Australasian Universities Power Engineering Conference, AUPEC 2020, Hobart, TAS, Australia, 29 November – 3 December 2020

How VPPs Facilitate the Integration of Renewable Energy Sources in the Power Grid and Enhance Dispatchability – A Review

Sumaiya Tasnim
School of Engineering
Faculty of Science, Engineering and Built Environment
Deakin University
Melbourne, Australia
tasnimsu@deakin.edu.au

Nasser Hosseizadeh
Centre for Smart Power and Energy Research
School of Deakin University (of Affiliation)
Melbourne, Australia
http://orcid.org/0000-0002-8755-1176

Apel Mahmud
Centre for Smart Power and Energy Research
School of Deakin University (of Affiliation)
Melbourne, Australia
apel.mahmud@deakin.edu.au

Ameen Gargoom
Centre for Smart Power and Energy Research
School of Deakin University (of Affiliation)
Melbourne, Australia
a.gargoom@deakin.edu.au

***Abstract*— Microgrids (MGs) and Virtual Power Plants (VPPs) have gained tremendous popularity in recent times. The paradigm of Smart Grid is a ground-breaking advancement in the sphere of electricity generation and transmission. To build a sustainable electricity network, the transition from centralized generation to decentralized generation brings a lot of challenges and difficulties which are addressed by MGs and VPPs. Both MGs and VPPs are crucial elements in the network architecture of a smart grid and need to be understood thoroughly to build a sustainable electricity network. In this paper, we will explore the concept of VPPs and MGs and how they facilitate the integration of distributed energy resources such as renewable energy sources, demand responsive loads, and energy storage systems into the grid and control the decentralized generation to improve dispatchability and resilience of the network.**

Keywords—Virtual Power Plant, Distributed Energy Resources, Prosumers, Particle Swarm Optimization, Backtracking Search Algorithm, IEEE 14 Bus System, Volt-Watt Control, Volt-Var Control.

I. Introduction

The “three Ds” (decentralize, decarbonize and democratize) in the electricity sphere across the globe is driven by the need to control the ever increasing cost of electricity, address climate changes by reducing carbon footprint, restore the ageing electricity network and supply electricity to remote areas with inadequate infrastructure [1]. Research have found that dividing the entire network into small groups would lead to better management of power generation, local electricity demand and other utilities. These groups are broadly named as Microgrids.

A Microgrid can be defined as an interconnection of multiple loads and DERs within electrical frontiers that is controllable with respect to the grid and turns the conventional grid into a “Smart” grid. Microgrid creates a platform where additional DERs can be engaged to improve the network reliability, mitigate load curtailments, and supply electricity to secluded areas not serviced by the centralized power network [2].

Governments are playing an important role in promoting sustainable network infrastructure by offering generous subsidies to encourage public to install renewable energy sources such as solar panels or photovoltaic cells on rooftops of households and businesses to contribute towards energy generation. These renewable energy sources are highly weather dependent; thus, their generation is intermittent [3]. It is important to emphasis on the fact that market penetration for such distributed facilities is highly challenging as their integration into the grid is complex and forecasting real-time energy output is nearly impossible. Therefore, to address this vulnerability of renewable energy sources and to ease the integration of distributed resources into the existing infrastructure, the notion of Virtual Power Plant (VPP) is brought into life [3].

VPP can be referred to as an integration of DERs, energy storage systems and responsive loads that collectively works to improve system reliability and dispatchability as well as build a trading infrastructure for prosumers [2,4]. There are two aspects of VPP that are widely known in literature; they are Technical VPP (TVPP) and Commercial VPP (CVPP). TVPP considers the systems’ constraints related to the operation of DERs, load responses, system voltage and frequency levels. On the other hand, CVPP focuses on improving the system reliability and reducing the operational cost [3]. The literature around VPPs are increasing rapidly and most of them highlight the importance of VPPs for the foundation of smart grids. [5] and [6] discuss the crucial role of VPP during the transition from a central to distributed power infrastructure. Cost-efficient integration of renewable energy sources, near optimal dispatchability, controllability and communication for profitable investment decisions are among the attributes of VPPs [2].

Both TVPP and CVPP are extremely important for the seamless operation of smart grids. TVPP focuses on delivering stability management services to the grid by directly communicating with the distributed system operator (DSO). CVPP focuses on operating methodology to maximize profit by participating in energy market by aggregating geographically distributed resources [7]. Typically, TVPP and CVPP are separate entities governed by DSOs and VPP operators, respectively. This arrangement hinders the flexible functionality of VPPs and does not provide optimal results. To address this issue, a combined VPP system is proposed, where the TVPP is governed by the VPP operator in conjecture with CVPP [8] and provide the ideal operating conditions for VPP.

