

Minimax-Based Distributed Energy Management for Optimal Renewable and Battery Storage Utilization in DC Microgrids

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Abstract

The growing complexity of renewable energy sources (RES) and energy storage systems (ESS) in DC microgrids requires sophisticated control schemes that may guarantee efficient and stable and collaborative work in the conditions of uncertainty. Nevertheless, renewable curtailment, nonlinear loads, and constraints of centralized structures frequently occur due to intermittency of RES, nonlinearity of load responses, and poor voltage regulations. This paper suggests a distributed control scheme integrating microgrid physical modeling, the aggregative game theory, and passivity-based analysis to optimize the use of RES and ESS and ensure stability of the system and proportional sharing of currents throughout the system. Fully distributed decision-making algorithm is created to calculate the primal and dual variables of Nash equilibrium with the assistance of a neighbor-based estimation system of the total generation current. The resulting controller drives to a normalized Nash equilibrium with a high level of robustness and allows the voltage to be regulated and power distributed jointly without centralized communication. The performance of the simulation under both linear and nonlinear load conditions shows that there is great enhancement in the stability of voltages and accuracy of current sharing and utilization of renewable. The suggested plan will reduce curtailment and maximize the contribution of the ESS and allow resilient micrograding performance even when the dynamic disturbances occur.

Keywords: DC microgrids Distributed control Aggregative game theory Passivity-based stability Renewable energy and energy storage systems

1. Introduction

The shift of the world energy production towards the sustainable one has contributed to the increased pace of implementation of renewable energy sources (RES) into the modern power networks, especially solar photovoltaic and wind systems. Microgrids have become one of the facilitators of this change with their ability to offer localized and flexible power management and improve resilience to grid disruptions. Direct current microgrids (DC-MGs) are becoming a popular trend among other architectures as they are highly compatible with RES and energy storage systems (ESS), have lower conversion losses, and can easily integrate distributed energy resources (DERs) [1]–[3]. One of the typical DC microgrids is illustrated in Fig. 1, which represents a combination of renewable sources, storage devices, and various types of loads.

The key to the efficient functioning of any DC microgrid is the choice of the adequate power electronic converters and the relevant control systems. Buck, boost, and buck-boost converters are still used because they are simple and easy to implement conventional non-isolated converters. The ability of these traditional converters is said to have intrinsic limits to the high-power applications that demand large ratio of voltage step-up/step-down and high power ratings. To address them, several sophisticated types of high-gain DC-DC converters topologies have been proposed in the literature [4], such as coupled-inductor-based designs [5], voltage multiplier designs [6], multilevel topologies [7], interleaved designs [8], switched-capacitor designs [9], and combinations of these [10], [11]. Such converters can be found with better performance, but have a much more complicated control because higher-order dynamics and closely coupled switching behaviour appear even when based on classical converter architectures. Figure 1. Shows that typical dc microgrid architecture:

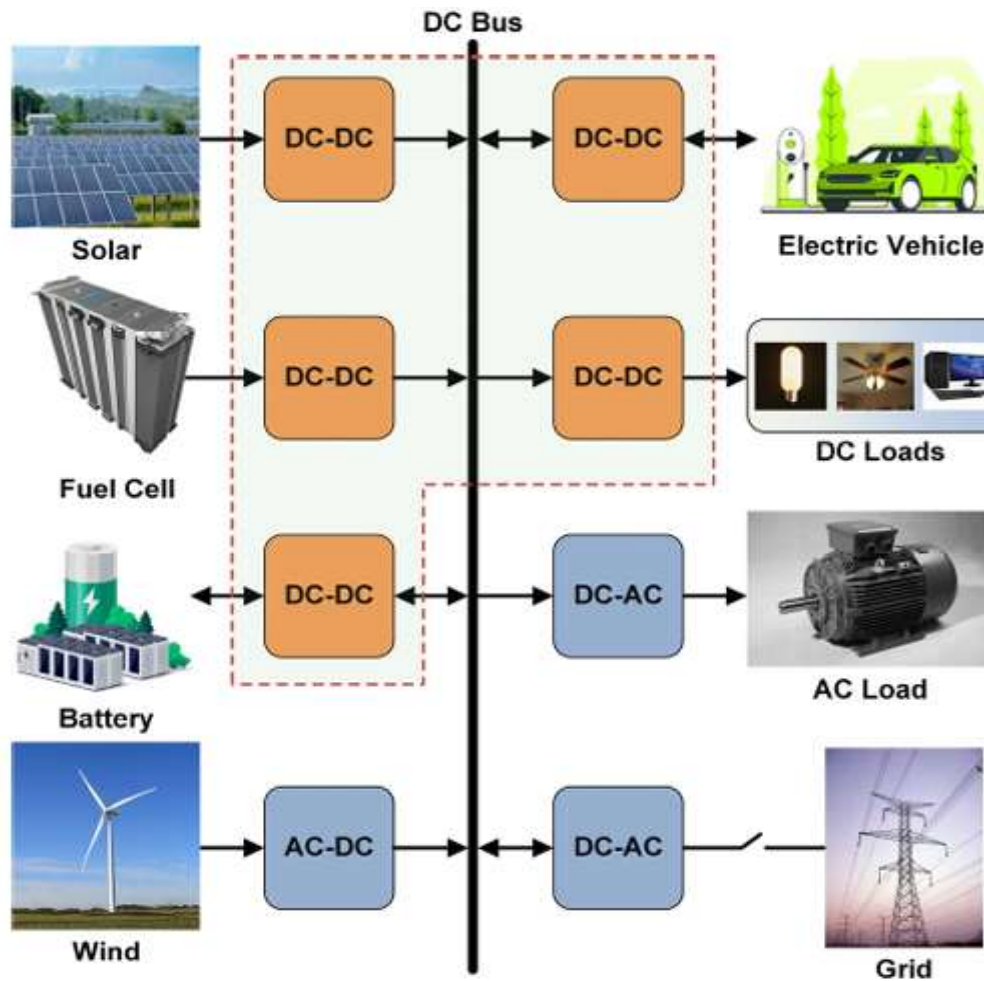


Figure 2 typical dc microgrid architecture

Regardless of these benefits, the very nature of intermittency and variability of RES remains a significant challenge to ensuring reliable and efficient operation of the microgrids. Bus-voltage variations, imbalanced current distribution, as well as an ineffective use of renewable and storage resources can be caused by fluctuations in solar irradiance, wind profiles and changing load requirements which vary rapidly. In this case, ESS units are important stabilizing elements absorbing surplus energy when renewable output is high and providing power when there is a shortage. But when there is no co-ordinating control measures, both RES and ESS will be under exploited causing renewable curtailment, more cycling of storage equipment, lower system performance and a chronic reliance on back-up fossil-fuel-based units.

Microgrid operation has been heavily supervised using conventional centralized control architectures. Although they are appropriate in small or medium-sized systems, the controllers have a number of limitations such as the lack of scalability, high communication and computation costs, as well as vulnerability to single-point failures. There are these disadvantages that render centralized schemes less and less practical as microgrids advance to high density of DER and multi-bus. Cooperative and distributed control strategies have also offered a viable alternative in order to curb these problems. These solutions enable every DGU or DER to make locally based decisions using local metering and minimal information about their neighbors, and yet attain system-wide goals such as voltage control, proportional current sharing, and optimal power allocation using consensus mechanisms or distributed optimization models.

More recent developments in the domain of microgrid control introduce additional event-based communication, multi-agent coordination, and data-driven or learning-based controls to improve the adaptability and resilience to uncertain and changing conditions at a rapidly changing rate. These techniques minimize the communication costs, enhance the disturbance response, as well as provide resilience to parametric uncertainty and measurement error. In addition, recent studies also emphasize the necessity to fulfill several and in many cases conflicting operational goals simultaneously, i.e. reducing power losses, achieving a fair distribution of currents, staying within reasonable limits of bus voltages and making maximum use of renewable and storage resources. Such balance would be critical to increasing the reliability of the microgrids and guarantee economical and energetically efficient functioning. Consequently, the creation of smarter distributed control schemes, which can synchronize DERs in complex, multi-bus DC microgrid systems, has emerged as a main trend towards effective, resilient, and sustainable energy systems.

The systems of energy storage(ESS) and the growing infiltration of renewable energy sources (RES) including photovoltaic (PV) systems and wind turbines have changed the working of contemporary power networks. Although microgrids in DC form provide a powerful and scalable platform to integrate the distributed energy resources (DERs), there are a number of challenges that are yet to be addressed. One of the underlying problems is that the process of renewable generation is unpredictable and intermittent, which causes changes in the flow of power and instability in the micro grid. These variations may lead to poor use of available renewable energy, overloading of specific DERs or poor use of ESS capacity without proper coordination. Moreover, since several distributed generation units (DGUs) are interconnected, equal load shedding of current and controlled voltage distribution throughout the DC bus are necessary in order to guarantee safe and reliable operation.

Traditional centralized means of control are often limited in scale, communication overhead and subject to single point failures. Such disadvantages limit their application in any large-scale microgrid in the future, with high renewable share. Hence, distributed control solutions that would enable the DGUs to coordinate their efforts with minimal local information and neighbor-to-neighbor communication yet achieve system-wide goal is urgently needed. In this direction, the microgrid dynamics are re-designed and re-modeled as a distributed optimization and game-theoretic decision-making problem, to allow coordination of DERs on a scale able to be resilient and efficient.

1.1 Motivations

DC microgrids increasingly rely on renewable energy sources and energy storage systems, but their intermittent nature and nonlinear load behavior often lead to voltage instability, poor current sharing, and renewable curtailment. Centralized control cannot scale and is vulnerable to single-point failures. A fully distributed, stable, and coordination-aware control strategy is needed to maximize RES–ESS utilization while maintaining reliable microgrid operation. Aggregative-game formulation: The microgrid coordination problem is modeled as a Cournot aggregative game to support optimal RES–ESS utilization under coupled constraints. Distributed control algorithm: A fully decentralized decision-making scheme is developed using only local and neighbor information, without any central controller. Passivity-based stability: A passivity-guided closed-loop design ensures convergence to a unique normalized Nash equilibrium. Distributed current estimation: A neighbor-based estimator computes aggregate generation, enabling cooperative optimization. Performance validation: Simulation results under linear and nonlinear loads show improved voltage stability, accurate current sharing, and reduced renewable curtailment.

