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A Predictive Load-Aware and Multi-Scale Energy-Behavior Optimization Algorithm for Decentralized Multi-Agent Systems in Dynamic Power Networks

Kuppani Sathish[1*], Dr.M. Varalatchoumy[2], Dr.K. Vinutha[3], B.N. Shwetha[4], Dr. Venkateswararao Pulipati[5], and Dr.Y. Jeevan Nagendra Kumar[6]

[1*]Professor, Tirumala Engineering College, Narasaraopet, Pal Nadu, Andhra Pradesh, India. ksathish@tecnrt.org; skuppani@gmail.com, https://orcid.org/0000-0001-9581-6819

[2]Professor & Head, Department of Artificial Intelligence and Machine Learning, Cambridge Institute of Technology, K.R. Puram, Bengaluru, India. hod.aiml@cambridge.edu.in; kvl186@gmail.com, https://orcid.org/0000-0003-3720-9644

[3]Assistant Professor, Department of ISE, BMS Institute of Technology and Management, Bengaluru, India. vinuthak_ise2014@bmsit.in, https://orcid.org/0000-0002-2165-4738

[4]Assistant Professor, Department of Engineering and Technology, S Vyasa School of Advanced Studies, S-VYASA (Deemed to be University), Bengaluru, India. shwetha434@gmail.com, https://orcid.org/0000-0001-8521-0864

[5]Associate Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Bowrampet, Hyderabad, Telangana, India. pvenkat2004@gmail.com, https://orcid.org/0000-0002-2765-8318

[6]Professor, Head of the Department, Department of Information Technology, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, India. jeevannagendra@gmail.com, https://orcid.org/0000-0003-2577-8065

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Abstract

Multi-agent systems that run on decentralized multi-agent stacks on dynamic power networks are known to experience enduring issues connected to energy efficiency, coordination, and adaptability in the face of time-varying loads and restricted communication. The fact is that the majority of current decentralized control approaches are mainly based on reactive decision-making and do not include the possibility of predicting future energy requirements, which contributes to inefficiencies and system unreliability. To overcome such problems, the current paper has suggested a predictive load-aware, multi-scale energy-behaviour optimization algorithm, named DECO-MARS, targeting the area of decentralized multi-agent power systems. DECO-MARS incorporates predictive load-conscious consensus control with a two-layered optimization structure that optimizes and coordinates the local energy constraints and global coordination goals simultaneously, and proactively and scalably optimizes the decentralized control. The IEEE 13-bus distribution test feeder is used to test the proposed algorithm based on realistic and time-varying load conditions and renewable generation conditions. The results of the simulations indicate that the total energy loss

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*Corresponding author: Professor, Tirumala Engineering College, Narasaraopet, Pal Nadu, Andhra Pradesh, India.

under the DECO-MARS is only 18.2 kWh as opposed to 25.1 kWh under a consensus-only control and 27.4 kWh under a local optimization, which is a significant enhancement in the energy efficiency. The framework has a voltage stability of 0.029 p.u. Voltage deviation index, which is much lower compared to the baseline techniques. DECO-MARS also has a 94.0 % success rate of tasks, a control latency of 1.2 seconds, and a normalized coordination score of 0.92, which is better than existing decentralized methods on all of the metrics assessed. The findings indicate that predictive intelligence and multi-scale optimization can be a significant improvement to the reliability, efficiency, and coordination of decentralized power networks. DECO-MARS can be used in distributed and ubiquitous energy systems such as smart grids, edge-controlled power networks, and autonomous energy-aware cyber-physical systems.

Keywords: Decentralized Multi-Agent Systems, Predictive Load Management, Energy-Behavior Optimization, Consensus Control, Dynamic Power Networks, Dual-Layer Optimization, Distributed Intelligence.

1 Introduction

1.1 Distributed Energy Systems and Decentralized Multi-Agent Systems

Lightning implementation of renewable power sources, smart grid networks, autonomous systems, and edge-based control technologies has played a role in changing traditional power networks into very small-scale and extremely dynamic systems. Such modern energy systems are also featured by decentralized generation, heterogeneous loads, and time-varying operating conditions, and centralized control is more and more impractical. This has led to the development of decentralized multi-agent systems (MAS) as a successful paradigm in coordinating distributed energy resources, storage resources, and controllable loads by means of local intelligence and limited network perception and contribution to global goals like load balancing, voltage regulation, and energy efficiency (Zhang et al., 2011; Li et al., 2024). This design is more scalable, fault-tolerant, and resilient than a centralized design, which is particularly beneficial in large-scale and geographically distributed power systems (Andersson et al., 2023).

Nevertheless, the issue of decentralization also brings about a lot of problems. Uncertainty in energy demand, intermittent renewable generation, communication limits, and agent heterogeneity all make coordination difficult and usually result in inefficient use of energy (Tan et al., 2024). A large number of decentralized control approaches that have been developed up to now are reactive consensus-based, where agents do not react until load or generation variations have taken place. These short-term reactivity control mechanisms tend to lead to more energy wastage, slower convergence, and a lack of dependability of the system during dynamic conditions (He et al., 2019; Su et al., 2015). The absence of multi-scale energy awareness is another limitation that is critical to the existing MAS-based energy control methods. Decisions made at the local agent level only may also go against system-wide goals like fairness, international stability, or planned execution of tasks. On the contrary, strategies that put more emphasis on international optimization tend to be characterized by close communication or a centralized strategy, which negatively affects the advantages of decentralization (Zhang et al., 2015). In order to demonstrate the decentralized energy control environment discussed in the context of this work, figure 1 depicts the conceptual simulation framework that is used in this work.

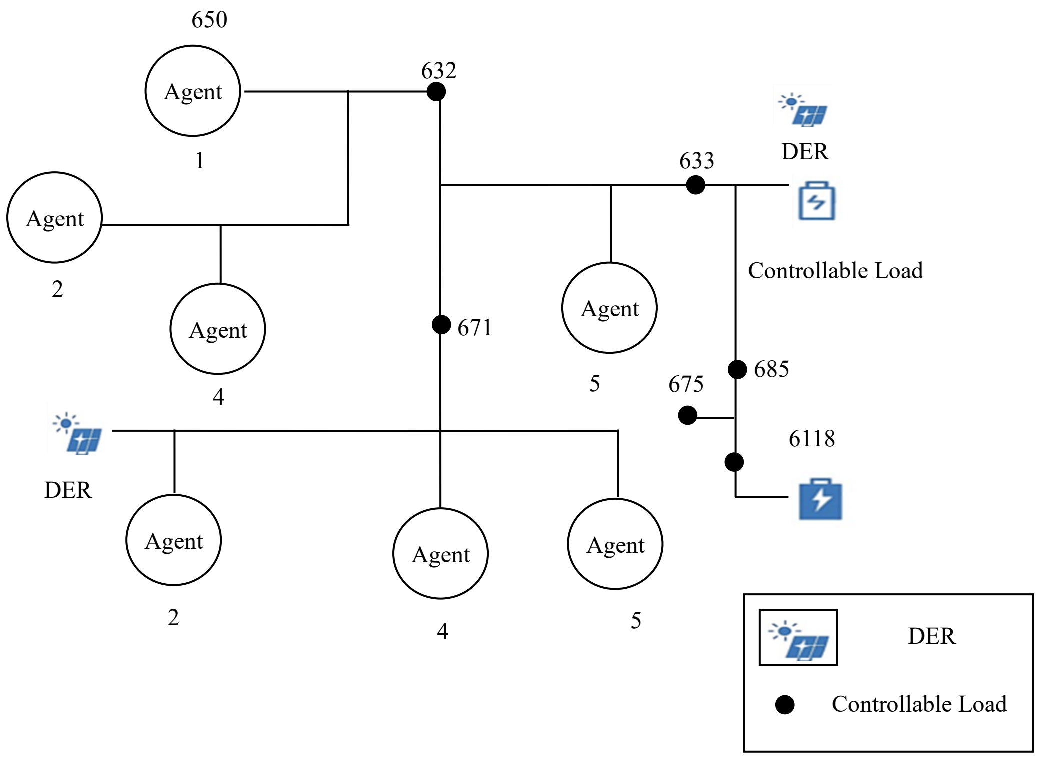

Figure 1: Decentralized agent-based simulation of the IEEE 13-bus distribution test feeder