This paper will explore the broader aspects of VPP and how it functions to mitigate the challenges of integrating DERs into the grid. Through communication and information exchanges, VPPs will intelligently take decisions to make the power system resilient, increase dispatchability and actively reduce operating costs and maximize profits for its users while providing ancillary and balancing services [9].

II. Literature Review

VPPs extensively support grid operators by enabling energy trades in wholesale markets [9]. VPPs also help in managing the generated energy within the community either in the form of network support and balance or originate revenue from energy trades by deploying ICT embedded communication to actively manage the electricity infrastructure [10].

Research on VPP has mainly focused on modelling the linear and nonlinear optimization problems that are associated with the intermittent energy generation within the grid. According to [11] VPP is often defined as a yielding representation of a single operating DER profile, where multiple DERs work together in full capacity assimilating composite characteristics and spatial constraints. Another definition cited by Asmus in [12] indicates that VPP is a software dependent system that functions remotely to optimize energy generation and automatically regulate demand side or storage entities in a single, secure web-connected system.

Information technology and software systems are the key aspects of VPPs. These software systems build up the control architecture of the VPP that remotely coordinates and controls the power flow within the grid [12]. Aggregation of DERs is essential as it allows VPP to work as a single unit, giving it the capacity to perform as a centralized energy system and participate in wholesale energy markets and/or get provision of grid services to system operators [12][14].

A. *Segments of Virtual Power Plant*

VPPs can be distinguished based on its three key segments: DER portfolio, control architect and serve as trader in energy market [7].

DER PORTFOLIO:

The main building blocks of DER are:

Distributed generation – consists of controllable and intermittent, renewable and/or non-renewable small-scale generators that are associated to the distribution side of the grid.

Controllable loads – includes several electrical components and appliances that can be governed to shift or adjust energy demand.

Energy storage system – it provides flexibility to the power network by providing standby energy. It can act either as a load (when charging) or as a generator (when discharging) [15].

CONTROL ARCHITECTURE:

Literature reveals that VPPs can adapt to various control architectures, the discussed ones in this paper are as follows:

Centralized control – centralized controlled VPPs have one central control system that regulates all DERs and acquires information about their constraints and consumers preferences.

Decentralized control – such VPPs have control systems integrated as different levels. This can be viewed as hierarchical control. A local VPP is liable for synchronizing a classified number of DERs in one geographic area, enabling local operations. All the critical decisions are taken by a VPP that functions at a superior level [13].

Distributed control – these VPPs cannot directly access the DERs. Instead of actively controlling DERs, it uses an 'information exchange agent' that conveys data to local controllers which in turn optimizes their policies.

ROLE IN ENERGY MARKET:

Commercial VPP creates a single operating unit through its DER portfolio and acts as a trader in the energy wholesale market. VPP facilitates the activities that contribute to the implantation or advancement of the DER profile, for example, informing, financing, advising, organizing, lobbying and joint procuring. VPP users can actively play the role of producers (prosumers). The generated electricity can either be used or traded with neighbors or sold to energy suppliers. Both the mediator and producer role promote domestic energy practices to develop collective electricity generation [11].

Communication is the key to build a resilient power infrastructure having innumerable DERs and RESs in MGs operating alongside the conventional grid. Internet of Energy (IoE) is an emerging concept that is utilized to ensure the robustness and sustainability of VPPs. IoE facilitates the coordination and management of user-end DERs; it closely monitors the consumers' power demand, generators' capacity and location and market price of energy to reduce the stress on transmission lines and upstream generation systems [6]. IoE enables VPP to support the bidirectional flow of power within the grid by exchanging information and useful data among DERs [16].

In smart grids, the bidirectional transfer of energy is crucial and VPPs need to address this aspect smartly to make the transition in power flow seamless. VPP deploys IoE to connect RESs and energy storage devices to the power grid and contribute to continuously meet the consumers' needs without causing any alterations to the grid architecture. Such communications maintain an open-standard protocol which allows immediate actions and grants bidirectional energy transactions to/from energy resources [17]. The existing communication technologies that are commonly used within VPP between DERs and users are ZigBee, WiMAX, GPRS, etc. [18,19].