2. Related Work

The distributed control approach presents various advantages to the operation of microgrids (MG) such as better durability, scalability, flexibility, as well as less reliance on fossil fuels. It also reduces overheads and communication expenses as it facilitates better collaboration of the distributed energy resources (DERs). In [11], a distributed control technique (DCT) interlinking converters was developed in MATLAB/Simulink to illustrate the successful power sharing in islanded MGs. In this research, however, the voltages and frequency regulation were not covered. In a similar fashion, [12] explored a DCT scheme with interlinking converters to share proportional power in Islanded MGs and also proposed a multi-agent DCT scheme to MGs and MG clusters. The article also analyzed mathematical and topological models of multi-agent systems (MAS), consensus procedures and their tolerance to communication delays. However, these strategies consider mostly the AC MGs, but not DC or hybrid MGs. High-tech ways of enhancing distributed control have also been advanced. In [13], a frequency control data-driven approach of islanded MGs was introduced, grounded on multi-agent quantum deep reinforcement learning, which integrates data-driven deep RL systems with quantum machine learning-based algorithms to identify the best collaborative strategy. On the same note, [14] used hierarchical and distributed MAS-based architecture which considers MG management, MG control, and local agents, and [15] has proposed power management system secondary control algorithm using MAS technology in MATLAB/Simulink and Java settings. A hierarchical multi-vision distributed decision-making architecture was presented in [16] based on the concept of digital twin and a bi-level cooperative control of multi-bus MGs so that the distributed generators (DGs) could coordinate themselves with limited sparse communications[17]. In [18], a distributed coordination control approach to DC MGs was outlined and it entailed a three-step procedure comprising of total generation cost functional estimation, multi-agent consistency algorithms, and DC bus voltage stabilization. A hierarchical coordinated control strategy was suggested in [19] through recursive fuzzy neural networks to increase the stability in DC MGs to minimize the occurrence of line faults. Further, [20], [21] considered adaptive fuzzy recurrent neural network controllers to manage frequency in MGs, and these approaches are based on frequency management by a fractional order proportional integral derivative controller. Higher order MAS-based control was proposed in [22] to restore voltage in islanded DC MGs and the agents exchange neighbors information to achieve load balancing and current sharing. The Lyapunov Analysis of stability of dynamic voltage and frequency control was done in [23]. In [24], a robust distributed secondary control system based on semi-Markov process was proposed to the AC islanded MGs. In [25], Cooperative distributed control was developed towards DC MGs, in which a voltage regulator instead of conventional secondary control was used, together with current regulation mechanisms. In an attempt to

minimize further the overhead of communication, event-triggered (ET) DCT schemes were experimented with in [26], [27], which allow secondary control and mitigate the effect of time delays. In [28] fault-tolerant ET control in DC MGs was suggested in order to recover the voltage, whereas in [29] the secondary control of frequency and voltage restoration in islanded AC MGs was developed based on ET. Parallel contributions were done in [30]- [33] where the use of ET-based distributed control was demonstrated to increase the stability, decrease communication exchanges, and enhance voltage/frequency regulation in DC MGs.

In [34], security considerations were explored of the distributed cooperative control showing weaknesses in the communication between DGs and vulnerabilities to attacks that alter reference voltage data. In [35], cooperative power-sharing strategies of DGs using interface converters were suggested, which guarantees the directional power flows and reduces the frequency response. The methods of advanced control based on deep deterministic policy gradient reinforcement learning were introduced in [36] to address DC bus voltage regulation and current sharing in DC MGs. The idea of quantum distributed controllers was introduced in [37], [38], where classical communication and quantum principle were used to enhance the synchronization, scalability, and safe distribution of power in multi-inverter MGs.

3. Proposed Methodology

3.1 Preliminary

This paper takes into account an islanded DC microgrid which is a collection of distributed generation units (DGUs), of which every unit could be attached to renewable energy sources (RES) or to energy storage systems (ESS). It is a modeled representation of the loads as a ZI, i.e. a constant impedance component and a constant current component, which is a close approximate to the nonlinear consumption nature that is prevalent in microgrids. The multiple transmission lines between the DGUs, and the topology of the system is a connected undirected graph given with an incidence matrix which defines the interconnections. Figure 3. shows that electrical system of DGU:

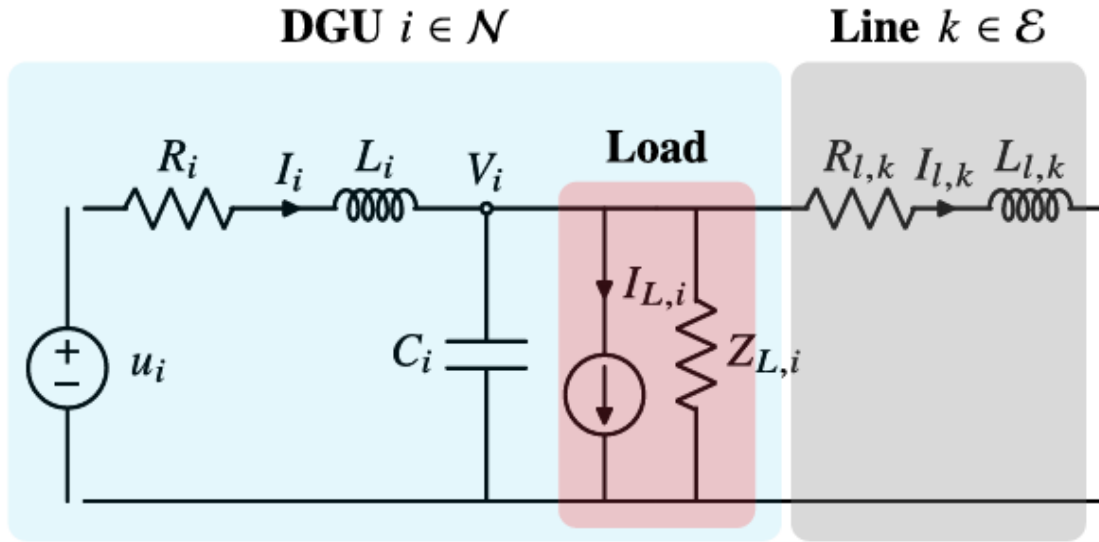


Figure 4 electrical system of DGU

All DGUs have the responsibility to one or more transmission lines attached to them. All of the line assignments together constitute a total partition of the whole network, where each line is distinctly controlled by a single DGU. Each DGU is represented by the current, voltage and related line current variables, with the overall state of the network of DGUs represented by the state of each DGU, whereas the aggregate state of all DGUs is represented by the state of the global state. The resulting dynamic equations, as they were worked out by Kirchhoff based on his laws, are the coupling between currents, voltages, and control inputs within the network as represented in figure.

