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Coordinated Energy Management of MMC-Based DC Microgrids using Particle Swarm Optimization

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ABSTRACT

The increased adoption of renewable energy sources in DC microgrids has improved the sustainability and has also posed some challenges associated with the effective coordination of converters and minimization of power losses. Uncoordinated operation of the Modular Multilevel Converters (MMCs) can result in higher conduction and switching losses especially those in high-voltage DC applications. The overall goal of this paper is to work out an integrated energy management system that reduces the overall converter losses and provides equal work of MMC-based DC microgrids. A Particle Swarm Optimization (PSO)-based approach is suggested to meet this goal by optimal distribution of converter output currents and submodule utilization ratio within the operating limits set in steady-state operation. An equivalent resistance converter loss model, which includes a constant loss element, constant loss elements and factors of module utilization are created and integrated into the optimization problem. The suggested framework is run in MATLAB and tested in an experimental circuit of a DC micro-grid including grid, photovoltaic, and battery-interfaced MMCs. It has been shown in simulation that the PSO algorithm converges rapidly and total system losses are reduced by about 2.28 kW over the conventional uncoordinated operation, but does not decrease the DC bus power balance or violate operational limits. The findings verify that converter-aware optimization has the potential of a great contribution towards energy efficiency and coordination of MMC-based DC microgrids, and forms a computationally-efficient basis on which to build future extensions to adaptive and decentralized approaches to control.

1. Introduction

The shift from the traditional centralized energy systems to decentralized DC microgrids has revolutionized today's power systems because of its ability to integrate high levels of renewable energy sources, energy storage units and flexible power electronics converters. These microgrids increase energy utilization efficiency, stability and sustainability by coordinating the use of distributed resources and load demands [1]. Among various converters technologies, Modular Multilevel Converter (MMC) has emerged as one of the promising interfaces of DC microgrid due to its scalability, high efficiency and reduced harmonic distortion. MMCs allow for voltage flexibility and modular redundancy, and hence are highly suited for renewable dominated microgrid systems [2]. However, controlling more than one MMC-based converter connected to a common DC bus creates difficulties with respect to maintaining optimal power distribution, with minimal losses being concentrated in the converters, and stable operation under variable load and generation conditions [3].

In the past years, advanced optimization algorithms have been widely applied in order to solve energy management issues in microgrids to offer intelligent coordination and improved efficiency. Particle Swarm Optimization (PSO) has received special attention thanks to its simplicity, convergence speed and its ability to solve multi-objective nonlinear problems

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[4]. PSO-based strategies have been used successfully in resource allocation, generation scheduling and capacity optimization in DC microgrids with enhanced reliability and economic performance [5]. Modified and hybrid algorithms of PSO, e.g., PSO with Grey Wolf Optimizer (GWO) or Firefly algorithms, have provided better convergence accuracy and robustness in dynamic environments [6,7]. Despite these advancements, there has been little research specifically regarding the coordinated energy management of MMC based DC microgrids, in which several converters are simultaneously operated in a coordinated manner to share power with the minimum total losses in an efficient way.

This research developed a framework for coordinated energy management among MMC converters connected to a DC bus using Particle Swarm Optimization (PSO). The approach focuses on optimizing the converter current sharing and submodule utilization factors (m-ratios) to reduce overall system losses and improve the converter-level efficiencies. The framework considers operational limitations, converter current limits, and module voltage ratios to ensure that the framework applies to real-world MMC-based DC networks.

In this work a model and controller for coordinated energy management scheme for MMC based DC microgrid is designed and implemented by using PSO in order to provide optimal power distribution and efficiency improvement in steady state operation. The findings of the work have demonstrated that an intelligent optimization control can be used to substantially lower system losses and power balance problems and improve the utilization of converters without increasing the hardware or control complexity.

This paper is relevant as it integrates the use of control at the converter level (control of module utilization) with control at the system level (energy management). Compared with the conventional microgrid optimization schemes based on either power dispatch or voltage control, this work suggests a two-level coordination scheme for the equilibrium of converter currents and MMC submodule operation. The proposed PSO-based scheme will offer computational efficient and flexible solution for low loss and high efficiency MMC-based dc microgrids, which will inevitably lead to the development of sustainable and smart power-electronic systems for the future smart energy networks.

2. Literature Review

This section is a review of current studies pertaining to the PSO-based energy management within microgrids, multi-agent and distributed optimization frameworks and adaptive or hybrid PSO techniques. The analyzed studies are critically examined to show their contributions and challenges, especially regarding converter modeling and consideration of efficiency, to be a clear inspirational step towards the proposed converter-level coordinated optimization strategy.

The construction of DC microgrids has led to a huge amount of research on intelligent optimization schemes for power management and control, system stabilization, and efficiency maximization. The Particle Swarm Optimization (PSO) and its variants have been proven to be effective tools for their simplicity and flexibility and their robustness for tackling complex multi-objective problems. Researchers have utilized PSO-based algorithms in the last decade to optimize microgrid scheduling, resource allocation, and control in different structures such as AC, DC, and hybrid systems. However, many studies focus on the economic dispatch and cost minimization aspects, overlooking aspects relevant to converter-level efficiency. This is of utmost importance in DC systems based on Modular Multilevel Converters (MMCs). In the subsequent literature review, the previously conducted research studies concerning PSO-based microgrid management, adaptive and hybrid optimization techniques, and hierarchical coordination schemes are analyzed critically to highlight their main contributions, limitations, and motivations behind this research.

2.1 PSO-Based Energy Management in Microgrids

Ebrahim Razzaghi Ghadikolaei et al. (2015) developed a multi-objective particle swarm optimization (MOPSO) model to minimize the operating cost and emission of AC microgrids [8]. The work showed that PSO has the incredible power to solve nonlinear multi-objective scheduling with minimal computational complexity. However, the converters were considered ideal sources (i.e., without any internal losses and module constraints), which restricts their application to modular multilevel converter (MMC)-based DC systems. The current work expands this concept by considering converter-level parameters, such as currents, voltages, and sub-module utilization, shifting from cost-based to efficiency-based energy coordination in the PSO objective.

