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Key activities to improve energy management in DC microgrids connected by urban traction

Abstract. *DC MicroGrids must have Energy Management Systems to guarantee efficient, dependable, and environmentally friendly electricity. The application of Model Predictive Control, proved to be helpful due to its adaptability and capacity to use non-linear models. This paper, based on an extensive literature review, identifies and discusses the three key activities to improve the characteristics of DC MicroGrids, i.e.: the use of Energy Storage Systems), the implementation of Demand Side Management, and the use of Model Predictive Control.*

Streszczenie. *Wydajna eksploatacja mikrosieci DC wymaga zastosowania efektywnych systemów zarządzania energią. W artykule przedstawiono przegląd proponowanych rozwiązań oraz omówiono trzy przykładowe podejścia ukierunkowane na poprawę efektywności mikrosieci DC, tj. wykorzystanie systemów magazynowania energii, wdrożenie zarządzania popytem oraz wykorzystanie do sterowania modelu predykcyjnego, który ze względu na możliwość adaptacji do dowolnej konfiguracji sieci oraz uwzględnienie procesów o charakterze nieliniowym stanowi atrakcyjną alternatywę w stosunku do innych rozwiązań. (**Kluczowe działania na rzecz poprawy zarządzania energią w mikrosieciach DC podłączonych do trakcji miejskiej**).*

Keywords: Energy Management, DC Traction Systems, DC microgrids, Energy Storage Systems, Model Predictive Control, Demand Response Program.
Słowa kluczowe: Zarządzanie energią, systemy trakcji prądu stałego, mikrosieci prądu stałego, systemy magazynowania energii, sterowanie z modelem predykcyjnym, program reagowania na zapotrzebowanie.

Introduction

Due to the growing demand for dependable, efficient, and sustainable electricity, the MicroGrid (MG), a concept that includes Energy Storage System (ESS), power flow control, distributed and renewable energy generation, has gained notice over the past few years. Additionally, DC MG has recently attracted a lot of attention due to the quick development of solar and energy storage technologies as well as the simpler control of energy transmission in DC networks compared to AC. The use of an Energy Management System (EMS) supported by an ESS that functions dependably and independently of external conditions is therefore a priority for the proper, efficient operation of such MG due to the multiple and distributed nature of the integrated facilities as well as the variability of electricity generation and consumption.

Besides, urban DC traction such as buses or charging stations in DC microgrids is a major source of electricity consumption in an urban environment and can help to reduce peak energy demand, optimize energy usage and improve energy efficiency. Additionally, DC traction can help reduce emissions and noise pollution from traffic, improve energy storage and management for electric vehicle fleets, and provide renewable energy access to electric vehicles and buses.

Model Predictive Control (MPC) is very helpful for defining energy management control methods in MG systems connected by urban traction. The potential of MPC depended not only on the prediction horizon but also on the use of non-linear models, both of which were not enabled by traditional control [1]. An intriguing paper showed an MPC-based EMS in which the performance of an MG system was modeled using a straightforward state-space model [2]. In this study, the electricity generation and consumption from Renewable Energy Sources (RESs) were taken into account as measured disturbance. As a result, the state-space equations were used to answer the MG system's constraints, such as the cost and storage systems.

A linear quadratic regulator (LQR) method for a standalone MG with electric vehicles and renewable energy sources is demonstrated [3]. Although the LQR provides closed-loop stability and feedback gains, its main flaws are its inability to function under constraints and its inability to handle system disturbances. Meanwhile, neural networks can be used in large-scale MG systems to handle problems involving nonlinear data [4, 5], due to their capacity for self-learning and prediction. However, neural networks can be prone to overfitting when the data is insufficient, resulting in poor generalization and suboptimal performance.

According to certain studies, combining MPC and Hybrid Energy Storage System (HESS) can be a potential way to increase the efficiency of microgrid operation. The MPC can optimize energy storage as efficiently as possible while taking power demand and current energy pricing into account. Additional research combine HESS with Adaptive MPC (AMPC). In this situation, the Adaptive MPC can linearize the HESS model to approach the original non-linear model.

