Review of Microgrid Energy Management Techniques on Virtual Power Plant System

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Abstract

The growing energy supply and demand are slowly changing the nature of power transmission and distribution, and the application of virtual power plant (VPP) has already gained traction in countries like Sweden, Germany, and Belgium. The dynamic nature of the VPP platform to connect multiple microgrids within the same geographical location, and to some degree, large-scale nationwide energy resources make it a state-of-the-art technological innovation. The platform has been applied for distributed energy resources (DERs) and dispatchable generation units such as combined heat and power (CHP) to monitor and control energy production and consumption, which also includes the integration of renewable energy sources (RES) into the energy mix. The energy management system (EMS) is one of the function modules in the control system of the VPP and can regulate energy stored and discharged from the energy storage system (ESS), generally, microgrids are known to connect regions far away from the main grid and can operate on islanding mode or on-grid, and they largely facilitate electrification of remote areas as energy production is done onsite. Therefore, in this review control strategies for energy management systems are analyzed and compared, e.g., Multi-Agent System (MAS), and Model Predictive Control (MPC), i.e., chance-constrained optimization, with the main emphasis being on minimizing costs and facilitating micro-grid stability through economical dispatch of energy generational units.

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1. INTRODUCTION

The future grid network also referred as the smart grid of the future is envisioned to accommodate variety of energy sources. In the scheme of availing energy to meet increasing demand, modern power transmission and distribution challenges are inevitable, for instance, integration of more RESs into the grid can potentially results in unexpected supply shortages depending on the weather conditions, which poses grid reliability issues such as power losses and prolonged outages, such issues can be contained by use of adaptive EMS methods to control PV production, energy stored in the battery and

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energy from diesel generators as per the set network constraints. Currently, the modern trends and the impact of climate change has forced the adoption of cleaner ways of generating electricity, and renewables are the best alternative to combat climate change, however integration of these resources is the main hurdle as power output is stochastic, in order to solve the emerging issues in smart grid systems, Scientists and the global energy community are at the helm of providing tools and software platforms meant for smooth energy transition, that is, a modernized grid network with increased RES and controllable loads which include roll out of electric vehicles, and improved demand response strategies, for instance using an EMS with the view of reducing carbon emissions, and applying intelligent IoT-driven systems, which can act as hubs for generating consumption data for households through a Multi-agent System (Omarov & Altayeva, 2018). The control methods are crucial for the diagnostic and predictive maintenance of energy systems, (Raju et al., 2016) MAS, control technique has been applied to model a microgrid with penetration of renewable energy sources, by use of multi-agent approach various energy sources have been modelled as agents participating in energy sharing through a collaborative approach. All agents are designed to meet grid requirements, in terms of supply and demand, in case violation of energy balance equation is violated, the Independent System Operator (ISO) steps in by assessing the stability of the grid, at the same time ensuring physical delivery of power without power quality setbacks, such as voltage sag, voltage swell and harmonics. MPC method uses long-short term memory (LSTM) neural network to predict load consumption pattern on hourly basis, by considering the generation of wind or photovoltaic forecasted information. The method can complement the solution strategy of having a reduced economic dispatch cost for a VPP platform, and the optimal scheduling problem is then solved by an advanced version of particle swarm optimization (PSO) algorithm (Chang et al., 2020). MPC method has been used for microgrid control through an EMS platform to optimally control flexible loads, heating systems and generation sources (Parisio et al., 2017), the user is given access to the control system and can view demand forecast, energy prices and all the microgrid constraints. According to (Grosso et al., 2014) chance constrained MPC (CC-MPC) has been used to calculate probabilistic modelling of system disturbances without violating system constraints specified within the model, meanwhile (Velarde et al., 2017) gives a detailed analysis of a two stage CC-MPC for unit commitment.

This paper review covers two techniques that have been uniquely identified in literature for micro-grid control, the two methods will be compared with reference to their existing case studies. This study forms the foundation on which VPP concept can be developed as a solution for renewables integration into the grid network.

2. FUNCTIONALITY OF THE CONTROL METHODS

The control method applied for micro-grid control is chosen depending on the problem at hand, MAS is actualized using software agents, which are instantiated in a distributed system, the agents are programmed in a way that they collaborate to solve problems beyond their individual capacity. MAS is part of distributed artificial intelligence (DAI), whereby the agents are sociable and autonomous and can reach each other through a unified communication language (Olivares, 2014). In regard to the MPC method, its various sub-techniques, i.e., multi-scenario, tree-based, and chance constrained model predictive control, they mostly end up with similar results (E.C.A, 2016). Generally, MPC method applicability is suitable for many industries, especially when solving problems associated with non-linearities and constraints that involve manipulated variables and latency. Additionally, MPC is a model-oriented method with a step-by-step algorithm that provides a feedback mechanism.