VPPs act as aggregator that is aware of every minute detail pertaining the power network topology. The VPP structure can be divided into two phases (1 and 2). Phase 1 includes the communication between the generator and the aggregator and Phase 2 involves interaction between the aggregator and regulator of the energy market. In technical VPP, the aggregator provides accurate data from DERs and future statistics to generate power profiles and forecast algorithms. TVPP not only provides continuous monitoring but also asset management based on statistical data. The power project portfolio is optimized through the quick identification of fault location and recovery and the fast metering services along with battery and inverter control systems [16]. In commercial VPP, the aggregator negotiates fair pricing for the produced electricity with the energy market regulators. The primary goal of CVPP is to maximize profits and assimilate various small-scale units to minimize the imbalance in capacity by offering visibility and contribution from several DERs within the network. It effectively deals with outage-demand management, DER character analysis, submission of bids and generation scheduling [20].

Integration of Distributed Energy Sources (DESs) via VPP offers load support during peak hours and uninterrupted support in case of any blackouts or power outages. The load support is beneficial as the DES charges during off peak hours and discharges during peak hours, herby contributing towards cost reduction. For MGs that have mostly RESs as the main generation powerhouse, DESs provide electrical stability to the network during critical circumstances such as voltage sags, flickers and/or frequency fluctuations by storing the surplus energy [21].

B. Optimization Algirithms for Scheduling VPPs

Research has shown that various optimization techniques are accompanied to manage VPPs. The most widely used techniques include linear programming, mixed-integer linear programming, particle swarm, backtracking search algorithm, genetic algorithm, etc. each optimization algorithm is specialized to solve targeted issues [22]. Table 1 provides a list of optimization techniques that can be employed to improve the functionality of VPP and its management.

TABLE I. OPTIMIZATION TECHNIQUES AND OBJECTIVE FUNCTION

Different Optimization Techniques in literature	
Optimization Techniques	**Attributes in VPPs**
Particle Swarm Optimization	Govern the electricity flow and regulate voltage and frequency to cut cost, enhance steady-state responses and power losses [25][28].
Mixed-Integer Liner Programming	Utilized to reduce the electricity production expenses, minimize carbon footprint, boost load equilibrium and reliability [23][25].
Backtracking Search Algorithm	Optimize Power flow, reduce generation cost, improve reliability, and enhance scheduling of DGs [23][25][29].
Stochastic Bi-level Optimization	Maximizes profit by employing least-cost bidding strategy for day-ahead energy market, reduces consumption imbalance charges, and controls real-time generation forecast [25,26]
Lagrangian Relaxation-based mechanism	Coordinates decentralized VPPs using active and reactive power flow [25][30]
Imperialist Competitive Algorithm	Regulate power loss and minimize energy production cost [25][31]
Two-stage Optimization Model	Manages outputs of DERs to adapt to real-time fluctuations in generation and minimizes the difference between actual output and forecasted output utilizing the renewable energy sources to their maximum potential [32]
Model Predictive Control Algorithm	Control reconfigurable inverters and manage hydrogen production and consumption in islanded MGs, optimize multiobjective functions and cut down operating costs of energy storage systems [33, 34].
Adaptive Robust Optimization	Resolves self-scheduling of a VPP trading in electricity markets [35]
Ant Colony and Genetic Algorithm	Reduce the electricity production expenses, minimize carbon footprint, boost load equilibrium and reliability [25,26].

Generation behavior, power demand characteristics, power storage performance, prosumers' preference, energy history, financial status, affordability and willingness to participate and maintain VPP infrastructure are attributed as internal factors that greatly influence the functions of VPP in managing the peak load demand and electricity cost are. Several external factors such as weather condition, government jurisdiction, electricity prices and incentives, energy trading opportunity greatly affects prosumers and thus affects VPPs [8][16][22].

Above all, the VPPs continuously strive to manage voltage and frequency range while trying to maximize the profit for its users. Scheduling of distributed resources within microgrid is essential as it would regulate the power generation and distribution within the network. It has been found in literature that Binary Backtracking Search Algorithm (BBSA) can be employed by VPPs to control the scheduling of distributed generators. The BBSA optimization algorithm yields a fitness value in binary which in turn generates the scheduling. Solar irradiation, wind velocity, charging/discharging conditions of battery, fuel states and/or the recent energy demand, all play an essential role in the generation of the fitness function. The BBSA algorithm provides optimization to the grid by reducing power losses, cutting down power generation costs, delivering top quality electrical power to the loads reliably, and adds priority-based MGs into the network to make it sustainable. This enables VPP to efficiently incorporate MGs into the existing infrastructure and balance their inconsistencies with the help of BBSA algorithm [23].