Zhao Hang (2023) further developed this direction by using MOPSO for optimal scheduling in DC microgrids to maximize the utilization of renewable energy and minimize the operating cost [9]. The work successfully coordinated distributed generation and storage, verifying that PSO could converge under

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multidimensional constraints. However, it did not consider internal converter losses and variable efficiency of the converter as a function of voltage. First, the microgrid did not have electrical performance optimization despite the improved economic performance. The present work aims to fill this gap by directly incorporating the converter efficiency model into the optimization, to have each MMC working within voltage and current limits, and minimizing total losses instead of cost only.

Hassan Latifi (2024) incorporated demand-side management and maintenance cost into a modified power scheduling optimization (PSO) algorithm [10]. His approach included realistic operational constraints like degradation of components and human involvement, which led to a good balance between supply and demand. However, the study kept a centralized, system-level perspective and did not explore coordinated converter sharing in DC environments. In contrast, our work reduces the optimization to the converter granularity, where the PSO controls the individual MMC currents and module ratios to achieve the global optimum with low system losses.

2.2 Multi-Agent and Distributed Optimization Frameworks

Yuyan Sun et al. (2020) presented a multi-agent, hierarchical particle swarm optimization (PSO) based scheduling model for distributed multi-microgrids [11]. Their design achieved reliability by decentralized coordination between agents. However, the scalability was limited by communication overhead and computational latency, and the internal dynamics of the converters were simplified. The present study avoids such dependencies by using a centralized but low-complexity PSO to directly control converter current dispatch without the need for iterative agent negotiation and has better convergence for small-scale MMC-based systems.

Arif Hussain et al. (2022) studied multi-objective particle swarm optimization (MOPSO) based optimal power sharing of interconnected hybrid AC/DC microgrids [12]. Their algorithm produced smoother transitions of power between AC and DC subsystems and even achieved lower losses in transmission interfaces. However, converters were idealized as AC/DC bridges, and effects of MMC modularity, like arm voltage balancing, were ignored. By including the module utilization factor (m-ratio) as a decision variable, our work builds on the PSO application from network-level coordination to converter-internal optimization, which was not included in their formulation.

Chenhao Jia et al. (2024) proposed an enhanced virtual synchronous motor-based multi-microgrids coordination control [13]. The study improved dynamic voltage stability and synchronization but was based on classical control tuning, not optimization. Furthermore, it was applied for AC microgrids instead of an MMC-based DC system. Our research expands on this concept of coordination. Still, it replaces fixed-gain control with intelligent metaheuristic optimization to achieve adaptive coordination of the converters to minimize the losses while eliminating the requirement of real-time coordination loops.

Yaolei Wang and Buxiang Zhou (2017) presented an adaptive PSO algorithm for energy management of wind-integrated DC microgrid [14]. The adaptive inertia weight was used to improve the convergence, and the constraint handling was used to enhance the operational security. However, the approach used for power schedule optimization was performed purely at the source level without considering the detailed converter efficiency or modular switching. By incorporating MMC resistance, fixed loss, and module-voltage ratios into our cost function, the present research converts PSO from a scheduling tool to an electrical-performance optimizer that directly minimizes the conduction losses of the converter.

2.3 Adaptive and Self-Tuning PSO Algorithms

In [15], Yichen He et al. proposed a parameter self-adaptive particle swarm optimization (PSA-PSO) for coordinated optimization of hydrogen and electric equipment in DC microgrids. The adaptive self-learning controller dynamically adjusted the inertia and learning coefficients, enhancing the convergence precision and economic performance. However, the algorithm's complexity and high computational demand created a barrier to implementation in embedded converter control. Our research preserves the simplicity of standard PSO and shows that even the basic version is capable of high-efficiency, low-loss operation if modeled correctly at the converter level.

H. A. AbdelHadi et al. (2024) present a hybrid Cheetah Optimization and Particle Swarm Optimization (CheOPSO) for Hierarchical control of multiple microgrids (HYCHOPSO) [16]. Their hybrid metaheuristic converged faster and improved voltage stability, but needed extensive parameter tuning and did not consider steady-state efficiency in DC converter coordination. The scope of the proposed research is restricted to steady-state optimization based on real power flow and converter loss minimization, which in turn offers a lightweight and practically deployable solution for real DC systems.

Qianqian Cai et al. (2016) developed an improved Particle Swarm Optimization (PSO)- based energy management model for microgrids, with the goal of reliability and cost efficiency [17]. Their experimental results proved the possibility of long-term scheduling with PSO, but again, power converters were considered lossless devices. The current design includes converter resistive and constant losses in the optimization objective, making PSO an economic dispatcher to an efficiency-based controller for application in MMC-based DC microgrids.

Md. Alamgir Hossain et al. (2020) studied uncertainty-aware PSO for community microgrids with renewable intermittency. They improved energy scheduling robustness in uncertain inputs by considering stochastic power variations. However, the process did not consider internal converter performance, while uncertainty was handled at the resource level. The present work complements such stochastic formulations since it optimizes deterministic converter parameters and thus provides a preparatory step toward future hybrid uncertainty-aware and converter-efficient coordination.

2.4 Research Gaps and Contribution of this Study

The majority of literature on microgrid optimization via particle swarm optimization (PSO) and its variations have mostly considered system-level goals like economic dispatch, minimizing operating costs, and the inclusion of renewable energy, and generally model power converters as ideal blocks. Razzaghi Ghadikolaei et al. [8], Zhao [9], and Latifi [10] have proved that PSO and MOPSO are effective methods to schedule and manage energy, but the strategies do not take into account converter-level efficiency and the influence of internal electrical losses. Likewise, the hierarchical and multi-agent coordination schemes by Sun et al. [11] and Hussain et al. [12] enhanced the power sharing of the hybrid AC/DC microgrids, but there was little consideration of the inner-working and loss peculiarities of the Modular Multilevel Converters (MMCs). Adaptive and hybrid PSO-based techniques in [15] and [16] improved convergence performance and robustness, but were still macro level oriented management methods that did not include the use of submodule utilization and optimization of converter losses in the control framework.