Previous research has demonstrated that these dynamics can meet a shifted passivity property, i.e. an inherent ability of the system to behave with stable energy levels about an operating point. An analogous storage capability may be established to measure the amount of energy in the system and show stability. This property offers a solid basis in the development of distributed control strategies. In terms of Objective 1, this modeling framework is relevant since it allows RES and ESS to be run in co-operation with keeping physical and operational limits. Through proper characterization of the dynamics, one will be able to design distributed controllers that do not only ensure stability but can also maximize the use of renewable energy, enhance coordination of ESS, and reduce the loss of curtailment at times of high variability.

3.2 Problem Formulation

The control design is defined as a Cournot aggregative game to find out the optimal operating conditions of the DC microgrid. This formulation regards every distributed generation unit (DGU) as a player in the game, and the Nash equilibrium that is desired to achieve is a safe and optimal point of operation of the microgrid dynamics.

DGUs have to meet some local requirements. These include: The power equilibrium at the DGU, which is a steady state with voltage, current and control input. Thresholds of the permitted voltage at every DGU that has a minimum limit and a maximum limit. Restrictions of the allowed line currents related to the DGU. These constraints determine the viable operating region of each DGU. In order to ensure that the microgrid is feasible in steady-state, further coupling constraints are added. These constraints enforce: Power balancing across all of the DGUs and loads in the network. Balance line current over transmission lines. A maximum amount of steady-state transmission losses. A combination of such local and coupling conditions comprises the viable system decision space.

In this viable space, every DGU will have an optimization problem over operational costs and economic goals. The cost is used to punish the deviations of the DGU input and state variables (current and voltage) (relativism) to the reference values to ensure a safe and efficient operation. Meanwhile, the role contains a profit term that is modeled based on the Cournot principle, whereby the revenue of any DGU is determined by the output of the DGU and the output of the entire set of DGUs in the microgrid. This pricing system reflects the competitive but cooperative-based distributed energy trading. Notably, the variable in this formulation that is aggregated is total current output of all DGUs, which is the summation of renewable and storage unit generation. The control strategy will ensure that the renewable energy sources and ESS are used optimally under the condition of balancing voltage and current limits by coordination via this common variable. Setting this problem enables the microgrid to arrive at a Nash equilibrium where each DGU has set itself to an overall efficient but individually rational point. In terms of the Objective 1, this kind of formulation directly contributes to the maximization of the use of RES and ESS, as it ensures equitable current distribution and inhibits unwarranted curtailment and storage devices would play a role in harmonizing the supply and demand.

In order to design the distributed decision-making system, Karush-Kuhn-Tucker (KKT) conditions of optimisation problem are obtained. All these conditions provide a framework that is required to make the microgrid run at a safe and efficient equilibrium state. As a standard assumption, to ensure that the problem is well-posed, we assume that the feasible set of solutions is non-empty. This assumption means that every DGU meets the Slater constraint qualification, which means that overall microgrid feasible steady-state solutions are available.

A generalized Nash equilibrium (GNE) is a state of the game that is the equilibrium between all the DGUs, with each one acting in their best interest under the actions of the other. At this point no one DGU can gain without implying believability constraints. The GNE makes sure that existing sharing, voltage limit as well as line restrictions are considered and at the same time without weakening the economic efficiency of the system. The local DGU constraints and the global coupling constraints of the network are included in the KKT conditions relating to the GNE. These conditions associate the system variables with their dual variables which are shadow prices associated with the voltage, current and line flow constraints. Notably, the formulation can be used to interpret dual variables as economic signals, which is also critical in distributed optimization.

As the GNE of the problem is not necessarily unique, the analysis of the problem is reduced to a subgroup of solutions referred to as the normalized Nash equilibrium (NNE). The NNE uniqueness assurances are ensured through the consensus of two variable variables in all DGUs. With this consensus condition, the system is in a matter of a steady equilibrium, which is indicative of both physically practicable and a just distribution of resources. Strong monotonicity of the operator on which the NNE operates and the non-existence of the NNE are conditions that can be satisfied by properly tuning the controller parameters. This ensures that the distributed control strategy reduces to trusted and unique equilibrium. In an attempt to execute this solution in a distributed manner, the communication network between DGUs is as an undirected and connected graph. The DGUs both provide mutual enforcement of the KKT conditions and agree over the dual variables through local information exchange. What is obtained is a distributed algorithm enabling every DGU to reach the equilibrium with merely local and neighbor data without a centralized coordination.

3.3 Controller Design and Convergence Analysis

This section involves designing a distributed decision system to the microgrid and interconnection of that system with the physical system is discussed. The control structure is a combination of passivity theory, dynamics of projection and Lyapunov stability analysis to ensure that it converges to a safe and optimal operating point.