By integrating MPC with HESS, a HESS unit efficiently manages the long and short-term power fluctuations caused by rapid load changes and unpredictability in RES power generation [6]. Another paper builds the EMS using an AMPC approach to ensure HESS operating within constraints while taking into consideration the semi-active structure's nonlinearity and the uncertainty of the driving conditions [7].

Changing the operating parameters could result in MGs performing badly overall, necessitating a retuning of the control settings [8]. Moreover, the majority of the studies that have been examined concentrate on the control system design for a single MG component. Typically, the overall MG control system architecture is not covered. Though, according to a few studies, it is possible to design control systems for the MG that take into consideration the non-linearity of the HESS, the effects of load fluctuations and disturbances from RES, as well as the Demand Response Program (DRP) altogether.

In this paper, the control system of the MG is considered to be optimized using a multi-objective optimization model. The objective is to provide an energy supply system with HESS, DRP and AMPC that is affordable, reliable, and resilient. The HESS enables more effective use of energy resources and adds reliability and resilience to the MG, while the Demand Response (DR) and AMPC help the DC MG connected by urban traction better manage its load and energy supply in reaction to changes in demand. Customers can save money, reduce their effect on the environment, and increase the reliability of their energy supply due to this system combination.

The remainder of this paper is organized as follows. Section 2 provides a description of the reviewed approaches as well as a summary of their advantages, disadvantages, and potential improvements. The proposed EMS model is outlined in section 3. Then, the discussion and conclusion are finally given in section 4 and 5 respectively.

The proposed methods

A. Adaptive Model Predictive Control .

An Adaptive MPC is an advanced kind of MPC that is able to respond to changes in system dynamics over time. It uses a model to predict the future behavior of a system, and optimal set points to ensure system performance meets its objectives, where 'e' represents the error signal between the output and the target, as shown in Figure 1. One of the main benefits of Adaptive MPC is the ability to adapt the weights parameters to changing conditions in the process without interrupting the process. This makes it highly suitable for processes with significant environmental or workload variations.

Traditional MPCs use a fixed internal plant model, which is ineffective for managing the changing dynamics. As the operating circumstances change, an AMPC allows you to provide a new linear plant model at each time step. As a result, it generates predictions for the new operating circumstances that are more precise. Therefore, an AMPC is advised in this situation to handle the changing plant conditions. The basic idea behind the proposed method is to formulate the control problem as a discrete-time state space model, and then implement a cost-based optimization of the control output signal by minimizing the weighted sum of square predicted errors and square future control values. The dynamic system's equation can be written as [2]:

(1) $$x(t+1) = Ax(t) + Bu(t) + B_d d(t)$$

(2) $$y(t) = Cx(t)$$

where $y(t)$ is the output vector, which in this situation coincides with the state, and $u(t)$ is the vector of manipulated variables, which includes the dispatchable generation, and the power exchanged by the ESSs. $x(t)$ denotes the system state, which is made up of the state of charge of the ESSs. Additionally, the state-space MPC formulation can include the impact of these disruptions, $d(t)$. A, B and C stand for the states, inputs, and ouputs matrices, respectively. B_d is the matrix used to measure how disruptions affect the states. The net impact of generation and demand can be used to classify these disturbances because both have the same influence on the energy balance (one is positive and the other is negative):

(3) $$d(t) = P_{gen}(t) - P_{dem}(t)$$

Systems with uncertain models, additive disruptions, state and control constraints are used in this adaptive MPC [9]. However, the reliability of the adaptive control system is not thoroughly investigated. The system's convergence happens comparatively slowly aside from that. Likewise, the method incurs high expenses and is quite complex [10]. Additionally, if unknown parameters enter the process model in complex ways, it might be difficult to build a continuously parameterized family of candidate controllers. Estimation across a range might be challenging. These issues get much worse if robustness and high performance are needed. Because of this, creating adaptive control algorithms frequently involves trial and error and the use of numerous specialist approaches [10].