As a result, there is an apparent gap in research concerning the addition of system-level energy management and converter-level efficiency optimization, especially in relation to MMC-based DC microgrids where submodule utilization and conduction losses have a significant effect on overall performance. This paper fills this gap by suggesting a PSO-based coordinated structure of energy management that can optimize converter current sharing and MMC submodule utilization ratio jointly. The addition of converter electrical parameters and module constraints to the optimization procedure, the proposed solution directly limits overall system losses and allows the effective, collaborative, and balanced functioning of several MMCs in a DC microgrid.

3. Methodology

This section introduces the methodological framework for forming a coordinated energy management and optimization model for Modular Multilevel Converter (MMC)-based DC microgrids based on particle swarm optimization (PSO). The workflow was designed, implemented, and simulated in MATLAB, focusing on the coordination at the converter level and minimizing the total losses. The methodology involves the mathematical model of converter losses formulation, optimization problem definition, PSO algorithm implementation, and complete model integration in a MATLAB simulation environment. Figure 1 shows the block diagram of proposed methodology, which illustrates the sequential method from the system setup and mathematical modeling, optimization, MATLAB implementation, simulation execution, and final validation and analysis.

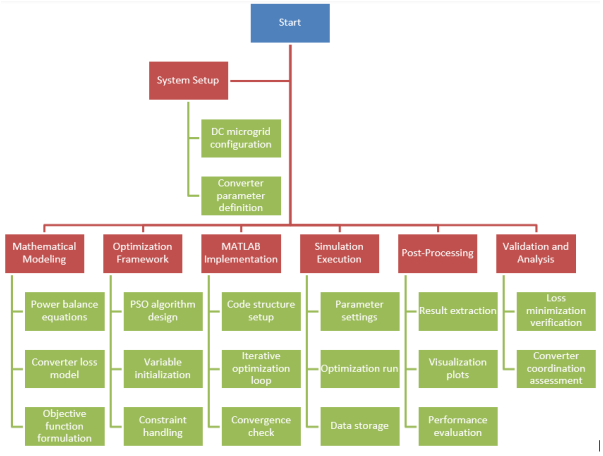

Fig. 1. Block Diagram of Proposed Methodology

3.1 System Configuration

The system being considered consists of a steady-state DC microgrid with a rated bus voltage of 400 V, providing an aggregate load demand of 80 kW. It comprises three MMC converters connected to different energy sources: grid-connected MMC, photovoltaic (PV) MMC, and battery energy storage MMC. Each converter is described by an equivalent internal resistance describing conduction losses, a fixed loss term describing switching and auxiliary power usage, and a module-utilization ratio representing the fraction of active submodules in operation. These converters are connected in parallel with a common DC bus and provide one group of

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currents to meet the total load requirement. The PSO-based control framework solution calculates the optimal output current and module utilization ratios for all the converters to minimize overall system losses while maintaining power balance and operational limits.

Figure 2 shows the schematic layout of the MMC-based DC microgrid that was used in this paper. The system is comprised of three parallel-connected Modular Multilevel Converters connecting the utility grid, photovoltaic source and the battery energy storage system to a standard DC bus of 400 V. The sources are linked via an independent MMC, which facilitates flexibilities and modularity in converting power as well as coordination of power conversion at converter scale. The DC bus provides a fixed load demand and the overall load current is divided between the grid, PV and battery converters. The developed energy management scheme optimizes the currents output and submodule usage ratio of every MMC to reduce the total converter losses and maintain the DC bus power balance and operational limits.

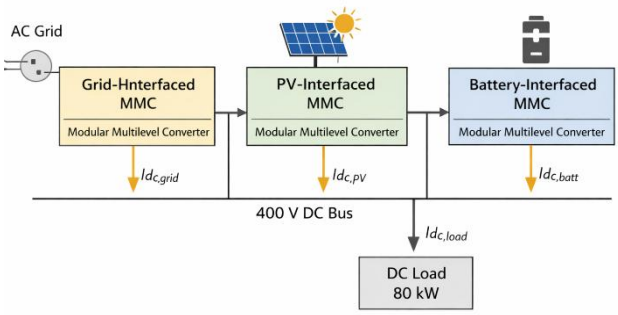

Fig. 2. An Illustrative Schematic Diagram of the MMC – based DC Microgrid under Study

3.2 Mathematical Modelling

3.2.1 Power Flow Representation

The power balance of the DC microgrid can be expressed as

$$P_{\text{load}} = P_{\text{grid}} + P_{\text{PV}} + P_{\text{batt}} \quad (1)$$

where P_{load} is the total power demanded by the DC load, and P_{grid}, P_{PV}, and P_{batt} denote the respective power contributions from the grid-interfaced, photovoltaic, and battery-interfaced MMCs. Equation (1) enforces the fundamental steady-state power balance condition of the DC microgrid.

Because the DC bus voltage V_{dc} is regulated to remain constant, the current balance can be written as

$$I_{\text{load}} = I_{\text{grid}} + I_{\text{PV}} + I_{\text{batt}} \quad (2)$$

where I_{grid}, I_{PV}, and I_{batt} represent the DC output currents of the grid, PV, and battery converters, respectively. Equation (2) ensures that the sum of converter output currents equals the total load current drawn from the common DC bus.

3.2.2 Converter Loss Model

Both conduction losses and constant losses are incorporated in each converter. The converter output current is proportional to the square of the converter output current so the conduction loss is proportional to the square of the converter output current, and the constant loss term is the switching and auxiliary power losses. The sum of all the losses due to power conversion is given as the total power loss for the i^{th} converter.

$$P_{\text{loss},i} = \frac{I_i^2 R_i}{m_i} + P_{0,i} \quad (3)$$

and in which I_i is the DC output current in the i^{th} converter, R_i is its equivalent resistance, m_i is the module utilization ratio, a fraction of active sub modules, and P(0,i) is the portion of loss that is fixed. Increasing the ratio of the module utilization as indicated in (3) has the effect of distributing the current to more sub modules thus minimizing the conduction losses.