Controllers are used to anticipate and smooth the operation process and guarantee control precision, steadiness, and cost reduction. The major drawback of conventional optimization algorithm is that it always hangs on the initial local global minimum and is incompetent for multi-objective models. The backtracking search algorithm resolves these issues of multimodal and global minimum trap [25,26].

Binary BSA algorithm has been developed to overcome the unrealistic constraint and deliver optimal search schedule [24]. The BBSA procedure is employed to find the best optimal schedule to integrate VPP and MGs in the prime network. Numerous iterations are run to test the VPP methodology to obtain the best schedule and get to the intended objective.

VPP is a multi-technology entity that is interconnected with savvy devices and state-of-art communication and information technology systems. MATLAB/Simulink has been used to implement an IEEE 14-bus system to model MGs including renewable and non-renewable energy sources and loads to test the efficiency of the process and algorithm [23].

In figure 1, the IEEE 14-bus system represents a distribution network structure with loads at per unit value. The system replicates actual grid values to supply real power to the controller. Generator at Bus 1 replicates the central power network and supplies 200MW through the substation transformer rated at 33kV/11kV at 50Hz. Multiple buses at each bus bar improve the reliability of the system and the maximum peak load of active and reactive power. The system contains nine loads at different buses. A feeder is represented by every bus bar that is specific to a loading area demand.

According to the IEEE standard, splitting the energy system in multiple MGs improves the operation and reliability of the distribution network thus, five MGs with similar characteristics have been installed at different buses. This is believed to reduce transmission line losses, provide better system reliability, and enhance power quality within the infrastructure. The MG location within the demo network is dependent upon the bus load; each bus with less than 10MW load is given a MG. This is mainly because MGs have the capability to maintain system reliability by supplying a steady rate of power in case of any emergency. Each MG supplies 10MW with 415V at 50 Hz to their respective buses as a size consideration to support the bus islanded mode. Each participating source utilizes the decision of the controller and deploys optimized binary scheduling upon considering the weather conditions, load capacity, kWh price, battery condition, fuel, etc.

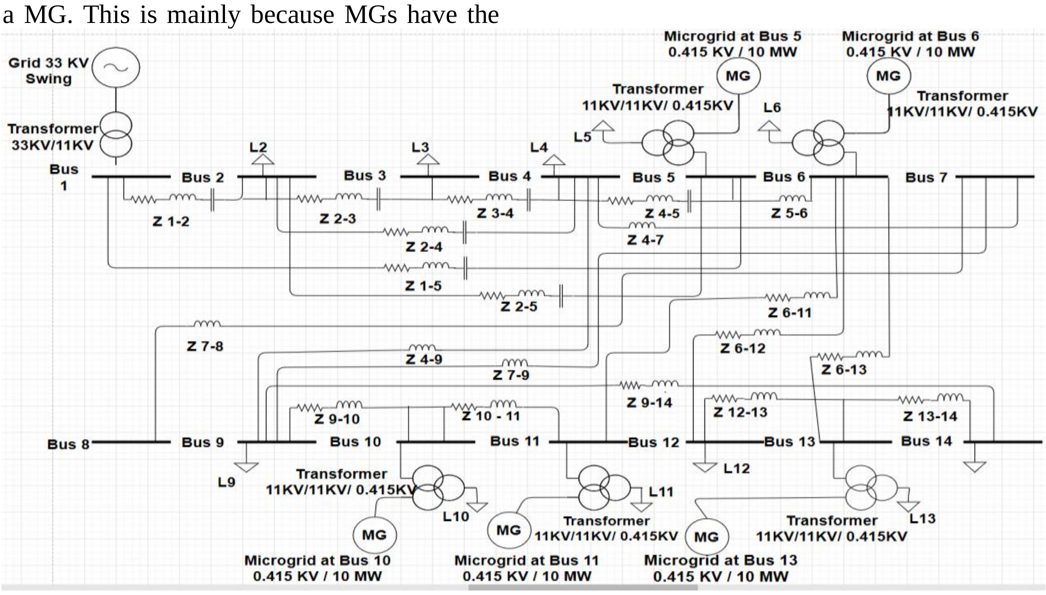

Fig. 1. ***IEEE 14 – Bus Test System in VPP with MGs [23]***

C. Optimal Scheduling Controller

The VPP has a dedicated controller that supervises and schedules the ON and OFF functioning of the MGs depending on the condition of DGs. The primary goal of the controller is to identify the right energy source within VPP to utilize its power economically to fulfill the load demand. Since the operating capacity of the renewable sources is intermittent, an optimized algorithm is of utmost importance. This algorithm would define the available energy capacity and convey signals that command power dispatchability to the loads [24].

