An Intelligent Model Predictive Control Approach for V2G Systems Using Grey Wolf Optimization

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ABSTRACT: - This work discusses the potential of integrating electric vehicles (EVs) with energy storage systems (ESS) to address the challenges of renewable energy integration and provide frequency support in microgrids. The high cost and degradation of ESS are limiting factors, and the collaboration with EVs offers a solution for stable microgrid operation. The combination of model predictive control (MPC) is proposed to regulate the ESS and EVs, respectively, in response to frequency irregularities caused by large-scale integration of renewables or changes in load demand. A Grey Wolf Optimization (GWO) is used to optimize the MPC parameters. The effectiveness of the proposed approach is demonstrated through MATLAB/Simulink simulations of an isolated microgrid.

Keywords: - power infrastructure, electric vehicles (EVs), energy storage systems (ESS), centralised model predictive control (CMPC)

INTRODUCTION

The DSOs, who are tasked with ensuring the availability of the distribution grid (medium and low voltage), are the primary emphasis among the potential customers for this thesis. Because of the increased demand for EV charging, the low voltage distribution grid is notably anticipated to be loaded closer to its capacity [1, 2]. A DSO must avoid congestion in order to guarantee the distribution grid's availability. Which occurs when an infrastructure component, such as a transformer or distribution line, is loaded near to its capacity and could, therefore, fail. We'll call these areas "congestion points" from now on. A fuse, for example, will act as grid security when a congestion point overloads. This is done for safety reasons, but it could put more strain on the local infrastructure.

DSOs could utilise congestion control using energy flexibility to avoid congestion. By utilising pricing systems and market forces, congestion management seeks to avoid creating congestion. A power scheduling aggregator can include congestion management limitations since it has control over the power interaction of its portfolio. Fig.1 shows a schematic representation of the distribution grid, including both a close-up of a single substation and a more comprehensive view of the entire system. With both a detailed for a single substation and the larger overview of the distribution grid. EVs are connected to branches in the distribution grid segment that is depicted in detail, and the branches are connected to the substation. Both of these elements can operate as congestion points, with the substation being nothing more than the combination of the branches. The substation is shown to have a critical branch flow in the example, meaning that this branch is in danger of becoming congested. The overview, where the numbers denote the branches connecting to substations, illustrates how the detailed portion is connected to the remainder of the network. Then, higher voltage substations are linked to the lower substations. The aggregator needs to know which congestion point energy flexibility providers are connected in order to be able to provide DSOs a congestion management solution. Subsets are used in the aggregator configuration to include this. All energy flexibility service providers associated with the respective congestion location are represented by each subgroup. In formulations of aggregator problems seen in the literature, geographical information is frequently ignored [6, 7] and just one overall network constraint is applied. However, from the perspective of an aggregator, this spatial information in particular can be useful because it can be used to offer congestion control services.

THE ELECTRIC VEHICLE AGGREGATOR

In the context of interest, an EV fleet is directly under the aggregator's control. The requirements that must be fulfilled for an EV are established by the owner, such as the intended departure time and the desired State of Charge (SoC).

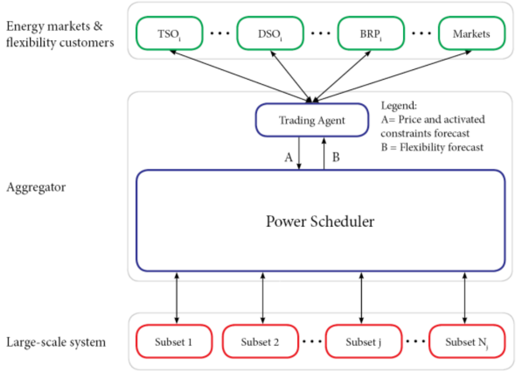

Fig 1: Schematic representation of the aggregator setting with respect to potential energy flexibility users and the EV fleet, which are divided over the subsets.