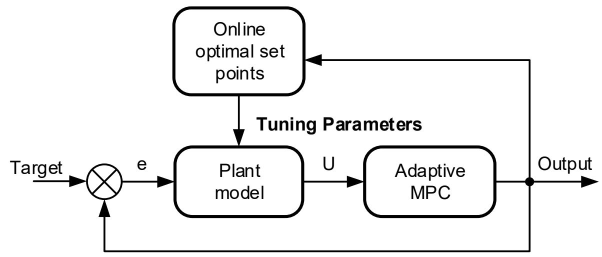

Fig 1. Adaptive Model Predictive Control scheme with online optimal set points and plant model

Applying algorithms to gauge system parameters and spot shifts in system dynamics is one way to enhance this method. Then, feed the models that were estimated online to an AMPC to manage a nonlinear plant with a broad wide range of operation. Within each control duration, a discrete-time online auto-regressive external model is found by a recursive polynomial model estimator. Through the AMPC, the latter is used to update the internal plant model [11]. Another choice is to add convex constraints that ensure excitation persistence in order to balance the potentially conflicting demands for achieving excellent tracking performance and improving parameter estimation [12].

B. Hybrid Energy Storage System

In this considered method, the battery provides the long-term power required, while the Super-Capacitor (SC) reacts to short-term power changes during the transient process. The SC offers higher cycle efficiency, faster power delivery, and more charge/recharge cycles than a battery. Additionally, There are three types of interconnection topologies for a HESS: passive, semi-active, and active. And based on the system requirements and the functions of the energy management system, a wide range of topologies can be chosen. Therefore, Table 1 provides the main aspects of some conventional and intelligent control strategies created for HESS. And Table 2 compares the HESS typologies from a few operational angles.

The most straightforward and cost-effective configuration that can beat a single energy storage technology is the passive HESS arrangement, which works best for low-power devices like household appliances.

Table 1: Comparison of some control strategies of HESS.

Controller technique	Features	Drawbacks	Ref
Rule based controller (conventional)	Simple to use and to implement, and requires minimal processing	Cannot responds well to parameter changes	[17]
Proportional intergral (conventional)	Simple to design	Uncertainty regarding the potential of modifying parameters	[18]
Model Predictive Control (Intelligent)	Can manage complex systems with lots of control variables	Cannot responds well to parameter changes	[19]
Neural Network and Fuzzy Logic (Intelligent)	It is unnecessary to use the system's exact model	Requires a lot of computing time, membership functions are adjusted through trial and error	[20]

Table 2: Comparison of HESS typologies [13]

	Complexity	Cost	Control	Flexibility	Efficiency
Passive	X	X	X	X	XXX
Semi-active	XX	XX	XX	XX	XX
Active	XXX	XXX	XXX	XXX	X

In this configuration, the SC mainly performs the function of a low-pass filter, and the filtering effects get stronger as the capacity increases. The internal resistances and voltage properties of the battery and SC also affect how power flows in this topology. For example, the low impedance of SC allows it to absorb the high power pulses in a HESS. Nevertheless, the voltage of the ESS must precisely match the voltage of the DC bus or load.

The battery's lifetime can be increased with an active HESS and an appropriate control algorithm. It is better suited to large-capacity systems that demand an improved dynamic response. However, there are higher system losses and greater demands on area and weight, which significantly raises the cost of an active HESS [14].

Additionally, a wide voltage range can be advantageous for a SC semi-active design. However, this topology is more expensive because the converter must be able to withstand large currents and substantial voltage swings [15]. For instance, in case of battery semi-active HESS, the DC bus voltage changes, and the DC-DC converter needs to be built to withstand the significant power spikes that occur in case of SC semi-active HESS. Although both the SC semi-active HESS and the three-level HESS (featuring Lithium, another form of battery, and SC) have benefits and drawbacks, it should be noted that the second is better suited for long-term applications while the first is preferable for short-term applications [16].

Table 3: A few studies on DR optimization.