The algorithm transits through three parts, i.e., predictive model, rolling optimization, and feedback correction (Parisio et al., 2014).

2.1 Multi Agent System Deployment

Normally, electrical substations are monitored using Supervisory Control and Data Acquisition (SCADA) system, which has wide geographical coverage, its centrality ensures remote monitoring of power distribution systems, and they are capable of reporting to the maintenance crew in real time to correct erroneous equipment and reduce power outage durations. However, the use of sensors mostly results in erroneous reporting and false alarm, which wastes a lot of time and operational resources for the utility providers. In comparison to the use of MAS approach, little to no error is an achievable fit, as the agents are distributed across the network, offering certainty on the operational nature of the equipment and instant reportage, as the agents are autonomous and when affected the source and the cause is identified with absolute certainty. Apparently, a micro-grid can be on-grid or islanded as per the state of the Breaker. The agent platform contains multiple energy agents representing unique power equipment, storage sources and generation units. A Circuit Breaker is modelled as a Switch Agent, Load Agent includes sensitive and critical loads, adjustable loads, and curtailable loads, also Generator Agent that include CHP, Non-dispatchable generation, Solar and small dispatchable generation (DG), etc. Consequently, Storage Agent considers thermal storage and Battery Storage. The agents are developed in an agent platform, for the demonstration purpose Java Agent Development Environment (JADE) is used to model MAS approach. JAVA upholds standards for intelligent agents as specified by Foundation of Intelligent and Physical Agent (FIPA), meanwhile JADE provides an environment that allows agents to execute without privy to the complex nature of operating system in use, and agents can be found in more than one computer in a network topology, and the communication among the agents is enabled by use of same type of code; used for sending and receiving messages, additionally JADE executes in a Java Virtual Machine (JVM), which live in a container that constitute a platform responsible for balancing of power in the micro-grid. The Agent Management System (AMS) has oversight over the agent platform and keeps a record of directory of agent identifiers (AIDS) together with agent states, AMS assigns each agent a unique identity. While the DF provides a channel for agents to be aware of other agents distributed in the platform. On the same note, the message transport service (MTS) maintains communication channel amongst the agents during task execution. MAS and IoT components interaction on the Multiagent System platform (Omarov & Altayeva, 2018), the Switch Agent connects the micro-grid and the utility grid, and the state of all the agents are recorded in the agent management system, and sensor variables such as temperature, air quality, humidity and illumination status are processed by respective controllers, which are connected to the central coordinator agent.

2.1.2 MAS Use Case Description

MAS method has been tried in multiples scenarios, and research shows effectiveness of the method in controlling a solar microgrid with JADE agents, (Raju et al., 2016) discusses multiagent system modelling of solar microgrid in Matlab and use of MACSimJX as a communication link between Matlab and JADE environment. MAS system architecture for West Virginia Super-Circuit (WVSC) physical Project (Chouhan et al., 2013), control is achieved by various agents instantiated in the distribution network, command and decision making starts at the substation agent and subsequent involvement of all the agents in the power distribution system. In real physical systems, MAS has been successful in fault identification within the transmission network, with an aim to show zones that are faulty in real time. WVSC is one such example, whereby agents have been designated to aid in faulty regional demarcation, the agents include Switch agent, zone agent and recloser agent. WVSC consists of many zones interlinked through intelligent electronic devices. Figure 1 shows the scale of WVSC project.