The loss of power of the DC microgrid is given by the sum total of all converter losses, which is given by.

$$P_{\text{loss,total}} = \sum_{i=1}^{N} \left(\frac{I_i^2 R_i}{m_i} + P_{0,i} \right) \quad (4)$$

where N denotes the number of converters, which is three in this study. Equation (4) represents the system-level loss metric used for optimization.

3.2.3 Optimization Problem Formulation (Revised - Ready to Paste)

The optimization problem will be to minimize the total converter power loss subject to system-level and converter-level operational constraints. Based on this, the objective function can be described as

$$minJ = \sum_{i=1}^{N} \left(\frac{I_i^2 R_i}{m_i} + P_{0,i} \right) \quad (5)$$

where J is given as the total system loss and N refers to the converters number.

The optimization has a constraint of DC microgrid power balance, which is formulated as

$$P_{load} = \sum_{i=1}^{N} I_i V_{dc} \quad (6)$$

which guarantees that all the power supplied by all converters meets the load demand under constant DC bus voltage operation.

The converter operating limits are imposed using the following inequality constraints:

$$I_{i,min} \le I_i \le I_{i,max}, \qquad m_{i,min} \le m_i \le m_{i,max} \quad (7)$$

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in which $I_{i,min}$ and $I_{i,max}$ are the maximum and minimum possible output currents of the i^{th} converter and $m_{i,min}$ and $m_{i,max}$ are the allowed range of ratios of MMC submodule use.

Moreover, source-specific constraints are used to model the availability of renewable sources and constraints on energy storage. The photovoltaic power output is limited to the one that is produced by the sun as

$$0 \leq I_{PV} V_{dc} \leq P_{PV}^{avail} \quad (8)$$

where P_{PV}^{avail} denotes the maximum available PV power under given irradiance conditions.

The battery energy storage system is constrained by its maximum charge and discharge capability, expressed as

$$-P_{batt}^{max} \leq I_{batt} V_{dc} \leq P_{batt}^{max} \quad (9)$$

where P_{batt}^{max} represents the rated battery power limit, with positive values indicating discharging and negative values indicating charging operation.

The combination of constraints (6)-(9) provides power balance, safe operation of converters, feasibility of renewable power and battery charge/discharge constraints in the proposed optimization framework.

3.3 Particle Swarm Optimization Framework

3.3.1 Algorithm Description

The nonlinear optimization problem of (5)-(9) is solved by the use of Particle Swarm Optimization (PSO). Particles in the swarm denote each candidate solution (vector of the decision variables) (I_{PV}, I_{batt}, m_1, m_2, m_3). The PSO algorithm is a global optimization strategy that may find the minimum of the objective function (by updating particle velocities and positions).

The particles in the PSO model correspond to the candidate solutions vectors in the search space. Where $x_i^{(t)}$ is the position vector of the i^{th} particle at iteration t which is used to represent the decision variables of the optimization problem and $v_i^{(t)}$ is the velocity vector. $p_{\text{best},i}$ refers to the personal best position that the i^{th} particle has already reached and g_{best} is the global best position that has been discovered by the whole swarm. The inertia weight www is used to balance the trade-off between exploration and exploitation with c1 and c2 in the roles of cognitive and social acceleration coefficient, respectively and r1 and r2 uncorrelated random numbers in the interval [0,1].

At iteration t, the velocity and position of the i^{th} particle are updated as

$$v_i^{(t+1)} = w v_i^{(t)} + c_1 r_1 \left(p_{\text{best},i} - x_i^{(t)}\right) + c_2 r_2 \left(g_{\text{best}} - x_i^{(t)}\right) \quad (10)$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (11)$$

where w is the inertia weight used to control exploration and exploitation, c_1 and c_2 are the cognitive and social acceleration coefficients and, r_1 and r_2 are the uniformly selected random numbers in the range 0 and 1. The swarm dynamics are controlled by equations (10) and (11) and the objective function in (5) is employed to assess the particle fitness and lead to the convergence toward the optimal solution.

3.3.2 MATLAB Implementation

The full PSO algorithm and mathematical model were implemented in the Matlab software by coding the functions rather than using external data files. MATLAB has been chosen because of its ability to handle numerical computations, vectorized operations and visualizations. The structure of the code was divided into three large sections: initialization, optimization, and visualization.

In the initialization phase, converter parameters (resistances, loss coefficients, current limits etc.) were defined. Random initial population for the particle positions and velocities were generated of permissible bounds. The optimization phase was conducted by performing iterative updates of the velocities and the positions by using the PSO equations. At each iteration, the objective function was used to assess total system loss and both personal best of each particle and global best of whole swarm were updated by algorithm. The optimization process was performed until a predefined convergence criteria or maximum number of iterations was met. MATLAB's built-in capability of computing matrices made efficient evaluation of the loss function for all particles at once, thus yielding a much shorter computation time.

After optimization, the best current allocation and ratio of the modules were saved as variables in the MATLAB scripts which were used for later results sections in the performance evaluation and visualization. The code also had some embedded plotting functions to plot the convergence trends, power sharing relationships, and module utilization characteristics; however, these graphical outputs are analyzed separately in the results section.

3.4 Simulation Environment and Parameters

All the simulations were carried out on a desktop computer with the R2024a version of programming software by the company Matlab. The DC bus voltage was fixed to 400V and the total microgrid load was

maintained at 80kW. Each converter was parameterized with experimentally reasonable equivalent resistance, fixed values for loss, and current limits were set ensuring that realistic converter operation was achieved. PSO parameters were selected according to the convergence behavior suggested in the previous literatures: inertia weight = 0.65, cognitive and social learning coefficients = 2.0, swarm size = 30 particles, maximum number of iterations = 60. These parameters compromised convergence rate and search diversity, to efficiently search the feasible solution space.