CENTRALIZED MODEL PREDICTIVE CONTROL

The assumption of a centralised model predictive control (CMPC) architecture is that a single, massive CMPC will have all system-related data. The CMPC has a constrained prediction horizon across which data regarding the network constraints and the behaviour of the Electric Vehicle (EV) fleet is available. interaction between the power scheduler, customers, EV fleet, and trading agent. The CMPC architecture's communication mechanism with the EV fleet is depicted in Fig. 2

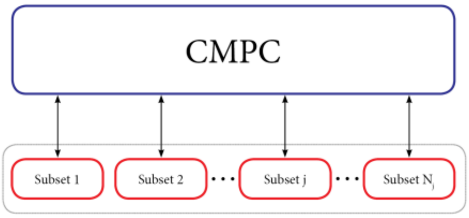

Fig 2: Communication structure of the CMPC algorithm

DISTRIBUTED MODEL PREDICTIVE CONTROL USING RESOURCE ALLOCATION

To address the power scheduling issue outlined in Section 2-1, a Distributed Model Predictive Control with Resource Allocation (DMPC-RA) method is created. It is illustrated how the created DMPC-RA algorithm communicates in Fig. 3.

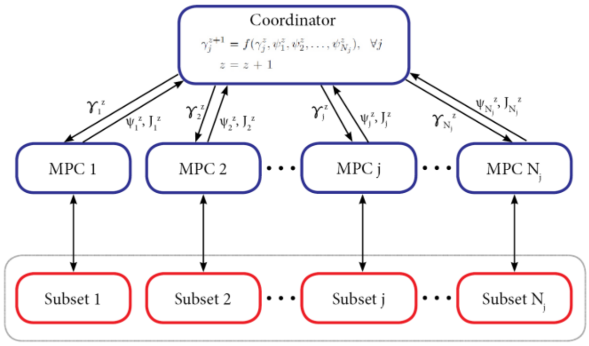

Fig 3: Communication structure of the developed DMPC-RA algorithm

LITERATURE REVIEW

Nguyen et al.[1] proposes a distributionally robust model predictive control (DRMPC) for energy management of a vehicle-to-grid (V2G)/vehicle-to-vehicle (V2V)-enabled smart electric vehicle charging station (EVCS) with a photovoltaic (PV) system and an energy storage system. To improve computational efficiency, a penalty method is proposed to relax the complementarity constraints, while still ensuring nonsimultaneous charging and discharging of EVs under the derived sufficient conditions.

Abdelghaffar et al.[2] outlines model predictive control (MPC) implementation to integrated onboard battery chargers (OBC) utilizing a multiphase EV-drive train. Unfortunately, as the number of phases increases, the adoption of MPC becomes more complex. Positively, the redundant phases facilitate the optimization of the control action. To transition between pre- and post-fault instances, the presented approach requires only a slight adjustment to the control mechanism.

Chai et al.[3] proposed a Two-stage optimization technique to determine the charging and discharging schedule for EVs participating in a vehicle-to-grid (V2G) programme at an office building. The EV owners' travel convenience is focused with more attention in the proposed model by giving them two V2G options. Firstly, day-ahead optimization (DAO) is applied, based on the expected building load profile and EV behaviour, the optimal charging or discharging control of the EVs is obtained in order to save electricity bills by minimizing the maximum demand of the building. In addition, a comprehensive cost–benefit analysis in utilizing V2G in peak load reduction is also performed to gain insight into the potential savings and discharging rewards attributable to the building and EV owner respectively.

Hou et al.[4] addresses the energy management of an integrated solar-hydrogen microgrid. The microgrid includes zero-emission vehicles, renewable energy sources, an electrolyzer, bidirectional charging stations, and a hydrogen refueling station with hydrogen storage. Vehicle-to-grid (V2G) charging stations can alleviate renewable electricity variability by discharging the energy of vehicle batteries back to the grid. The electrolyzer can absorb excess solar generation to balance supply and demand with power-to-gas (P2G) transactions. Given the uncertainties from intermittent renewable generation and energy demand, a two-stage stochastic optimization framework derives the optimal power management strategy for the component subsystems, aiming to minimize operating costs. The first stage of the model determines the day-ahead charging price and power supply for electric vehicle charging and hydrogen production, and the second stage performs real-time energy scheduling under different scenarios. The performance of the proposed optimization strategy is examined through a case study using real-world data, and the results demonstrate that daily operating costs can be reduced by up to 27.5%.