DRP	Objective function	Optimization algorithm	Category of optimisation algorithms	Ref
Real time pricing	Cost of production for utilities and overall user convenience	Nonlinear programming	classic	[29]
Real time pricing Inclining block rate	Saving on bills and waiting time for consumers' convenience	Mixed integer linear programming	classic	[30]
Direct load control	Lowering the demand at its peak while raising customer comfort levels	Binary Particle swarm optimization	metaheuristic	[31]
Real time pricing	Decreasing the squared deviations between the load and the planned load	Genetic algorithm	metaheuristic	[32]
Real time pricing	Utility, retailer, and consumer payouts	Simulated annealing	metaheuristic	[33]
Time of use Critical peak pricing	Consumers' payment of bills	Teaching learning-based optimisation	metaheuristic	[34]

Table 4: The main features of DR.

Mechanism type	Price based			Incentive based			
DR program	Real Time Pricing (RTP)	Time of Use (ToU)	Critical Peak Pricing (CPP)	Direct load control	Bidding	Interruptible	Emergency
Advantages	Customer can minimize the cost with respect to price change	Low price rate during off peak	Customer response for a short period to get discount offers	Utility offers good discount for limited load reduction or shifting	Utility offers good discount for limited load reduction or shifting	Customers respond for a short period to get discount rates	Customer can get credit or discount rate for the short response
Disadvantage	Customer must answer right away to reduce the bill.	User should follow the price change with respect to time	Customer should shift or curtail home resource for a certain time	Customer should give the utility a level of authority to shift or curtail certain load	Customer should shift or curtail home resource for a certain time	Customer should shift or curtail home resource for a certain time	Customer should shift or curtail home resource for a certain time

In addition to intermittent RES, it has been demonstrated that the HESS can stabilize the energy supply for uses involving changing loads. However, the HESS' expensive price is a drawback. The lifelong economics of a HESS has not yet been thoroughly studied. Sizing the system components in accordance with a techno-economic analysis is one way to enhance this method [21, 22,23]. Using rule-based coordinated operation methods, the charging/discharging priority and optimal operating limits can be considered, and multi-objective sizing optimization models can be used to lower net present cost [24]. Additionally, one method to improve the performance of this system involves the integration of thermal and aging models into the EMS because an adequate thermal management system is required to increase battery life and efficiency [25]. The power exchanged by passive, semi-active and active HESS is the sum of power contributed by the battery and the SC as given by Eq. 3, 4 and 5 respectively:

(3) $$P_{HESS} = P_{bat} + P_{sc}$$

(4) $$P_{HESS} = \alpha P_{bat} + P_{sc} \quad \text{or} \quad P_{HESS} = P_{bat} + \beta P_{sc}$$

(5) $$P_{HESS} = \alpha P_{bat} + \beta P_{sc}$$

where α and β represent, respectively, the controllability of the battery and the supercapacitor.

C. Demand Response Program

Another way to lower energy costs and keep production and consumption in balance is to reduce customer usage during the system's energy shortage period through a DRP. With and without responsive loads, the optimization goal is to lower operating costs and pollutant emissions while taking into consideration constraints to account for the uncertainties associated with the production of wind and solar energy [26]. Table 3 summarizes some optimization methods that can be utilized to solve the DR optimisation problem. In addition, a range of DR systems are shown in Table 4.

The simplicity of a DR algorithm's implementation is one of its primary advantages. However, technological difficulties with pricing, rules, adaptive decision-making, user interactions, and dynamic operation will always exist [27]. The real-time response process, for instance, is only guaranteed to achieve equilibrium for some categories of utility functions. Furthermore, because the initial circumstances are so crucial to the dynamics of the optimum response, any changes to them could lead to a different equilibrium.

It ought to note that residential consumers have shown to be more receptive to DRP than other consumer categories, this result from the fact that the majority of commercial enterprises, including retail stores and office buildings, operate according to set business hours and lack incentives to shift their workloads.

Additionally, it is challenging to predict how consumers will react to the DR program. This line of inquiry creates a more practical formulation and solutions for the DR optimization issue, so further research in this area is encouraged [28]. It is also advised that future research concentrate on comparison of various DR programs' effects on various objectives, such as cost minimization, reliability enhancement, etc.