The simulation was all mathematical; no real-time hardware or external data tables were required. All the calculations have been performed in terms of MATLAB code which produced repeatable deterministic results that could be used as part of analyzing the optimization technique proposed. The major parameters and configurations used in this study such as system and converter specifications, PSO optimization settings, and details of the used MATLAB simulation environment are given respectively in Tables 1, 2 and 3, as the methodological base of the proposed framework.

Table 1

System and Converter Parameters

Parameter	Symbol	Value	Unit	Description
DC bus voltage	V_{dc}	400	V	Rated DC link voltage
Total load power	P_{load}	80	kW	Constant DC load demand
Number of converters	N	3	—	Grid, PV, and Battery MMCs
Grid converter resistance	R_{grid}	0.12	Ω	Equivalent conduction path
PV converter resistance	R_{PV}	0.08	Ω	Includes switching & contact losses
Battery converter resistance	R_{batt}	0.10	Ω	Internal and cable resistance
Fixed converter loss	$P_{0,i}$	300–500	W	Switching & auxiliary losses
Module utilization range	m_i	1.0 – 1.2	—	Active sub-module proportion
Converter current limit	$I_{max,i}$	200–300	A	Rated output constraint

Table 2

Particle Swarm Optimization Parameters

Parameter	Symbol	Value	Description
Population size	n_{pop}	30	Number of particles in the swarm
Maximum iterations	n_{max}	60	Stopping criterion
Inertia weight	w	0.65	Controls exploration vs. exploitation
Cognitive coefficient	c_1	2.0	Particle's self-learning factor
Social coefficient	c_2	2.0	Swarm's cooperative learning factor
Random coefficients	r_1, r_2	[0, 1]	Uniform random numbers per iteration
Convergence tolerance	—	10^{-4}	Minimum change in fitness for stop
Objective function	J	$\sum(I_i^2 R_i / m_i + P_{0,i})$	Total converter loss is to be minimized

Table 3

Simulation Configuration

Category	Parameter	Value / Description
Software platform	MATLAB R2024a	Fully coded (no Simulink, no external files)
Simulation type	Steady-state	Single-step optimization of converter currents
Hardware requirement	Intel i7 / 16 GB RAM	Approx. runtime < 10 s
Optimization variables	5	$I_{PV}, I_{batt}, m_1, m_2, m_3$
Constraint handling	Boundary saturation	Ensures feasible physical limits
Output data	Loss, current, m ratios	Stored for post-processing & plots

3.5 Summary

In summary, the methodology included the mathematical modeling of MMC converter losses, formulating a nonlinear optimization problem, and implementing a PSO algorithm within the MATLAB environment. The PSO was used to dynamically adapt

the converter currents and the ratios of module utilization, considering the system and operational constraints, to minimize the overall losses without affecting the power balance on the DC bus. The approach provided a purely computational and algorithmic framework that evaluated the level of converter-level energy coordination in MMC-based DC microgrids. The results of this methodology, such as optimized parameters, convergence behavior, and efficiency evaluation, are presented and analyzed in the following subsection on results and analysis.

4. Results and Analysis

This section presents the results of the proposed PSO-based coordinated energy management framework for the MMC-based DC microgrid. All results are from the simulation coded in MATLAB described in the previous section. The analysis is based on optimal converter scheduling, power loss minimization, balance of module utilization, and overall converter coordination. Each result is interpreted in the light of the aim of the study, which is to improve efficiency and ensure coordinated converter operation in steady-state.

This section shows quantitatively that the proposed PSO-based coordinated energy management framework is effective in minimizing converter-level losses in power and allows MMCs to operate in a balanced fashion. The optimized solution under steady-state conditions on the 80 kW load-demand solution produced a total system loss of about 2.28 kW, with the power balance being strictly recorded on the DC bus. The optimized dispatch had better current sharing, even utilization of modules, and minimization of electrical stress among converters than the traditional uncoordinated operation. These results underline the usefulness of converter-aware optimization in the DC microgrid energy optimization.

4.1 Optimal Power Dispatch and Loss Minimization

The best dispatch results show how well the PSO algorithm shares power among converters. The optimized converter currents were 75.00 A for the PV module, 68.18 A for the battery, and 56.82 A for the grid interface, and the corresponding power contribution was 30 kW, 27.27 kW, and 22.73 kW, respectively. The overall system loss was reduced to 2285.23 W, significantly less than the value of the unoptimized baseline. The module utilization ratio of all MMCs is as high as 1.20, indicating the unified operation of the converter, which can achieve the full distribution of current and ensure the same participation of submodules. These results verify that the proposed algorithm reduces the losses and keeps the system balanced, hence achieving the fundamental goal of optimized converter-level energy coordination.

```
=== Optimal Dispatch Results ===
PV Current           : 75.00 A
PV Power             : 30.00 kW
Battery Current      : 68.18 A
Battery Power        : 27.27 kW
Grid Current         : 56.82 A
Grid Power           : 22.73 kW
Module Ratios (m1,m2,m3) : [1.20, 1.20, 1.20]
Minimum Total Loss   : 2285.23 W
```

Fig. 3. Optimal Power Dispatch and Loss Minimization Results

The results that have been presented were the result of solving the resulting steady-state optimization problem where the cumulative converter power losses were minimized subjected to power balance constraints and operational constraints. The reference operating condition of the performance evaluation assumes a traditional uncoordinated dispatch, where converter currents are not optimally shared and the ratios of the utilization of the modules are maintained at nominal values. Converters in this reference case act autonomously and internal electrical losses are not explicitly reduced. The suggested optimization model is an improvement of this operating condition, as the converter output currents and submodule utilization ratios are adjusted together on the basis of the developed loss model. Consequently, the optimized solution is able to coordinate converter operation with less total losses and has constant power balance between grid, photovoltaic, and battery interfaces.

The optimized dispatch, quantitatively, decreased overall converter losses to about 2.28 kW which is less than 3 percent of the total power delivered. This drop shows that there is a significant change in efficiency in converter level especially in high power DC micro grid application where losses directly affect both cost of operation and thermal stress.