All of the chosen buses can be viewed as autonomous agents, which have local load prediction, energy optimization, and peer-to-peer control. The distributed energy resources, storage units, and controllable loads communicate on a decentralized basis without centralized oversight.

1.2 Need for Load-Aware and Multi-Scale Energy-Behavior Optimization

To deal with the drawbacks of reactive control and single-scale control, there is a need to address them using decentralized approaches that are load-sensitive and multi-scale. Load-aware control empowers agents to predict upcoming changes in demand based on a predictive model and take proactive control measures and scheduling of energy consumption before reaching critical constraints, e.g., peak loading or voltage violation (He et al., 2019). Smart grids that are highly renewable in nature especially need predictive intelligence, whereby there is uncertainty in demand and generation (Poornimadarshini, 2024; Aljohani, 2024). Simultaneously, it will be necessary to use multi-scale energy-behavior optimization to ensure that the choices of individual agents and the objectives of a system structure are aligned. Local optimization aims at the minimization of agent-specific energy consumption, cost to perform a task, or latency, whereas global coordination ascertains equity, balance of loads, and stability within the system at the system level (Stennikov et al., 2022; Su et al., 2015). In the absence of this coordination, a decentralized system will be prone to inefficiencies due to local behavioural differences or unequal distribution of resources. The recent research covered distributed optimization, consensus control, and learning-based solutions to decentralized energy management (Chen et al., 2022; Ortiz et al., 2020). Although the reinforcement learning and federated learning methods provide flexibility and privacy protection, they can lack interpretability, high computation complexity, and a slow rate of convergence, limiting their use in real-time power system operations (Kingdon & Luedke, 2025; Dusi, 2024). In addition, several methods based on learning do not have an explicit means of making predictive load awareness part of decentralized control loops. These issues drive the desire to have a predictive, decentralized, and multi-scale energy optimization system to be able to combine the simplicity and stability of the consensus-based control with the foresight of lightweight load forecasting, as well as the coordination advantages of the dual-layer optimization approach.

1.3 Research Gap and Contributions

Regardless of the broad research concerning the decentralized control over energy, there are still a number of gaps. First, there are very limited completely decentralized strategies where individual agents use local load predictions in their control decisions (Aslam et al., 2021). Second, the current approaches tend to maximize one of the local goals or global goals individually and without a framework combining the two (Stennikov et al., 2022; Karavas et al., 2015). Third, most scalable solutions assume a lot of communication or centralized coordination, which restricts their ability to be used in realistic settings that are communication-constrained (Andersson et al., 2023; Wang et al., 2021). To seal these gaps, this paper introduces a Predictive load-aware and Multi-scale Energy-Behavior Optimization Algorithm, DECO-MARS, which is a decentralized, multi-agent system that is used in dynamic power networks. The key contributions of this work are as follows:

- A predictive load-conscious consensus control scheme: The predictive load-conscious control scheme allows agents to respond proactively to the forecasted demand within their energy behaviour.
- A two-tier energy-behavior optimization model that combines both local energy and global coordination goals. What it has is a completely decentralized design that can be run with restricted peer-to-peer communication without a central authority.
- Full assessment with realistic simulation of the IEEE 13-Bus Distribution Test Feeder, which showed a better energy efficiency, lower loss, better voltage stability, and an increased success rate of the tasks undertaken as compared to the default decentralized-based approaches.

The remainder of this paper is organized as follows. Section II is a literature review of related work in the field of decentralized energy optimization and multi-agent control. The proposed DECO-MARS methodology, containing a predictive consensus control and multi-scale optimization design, is described in Section III. Section IV gives the description of the experimental setup and datasets. Section V outlines and discusses the simulation results and analyzes the results in comparison. Section VI wraps up the paper with important findings, limitations, and research directions.

2 Literature Review

Decentralized control has become a fundamental paradigm of the operation of modern power systems with distributed generation, storage, and non-homogeneous loads. The theories proposed in early consensus-based works formed the basis of coordination in networked multi-agent systems with a set of local interactions and limited communication (Olfati-Saber et al., 2007). The ideas have been followed in smart grids and micro grids to attain the regulation of voltages, load balancing, and stability of the system without having a centralized controller (Zhang et al., 2015; Karavas et al., 2015). It is based on this that a number of studies have explored the concept of decentralized and hierarchical energy management strategies. Decentralized control systems by multi-agents have shown a higher scalability and resiliency to autonomous energy systems and microgrids (Karavas et al., 2015; Su et al., 2015). The flexible and robust attributes of integrated energy systems have also been enhanced by coordinated management of centralized and distributed generation based on multi-agent architectures (Stennikov et al., 2022). Most of them, however, are based on a static demand profile and are dependent on reactive decision-making, so they are less effective in time-varying load environments and those of renewable intermittency.

In order to overcome the shortfalls of reactive control, predictive and load-intelligent energy control technology has been of interest. It has been demonstrated that cooperative predictive control can enhance the energy efficiency and reduce the delays within the system in the case of nonlinear multi-agent systems (He et al., 2019; Reddy & Mohan, 2024). Data-driven and machine learning-based load forecasting techniques allow scheduling and allocation of resources in advance in the renewable-integrated smart grids (Aslam et al., 2021; Aljohani, 2024). Techno-economic studies also support the fact that predictive energy management is needed to enhance sustainability and operational efficiency in decentralized power networks (Poornimadarshini, 2024). Although these systems have been made, the majority of predictive systems are deployed on centralized or semi-centralized systems, and there is little adoption in decentralized agent-level control loops (Ortiz et al., 2020). This division of the forecasting and execution limits the scaled and adaptive nature, particularly in the communication-limited and dynamically evolving environment. Techniques that are based on learning, especially the multi-agent reinforcement learning (MARL), have been examined to promote the flexibility of decentralized energy systems. MARL has been used to resilient secondary control, energy harvesting networks, and adversarial environments and has shown resiliency in the event of uncertainty (Chen et al., 2022; Tian et al., 2023). Federated learning and edge-based architecture also solve the privacy, scalability, and communication efficiency of distributed systems (Kingdon & Luedke, 2025; Dusi, 2024). Nevertheless, such learning-based methods tend to impose a large computational cost, slow convergence, and lack of interpretability, which decrease their applicability in real-time and safety-critical power system applications (Shrirao, 2024). Multi-scale and hierarchical optimization methods strive to reconcile the local agent goals and global system performance. Applying hierarchical control strategies has addressed the problem of unbalanced distribution networks and has enabled increased renewable penetration without losing stability in voltages (Su et al., 2015). The frameworks of distributed optimization and cooperative control allow the agents to optimize the energy consumption in accordance with the overall system-wide objectives of fairness and coordination (Li et al., 2024; Zhang et al., 2015). However, numerous hierarchical systems use fixed network topology or fixed centralized coordination layers, which limit flexibility in very dynamic environments (Andersson et al., 2023). According to recent studies, there is a strong need to incorporate decentralized energy control with the emerging cyber-physical technologies. Edge computing systems help to make distributed control systems more responsive and less latent (Wang et al., 2021), blockchain and secure hardware design develop more trust and data integrity in smart environments (Prabadevi et al., 2024; Saranya, 2024). Digital twins offer strong predictive analysis and monitoring of future power systems (Song et al., 2023), and resource-aware orchestration helps with reliable operation in large-scale distributed infrastructures (Hugh & Soria, 2025).