Zhang et al.[5] proposed an online CEV system for joint ride-sharing and dynamic V2G scheduling. Specifically, the joint problem is formulated as a mixed-integer quadratic programming (MIQP) problem. To deal with the forecast uncertainties, an online scheduling problem is thereby formulated, which also accounts for the communication effect to the real-time interactions. In the meantime, a bi-level system algorithm is devised to coordinate the CEV operations through the Benders decomposition. The case studies demonstrate that the proposed model can effectively provide high quality citywise ride-sharing and V2G regulation services through reliable vehicular communications. In addition, the computational time of the proposed online bi-level algorithm can be greatly reduced under different network scales. Furthermore, the sufficient utilization of coordinated CEVs can significantly decrease the system operation cost by approximately 43.71% while alleviating city grid stability issues.

Mehsra et al.[6] focuses on the challenge to develop coordination between an electric vehicle (EV) charger, energy storage system (ESS), and smart charging/discharging strategy in a low-inertia grid-connected vehicle-to-grid system. Two smart bidirectional charging strategies are proposed to control EV and ESS for minimizing the frequency error by considering the EV constraints. A linear programming optimization algorithm with modified objective function is employed to design a smart charging technique for EVs. For ESS, three operating scenarios are assessed 1) without ESS, 2) with ESS, and 3) with ESS and considering the state of charge (SOC) drop. In the comprehensive charging strategy for ESS, the same LPOA designed for EV has been employed wherein EV SOC drop is observed to noticeably increase frequency regulation ability while the EV has a determined low SOC during a specified interval. The simulation results in MATLAB/SIMULINK environment validate the accuracy of these smart charging techniques.

Mignoni et al.[7] propose a novel control strategy for the optimal scheduling of an energy community constituted by prosumers and equipped with unidirectional vehicle-to-grid (V1G) and vehicle-to-building (V2B) capabilities. In particular, V2B services are provided by long-term parked electric vehicles (EVs), used as temporary storage systems by prosumers, who in turn offer the V1G service to EVs provisionally plugged into charging stations. To tackle the stochastic nature of the framework, we assume that EVs communicate their parking and recharging time distribution to prosumers, allowing them to improve the energy allocation process.

Ueda et al.[8] predicted the amount of electricity generated by renewable energy using model predictive control, and we considered the operation of a complete island-operated park and ride EV parking station that does not depend on commercial electricity. To perform appropriate model predictive control, we performed comparative simulations for several different forecast interval cases. Based on the obtained results, we determined the forecast horizon and we simulated the economic impact of implementing EV demand response on the electricity demand side. We found that without demand response, large amounts of electricity are recharged and a very high return on investment can be achieved, but with demand response, the return on investment is faster. The results provide a rationale for encouraging infrastructure development in areas that have not yet adopted electric vehicles.

Azar et al.[9] proposed BC-ST SMC solves these problems by providing anti-windup and un-bounded disturbance rejection. Lyapunov stability criterion is used to prove the asymptotic stability of the system. The PEV comprises of two subsystems namely: bidirectional charging unit (BCU) and hybrid energy storage system (HESS). The BCU comprises of a totem pole power converter between the PEV and grid which operates in two modes of grid to vehicle (G2V) and vehicle to grid (V2G). The components of the HESS are the battery and regenerative fuel-cell (RFC) (i.e. fuel-cell (FC) with an electrolyzer). he simulations are performed on MATLAB® Simulink (2022b) which proves the superior performance of BC ST-SMC over conventional nonlinear controllers in the presence of saturated inputs. Finally, hardware-in-loop (HIL) based experimental results verify the real-time control of the proposed PEV.