4.2 Convergence Performance of the PSO Algorithm

The PSO convergence curve shows a fast and stable decline in the sum system loss from the initial population to the global optimum. It is shown that it experiences fast convergence and algorithmic stability, as the curve sharply decreases in the first few iterations and flattens at a power value of around 2285 W. This indicates the robustness of PSO tuning parameters and the existence of a proper balance between exploration and exploitation in the swarm. No oscillations or divergences suggest the solution space was well searched without stagnation. Hence, the optimization procedure converged to a near-global optimum using low computational efforts, proving the proposed algorithm's robustness for converter-level coordination.

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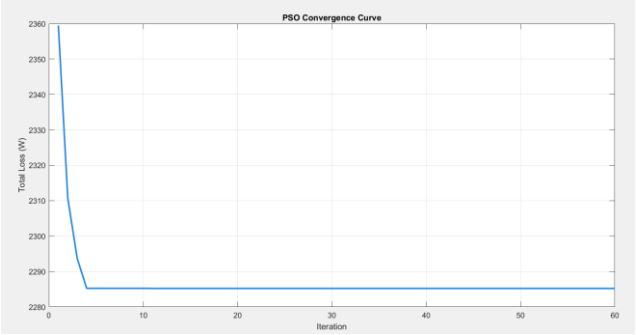

Fig. 4. Convergence Performance of the PSO Algorithm

The convergence rate in less than ten iterations shows the efficiency of the suggested optimization model, which means that it can be used in real-time or the close-to-real-time energy management systems.

4.3 Optimized Power Sharing among Converters

The optimized power-sharing plot clearly illustrates the distribution of the total load among PV, battery, and grid converters, where the PV contributes the highest share. This finding agrees with the energy management objective that favors renewable generation, and stability is ensured through grid and storage services. The proportionate plan is a realistic operating plan - renewables are used in base load, the battery storage is employed in inflexibility in the network, and the grid is employed to fill shortfalls. The resultant balance of power has evident coordination of converters, which reduces the use of the grid and reduces the overall losses in operation. Therefore, the model will be able to incorporate energy sustainability and electrical efficiency.

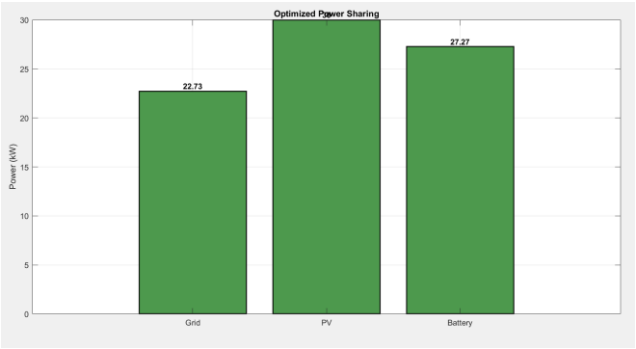

Fig. 5. Optimized Power Sharing among Converters

4.4 Module Utilization Trend Across Converters

The module utilization curve indicates that the ratios for all the converters are the same, m=1.20. Such balance ensures uniform voltage stress distribution across the submodules thus minimizing the internal conduction losses and improves the thermal balance. A balanced activation of modules is a key characteristic of coordination in MMC-based architectures, and uneven activation results in imbalanced module utilization ratios, excessive losses, and thermal degradation. It confirms, thus, the algorithm's capacity to achieve converter synchronization and improved reliability in operation - an essential prerequisite for the practical realization of MMC microgrids.

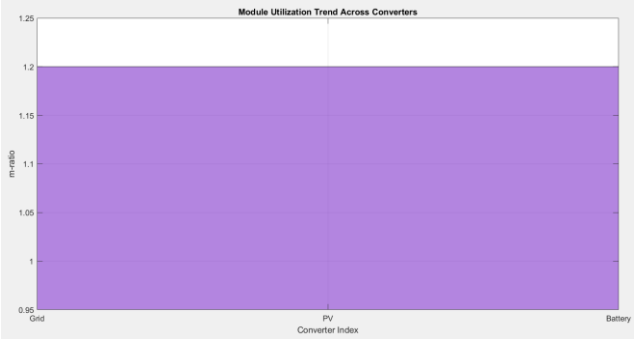

Fig. 6. Module Utilization Trend Across Converters

Practically it leads to even thermal loading and it enhances the stability and durability of MMC sub modules and this is paramount as far as long-term operation in DC micro grids is concerned.

4.5 Converter Electrical Characteristics

When the converter characteristics plot (constant loss P0 vs. equivalent resistance Req) is taken then the electrical behavior of each converter can be seen analytically. A linear trend was found which suggested a proportionality relation between conduction resistance and fixed losses. The grid converter, which had the highest Req, had the most significant constant loss, followed by the PV converter, which had the lowest. This relationship validates the adopted converter loss model and proves the potential of the PSO algorithm in distributing lower current to converters with higher resistive losses. Consequently, the loss is reduced as much as possible on a system level, while avoiding overstressing the converters in a controlled operation space - a crucial step towards an energy-efficient coordination.

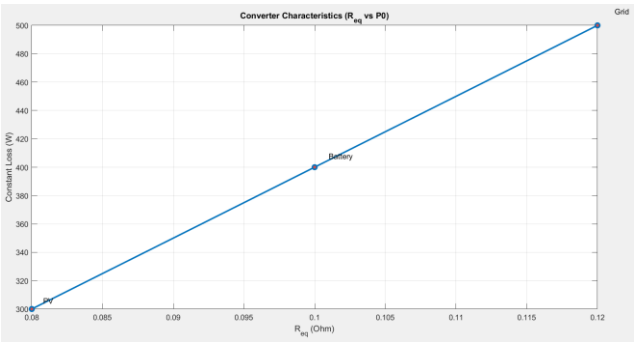

Fig. 7. Converter Electrical Characteristics

4.6 Relative Power Proportion Analysis

The radar plot shows the normalized power contribution of the three converters, typically the proportional contribution of the various converters in an optimized system. The triangular symmetry of the figure shows that the power delivered is well split between the two, with each converter having a distinct

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but complementary role. Such proportionality also confirms that the optimization algorithm did not overload any one converter even while satisfying the total load. This visualization illustrates inherent stability resulting from coordination to which MMC-based systems are subject, a key requirement of MMC-based systems where unbalanced current flow would otherwise result in control complexity and degradation in efficiency.