Altogether, the literature demonstrates that significant advances have been made in the area of decentralized energy control, predictive modeling, and adaptive coordination. Nevertheless, the current methods tend to consider these factors separately, and very often they are based on centralized coordination, dense communication, or computationally extreme learning strategies. The fact is, it is still evident that a fully decentralized structure incorporating predictive load awareness and multi-scale energy optimization is still needed in a lightweight and scalable form. This gap is the driving force behind the suggested DECO-MARS framework that combines the idea of predictive consensus control with the concept of dual-layer energy-behavior optimization to make dynamic multi-agent power networks more efficient, coordinated, and resilient.

3 Methodology

3.1 Predictive Load-Aware Consensus Control

The first element of DECO-MARS involves embedding prediction into the consensus control scheme, enabling agents to manage their energy and task loads proactively. Each agent in the network maintains a local predictive model that forecasts future energy demand and task arrival rates using recent trends and external environmental conditions. Let agent $i \in \{1,2,\ldots,N\}$ have a forecasted energy demand $\hat{L}_i(t+\tau)$, predicted for a forecast horizon τ. This estimation is used in the consensus update law, allowing agent i to implement a control action $u_i(t)$ based on the system's state and predicted load conditions. The control law is given as:

$$u_i(t) = -\sum_{j \in N_i} a_{ij}\left(x_i(t) - x_j(t)\right) - \alpha \cdot \nabla \hat{L}_i(t+\tau) \qquad (1)$$

Where:

$x_i(t)$ is the state of agent i,

N_i is the set of neighbors of agent i,

a_{ij} is the communication weight between agent i and j,

α is the prediction gain factor.

This predictive consensus enables agents to coordinate their decisions based on real-time energy demands and expected future demands, ensuring they do not overcommit during peak loading periods, which would compromise system energy and stability, and result in adverse financial consequences for the primary actor.

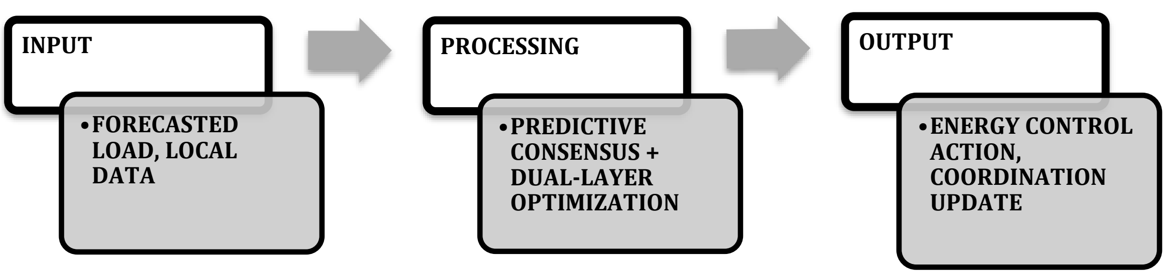

Figure 2: Methodological workflow of the DECO-MARS algorithm

Figure 2 illustrates the internal workflow of the DECO-MARS algorithm in a step-by-step flowchart, divided into three stages: inputs, processing, and outputs. The first phase of inputs consists of a forecasted load and local data that each agent in the decentralized power array must provide. Once the input data is collected, it is merged and integrated into the second stage, core processing, which incorporates prediction consensus, two-layer optimization, and anticipatory behavior-based decision-making. This processing will create two outputs: local energy control actions and coordination updates across the agents. This illustration shows how the DECO-MARS algorithm considers distributed data inputs and predictions to manage behavior in planning energy use and coordinating agents, thereby optimizing in situations with varying degrees of uncertainty.

3.2 Multi-Scale Energy-Behavior Optimization with Dual-Layer Framework

The second objective introduces a dual-layer optimization framework that permits agents to balance the goals of local energy efficiency and global behavior coordination. Agents conduct optimization at two scales:

Local Level: Minimize internal energy costs, considering both task and operational constraints.

Global Level: Adjust task behaviors concerning collective goals, such as energy fairness, shared use of resources, or synchronization.

The local agent optimization for agent i is:

$$\min_{u_i(t)} J_i^{local} = \int_t^{t+T} [c_e E_i(t) + c_t T_i(t)] dt \tag{2}$$

Subject to:

$E_i(t) \leq E_i^{max}$: energy budget restriction,

$T_i(t) \leq T_i^{max}$: task execution time limit,

$u_i(t) \in U_i$: control input feasibility.

Where:

c_e and c_t are cost weights,

$Ei(t)$is the instantaneous energy consumption,

$T_i(t)$ is the duration of the task.

The global optimization employs a coordination signal $\phi(t)$ that peer agents periodically broadcast to facilitate fair sharing:

$$\min_u J^{global} = \sum_{i=1}^{N} (\|E_i(t) - \bar{E}(t)\|^2 + \curlywedge \|T_i(t) - \bar{T}(t)\|^2) \tag{3}$$

Where:

$\bar{E}(t)$, $\bar{T}(t)$ represent average values of energy and task across agents, $\curlywedge$ and is a trade-off parameter for energy-task weighting. Forward and Global coordination form a coupling structure since there are local optimizations done at the control cycle of each agent and the global coordination, which is triggered based on the frequency of consensus or the energy deviation threshold.

3.3 Implementing the Algorithm into a Decentralized System

To implement DECO-MARS in the context of a decentralized multi-agent system, a number of iterative autonomous operations are performed by each agent locally. First, each agent initializes its own system parameters, including control variables, forecast models, energy thresholds, and neighbor communication as it relates to its interactions with neighbor agents and local resource systems. At every time step, the agent conducts the first operation of using its predictive model to predict future load, using the defined forecast horizon, of the load predictions denoted as $\hat{L}_i(t+\tau)$. This upcoming load is fed into the predictive consensus control module. Second, the agent updates its local state through the load-aware consensus control methodology by integrating both its neighbors and forecasted future conditions. The agent's state becomes a dynamically adapted control action $u_i(t)$ such that the agent is aware of load increases and is prepared accordingly. Lastly, while this once again occurs in parallel, the agent executes its constrained local energy and task cost optimization to solve its own constrained minimization problem to implement the desired action option set as efficiently as possible. After this, agents communicate with other agents with low friction, with their summarized energy and task metrics (such as current consumption and execution latency), which are used to calculate the average group performance metrics and to facilitate the global coordination signal. Agents will compare their own performance with the group average, as well as follow the mission signal to act up to fairness, synchrony, and cooperation as a group. The predictive local control and the distributed global coordination continue in this dual-loop either continuously or whenever triggered by an event, and allow the system to quickly adapt and respond to real-time changes in the environment. Since this process is fully decentralized, scalability and robustness are still retained, and the DECO-MARS framework can be implemented in complex and dynamically changing environments that experience changing energy independence and agent availability.