Zhnag et al.[10] presents a constrained hybrid optimal model predictive control method for the mobile energy storage system of Intelligent Electric Vehicle. A novel adaptive cruise control system is designed to optimize mobile energy storage management, active safety control, and fuel economy. A hierarchical control structure is proposed for active safety control and energy flow management. The main-loop is proposed to analyze and optimize active cruise safety control and energy management index using non-linear constrained hybrid optimal model predictive control method. The inner loop is used to chase the aim signal from the main loop using hysteresis current control method. Then, an electronic longitudinal control system is designed to avoid the collision and optimize energy management between the IEV and cruise following vehicles. At last, the simulations with typical driving conditions are built to justify the performance of the proposed controller. The results illustrate that the IEV with the designed hybrid controller can adaptively tracking the following vehicles, reduce the possibility of collision with optimal energy flow management.

Masood et al.[11] proposed the entire system's state model has been derived. An adaptive supertwisting sliding mode controller (AST-SMC) HESS results presents negligible convergence time and overshoots/undershoots even at the transients, and no steady state error. For the driving mode, the switching between dynamic and static behaviors and for parking mode, vehicle to grid (V2G) and grid to vehicle (G2V) operations have been proposed. In order to make nonlinear controller intelligent to achieve the V2G and G2V functionality, a state of charge based high-level controller has also been proposed. A standard Lyapunov stability criteria has been used to ensure asymptotic stability of the entire system. The proposed controller has been compared with sliding mode control (SMC) and finite time synergetic control (FTSC) by the simulation results using MATLAB/Simulink. Also, the hardware in loop setup has been used to validate the performance in real-time.

Kumar et al.[12] presents Harris hawks optimized model predictive controller (MPC-HHO) to curtail the frequency and voltage fluctuations caused due to the sudden change in loading pattern. Additionally, the authors have incorporated various dynamic energy storage devices like virtual inertia and redox flow battery (VI-RFB) in coordination with the MPC-HHO controller. From the obtained results, it has been validated that the transient response from the proposed MPC-HHO controller coordinated with VI-RFB has superior characteristics when compared with state-of-the-art methodologies available in the existing literature. Further, the most prevalent nonlinearities present in the realistic power system have been considered and their effects on the controller's performance have been investigated and the robustness of the proposed MPC-HHO controller coordinated with VI-RFB has been successfully validated.

Kannayeram et.al.[13] proposes a new hybrid system to analyze the impact of the electric-vehicle-charging-station with the combination of renewable energy and grid-connected system. The proposed method is the implementation of Forensic-Based Investigation (FBI) and Artificial Transgender Longicorn Algorithm (ATLA) called FBI–ATLA method. The objective of the proposed system is to provide the computational complexity, reduce the cost, improve efficiency and enhance the network power. Here, two sorts of charging stations are deemed regarding with power supply capabilities. In ANN, PSO, GA and proposed technique, the values of effectiveness during 100, 200, 500 and 1000 is 99.0037%, 99.2356%, 99.8363% and 99.9373%.

Itoo et al.[14] propose a new authentication protocol based on Elliptic Curve Cryptography (ECC) that enables secure communication between EVs and charging stations in V2G networks. Our contributions are: 1) A new ECC-based authentication framework for energy Internet (EI)-based V2G communication systems, and 2) The use of lightweight cryptographic operations to reduce computational expenditure and improve resource utilization. Overall, our proposed protocol provides a robust and secure framework for V2G communication that can address the significant security and privacy challenges facing V2G networks.