3.3.1 Feedback Interconnection and Estimation of Aggregate Current

3.3.1.1 Interconnection of Physical and Decision Systems

The decision system proposed has two subsystems. The former subsystem determines the distributed decision variables, which meet the equilibrium conditions that were estimated in problem formulation. The second subsystem is a distributed estimate of the sum of the current generated by all the DGUs, which is the aggregative quantity that alter every local objective. These decision subsystems are connected to the physical

microgrid dynamics to form a closed-loop system through which DGUs can be adaptively updated of their inputs without violating network and operational constraints. The decision system is made in a way that only the DGUs will communicate with their immediate neighbors. This makes sure that the algorithm is fully distributed and scalable and does not rely on centralized coordination. Passivity is ensured by the interconnection between physical dynamics and decision dynamics, and is necessary to ensure stability in the system.

3.3.1.2 Local Estimation of Aggregate Current

The reason that the aggregative quantity is not directly measurable in individual units is that the aggregative quantity is the sum of the total current output of all the DGUs. To solve this, a distributed estimator is presented where each DGU is expected to obtain a local estimate of the global variable by connecting with the neighbors. These local estimates approach the actual aggregate current as time goes by. This may be implemented in the whole control scheme without having to share any information worldwide.

3.3.2 Closed-Loop System Dynamics

The ensuing closed-loop dynamics consists of three parts that are related to each other: Microgrid dynamics, which characterize physical development of voltages and currents at DGUs and transmission lines. Distributed estimation subsystem is the one that computes the aggregate current using the local information. Decision subsystem, that calculates primal and dual variables of the distributed optimization problem and achieves agreement between DGUs. These subsystems together apply the distributed control strategy. The design guarantees that DGUs collaborate in order to determine optimality of control measures and the physical system provides feedback to rectify deviations.

3.3.2.1 Convergence Properties

The proposed framework has been demonstrated to reach a steady equilibrium point through passivity theory and Lyapunov analysis. At this point, the distributed optimization problem is addressed, the constraints of voltage and current are met, and the aggregative variable is estimated in an appropriate way. The system also ensures load elasticity, since the decision subsystem automatically causes the DGUs to move to a new equilibrium, without parameter retuning. Practically, the framework can be scaled to large networks by grouping DGUs together to form much smaller groups, each of which performs the distributed control locally but coordinates on a larger level. By ensuring distributed stability, fair current sharing, and accurate estimation of global quantities, the proposed controller maximizes the utilization of renewable energy and storage units. RES outputs are fully absorbed into the network without unnecessary curtailment, while ESS units are coordinated to support balancing during variability. The distributed and scalable design also guarantees that increasing numbers of RES and ESS can be integrated seamlessly, making the framework directly aligned.

3.4 Deviation and Convergence Analysis

In order to investigate the stability of the distributed decision system, we declare the collective state of the decision dynamics as the jointness of the estimation, primal and dual variables. This system dynamics can be then conveniently expressed in a form that is similar to the decision dynamics that were introduced previously. With this formulation, we are able to examine the distinctiveness and convergence of the equilibrium.

Proposition 2 confirms the fact that, in the given assumptions, the distributed system equilibrium is unique. In particular, the physical conditions of the microgrid as well as the decision variables approach a common operating point which is associated with the Nash equilibrium obtained in the formulation of the problem. This finding is to guarantee that the algorithm that is distributed does not have several steady-state solutions, which is essential to stable operation. Expanding on this finding, Corollary 1 presents the finding that the equilibrium incorporates a single value of the auxiliary variables that are used to impose agreement among DGUs. This also enhances the uniformity of the given solution. Prop. 3 presents a monotonicity requirement of the distributed control system which incorporates controller tuning parameters. Although the control law is deployed in a fully distributed fashion, the tuning of these parameters might have to be synchronized at the outset to ensure monotonicity and stability. However, this condition guarantees that the closed-loop system has robustness and convergent behavior in a large variety of working conditions.

The passivity and convergence properties of the distributed system are formalized in Theorem 1. It demonstrates that the decision system under the condition that the controller parameters are selected in the desired way is stable and will reach the desired equilibrium. Notably, the system meets the necessary feasibility conditions at any given time, and its passivity features also guarantee that the variation of the system towards its equilibrium also reduces with time. Theorem 2 also affirms that the paths of the interconnected micro grid and decision system also meet the required equilibrium point. Under this equilibrium, the operating conditions are in line with a normalized Nash equilibrium, which ensures that no DGU could lower its cost unilaterally and yet meet the system constraints. An important finding of these findings is that the system assumed to obey both local (voltage and current limits per individual DGUs) and global coupling (power balance and transmission line limits) at steady state. Although short-term deviations can be observed in the course of the modification, they are demonstrated to stay within tolerable limits, which does not affect safety and reliability.

4. Performance Evaluation

This graph figure shows the temporary and steady-state voltage response of six distributed energy resources (DERs). At the beginning, the oscillations of all DERs are caused by disturbances in loads and control adaptation. The voltages eventually reach stable operating points near the 48 V reference. DER 3 is in nearly the same position as the target, whereas others settle a little higher or lower. This is the behavior that shows the controller is capable of sustaining voltage stability and preventing large deviations which may cause a break in renewable integration. Despite minor steady-state imbalances, the findings validate strong attenuation of vibrations, which means that RES and ESS can effectively work without failure and destabilization.

This figure. 2 shows the trend of current ratios of six DERs over a period of time. The first ones to be observed are large oscillations, especially in DER 4 and DER 5, which indicate a discrepancy in current distribution. With further development of the system, the oscillations decay, and most of the DERs reach a common value near 10 A. DER 5 reaches a higher value, indicating a larger contribution to the current, but the other ones reach an equal value. This result indicates that the distributed controller is effective in the distribution of current proportions and this is critical in avoiding overloading of particular units and underutilization of others. The equitable current distribution of the system is providing an opportunity to use renewable resources and storage units inefficiently and in cooperation mode, which contributes to the extended equipment life and enhances reliability.