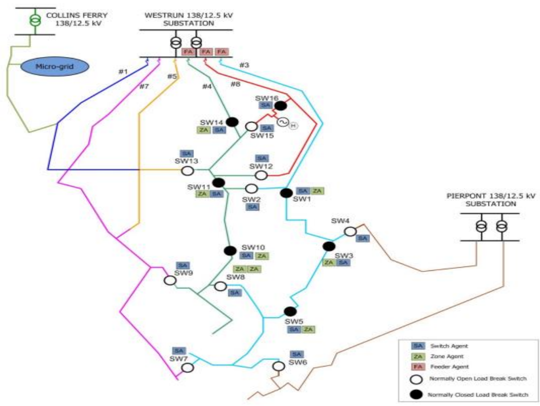

Figure 1. The WV MAS controlled super circuit (Chouhan et al., 2013)

The use of MAS for control purposes facilitates grid resiliency and with the view of incorporating renewable energy sources, the method can easily balance supply and demand in real-time through the defined agents. Each of the agents is fully aware of its environment and they are connected one level above the other, for example, Switch Agent obtains voltage and current RMS values with a resolution of 16 samples per cycle (Chouhan et al., 2013), meanwhile, the Zone agent is above the switch agent, and is able to gather all the information concerning all the switch agents and exchanges the information with other zone agents, at the same time flags the faults that occur within the specified zones. Finally, the recloser agents ensure the safety of the feeder lines and monitor the situation by closing and opening the feeder lines.

2.2 Model Predictive Control

The objective of MPC is to minimize costs by dispatching network resources at the least cost, this way the consumers get energy at low tariffs, at the same time ensuring stability of the network as top priority to the system operator. The MPC approach has a set of simplified steps and due to its feedback mechanism concept, stochastic nature of renewables can be modeled as a forecast model input to the objective function to derive continuous set-points for dispatch of the network resources.

2.2.1 Model Predictive Control Mathematical Modelling (Grosso et al., 2014)

In the mathematical problem formulation, the CC-MPC approach is used to solve equation 1, and the essential part is minimizing the objective function by use of expected values and decision variables.

$$\underset{u[k:k+N-1}{\text{Min}} \sum_{i=k}^{k+N-1} \mathbb{E}\left[J\big(x(i), u(i)\big)\right] \tag{1}$$

Objective function shown in equation 1 is subject to the following constraints,

$$x(i+1) = Ax(i) + Bu(i) + E\omega(i) \quad (2)$$

$$\mathbb{P}[x_{min} \leq x(i+1) \leq x_{max}] > 1 - \delta_x \quad (3)$$

$$u(i) \in U, \qquad \forall i \in \mathbb{Z}_0^{N-1} \quad (4)$$

Whereby; $\mathbb{E}$ represents the expected value of the loss function and $\mathbb{P}$ is the probability operator, and N is required for the computation of the controller, while $\delta_x \in (0,1)$ is the penalty applied when the constraint is out of bounds. Also x_{max} and x_{min} represent the upper bound and lower bound respectively. Additionally, disturbances are modeled as Gaussian random variables, x being a normal variable with mean $\bar{x}$, and $\sigma_{x(k)}$ being the standard deviation indicated as $x(k) = N(\bar{x}, \sigma_{x(k)})$. For CC-MPC deterministic equivalent is obtained by equation 5 below.

$$\mathbb{P}[x(i+1) \geq x_{min}] \geq 1 - \delta_x \quad (5)$$

Variable x is standardized by applying Z score to establish the relationship between the data point and the mean divided by the standard deviation, as shown by the manipulations below.

$$Z = \frac{x(i+1) - \bar{x}(i+1)}{\sigma_{x(i+1)}} \quad (6)$$

$$\mathbb{P}(Z \geq= \frac{x_{min} - \bar{x}(i+1)}{\sigma_{x(i+1)}} \geq 1 - \delta_x \quad (7)$$

This can further be written as,

$$\mathbb{P}(\boldsymbol{Z} \leq= \frac{\boldsymbol{x_{min}} - \boldsymbol{\bar{x}(i+1)}}{\boldsymbol{\sigma_{x(i+1)}}} \leq \boldsymbol{\delta_x} \quad (8)$$

$$\boldsymbol{\varphi}(\frac{\boldsymbol{x_{min}} - \boldsymbol{\bar{x}(i+1)}}{\boldsymbol{\sigma_{x(i+1)}}} \leq \boldsymbol{\delta_x} \quad (9)$$

And ***φ(.)*** is for the probability distribution function, which shows whether the random value, i.e., x takes an equal value at $\mathbb{P}(x)$.

$$\frac{x_{min} - \bar{x}(i+1)}{\sigma_{x(i+1)}} \leq \varphi^{-1}(\delta_x) \quad (10)$$

$$\bar{x}(i+1) \geq x_{min} - \varphi^{-1}(\delta_x)\delta_{x(i+1)} \quad (11)$$

Finally, the deterministic equivalent of the lower and upper bound of the chance constraints can be expressed as shown by equation 10 and 11, respectively.