Jang et al.[15] proposes a data-driven modeling method to estimate the V2G flexibility. A charging station is a control point connected to a power grid for V2G operation. Therefore, the charging stations' statuses were analyzed by applying the basic queuing model with a dataset of 1008 chargers (785 AC chargers and 223 DC chargers) from 500 charging stations recorded in Korea. The basic queuing model obtained the long-term average status values of the stations over the entire time period. To estimate the V2G flexibility over time, a charging station status modeling method was proposed within a time interval. In the proposed method, the arrival rate and service time were modified according to the time interval, and the station status was expressed in a propagated form that considered the current and previous time slots. The simulation results showed that the proposed method effectively estimated the actual value within a 10% mean absolute percentage error. Moreover, the determination of V2G flexibility based on the charging station status is discussed herein. According to the results, the charging station status in the next time slot, as well as that in the current time slot, is affected by the V2G. Therefore, to estimate the V2G flexibility, the propagation effect must be considered.

PROPOSED METHODOLOGY

THE PROPOSED CONTROL SYSTEM DESIGN

PROBLEM FORMULATION

In this study, a single MG is examined to see how ESS and EVs affect the frequency regulation of the MG. While an MPC controller is used to regulate the output of the energy storage system (ESS) in accordance with the system frequency deviation, adaptive droop control (ADC) is a technique for controlling the regulation of an electric vehicle's battery (EVB). Additionally, in order to find the best solution, Gray wolf optimization (GWO) is used on the MPC and ADC parameters.

FUZZY LOGIC PI CONTROLLER

To compare their performance to that of the model predictive controller (MPC), the proportional-integral (PI) and fuzzy logic PI (FPI) controllers are used. Frequency deviation (1f) and its derivative (d1f), as illustrated in Fig. 4, are the inputs to the FPI controller. Fuzzification, fuzzy inference system (FIS), and defuzzification make up the fuzzy process. The crisp value is mapped to a fuzzy input value based on the matching membership function as the fuzzification process begins with the crisp input data.

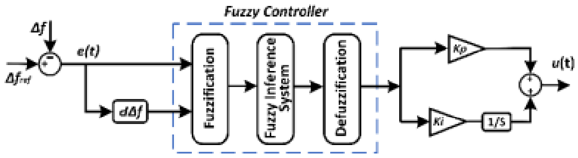

Fig 4. Fuzzy PI Controller

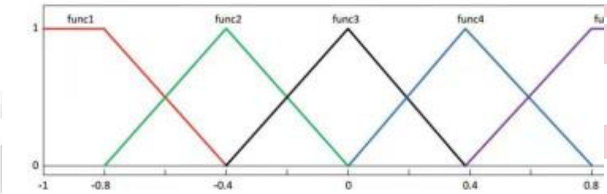

Fig 5. Mamdani type FIS output pattern

Fig. 5 shows the Mamdani-type FIS output variables. The output is produced by the FIS in the following stage using membership functions (MFs) and fuzzy rules.

RESULTS AND DISCUSSIONS

Result Analysis

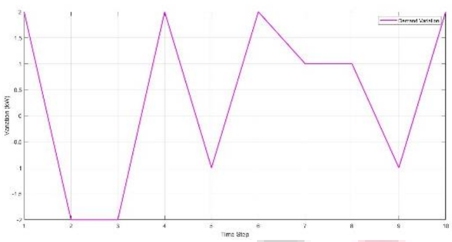

Figure 6: Demand Variation

Figure 6 shows the graph of Demand Variation which is plotted between Variation and Time step showing that time step is fluctuating as increasing of variation and at 1.5 it gradually increses.

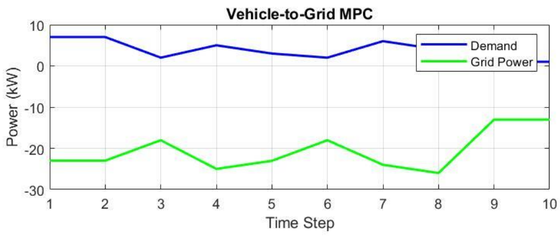

Figure 7: Grid Demand Vs Power using GWO based PI Controller

Figure 7 shows the graph of Grid Demand Vs Power using GWO based PI Controller which is plotted between Power and Time step showing that time step is fluctuating as increasing of power and at 10 it remains constant.