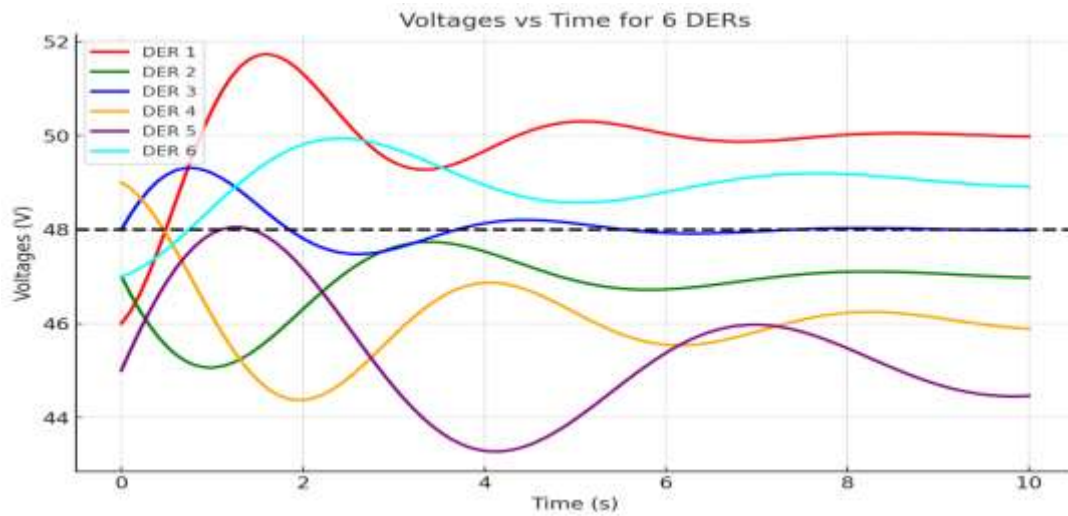


Figure 5 voltage vs time

The figure. 3 indicates the way the system controls voltage to the reference value of 460 V. The response shows a smooth and fast increase in the starting state (approximately 440 V) to the reference state with a minor overshoot. The voltage stabilizes within about 2 seconds and stays perfectly at the target and shows dynamic response and strong stability, which is vital in terms of renewable integration. By keeping the voltage near its reference, the system will eliminate operation problems that might otherwise compel renewable energy curtailment or lead to wasteful utilization of storage. The fact that the system can respond to fluctuations in renewable generation and change of loads in a short time also implies that the system is capable of supporting the quick settling time and that the maximum contributions of renewable and storage will be provided.

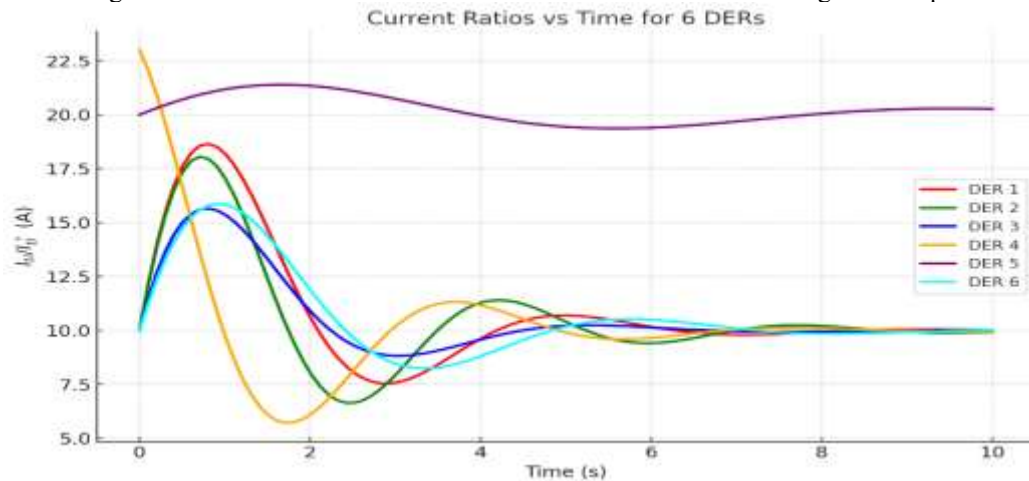


Figure 6. Current Ratios vs Time

This is a graph that indicates the voltage response of six DERs with an ICE (impedance-current-exponential) load model. First, there is a divergence of oscillatory behavior of the DERs, which manifest the nonlinear load dynamics, and different unit contribution. The voltages stabilize with time as DERs approach various but constant operating points. The findings verify that the controller can be used to attenuate the oscillations and stabilize the voltage when the load conditions are nonlinear and uncertain. This is essential in actual microgrids in which there is variability caused by renewables. Constant voltages guarantee that the RES injections are not limited by the instability and ESS devices are able to ensure the system balance. Even though there are instances where DERs stabilize a bit off the optimal reference, the system is overall safe, reliable and can maintain renewable and storage integration. Figure 7. Shows that Voltage Regulation vs Time