The suggested Model

This paper suggests a multi-objective optimization model to optimize the control system of the MG. The goal is to offer a low-cost, dependable, and resilient energy supply system using a Hybrid Energy Storage System (HESS) with Demand Response Program (DRP) and Adaptive Model Predictive Control (AMPC). The DR and AMPC enable the DC MG to better manage its load and energy supply in response to changes in demand, while the HESS allows for more efficient use of energy resources and provides additional reliability and resilience to the MG. This combination of technologies helps customers save money, reduce their environmental impact, and improve their energy reliability.

Equations 7 and 8 is an example of a dynamic model that combines state-space representation with the three previously mentioned techniques [35, 36]. Figure 2 shows this model in its general configuration as an MG connected by urban traction. In equation 7, the system states SOC_{bat} and SOC_{SC} indicate the state of charge of the battery and the supercapacitor. The manipulated variables P_{grid}, P_{ESS} and P_{load} represent the dispatchable generation, the power exchanged by the ESSs, and the power of load respectively. In addition, the system is being disturbed while it is functioning normally. Power from RESs and load are two distinct sources of disturbances. Both are system inputs that come from outside the system and that the controller cannot regulate. However, since the demand response program is introduced, renewable energy sources are the sole disturbances. The effect of these disturbances, *d(t)*, is included to the state-space MPC formulation. It is important to note that P_{load} has no effect, because the model is focused on the internal characteristics, equations, and parameters of the system.

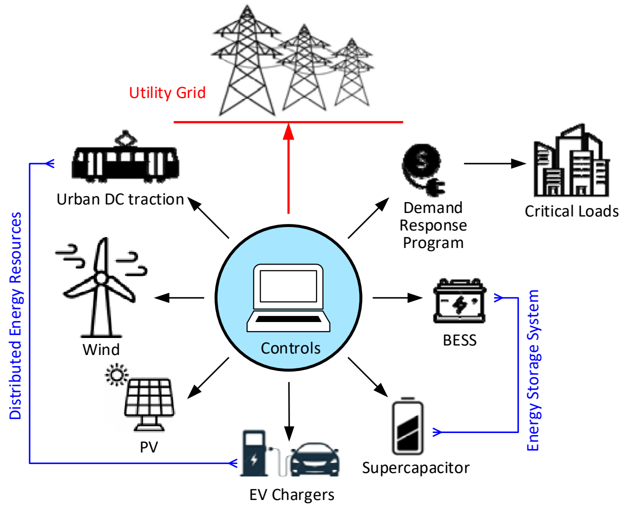

Fig.2. Conceptual illustration of the considered MG system.

In this example, the objective function is based on the economic benefits of buying and selling energy avoiding the intensive use of ESS. This optimization problem aims to satisfy different objectives in a weighted manner to meet one common goal. However, the cost function doesn't have any units. Additionally, the basic cost function of the controller do not take into account the operating cost of ESS. For this, the last equation is introduced based on parameters provided by the manufacturers. As for the cost function corresponding to residential loads it goes on fulfilling the required demand to satisfy the residential loads. The cost function J is given by equation 8, where N_p is the prediction horizon and a_1, a_2, a_3, β_1, β_2, β_3, y_1, y_2 and y_3 represent the weights of the cost function, which are chosen based on the tuning parameters of the AMPC; T_s [s], N_c [s] and N_p [s] stand for the sampling time, the control and the prediction horizon respectively, CC_{bat} [\$/kwh] is the purchase price, $Cycles_{bat}$ and V_{dcbus} [V] are the number of charging and discharging cycles and the bus voltage; The PB_{pb} [kwh] and PB_{li} [kwh] are the power exchange with the Vdc_{bus} of a Lead-acid and ion-Lithium batteries, and $Cost_{degr}$ [\$/w^{2}h] is a factor that battery breakdown process brought on by heavy charging stress and discharge procedure. η_{bat} is the charging and discharging process efficiency.