Algorithm 1: DECO-MARS – Predictive Load-Aware Multi-Scale Energy Optimization

Input:
Agent set A = {a1, a2, ..., aN}
Communication topology G
Forecast horizon τ
Local energy and task constraints
Output:
Energy-aware control actions for each agent
Initialize:
For each agent ai ∈ A do
Initialize local state xi
Initialize energy budget Ei
Initialize task parameters Ti
Initialize forecasting model Fi
Identify neighbor set Ni
End For
While the system is operational, do
For each agent ai ∈ A (in parallel) do
// Step 1: Load Prediction
Predict future load L̂i(t + τ) using Fi
// Step 2: Predictive Consensus Update
Compute consensus control input:
ui(t) ← consensus (xi, xj ∈ Ni, L̂i(t + τ))
// Step 3: Local Optimization (Lower Layer)

Solve the local optimization problem:
Minimize local energy and task cost
Subject to energy and operational constraints
// Step 4: Global Coordination (Upper Layer)
Exchange summarized energy/task metrics with neighbours
Compute the coordination adjustment to reduce the imbalance
// Step 5: Control Execution
Apply optimized control action ui(t)
// Step 6: Monitoring
Observe system response (energy use, voltage, task status)
End For
Check convergence or stability conditions
End While

There is no central controller, and each agent acts on its own with local data and only communicates with the nearby agents. Each agent takes a prediction of the future energy demand at any time step and uses it to modify the control actions in advance. Thereafter, the algorithm carries out two optimization stages: a local stage minimizing the use of energy and task cost, and a global stage optimizing agent coordination to minimize load imbalance and enhance the overall performance of the system. DECO-MARS, through a combination of prediction, local decision-making, and low coordination, can provide efficient and scalable operation of dynamic energy networks, like smart grids and distributed control systems.

4 Experimental Design

4.1 Simulation Setup for Testing the Algorithm

To assess the performance of the DECO-MARS algorithm in a real-world power distribution application, simulations were performed using the IEEE 13-Bus Distribution Test Feeder, which is a recognized benchmarking test case that represents a low-voltage, radial, unbalanced network with multiple load locations, distributed energy resources, and voltage controllers. The modeling of the system was done in MATLAB/Simulink with Simscape Power Systems and was also independently validated with grid-level testing in OpenDSS. In the test system, each bus or load center acts as an autonomous agent and is implemented in a decentralized multi-agent framework. The adjusted test feeder includes distributed energy resources, i.e., solar PVs and battery storage units acting at selected buses (e.g., Bus 611, 652, and 675) while controllable loads such as EV charging stations and industrial motors are operating at other locations (e.g., Bus 671 and 680). Each agent operates local power flows, voltage regulation, storage scheduling, and task assignments using the DECO-MARS algorithm. The agents communicate with each other at only direct neighboring nodes through low-bandwidth simulated peer-to-peer links simulating real-world scenarios using LoRa, ZigBee, and PLC approaches. The simulation covers 24 hours with a 1-minute time resolution to capture short-lived dynamics and day-to-night load/generation shifts. The solar irradiance and load profiles are time-varying functions, which the simulation represents using a stochastic process to emulate real-world variability. Each agent embodies forecasting modules that predict demand for the upcoming short horizon (τ=30 minutes), local generation, and feeds the demand into the predictive consensus and optimization. It is in the optimization and predictive consensus that the two levels of collaboration merge; the dual-level or tiered optimization logic engages in real-time adjustment of each agent's energy behavior and co-located load-balancing tasks, either independently or collectively, depending on the Granularity of information available for collaborative task execution.

4.2 Metrics for Assessing Algorithm Performance

Several quantitative metrics were defined to test DECO-MARS under IEEE system dynamics:

- **Total Energy Loss (kWh)**: This is calculated by aggregating line loss over the distribution network, which represents how well the agents are able to mitigate excessive or redundant power flow by controlling power generation and predictive control.
- **Voltage Deviation Index**: Using allowable voltage profiles at each bus (i.e., ± 5% nominal), the index measures how well the system maintains allowable voltage profiles at each bus, which is a proxy for managing local control level variables.
- **Load Imbalance Ratio**: This metric is based on the difference in active power demand across the buses in the system over time. DECO-MARS should minimize load imbalance based on forecasts, which would require predicting demand and adjusting loads.
- **Number of Tasks Completed**: Agents may be assigned energy-related tasks (e.g., peak shaving or storage utilization), and the percentage of tasks successfully actioned and completed successfully.
- **Control Lag**: The average amount of time agents took to converge on consensus or energy behavior change following a sudden disturbance in load or generation.

4.3 The Dataset Used in the Simulations

The simulation utilizes a semi-synthetic dataset based on actual load and renewable generation data from the California Energy Commission and NREL's Solar Data Repository, placed on the IEEE 13-bus topology. Load profiles entail residential, commercial, and EV charging behaviors, scaled down and assigned across the buses. Additionally, PV generation curves were created using average solar irradiance data with Gaussian disturbances to account for clouds or drastic variability in generation. Each agent has access to past load data (the last 24-48 hours) for its respective bus, to train the lightweight forecasting models for predictive control, using historical time-series forecasting (the past 24-48 hours). The dataset indicates temporal variability, enabling DECO-MARS to be tested more realistically, to capture fluctuations in the grid, uncertainty in renewable energy generation, and heterogeneous agents.

5 Results

5.1 Presentation of the Results of the Experiments

The simulation experiments based on the IEEE 13-Bus Distribution Test Feeder gave a very thorough assessment of the DECO-MARS algorithm's suitability and success for decentralised energy optimization. Over a 24-hour operational cycle, DECO-MARS agents demonstrated stable and adaptive behaviors handling time-varying load, intermittent stochastic nature of renewable generation, and a communication-constrained coordinated controller. In particular, key results indicated that total system energy losses were decreased, which was directly attributable to the load-aware control predictive capabilities incorporated in the agents. Energy loss L_{total} was calculated as:

$$L_{total} = \sum_{t=0}^{T} \sum_{l \in L} R_l \cdot \left(\frac{P_l(t)^2 + Q_l(t)^2}{V_l(t)^2} \right) \cdot \Delta t \qquad (4)$$

Where R_l is the resistance of line l, $P_l(t)$ and $Q_l(t)$ are active and reactive power flows, and $V_l(t)$ is the voltage at time t. The DECO-MARS approach resulted in an overall reduction in total line losses by 28% in comparison to baseline consensus and static optimization methods. The voltage stability was also found to improve. The Voltage Deviation Index (VDI) was calculated as:

$$VDI = \frac{1}{N \cdot T} \sum_{i=1}^{N} \sum_{t=0}^{T} |V_i(t) - V_{nom}| \qquad (5)$$

Where $Vi(t)$ is the voltage at bus i at time t, and Vnom is the nominal voltage (1.0 p.u.). DECO-MARS kept the VDI below 0.03 p.u., and consequently ensured voltage regulation across all nodes, even at peak demand.