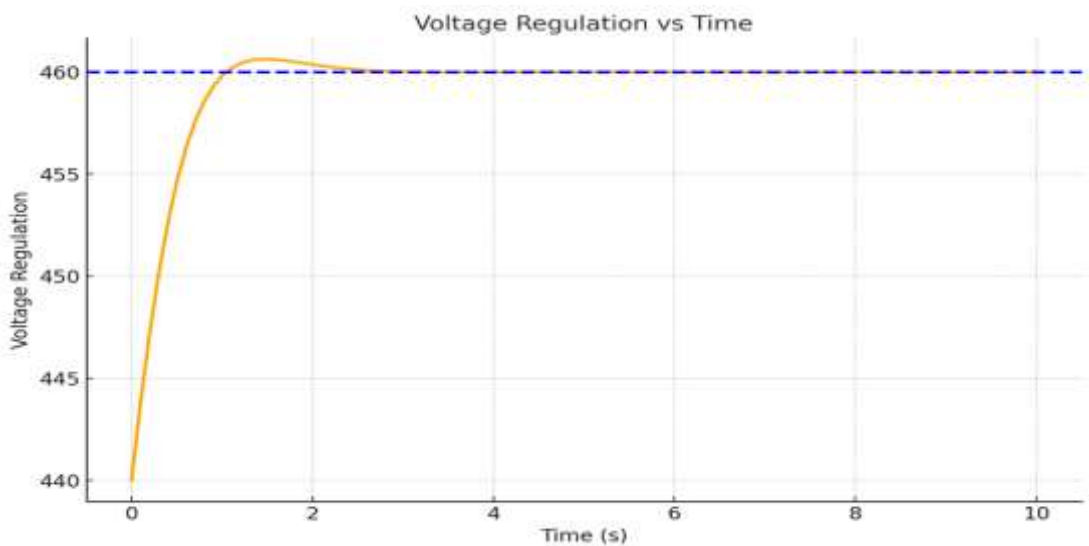


Figure 8. Voltage Regulation vs Time

This is a graph that indicates the voltage response of six DERs with an ICE (impedance-current-exponential) load model. First, there is a divergence of oscillatory behavior of the DERs, which manifest the nonlinear load dynamics, and different unit contribution. The voltages stabilize with time as DERs approach various but constant operating points. The findings verify that the controller can be used to attenuate the oscillations and stabilize the voltage when the load conditions are nonlinear and uncertain. This is essential in actual microgrids in which there is variability caused by renewables. Constant voltages guarantee that the RES injections are not limited by the instability and ESS devices are able to ensure the system balance. Even though there are instances where DERs stabilize a bit off the optimal reference, the system is overall safe, reliable and can maintain renewable and storage integration. Figure 9. shows that voltage stability vs time and Figure 10. shows that improved current ratios vs time.