Additionally, θ and σ are binary variables for each electrical device that can be turned on or off using the curtail approach, P_{dem} (equation 9) is the term used to describe the energy demand from residential loads, and the power in the equation corresponds to the power used respectively by the fridge, freezer, lighting, shower, air conditioning, TV, washing machine, microwave, notebook, and water pump.

$$\begin{bmatrix} SOC_{bat}(t+1) \\ SOC_{sc}(t+1) \end{bmatrix} = \begin{bmatrix} SOC_{bat}(t) \\ SOC_{sc}(t) \end{bmatrix} + \begin{bmatrix} 0{,}0936 & 0{,}0936 & 0 \\ 0 & 0{,}0752 & 0 \end{bmatrix} \begin{bmatrix} P_{grid(t)} \\ P_{EES}(t) \\ P_{load}(t) \end{bmatrix} + \begin{bmatrix} 0{,}0936 \\ 0 \end{bmatrix} d(t) \tag{7}$$

$$\begin{aligned} J = {} & \sum_{k=1}^{N_p} \Big[a_1 P_{grid}^2(t+k) + a_2 P_{ESS}^2(t+k) + a_3 P_{load}^2(t+k) + \beta_1 \Delta P_{grid}^2(t+k) + \beta_2 \Delta P_{ESS}^2(t+k) + \beta_3 \Delta P_{load}^2(t+k) \Big] + \\ & + \sum_{k=1}^{N_p} \left\{ \begin{aligned} & \gamma_1 \left[SOC_{bat}(t+k) - SOC_{bat/ref} \right]^2 + \gamma_2 \left[SOC_{sc}(t+k) - SOC_{sc/ref} \right]^2 + \gamma_3 \left[P_{load}(t+k) - P_{dem} \right]^2 + \\ & + \frac{CC_{bat}^{li}}{2Cycles_{bat}^{li} C_{bat}^{li}} PB_{li}(k) T_S \eta_{bat}^{li} + Cost_{degr} PB_{li}^2(k) + \frac{CC_{bat}^{Pb}}{Cycles_{bat}^{Pb} C_{bat}^{Pb} Vdc_{bus} \eta_{bat}^{Pb}} PB_{Pb}^2(k) T_S \end{aligned} \right\} \end{aligned} \tag{8}$$

$$\begin{aligned} P_{dem} = {} & P_{fdg}(t) + P_{fzr}(t) + P_{lgt}(t) + \theta P_{shw}^a(t) + \sigma P_{shw}^b(t) + \theta P_{ac}^a(t) + \sigma P_{ac}^b(t) + P_{mwv}(t) \\ & + \sigma P_{TV}^a(t) + \theta P_{TV}^b(t) + (\theta\sigma) P_{bba}(t) + \sigma P_{not}^a(t) + \theta P_{not}^b(t) + (\theta\sigma) P_{wsh}(t) \end{aligned} \tag{9}$$

Discussion

The creation of an optimized MG system through the integration of several strategies is a crucial step in increasing energy efficiency. The performance of an MG system connected by urban traction can be improved through hybrid energy storage systems, demand response attempts, and adaptive model predictive control, among other techniques. Hybrid energy storage systems offer a dependable and adaptable energy source, while demand response programs allow customers to react quickly to changes in prices in order to save money. And, urban DC traction is used in mass transit systems where it is necessary to efficiently serve high demand areas. The MG system can also be adjusted in real-time using AMPC to account for nonlinear or time-varying plant characteristics. An ideal MG system can be created by combining these techniques, allowing for an efficient balance of energy demand and supply. The operating and degradation costs could be added to the energy management system (EMS) described in this study. Additionally, it might include a formulation that incorporates the terms for operating and degradation problems with hybrid storage systems in an EMS built on the MPC architecture.

Conclusion

To compensate for nonlinear or time-varying plant features, AMPC adjusts its prediction model at run time. This qualifies it for MGs that use hybrid energy storage systems and renewable energy. This paper discusses the integration of different approaches to creating an optimal MG system. The discussed methods include Hybrid Energy Storage System, a Demand Response Program, and Adaptive Module Predictive Control. Finally, these methods will be used together to create an optimal MG DC system, especially one connected to a urban DC traction network. With these techniques, the DC traction system can be optimized in an urban environment to achieve higher power delivery efficiency, reduce equipment maintenance cost, decrease environmental impact and improve energy efficiency. The reduction of energy costs can also be facilitated through peak load management and enhancement of the overall power system performance.