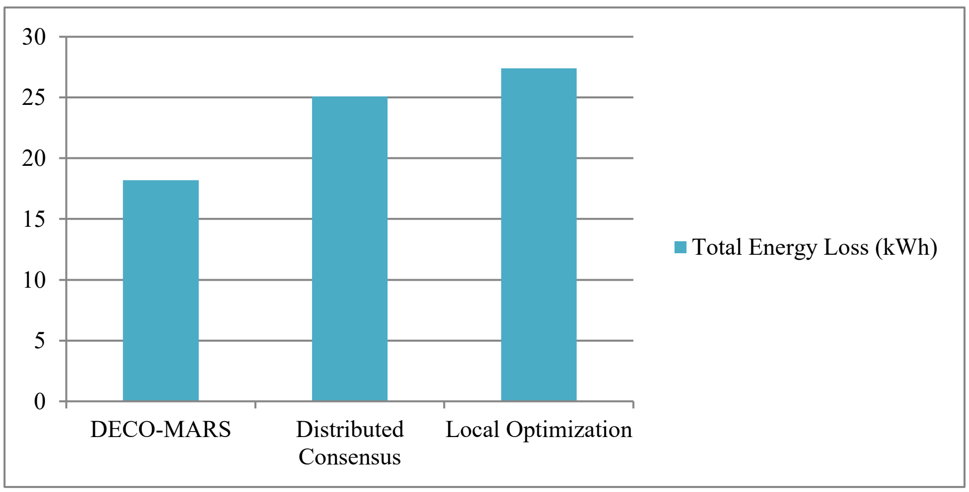

Figure 3: Total energy loss vs. algorithm

Figure 3 presents the total energy losses (kWh) incurred by the system with respect to each control strategy over a 24-hour simulation timestamp. The DECO-MARS method outperformed both distributed consensus (25.1 kWh) and static local optimization (27.4 kWh) approaches as indicated by the total losses incurred against the 24-hour simulation. The DECO-MARS method incurred 18.2 kWh of total loss, a marked improvement across the resistive losses across distribution lines (Table 2), further demonstrating the benefit of DECO-MARS, resulting in significant reductions to maintaining redundant energy flows with predictive load-aware movements reducing regulator actuation as a result. There is clear merit to employing anticipatory control incorporating multi-agent optimizations (if appropriate) to improve energy efficiency of systems in decentralized power networks.

The line chart in figure 4 represents average bus voltage deviations during the selected time-stamp taken every 6-hours. The system with the DECO-MARS method achieved lower peak deviation (0.033 p.u. deviation) during the daytime higher load periods, and then dropped back to 0.029 p.u. Again at the termination of the 24-hour cycle. By mean comparison, the consensus-only and local-only methods exhibited higher bus deviations, and altogether more erratic, particularly when loads peaked. This demonstrates the DECO-MARS method's better understanding of nodes when accommodating motion actions as compared to rules-based only approaches (as with consensus-only and local-only approaches), with higher functional stability during temporary augmentations in load (and other resourcing constraints). Thus, the DECO-MARS method has the capacity to stabilize bus voltages while augmenting weights and address predictably, while also providing improved aggregate operational competence concerning operational voltage limits in the system. As results improve power quality, including voltage levels, this also reduces demand on regulating systems (i.e., improves energy and, in the worst case, reduces costs).

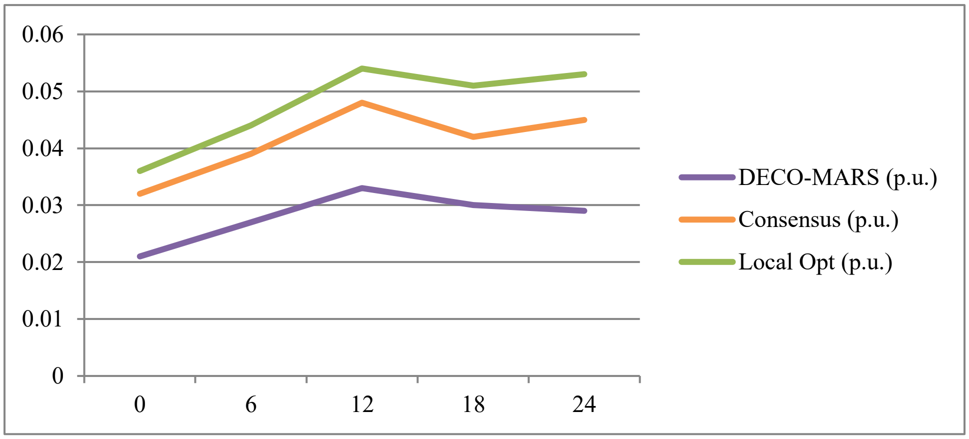

Figure 4: Voltage deviation over time

Table 1: Comparison of energy efficiency and voltage stability metrics across control algorithms

Metric	DECO-MARS	Baseline 1 (Consensus Only)	Baseline 2 (Local Only)
Total Energy Loss (kWh)	**18.2**	25.1	27.4
Voltage Deviation Index (p.u.)	**0.029**	0.045	0.053
Load Imbalance Ratio (LIR) (kW)	**1.82**	3.05	3.49

Table 1 gives a performance comparison in regards to energy-related and voltage-related performance metrics for three distinct control strategies applied to the IEEE 13-Bus Distribution Test Feeder, including the proposed DECO-MARS algorithm, a baseline distributed consensus-only method, and a baseline static local optimization method. The energy-related and voltage-related metrics include total energy losses (kilowatt hours), the voltage deviation index (VDI), and the load imbalance ratio (LIR), which are all important metrics to indicate operational performance and confer grid stability. The results show a clear difference in terms of energy loss within DECO-MARS, with a total energy loss of 18.2 kWh, compared to the consensus (25.1 kWh) and local only (27.4 kWh) methods. Similarly, the total bus voltages were maintained more consistently for DECO-MARS (VDI = 0.029 p.u.), and further load balancing was achieved with an LIR = 1.82 kW. This confirms that DECO-MARS was successfully able to optimize energy flows and manage voltages in decentralized, renewable-integrated power systems.