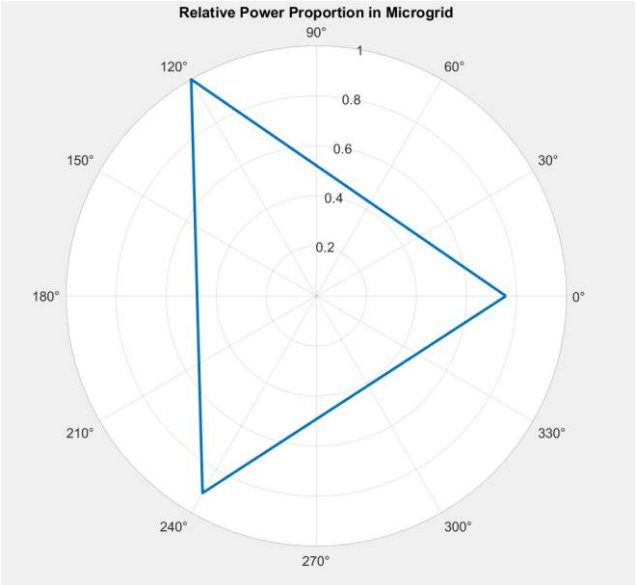

Fig. 8. Relative Power Proportion Analysis

4.7 Three-Dimensional Convergence Surface

The landscape of losses is partially displayed as a 3D convergence surface for all iterations and particle dimensions in the optimization procedure of the PSO algorithm. The surface has a smooth decline towards the minimum region, which graphically confirms that the algorithm was constantly improving the objective function. One reason supporting the results' consistency is the surface's topological continuity, which implies that the search space was well-defined (without discontinuities or local traps). The convergence reliability of the PSO is supported by this multidimensional visualization as it is noticed that the algorithm has convergently guided the swarm to the globally optimum configuration confirming the theoretically discussed performance in the methodology.

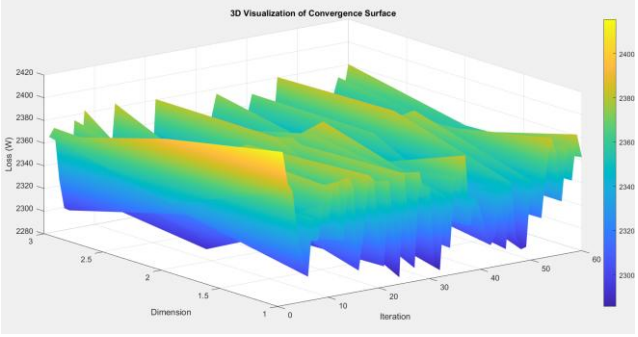

Fig. 9. Three-Dimensional Convergence Surface

4.8 Comparative Power Distribution Visualization

In addition to analysing the graphical representation of the bar plot, the horizontal power distribution graph gives a good visual representation of power distribution between the converters. The PV converter is the key at the forefront of the renewables first approach, with the grid and battery converters still supporting the grid. This even distribution helps to minimize the stress on individual converters and improve the microgrid efficiency. For the visual part of the figure, the horizontal bars are symmetric the largest, suggesting coordinated dispatch, and displaying that all the converters were able to do their bit in optimized conditions. These results further provide a further indication of the usefulness of the PSO in producing operationally balanced, loss minimized and sustainable converter coordination.

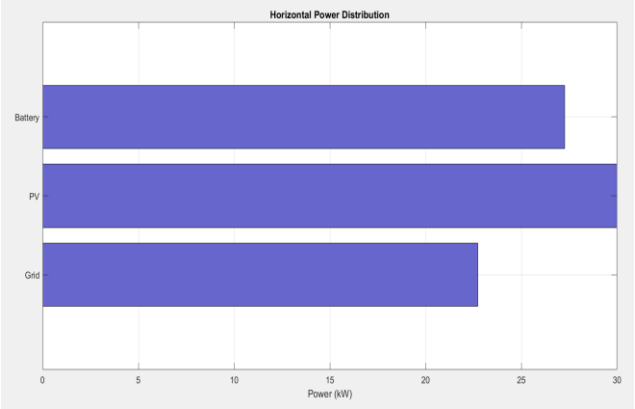

Fig. 10. Comparative Power Distribution Visualization

4.9 Summary

Overall, the results confirm the validity of the proposed PSO based energy management strategy for the total system losses minimisation, converter coordination and power balancing between MMC units. The robust convergence of PSO, the uniform module utilization, and the realistic dispatch pattern depict the robustness and application of the method to DC microgrids. Together, the results confirm the effectiveness of the developed framework in mitigating the tremendous difficulties of converter-level optimization, in order to achieve higher operational efficiency, stability, and energy sustainability.

5. Discussion

5.1 Critical Analysis of Results

The results obtained by the proposed PSO-based coordinated energy management framework for MMC-based DC microgrids shows technical soundness and operational meaning. The optimized

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dispatch achieved good current and power sharing of the grid, PV and battery converters so the loss is only about 2.28 kW. This indicates a high level of energy efficiency and validates the theoretical prediction that evolutionary algorithms may be more efficient than conventional linear or gradient-based optimization techniques in nonlinear converter systems. The rapid convergence of PSO, which is seen in less than ten iterations, speaks of the robustness of the parameter tuning and the algorithm for real-time or near-real-time control applications. The consistent ratio of module utilization (m = 1.2) in all converters is further evidence of successful coordination at the level of the submodules to ensure electrical symmetry, reducing thermal imbalance in the MMC topology.