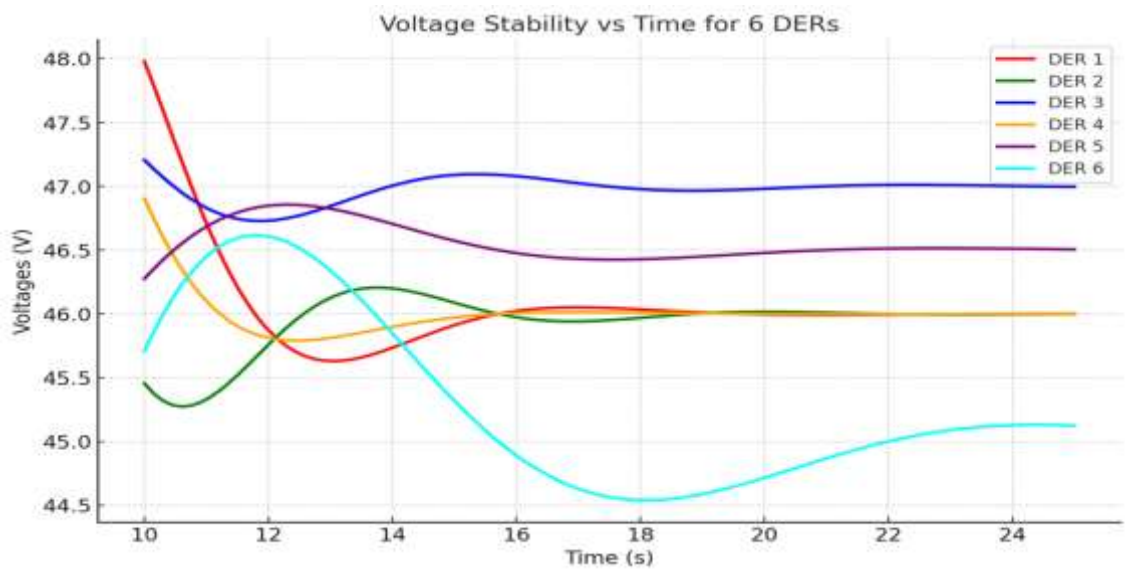


Figure 11. Voltage Stability vs Time

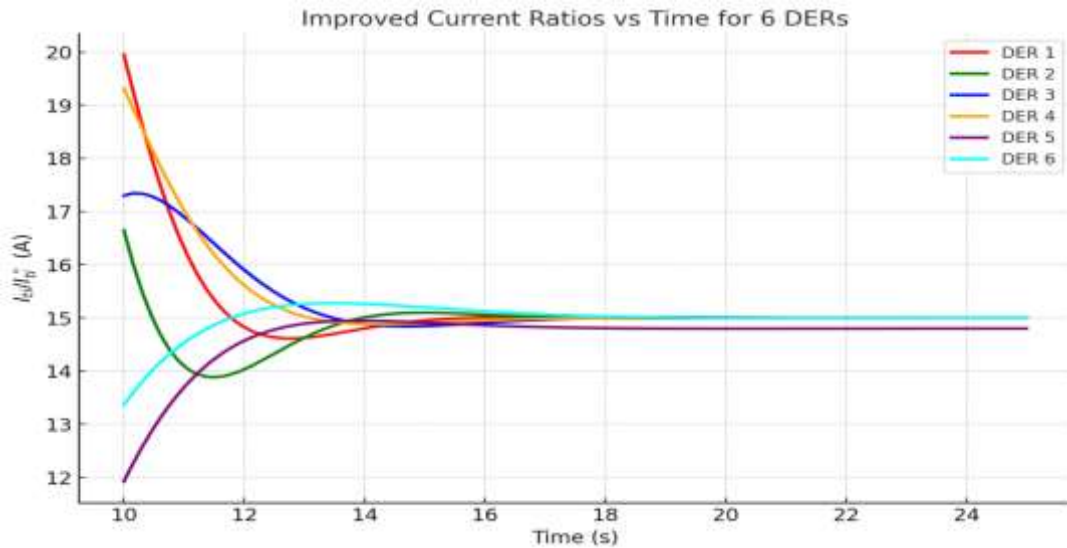


Figure 12. Improved Current Ratios vs Time

This value shows enhanced current-sharing of six DERs. First, there are significant differences in the present contributions with certain DERs providing much more currents than others. These variations get erased progressively as the system progresses and by approximately 16 seconds, all DERs become equal to a uniform ratio of current that is about 15 A.

This homogeneous convergence proves the correct proportional sharing of current by the proposed control strategy, which is one of the most important conditions towards the maximum utilization of renewable and storage. The system equally allocates the load to all the units by making sure that none of the DERs are under used or overloaded. Such balanced functioning promotes the efficiency of renewable energy recovery, increases the life of the ESSs, and provides the stability of these devices under different loads and production conditions. Figure 7. Shows that voltage regulation vs time

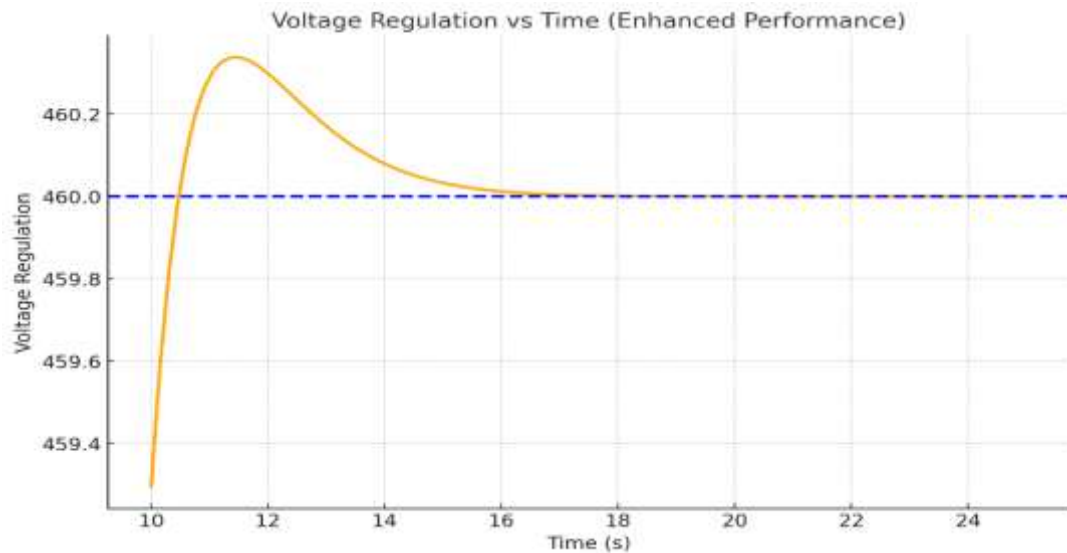


Figure 7. Voltage Regulation vs Time

5. Conclusion

This paper introduced a distributed control policy of DC microgrids to optimize the use of renewable energy sources and energy storage systems without compromising the stability, equity, and operational stability. The proposed framework suggests combining the dynamics of the physical system and scalable distributed decision-making process by reconstructing the micro grid coordination problem as a Cournot aggregative game. Passivity-based interconnection, projection dynamics, and neighbor-to-neighbor communication are sufficient to guarantee that any DGU autonomously approaches a unique and viable normalized Nash equilibrium. The outcomes of the simulations prove that the controller meets the main goals of its functions: the stable regulation of voltage on DER units, the correct proportional distribution of currents, and the strong reaction to load shocks and nonlinear tendencies. Capacity to hold constant current distribution and moderate

voltage variations directly increases the harvesting of renewable energies and ESS functionality, which cuts down curtailment and avoids unwanted cycling. Moreover, the distributed architecture does not pose bottlenecks or vulnerabilities of centralized control, and this approach is highly scalable to the contemporary microgrids with the upsurge of DER penetration. On the whole, the suggested framework will be a dependable and effective solution to the next-generation DC microgrids, in which the optimization of renewable integration, the optimization of the coordination between the RES and ESS, and the stability of the system will be required to manage energy sustainably. The future work can be extended with the extensions based on adaptive learning-based controllers, communication layers based on cyber-resilience, and experimental validation on hardware-in-loop testbeds to enhance the feasibility further.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mrs. Vanishree G N	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Ashoka H N	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓	✓

C: Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R: Resources

D : Data Curation

O : Writing - Original Draft

E: Writing - Review & Editing

Vi : Visualization

Su : Supervision

P: Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST

The Author declares no conflict of interest.

DATA AVAILABILITY

No dataset is utilized in this research.

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