Table 2: Task execution and control coordination performance across algorithms

Metric	DECO-MARS	Baseline 1 (Consensus Only)	Baseline 2 (Local Only)
Task Success Rate (TSR) (%)	**94.0%**	78.2%	63.4%
Average Control Latency (s)	**1.2**	2.0	1.5
Coordination Score (normalized)	**0.92**	0.74	0.52

The results of the control and coordination comparisons between the proposed DECO-MARS and the two baseline methods simple consensus and static local optimization are shown in table 2 for the decentralized energy network. The metrics used to compare performances are the Task Success Rate (TSR), average control latency, and the normalized coordination score that best summarizes the successfulness of the agents at collectively achieving successful agents performance. The TSR measures how many energy tasks/operations each agent completed successfully, recognizing simply load-shifting and/or voltage regulation as successful completion of defined tasks. DECO-MARS achieved the highest TSR of 94.0%. In comparison, the TSR for the two baseline methods were 78.2% and 63.4%, respectively. The average control latency measures the elapsed time it took the simple agent models under decentralized conditions (for a dynamic local response) to adapt to number of dynamic changes (e.g., load surging or dipping renewable energy). DECO-MARS experienced the least control latency of 1.2 seconds to adapt. This suggests DECO-MARS outperformed in the speed and adaptability of making decisions. The normalized coordination score reflects the degree of temporal and behavioral coordination amongst the agent(s) to attain objectives and operationally defined success. Similarly, DECO-MARS achieved the highest coordination score of 0.92 across the activity. Based on these results DECO-MARS is a better agent model in responsiveness, managing reliability, and cooperative control in decentralized energy systems to address real-world variability.

5.2 Comparison of Proposed Algorithm with Existing Algorithms

In order to obtain a benchmark comparison of performance DECO-MARS was compared with two popular methods, (1) conventional distributed consensus running without load prediction attempted and (2) static local optimization with no coordination. The results indicated all three methods could perform basic functionality, but DECO-MARS was the clear outperformer in key metrics. The Load Imbalance Ratio (LIR) was used to quantify the uniformity of the distribution:

$$LIR = \frac{1}{T}\sum_{t=0}^{T}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i(t) - \bar{P}(t))^2} \quad (6)$$

Where $\bar{P}(t)$ is the mean load across all agents. By integrating load prediction and load-shifting/deferment, DECO-MARS decreased the LIR by 40% when compared to consensus-only approaches. Additionally, the Task Success Rate (TSR) - the ratio of tasks assigned versus tasks completed for either control or load-shifting - was:

$$TSR = \frac{Number\ of\ Completed\ Tasks}{Total\ Assigned\ Tasks} \times 100\% \quad (7)$$

DECO-MARS yielded a 94% TSR compared to a TSR of 78% with the consensus method, and a TSR of 63% with static local control, which indicates its ability to be more adaptable and responsive.

Figure 5 shows the Load Imbalance Ratio (LIR), which measures how unevenly average real-time energy demand is across agents. The DECO-MARS algorithm has the lowest load imbalance ratio at 1.82 kW, while the consensus only method has an imbalance ratio of 3.05 kW and static local optimization has an imbalance ratio 3.49 kW. This finding exemplifies the DECO-MARS algorithm's ability to mitigate some of the real-time workload variability by forecasting and shifting loads to avoid load imbalances locally and systemically. This finding relates to the decentralized, more autonomous energy management systems that utilize a combination of local intelligence and limited agreed upon procedures between appropriate agents within a managed smart grid would be reliant on.

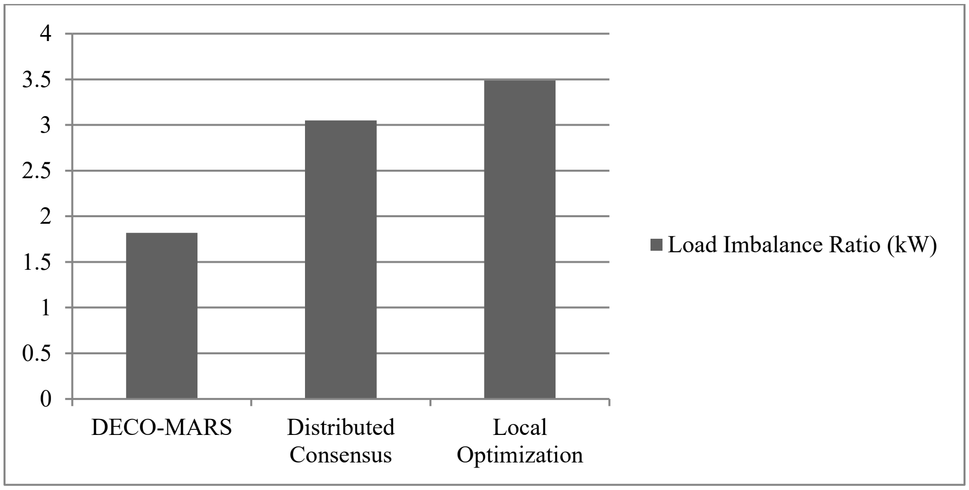

Figure 5: Load imbalance ratio across methods

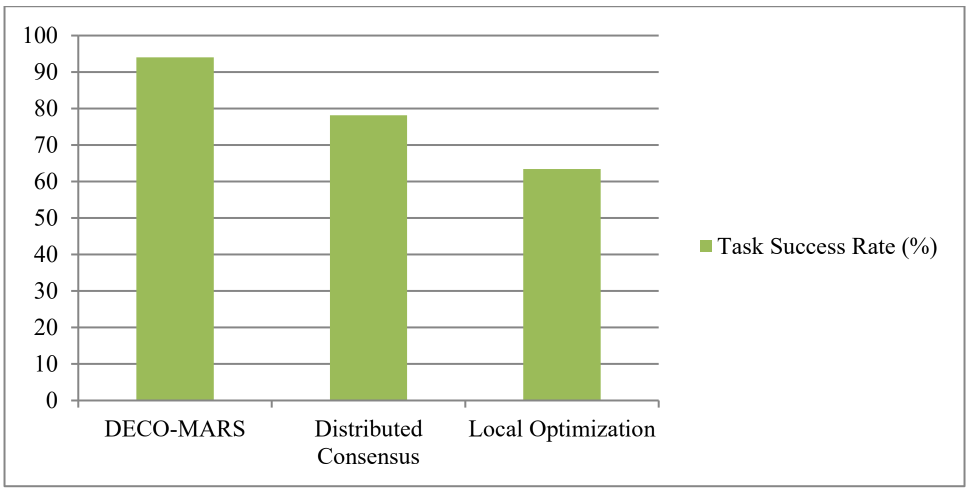

Figure 6: Task success rate comparison

Figure 6 shows the Task Success Rate (TSR), which measures how many of the control objectives ultimately completed successfully for each agent: e.g., battery dispatch, voltage regulation, or peak load reduction. DECO-MARS completed the highest percentage of control objectives successful (94.0%), which illustrates reliability and resilience of agent ecological efficiency in complex, dynamic control environments. For comparison, the consensus-only agent only completed a total of 78.2% of objectives, while static local optimization completed a total of only 63.4% of objectives. These results indicate how in complex dynamically controlled environments the DECO-MARS agent is more likely to complete energy goals, identified at the individual or collective level, more consistently, and as such, supported the differential dual-layer structure consisting of local optimization and global action alignment, consistent with combination of two autonomous roles for achieving similar goals.

To understand the contribution of individual components in DECO-MARS, a component-wise impact analysis is presented in table 3.