2.2.2 CC-MPC Use Case Description

Application of CC-MPC method has been realized in a microgrid owned and run by HyLab, the system consisted of a photovoltaic field represented by an electronic power source that supplies power to the load, the remaining power in case of oversupply is stored in a battery, there is also an electrolyzer that can supply power when the overall demand is not met. Additionally, the Hydrogen Path available onboard serves two purposes, the first path produces and stores hydrogen while the second path feeds the fuel cell with hydrogen to supply the grid with power. Both the fuel cell and the electrolyzer are of proton exchange membrane (PEM) and hydrogen is in the form of metal

hydrides to facilitate storage. Additionally, energy transfer is enabled by converters that connect multiples devices in the system topology.
The results were gotten from the simulations that employed a nonlinear model (Valverde et al., 2013), and generally applied prediction horizon, N=5, sampling time 30s and simulated for a period of 36 hours, the HyLab linear model constituted the internal model of the controller. Furthermore, disturbances used in the simulation exercise were from the registered real demand of May 23,2014 as shown in figure 2.

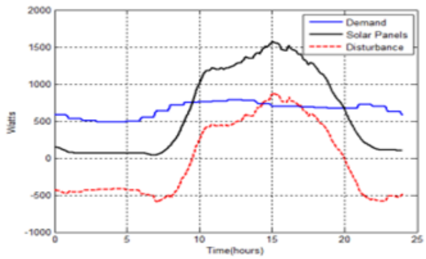

Figure 2. Energy demand, solar PV production and disturbance as of May 23,2014

The appication of CC-MPC factors in the failure probabilty of $\delta\_x<1\%$, and the disturbances follow a normal function whereby μ=0.3020 and σ=0.5245 as per historical data of May 23, 2013, exactly one year before the simulation was carried out. It was found that the average tracking error of the desired point for the State of Charge (SoC) of the battery was 6.88% and the one corresponding to the metallic hydrogen or (metallic hydrides level) MHL was 2.2%. In literature, when traditional MPC control strategy is compared with the robust control method in this case CC-MPC, there is a world of a difference in terms of computational time, and cumulative final cost.

3. DISCUSSION

The two methods are generally used for the micro-grid control and to some extent are candidates for application of VPP, in terms of DERs scheduling and curtailment planning especially when the highest percentage of generation is obtained from renewables. MAS method application basis emerges from the limitation of SCADA systems, which typically can suffer huge errors emanating from system noise that corrupts the accuracy of measurements, through an agent managed approach such errors can be minimized to a confidential interval suitable for the micro-grid stability. (Luo et al., 2017) MAS and MPC method have been used together to coordinate and optimize the micro-grid, the two methods work in synchronicity to control the microgrid, while the agents use a consensus algorithm as a distribution control strategy. The MPC obtains network information and using rolling optimization external disturbances are minimized, however if MAS is used alone limitations exist and performance of the micro-grid in regard to power delivery would not be effective as much (Parisio et al., 2014), since a lot of constraints such as DG, storage dynamics and curtailments are not considered. It is for this reason MPC method is preferred for multiple DGs and storage systems connected to the micro-grid, research also shows the method has a profound effect in storage systems economical dispatch, as operational and cost constraints are factored in the optimization time horizon. The performance of MPC method has also been comprehensively discussed in (Fernández et al., 2020), meanwhile tunning parameters have been clearly outlined to indicate decrease and increase impact on the MPC controller, additionally design fundamentals of a MPC controller have been applied to a renewable penetrated micro-grid.

4. CONCLUSION

It is imperative to note that depending on the magnitude of the scale of control, MAS and MPC can be chosen, in case the application is on a small-scale MAS method can be applied by instantiating socially, autonomous agents that can take care of their individual needs without violation of the micro-grid energy demand and supply constraints. The two methodologies encompass the working principle of a VPP that intends to dispatch DGs with minimal cost while maximizing cost function for participants who entirely form the prosumer class, and by virtue of storage becoming indispensable part of the grid network infrastructure, the set points to discharge and charge must be considered to avoid battery degradation and CC-MPC methods by far show high performance in literature as modeling is specifically done to incorporate Wind and PV generation.

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Conflict of Interest

The authors have no known competing interests as far as preparation of this article is concerned.

Authors Contribution

First author identified critical control methods and mathematical modeling. Second author, supervised this work and provided utmost guidance during preparation of the manuscript.

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