The conventional scheduling comes with multiple challenges such as control precision, steadfastness, reduction of cost, etc. An optimization algorithm is deemed best to build a scheduling controller that would perform without any human intervention. A decent optimization procedure is determined by its capability to run smoothly around the local minimum without getting stuck and obtain the most augmented values [23]. BBSA is a dual-population algorithm that follows arbitrary mutation tactic to find one direction for each specific target. The simple structure of BBSA makes it easier to implement as it does not rely on the initial values for enhancing or restricting the objective function compared to other evolving optimization techniques. The fundamental components involved in optimization are input vectors, objective function formulation and constraints. For the development of a good optimizing schedule every component is vital. In what follows, these components are explained [23].

INPUT VECTOR:

The BBSA optimization algorithm functions by defriending the input vectors. These vectors include schedule matrix cell, maximum iterations, population size, number of problem dimension, number of hours and status.

OBJECTIVE FUNCTION FORMULATION:

The objective function is the primary framework for the optimization prototype that either needs to be minimized or maximized. For the BBSA algorithm the objective function is formulated to be the global minimizer. This explains the working strategy of BBSA algorithm into stages that include initialization, selection, mutation and selecting minimum fitness with global minimum to obtain the best cell.

CONSTRAINTS:

Constraints are set to steer the objective function to find the minimum targeted value by the end of the last iteration. For BBSA, the status of the grid power, solar irradiance, wind speed, energy price, etc. are considered as constraints. The matrix value of the objective function is weakened satisfying the constraints by manipulating the historical matrix and setting minimum fitness for each iteration of the objective function.

The BBSA converts the decimal number of BSA into a binary number using the sigmoid function for every search and returns the optimized binary schedule. BBSA generates the global minimum fitness and finds the best cell for optimal scheduling. The primary goal of the algorithm is to diminish the excessive power flow within the network architecture, contribute to build a thriving distribution system and use the ecological resources in a lucrative way.

D. Distributed System Operator

Along with the optimization algorithm, it is paramount to understand the role of Distributed System Operator (DSO) to fully incorporate dispatchability in VPPs. DSOs are responsible to assess the status of DERs to help VPPs increase the profit margins and maintain the network security [27]. DSOs and VPPs communicate to dissolve congestion issues within the grid that results from voltage rises if DERs overload the feeders. In [7], a rolling horizon-based approach has been utilized to minimize the operational uncertainties at initial planning stage. Prosumers' behaviors and energy rebound effect have been taken into consideration to mitigate congestion in the system. Two-level coordination approach [36] as well as center of mass load model [37] have been proposed to relief the grid of congestion and voltage instability based on power tariffs.

VPPs have actively contributed towards voltage management at consumers' end by employing Volt-Watt Control (VWC) and Volt-Var Control (VVC) for both active and reactive powers, respectively [7]. Distributed System Constraints (DCSs) are assigned by DSO as a representation of appropriate power output to manage voltage stability when VPP bids in the wholesale energy market [37]. For the most optimal outcomes in terms for system efficiency and economical leverage, DERs within the network are grouped according to their geographical locations along the distribution lines and assigned corresponding DSCs to each group. A DSC calculation algorithm is proposed that can effectively minimize changes in the fundamental scheduling offered by VPP at the energy market to reduce any additional operational cost. It also works to mitigate any power losses throughout the distribution network that may result from scheduling adjustments [7]. To fully understand the dynamics of optimal scheduling algorithms and voltage management using VWC and VVC, it is of utmost importance to explore the fundamentals for an interaction-based operation between VPP and DSO.