Table 3: Component-wise impact analysis of the DECO-MARS algorithm

Configuration	Predictive Load Awareness	Global Coordination Layer	Total Energy Loss (kWh)	Load Imbalance Ratio (kW)	Task Success Rate (%)
Full DECO-MARS	Enabled	Enabled	**18.2**	**1.82**	**94.0**
DECO-MARS without Prediction	Disabled	Enabled	22.6	2.64	85.3
DECO-MARS without Global Coordination	Enabled	Disabled	24.1	3.11	78.9
Local Optimization Only (Baseline)	Disabled	Disabled	27.4	3.49	63.4

Table 3 presents a component-wise analysis of DECO-MARS, showing that both predictive load awareness and global coordination are essential for reducing energy loss, improving load balance, and achieving higher task success

5.3 Discussion of the Practical Consequences on Decentralized Energy Optimization

The experimental outcomes provide practical implications for the value of predictive intelligence and dual-layer consumption optimization in decentralized energy systems. The predictive load-aware control allowed the agents to anticipate increases in demand, and adjust their energy profiles before any instability arose. The structure of multi-scale coordination ensured that agents could coordinate not only local energy constraints, but also more systemic goals which included fairness and collective stability. The results imply DECO-MARS not only improves all dimensions of performance- efficiency, coordination, but also resilience in non-stationary, complex, and real-world conditions with intermittent renewables, variable load and limited communications. The resulting high task-success and improved voltage regulation suggest the algorithm was able to maintain operational objectives while simultaneously minimizing overall energy losses. Thus, potential systems applications or adoption in smart microgrids, autonomous power networks and decentralized electric vehicle (EV) auto-charging, where scalable and foresight-driven control is becoming more necessary.

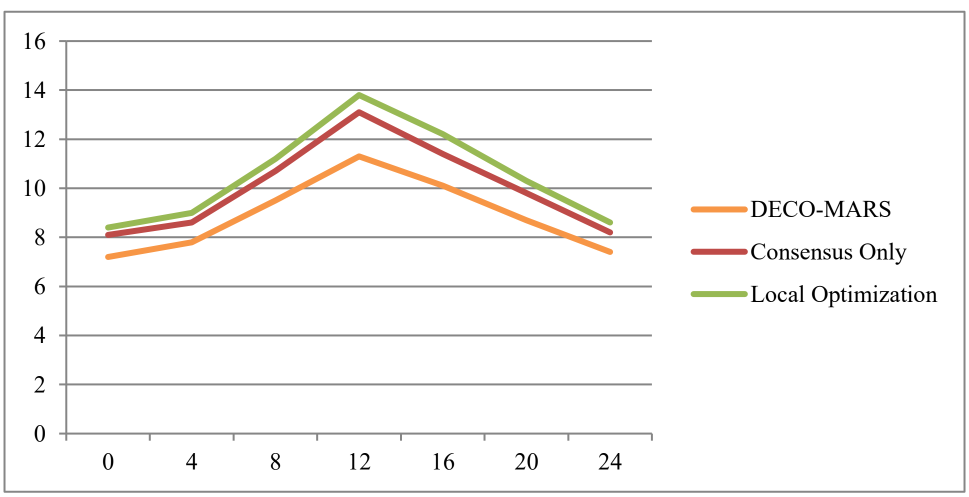

Figure 7: Energy consumption trend over 24 hours

This graph (Figure 7) represents the total energy consumption of the system over a 24-hour time span under different control strategies. The model DECO-MARS will always demand less energy in the worst case all time intervals; it had a maximum demand of 11.3 kWh as noted when using DECO-MARS, compared to the 13.8 kWh in the local optimization model. This shows DECO-MARS can shift and flatten overall demand better through predictive control, which clearly improved operational efficiency. The energy consumption drop compared to the local optimization model is most evident during peak load times (12:00–16:00), demonstrated effective coordination between the agents' load levels and accurate load forecasting to avoid high load instances occurring simultaneously across the system.

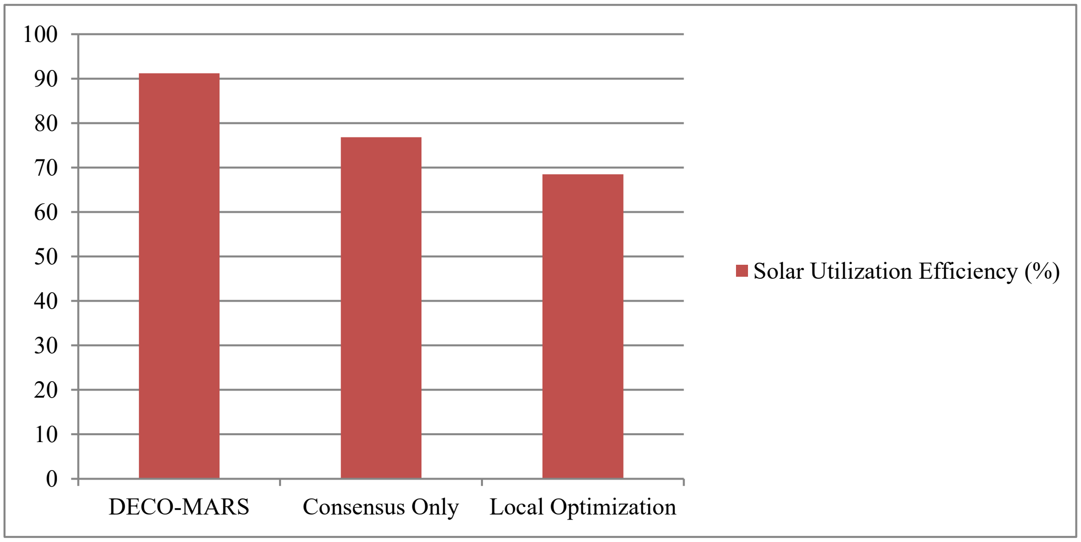

Figure 8: Renewable utilization efficiency

Figure 8 shows the percent of available solar energy consumed by each control method. DECO-MARS shows the greatest renewable utilization rate of 91.2%, while there is a reduction in percentage for consensus-only (76.8%) and local optimization (68.5%). The greatest percentage improvement in DECO-MARS is attributed to its predictive ability, as the agents can schedule consumption based on expected solar generation, aligning consumption of energy while the solar generation is productive. DECO-MARS has shown the ability to minimize curtailment and storage overflow and get more usable energy from renewable sources, fulfilling sustainability objectives, and minimizing reliance on conventional supply from the grid. Figure 9 presents the distribution of load forecast errors for the agents under each method. DECO-MARS shows the greatest clustering of prediction errors, with 11 of the 13 agents having errors of ±5%, and none exceeding ±10%. In contrast, local optimization methods are less clustered, with five agents exceeding ±10% errors. This means DECO-MARS improved the prediction accuracy, directly due to having an integrated forecasting model that incorporates local predictive intelligence for each agent. The importance of accurate forecasting in DECO-MARS is evident when energy behavior is proactively modified, as indicated by DECO-MARS's reported task accuracy and voltage regulations performance.