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REFERENCES

[1] Hanema J., Toth R., Lazar M., "Stabilizing non-linear mpc using ´ linear parameter-varying representations," in 2017 IEEE 56th *Annual Conf. Decision Con*trol (CDC), Dec 2017, pp. 3582–3587.

[2] Bordons C., Teno G., Marquez J. J., Ridao M. A., "Effect of the integration of disturbances prediction in energy management systems for microgrids," in 2019 *Int. Conf. on Smart Energy Systems and Technologies* (SEST). IEEE, 2019, pp. 1–6.

[3] Sanki P., Basu M., Pal P. S., Das D., "Implementation of linear quadratic regulator in an isolated microgrid system," in 2022 *IEEE VLSI Device Circuit and System* (VLSI DCS). IEEE, 2022, pp. 104–109.

[4] Mahmoud M. S., Alyazidi N. M., Abouheaf M. I., "Adaptive intelligent techniques for microgrid control systems: A survey," *Int. Journal of Electrical Power & Energy Systems*, vol. 90, pp. 292–305, 2017.

[5] Roslan M., Hannan M., Ker P. J., Uddin M., "Microgrid control methods toward achieving sustainable energy management," *Applied Energy*, vol. 240, pp. 583–607, 2019.

[6] Majji R. K., Mishra J. P., Dongre A. A., Model predictive control based autonomous DC microgrid integrated with solar photovoltaic system and composite energy storage. *Sustainable Energy Technologies and Assessments*, *54*, 102862, 2022.

[7] Zhou F., Xiao F., Chang C., Shao Y., Song C., "Adaptive model predictive control-based energy management for semi-active hybrid energy storage systems on electric vehicles," *Energies*, vol. 10, no. 7, p.1063, 2017.

[8] Chaudhary G., Lamb J. J., Burheim O. S., Austbo B., "Review of energy storage and energy management system control strategies in microgrids," *Energies*, vol. 14, no. 16, p. 4929, 2021.

[9] Zhang S., Dai L., Xia Y., "Adaptive mpc for constrained systems with parameter uncertainty and additive disturbance," *IET Control Theory & Applications*, vol. 13, no. 15, pp. 2500–2506, 2019.

[10] Zhang C., Yan H.-S., "Multidimensional taylor network adaptive control for mimo time-varying uncertain nonlinear systems with noises," Int. Journal of Robust and Nonlinear Control, vol. 30, no. 1, pp. 397– 420, 2020.

[11] Mohamed M. A., Diab A. A. Z., Rezk H., Jin T., "A novel adaptive model predictive controller for load frequency control of power systems integrated with dfig wind turbines," *Neural Computing and Applications*, vol. 32, no. 11, pp. 7171–7181, 2020.