Upon research, it has been found that VPPs are not bound by geographic locations of DERs, which enables DERs to be associated with different feeders; thus, giving VPPs the advantage of controlling the local units. For example, if a feeder is faced with overvoltage issues, the VPP can instantly reduce the power supply of DERs associated to that feeder and increase the generation of other DERs to match scheduling committed at energy market. DSO plays a vital role in voltage management by providing corresponding DSC to VPP that establishes operating plans according to energy market requirements. DSC is a by-product of continuous information exchange between DSOs and VPPs. DSO does not directly control the DERs to manage the proper functioning of the system, it rather provides VPPs with DSC with a calculated constraint capacity for specific location and thus maintains transparency and neutrality. On the other hand, VPPs provide the wholesale energy market scheduling and DER locations to DSO, DSO then divides the DERs into groups based on their feeder section and location along the distribution line. VPPs then receive information about each group and anticipates the available energy capacity range depending upon the allocation of power supply to each DERs. This data is sent back to DSO which then continues to perform its function and generate DSCs. This establishes a group level communication between the DSO and VPP and ensures voltage management without exchanging vital information and upholding network security [7][37]. This entire process loops until the targeted voltage value is reached. The DSC calculation algorithm significantly reduces economic losses by 24% [37]. An optimal balance between VWC and VVC is essential to increase the profits and decrease operational costs.

Since VPP is an emerging concept there are many operational methodologies that are under assessment. IoE is actively employed to establish communication infrastructure within the VPP network. Energy routers and solid-state transformers are extensively used to connect demand responsive loads and build an interface for information exchange [16]. VWC and VVC are investigated to help the Distributed System Operators to regulate the voltage management and keep the network stable [7]. Machine learning, reliability index, neural network-based studies are simultaneously run to develop the best optimization algorithm that would enable the VPP to function at its best. MATLAB, SCADA, PSCAD and many other software are being exploited to test the concepts and generate results to compare system functions [4][12][22].

III. Conclusion

Smart Grids, Microgrids, VPPs are the future of the electricity world. The energy industry will heavily rely upon the performance of these entities to ensure network stability and robustness. The addition of RESs and DERs will certainly impact the performance of the incumbent architecture and increase complexity. The increasing number of prosumers and bidirectional power transaction will create numerous challenges for DSOs and the energy market will be overwhelmed. All these challenges can be addressed if VPPs are brought to play. The proper implementation of VPP will significantly reduce the operational complexities and improve the system characteristics. The vision of reducing carbon footprint and having a greener world will come into being through the successful execution of VPPs and MGs. Voltage and frequency stability will be established through continuous real-time interaction between DERs and DSOs. Scheduling the ON and OFF of DGs is done and dispatchability of weather dependent energy sources can be ensured. Energy storage systems and batteries play a vital role in making the electricity network reliable and resilient. VPPs bargains in the wholesale energy market on behalf of its users to ensure that prosumers are making the maximum profit by sharing or selling energy to neighbors or in the market. VPPs also utilize the off-peak hours to charge batteries and other storage devices and discharge during peak hours to ensure energy cost is minimum. Overall, VPPs are the promising future of energy system management. It has tremendous potential and would change the dynamics of electricity infrastructure, making it reliable, sustainable, and robust.

Acknowledgment

I am grateful to Deakin University for providing scholarship to pursue my PhD studies, which I have started recently.

REFERENCES

[1] A. Hirsch, Y. Parag and J. Guerrero, "Microgrids: A review of technologies, key drivers, and outstanding issues", *Renewable and Sustainable Energy Reviews*, vol. 90, pp. 402-411, 2018.

[2] G. Gersema and D. Wozabal, "Risk-optimized pooling of intermittent renewable energy sources", *Journal of Banking & Finance*, vol. 95, pp. 217-230, 2018.

[3] D. Blumberga, B. Chen, A. Ozarska, Z. Indzere and D. Lauka, "Energy, Bioeconomy, Climate Changes and Environment Nexus", *Environmental and Climate Technologies*, vol. 23, no. 3, pp. 370-392, 2019.

[4] F. Sheidaei and A. Ahmarinejad, "Multi-stage stochastic framework for energy management of virtual power plants considering electric vehicles and demand response programs", *International Journal of Electrical Power & Energy Systems*, vol. 120, p. 106047, 2020.

[5] M. Ilic, J. Black and M. Prica, "Distributed electric power systems of the future: Institutional and technological drivers for near-optimal performance", *Electric Power Systems Research*, vol. 77, no. 9, pp. 1160-1177, 2007.

[6] D. Pudjianto, C. Ramsay and G. Strbac, "Virtual power plant and system integration of distributed energy resources", *IET Renewable Power Generation*, vol. 1, no. 1, p. 10, 2007.

[7] S. Park and S. Son, "Interaction-based virtual power plant operation methodology for distribution system operator's voltage management", *Applied Energy*, vol. 271, p. 115222, 2020.