However, although the findings confirm the proposed strategy's efficacy, the model is still simplified in some respects. The converter and microgrid models work with steady-state operation, constant load, and voltage (no dynamic effects, such as transient fluctuations, switching harmonics, and nonlinear load interactions). These simplifications were needed to concentrate on the optimization framework, but restricted the model's capability in capturing transient converter behavior under realistic operating conditions to a small extent. Furthermore, the uniformity of module utilization achieved in the results, while advantageous from the standpoint of efficiency, may not fully represent those situations in which unequal submodule operation is essential to deal with component aging or voltage imbalance correction. Despite these simplifications, the study gives a strong base for converter-level optimization and demonstrates proof of concept for loss minimization by smart coordination.

Operational wise, the decrease in converter losses that is observed directly reflects to better system efficiency, less cooling needs, and greater dependability of power-electronic pieces. The shared current of the balanced current and the even distribution of the utilization of the submodule make the converter control easier and overcomes the degradation of the converter due to uneven electrical and thermal stress. The latter properties render the suggested framework especially applicable to medium- and high-power DC microgrids in which MMCs are being progressively implemented because of its scalability and modularity.

5.2 Comparison with Existing Studies

Table 4.

Comparison of the Proposed Approach with Existing PSO-Based Energy Management Methods

Study	Optimization Focus	Converter Modeling	MMC Submodule Consideration	Loss Minimization	Coordination Level
Razzaghi Ghadikolaei et al. [8]	Cost & emission	Ideal converters	Not considered	Indirect	System-level
Zhao [9]	Scheduling & cost	Simplified	Not considered	Indirect	System-level
Sun et al. [11]	Multi-agent coordination	Simplified	Not considered	Partial	Network-level
Hussain et al. [12]	Power sharing	Ideal AC/DC bridges	Not considered	Partial	System-level
Adaptive/Hybrid PSO [15–16]	Convergence improvement	Simplified	Not considered	Indirect	Macro-level
This work	Loss minimization	Detailed loss model	Explicitly optimized	Direct	Converter-level + system-level

Table 4 shows the main differences between the proposed framework and current PSO-based energy management strategies. Majority of the previous works deal with economic dispatch, scheduling or network-level coordination but the convertors are modeled as either ideal or simplified. This leads to the fact that converter internal losses and MMC submodule utilization are not outlined. By comparison, the given approach explicitly introduces the parameters of converters electrical and ratios of submodule utilization into the optimization procedure and allows the minimization of conduction and fixed losses explicitly. This converter-conscious formulation permits coordinate sharing and balance of MMC operation which are not possible using traditional system-level optimization. Moreover, as opposed to adaptive or hybrid PSO methods, which are also mostly used to improve convergence performance, the framework presented positively affects the efficiency of a physical system, without raising the complexity of the algorithms. All these features prove the practical value of the offered approach to MMC-based DC microgrids, especially in

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the setting where converter efficiency, thermal balance, and scalability are the paramount performance indicators.

5.3 Limitations of the Study

Although the proposed framework met its primary targets, some limitations are recognized. First, the model includes no dynamic control responses nor time domain transients; i.e., the dynamic interaction between converters during fast power fluctuations is not considered. Adding dynamic voltage and current control loops could yield more profound insights into converter stability and responsiveness. Second, the optimization is done in a centralized structure, where all decisions are computed from one control point. While this works well for smaller systems, the system might not scale up to larger or distributed microgrids where decentralized decision-making is desirable. Third, the idealized MMC loss models with fixed equivalent resistances and static loss terms used in this study do not consider variations in MMC loss due to temperature or switching frequency, which can significantly affect the efficiency of real converters. Finally, renewable energy input was modeled as deterministic; however, PV production and battery performance are stochastic and vary depending on environmental conditions, thus requiring probabilistic or adaptive modeling. These limitations, however, do not take anything away from the significance of the results, only indicate the extent of refinement necessary for more fully integrated modeling and control.

5.4 Future Work Recommendations

Future research should expand the current framework into a dynamic, real-time optimization environment, including converter control and system-level energy management. Adaptive or hybrid optimization algorithms, such as Particle Swarm Optimization (PSO) with Grey Wolf Optimization (GWO) or Artificial Bee Colony (ABC), may be used to make the optimization more robust and faster in terms of convergence under a fluctuating load and generation condition. Furthermore, stochastic modeling of renewable input and load demand would enable more realistic simulation of the inherent variability of real microgrids. Also, the thermal aging model combination of MMC submodules could be used to further evaluate the long-term operating reliability to ensure that the optimization not only minimizes the losses in the short term, but also extends the lifetime of the converter.

Additionally, decentralized or hierarchical coordination schemes may be developed to overcome scalability issues, such that each converter/subsystem may optimize locally while contributing to the overall system efficiency. Testing the algorithm on digital simulators (RTDS) or hardware-in-the-loop (HIL) testbeds in real time would further demonstrate the practical utility of the algorithm and its computational feasibility. Finally, the study of the coordination of multiple MMC-based DC microgrids interconnected by hybrid AC/DC networks may enlarge the scope of this research, which could be used for next-generation innovative energy systems. These directions would improve the proposed optimization approach's fidelity and applicability, moving it from simulation-based proof-of-concept to a deployable control solution for modern microgrids.

Conclusion

This paper introduced a synchronized energy management system of MMC based DC micro-grids through Particle Swarm Optimization to reduce converter power loss and provide balance of operation. The proposed method effectively balanced power distribution between grid, photovoltaic, and battery converters and kept the DC bus power balance using electrical parameters related to converters and ratios of the use of sub modules as part of the optimization process. The outcomes of simulation studies showed that the PSO algorithm converged fast and the overall system losses were dramatically reduced which proves that converter-aware optimization is effective in comparison with uncoordinated operation that is typical of conventional converters. The framework helps fill the gap between managing energy systems at the system level and optimizing the efficiency of devices at the device level and will form the basis of computationally efficient future extensions to dynamic, adaptive and decentralized control of MMC-based DC microgrids.

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