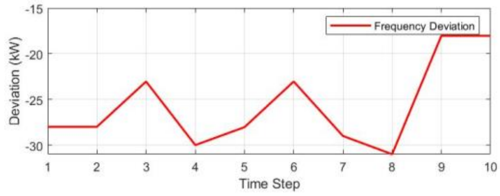

Figure 8: Frequency Deviation for GWO based PI Controller

Figure 8 shows the graph of Frequency Deviation for GWO based PI Controller which is plotted between Deviation and Time step showing that time step is fluctuating between 1 to 8 then gradually increases at 10.

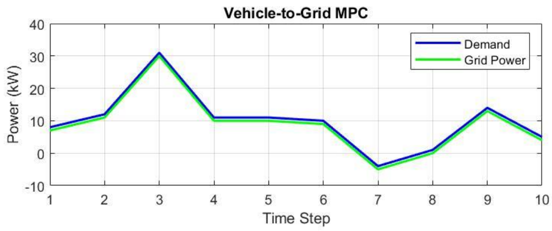

Figure 9: Grid Demand Vs Power using GWO based Fuzzy Controller

Figure 9 shows the graph of Grid Demand Vs Power using GWO based Fuzzy Controller which is plotted between Power and Time step showing that time step and power is fluctuating between 10 to 7 then gradually increases at 9 then comes down at 10.

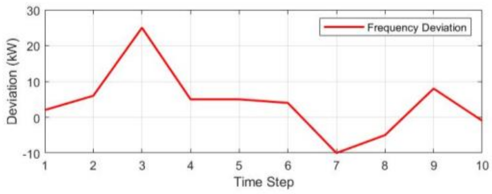

Figure 10: Frequency Deviation for GWO based Fuzzy Controller

Figure 10 shows the graph of Frequency Deviation for GWO based Fuzzy Controller which is plotted between Deviation and Time step showing that time step is fluctuating at 0 to 7 then gradually increases at 9 then comes down at 10.

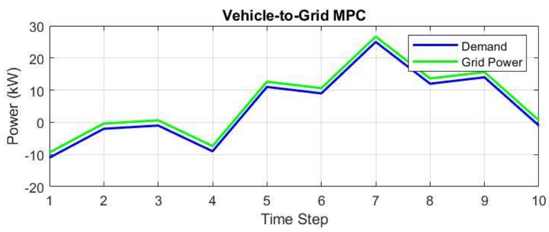

Figure 11: Grid Demand Vs Power using GWO based MPC Controller

Figure 11 shows the graph of Grid Demand Vs Power using GWO based MPC Controller which is plotted between Power and Time step showing that time step and power is fluctuating between -10 to 9 then comes down at 10.

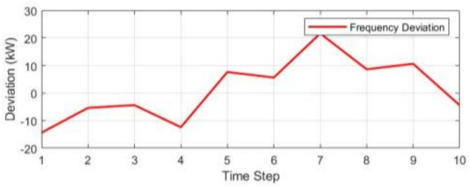

Figure 12: Frequency Deviation for GWO based MPC Controller

Figure 12 shows the graph of Frequency Deviation for GWO based MPC Controller which is plotted between Deviation and Time step showing that time step is fluctuating between -10 to 9 then comes down at 10.

CONCLUSION

This research focuses on addressing the frequency stability control issue in isolated microgrids (MGs). Various control techniques, including proportional integral (PI), fuzzy logic proportional integral (FPI), and model predictive control (MPC), are employed. The system comprises electric vehicles (EVs), an energy storage system (ESS), a wind turbine, a solar system, and a diesel generator. The controllers are used to regulate the output of the ESS and the EVs' batteries. The impact of load variation and high renewable energy penetration on system frequency is analyzed. The controllers' parameters are optimized using a GWO algorithm. MATLAB/Simulink is used for validation, showing that the proposed control techniques effectively restore frequency deviation and outperform other controllers in terms of efficiency. Future work includes designing a single controller to regulate the state of charge (SOC) of both ESS and EVs and considering the role of converters controlling wind and solar power in the frequency response model.

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