[8] A. Mahmood, A. R. Butt, U. Mussadiq, R. Nawaz, R. Zafar and S. Razzaq, "Energy sharing and management for prosumers in smart grid with integration of storage system," *2017 5th International Istanbul Smart Grid and Cities Congress and Fair (ICSG)*, Istanbul, 2017, pp. 153-156, doi: 10.1109/SGCF.2017.7947623.

[9] L. van Summeren, A. Wieczorek, G. Bombaerts and G. Verbong, "Community energy meets smart grids: Reviewing goals, structure, and roles in Virtual Power Plants in Ireland, Belgium and the Netherlands", *Energy Research & Social Science*, vol. 63, p. 101415, 2020.

[10] N. Verkade and J. Höffken, "Collective Energy Practices: A Practice-Based Approach to Civic Energy Communities and the Energy System", *Sustainability*, vol. 11, no. 11, p. 3230, 2019.

[11] A. Rosato, M. Panella and R. Araneo, "A Distributed Algorithm for the Cooperative Prediction of Power Production in PV Plants", *IEEE Transactions on Energy Conversion*, vol. 34, no. 1, pp. 497-508, 2019.

[12] P. Asmus, "Microgrids, Virtual Power Plants and Our Distributed Energy Future", *The Electricity Journal*, vol. 23, no. 10, pp. 72-82, 2010.

[13] T. L. Vandoorn, B. Zwaenepoel, J. D. M. De Kooning, B. Meersman and L. Vandevelde, "Smart microgrids and virtual power plants in a hierarchical control structure," *2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies*, Manchester, 2011, pp. 1-7, doi: 10.1109/ISGTEurope.2011.6162830.

[14] B. Behi, A. Baniasadi, A. Arefi, A. Gorjy, P. Jennings and A. Pivrikas, "Cost–Benefit Analysis of a Virtual Power Plant Including Solar PV, Flow Battery, Heat Pump, and Demand Management: A Western Australian Case Study", *Energies*, vol. 13, no. 10, p. 2614, 2020.

[15] B. Koirala, E. Koliou, J. Friege, R. Hakvoort and P. Herder, "Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems", *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 722-744, 2016.

[16] K. Mahmud, B. Khan, J. Ravishankar, A. Ahmadi and P. Siano, "An internet of energy framework with distributed energy resources, prosumers and small-scale virtual power plants: An overview", *Renewable and Sustainable Energy Reviews*, vol. 127, p. 109840, 2020.

[17] N. Liu, X. Yu, C. Wang, C. Li, L. Ma and J. Lei, "Energy-Sharing Model With Price-Based Demand Response for Microgrids of Peer-to-Peer Prosumers," in *IEEE Transactions on Power Systems*, vol. 32, no. 5, pp. 3569-3583, Sept. 2017, doi: 10.1109/TPWRS.2017.2649558.

[18] K. Gill, S. Yang, F. Yao and X. Lu, "A zigbee-based home automation system," in *IEEE Transactions on Consumer Electronics*, vol. 55, no. 2, pp. 422-430, May 2009, doi: 10.1109/TCE.2009.5174403.

[19] F. Aalamifar, L. Lampe, S. Bavarian and E. Crozier, "WiMAX technology in smart distribution networks: Architecture, modeling, and applications," *2014 IEEE PES T&D Conference and Exposition*, Chicago, IL, 2014, pp. 1-5, doi: 10.1109/TDC.2014.6863432.

[20] A. Tascikaraoglu, O. Erdinc, M. Uzunoglu and A. Karakas, "An adaptive load dispatching and forecasting strategy for a virtual power plant including renewable energy conversion units", *Applied Energy*, vol. 119, pp. 445-453, 2014.

[21] A. Mohd, E. Ortjohann, A. Schmelter, N. Hamsic and D. Morton, "Challenges in integrating distributed Energy storage systems into future smart grid," *2008 IEEE International Symposium on Industrial Electronics*, Cambridge, 2008, pp. 1627-1632, doi: 10.1109/ISIE.2008.4676896.

[22] F. Chen, D. Liu and X. Xiong, "Research on Stochastic Optimal Operation Strategy of Active Distribution Network Considering Intermittent Energy", *Energies*, vol. 10, no. 4, p. 522, 2017.

[23] M. Abdolrasol, M. Hannan, A. Mohamed, U. Amiruldin, I. Abidin and M. Uddin, "An Optimal Scheduling Controller for Virtual Power Plant and Microgrid Integration Using the Binary Backtracking Search Algorithm", *IEEE Transactions on Industry Applications*, vol. 54, no. 3, pp. 2834-2844, 2018.

