr V. Multi-objective optimization problems concepts and self-adaptive parameters with mathematical and engineering applications. Springer Press; 2017.
- [36] https://www.gams.com/latest/docs/S_DICOPT.html [last checked 02/09/2022].
- [37] <https://matpower.org/dld/1244/> [last checked 02/09/2022].
- [38] Tabatabaei M, Setayesh Nazar M, Shafie-khah M, Catalão JPS. An integrated framework for dynamic capacity withholding assessment considering commitment strategies of generation companies. *Int J Electr Power Energy Syst* 2022;134: 107321.
- [39] Xiao, Dongliang, AlAshery, Mohamed Kareem, Qiao Wei. Optimal price maker trading strategy of wind power producer using virtual bidding. *J Modern Power Syst Clean Energy* (Early Access), <https://doi.org/10.35833/MPCE.2020.000070>.
- [40] Li T, Shahidehpour M. Risk-constrained FTR bidding strategy in transmission markets. *IEEE Trans Power Syst* 2005;20:1014–21.