[12] Lu X., Cannon M., Koksal-Rivet D., "Robust adaptive model predictive control: Performance and parameter estimation," *Int. Journal of Robust and Nonlinear Control*, vol. 31, no. 18, pp. 8703–8724, 2021.
[13] Amirthalakshmi T., et al., "A novel approach in hybrid energy storage system for maximizing solar pv energy penetration in microgrid," I*nternational Journal of Photoenergy*, vol. 2022, pp. 1–7, 2022.
[14] Xiong R., Chen H., Wang C., Sun F., "Towards a smarter hybrid energy storage system based on battery and ultracapacitor-a critical review on topology and energy management," *Journal of Cleaner Production*, vol. 202, pp. 1228–1240, 2018.
[15] Lin X., Zamora R., "Controls of hybrid energy storage systems in microgrids: Critical review, case study and future trends," *Journal of Energy Storage*, vol. 47, p. 103884, 2022.
[16] Ma T., Yang H., Lu L., "Development of hybrid battery–supercapacitor energy storage for remote area renewable energy systems," *Applied Energy*, vol. 153, pp. 56–62, 2015.
[17] Zhou, S., Chen, Z., Huang, D., Lin, T., Model prediction and rule based energy management strategy for a plug-in hybrid electric vehicle with hybrid energy storage system. *IEEE Transactions on Power Electronics*, *36*(5), 5926-5940, 2020.
[18] Tapia G., Tapia A., Ostolaza J. X., Proportional–integral regulator-based approach to wind farm reactive power management for secondary voltage control. *IEEE Transactions on Energy Conversion*, *22*(2), 488-498, 2007.
[19] Zheng Ni. F., et al., Enhancing resilience of DC microgrids with model predictive control based hybrid energy storage system. *International Journal of Electrical Power & Energy Systems*, *128*, 106738, 2021.
[20] Zhang Q., Wang L., Li G., Liu Y., A real-time energy management control strategy for battery and supercapacitor hybrid energy storage systems of pure electric vehicles. *Journal of Energy Storage*, *31*, 101721, 2020.
[21] Wang Y., Wang L., Li M., Chen Z., "A review of key issues for control and management in battery and ultra-capacitor hybrid energy storage systems," *ETransportation*, vol. 4, p. 100064, 2020.
[22] Liedke M., Łowiec E., Matelski W., Wolski L., Strzelecki R., Selection of AHI + SC Hybrid Storage Based on Mathematical Models and Load Variation Characteristics, *Przegląd Elektrotechniczny*, 94, nr 5, 120-127, 2018.
[23] Mohseni P., Husev 0., Vinnikov D., Strzelecki R., Romero-Cadaval E., Tokarski I., Battery Technologies in Electric Vehicles: Improvements in Electric Battery Packs," in *IEEE Industrial Electronics Magazine*, doi: 10.1109/MIE.2023. 3252265.
[24] He Y., Guo S., Dong P., Wang C., Huang J., Zhou J., "Technoeconomic comparison of different hybrid energy storage systems for off-grid renewable energy applications based on a novel probabilistic reliability index," *Applied Energy*, vol. 328, p. 120225, 2022.
[25] Kandidayeni M., Macias A., Boulon L., Kelouwani S., "Investigating the impact of ageing and thermal management of a fuel cell system on energy management strategies*," Applied Energy*, vol. 274, p. 115293, 2020.
[26] Derakhshan G., Shayanfar H. A., Kazemi A., "The optimization of demand response programs in smart grids," *Energy Policy*, vol. 94, pp. 295–306, 2016.
[27] Golmohamadi H., "Demand-side management in industrial sector: A review of heavy industries," Renewable and *Sustainable Energy Reviews*, vol. 156, p. 111963, 2022.
[28] Jordehi A. R., "Optimisation of demand response in electric power systems, a review," *Renewable and sustainable energy reviews*, vol. 103, pp. 308–319, 2019.
[29] Samadi P., Mohsenian-Rad A. H., Schober R., Wong V. W., Jatskevich J., Optimal real-time pricing algorithm based on utility maximization for smart grid. *First IEEE international conference on smart grid communications*, 415-420, 2010.
[30] Mohsenian-Rad A. H., Leon-GarciaA., Optimal residential load control with price prediction in real-time electricity pricing environments. *IEEE transactions on Smart Grid*, *1*(2), 120-133, 2010.
[31] Sepulveda A., Paull L., Morsi W. G., Li H., Diduch C. P., Chang, L., A novel demand side management program using water heaters and particle swarm optimization. *IEEE Electrical Power & Energy Conference*, 1-5, 2010.
[32] Logenthiran T., Srinivasan D., Shun T. Z., Demand side management in smart grid using heuristic optimization. *IEEE transactions on smart grid*, *3*(3), 1244-1252, 2012.
[33] Qian L. P., Zhang Y. J, Huang J., Wu Y., Demand response management via real-time electricity price control in smart grids. *IEEE Journal on Selected areas in Communications*, 31(7), 1268-1280, 2013.
[34] Derakhshan G., Shayanfar H. A., Kazemi A., The optimization of demand response programs in smart grids. *Energy Policy*, *94*, 295-306, 2016.
[35] Gbadega P. A., Saha A. K., Impact of incorporating disturbance prediction on the performance of energy management systems in micro-grid. *IEEE Access*, *8*, 162855-162879, 2020.
[36] Freire V. A., De Arruda L. V. R., Bordons C., Márquez, J. J., Optimal demand response management of a residential microgrid using model predictive control. IEEE Access, 8, 228264-228276, 2020.