[24] P. Civicioglu, "Backtracking Search Optimization Algorithm for numerical optimization problems", *Applied Mathematics and Computation*, vol. 219, no. 15, pp. 8121-8144, 2013.

[25] T. Sikorski et al., "A Case Study on Distributed Energy Resources and Energy-Storage Systems in a Virtual Power Plant Concept: Technical Aspects", *Energies*, vol. 13, no. 12, p. 3086, 2020.

[26] E. Kardakos, C. Simoglou and A. Bakirtzis, "Optimal Offering Strategy of a Virtual Power Plant: A Stochastic Bi-Level Approach", *IEEE Transactions on Smart Grid*, pp. 1-1, 2015.

[27] D. Koraki and K. Strunz, "Wind and Solar Power Integration in Electricity Markets and Distribution Networks Through Service-Centric Virtual Power Plants", *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 473-485, 2018.

[28] Z. Liang, Q. Alsafasfeh, T. Jin, H. Pourbabak and W. Su, "Risk-Constrained Optimal Energy Management for Virtual Power Plants Considering Correlated Demand Response", *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 1577-1587, 2019.

[29] M. Abdolrasol, M. Hannan, A. Mohamed, U. Amiruldin, I. Abidin and M. Uddin, "An Optimal Scheduling Controller for Virtual Power Plant and Microgrid Integration Using the Binary Backtracking Search Algorithm", *IEEE Transactions on Industry Applications*, vol. 54, no. 3, pp. 2834-2844, 2018.

[30] D. Papadaskalopoulos, D. Pudjianto and G. Strbac, "Decentralized Coordination of Microgrids With Flexible Demand and Energy Storage", *IEEE Transactions on Sustainable Energy*, vol. 5, no. 4, pp. 1406-1414, 2014.

[31] M. Kasaei, M. Gandomkar and J. Nikoukar, "Optimal management of renewable energy sources by virtual power plant", *Renewable Energy*, vol. 114, pp. 1180-1188, 2017.

[32] W. Guo, P. Liu and X. Shu, "Optimal dispatching of electric-thermal interconnected virtual power plant considering market trading mechanism", *Journal of Cleaner Production*, vol. 279, p. 123446, 2020.

[33] A. Cecilia, J. Carroquino, V. Roda, R. Costa-Castelló and F. Barreras, "Optimal Energy Management in a Standalone Microgrid, with Photovoltaic Generation, Short-Term Storage, and Hydrogen Production", *Energies*, vol. 13, no. 6, p. 1454, 2020.

[34] X. Wang, L. Li, A. Palazoglu, N. El-Farra and N. Shah, "Optimization and control of offshore wind farms with energy storage systems", *IFAC-PapersOnLine*, vol. 51, no. 18, pp. 862-867, 2018.

[35] A. Baringo, L. Baringo and J. Arroyo, "Day-Ahead Self-Scheduling of a Virtual Power Plant in Energy and Reserve Electricity Markets Under Uncertainty", *IEEE Transactions on Power Systems*, vol. 34, no. 3, pp. 1881-1894, 2019.

[36] J. Hu, H. Morais, T. Sousa, S. You and R. D'hulst, "Integration of Electric Vehicles into the Power Distribution Network with a Modified Capacity Allocation Mechanism", *Energies*, vol. 10, no. 2, p. 200, 2017.

[37] U. systems, "Blog: Virtual Power Plants (VPP): Applications for Power System Management - Example Germany - ESIG", *ESIG*, 2020. [Online]. Available: https://www.esig.energy/blog-virtual-power-plants-vpp-applications-for-power-system-management-example-germany/. [Accessed: 13- Oct- 2020].

[38] "Why (and How) Microgrid Technology Is a Good Power Source", *Pewtrusts.org*, 2020. [Online]. Available: https://www.pewtrusts.org/en/research-and-analysis/issue-briefs/2016/02/why-and-how-microgrid-technology-is-a-good-power-source. [Accessed: 13- Oct- 2020]

[39] M. Shabanzadeh, M. Sheikh-El-Eslami and M. Haghifam, "An interactive cooperation model for neighboring virtual power plants", *Applied Energy*, vol. 200, pp. 273-289, 2017

[40] L. Hernández, C. Baladrón, J. Aguiar, B. Carro, A. Sánchez-Esguevillas and J. Lloret, "Artificial neural networks for short-term load forecasting in microgrids environment", *Energy*, vol. 75, pp. 252-264, 2014.