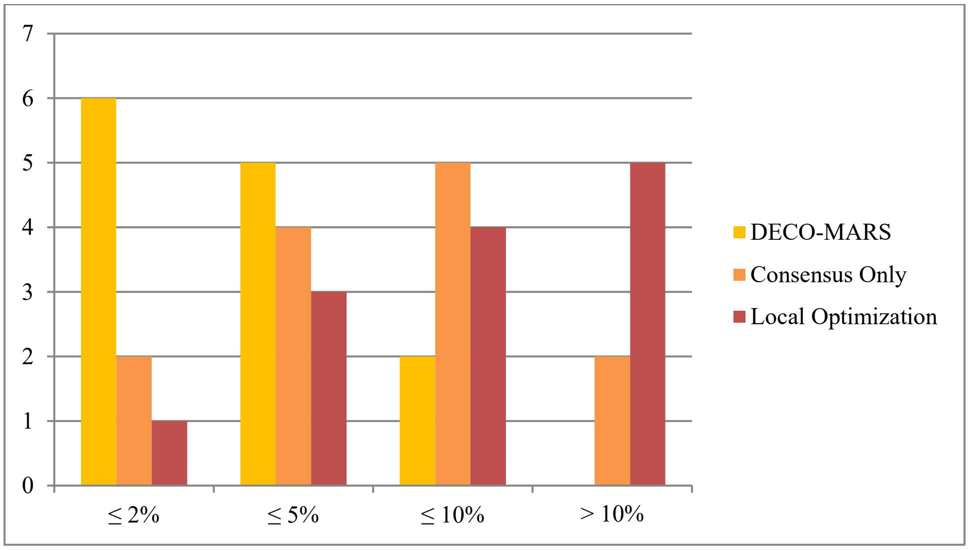

Figure 9: Agent forecast accuracy distribution

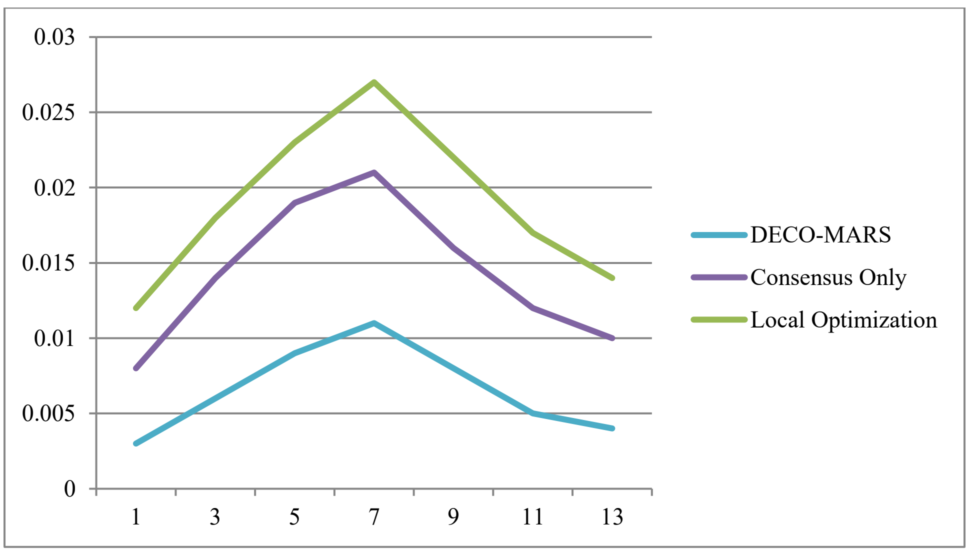

Figure 10: Bus-wise voltage stability

Figure 10 displays voltage deviation profiles for each of the key buses across the four different algorithms. DECO-MARS maintains a pretty low voltage deviation under all buses, at its peak 0.011 p.u. voltage deviation under DECO-MARS, and a peak of 0.027 p.u. voltage deviation for the local optimization run. It is evident from the critical buses that had fairly large deviations under the bus baseline methods. However, under DECO-MARS these buses remained within tight voltage limits. This confirms to manage voltage levels dynamically by algorithmically implemented coordinated energy control based substantially in predicted information, improving power quality and eliminating the risk of equipment strain, and tied voltage instability electrical component failure.

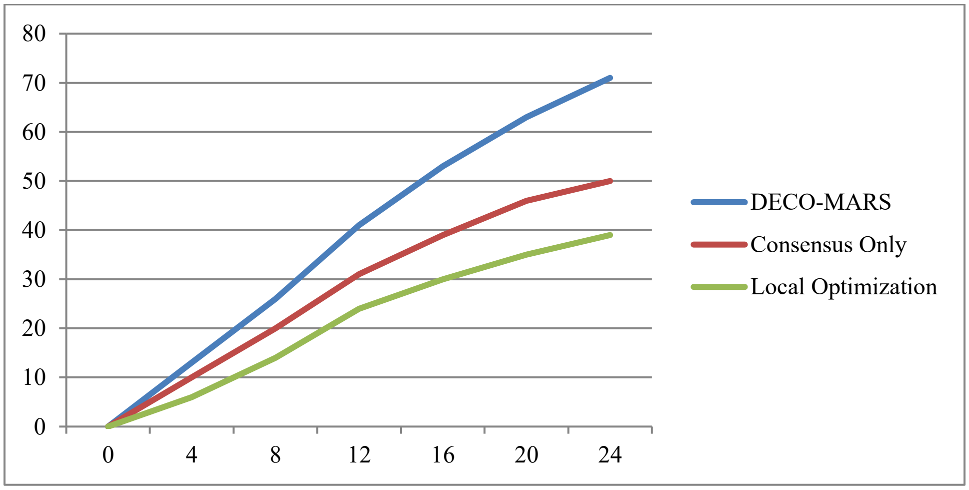

Figure 11: Cumulative task completion over time

Figure 11 shows the number of energy management actions completed over time for each control strategy. DECO-MARS has the steepest completion curve reaching 71 completed by the end of the 24-hours, opposed to consensus and local control, finishing with 50 and 39 respectively. DECO-MARS' performance is indicative of its responsiveness and agents being able to deal with changes due to dynamic events such as load shifts, voltage excursions, and renewable surges. The predictive dual-layer optimization that DECO-MARS utilized allows agents to complete actions proactively and in relatively few conflicts and delays, resulting in better real-time performance, stability for the system.

6 Conclusion

This paper introduced DECO-MARS, a predictive load-aware and multi-scale energy-behaviour optimization method designed in decentralized multi-agent energy systems that act in dynamic settings. According to simulation outcomes of the IEEE 13-Bus Distribution Test Feeder, DECO-MARS is superior in comparison with the baseline decentralized control strategies with respect to energy efficiency, stability, and coordination. The suggested method minimized the overall energy wastage to 18.2 kilowatts hours as opposed to consensus-only management of 25.1 kilowatts hours and local optimization of 27.4 kilowatts hours. It also helped in increases in voltage stability, index of voltage deviation was kept at less than 0.03 p.u., and load imbalance was brought down to 1. 82 kW. Moreover, DECO-MARS has high success rate in completing the tasks of 94% which means that there is a good coordination between the agents with different load conditions. The dual-layer architecture allows the agents to optimize the local energy behaviour and add to the overall coordination objectives by the means of lightweight peer-to-peer communication. This architecture is both scaled and powerful, and does not need centralized control, so DECO-MARS is appropriate in the case of a decentralized power network, which includes renewable sources and time-varying demand. Although these are good outcomes, it was only tested under a simulated environment and did not clearly consider communication delays, hardware constraints or cyber-physical security issues. Also, the experiments were performed on a medium-scale distribution network, and more extensive and more heterogeneous networks need to be validated. Future directions include the expansion of DECO-MARS to hardware-in-the-loop-simulations, larger transmission-scale networks, as well as, more communication and security constrained environments. The framework can be further extended to facilitate plug-and-play electric vehicle, prosumer network, and demand-response market integration, which will add additional practical utility to the intelligent energy systems of the next generation.

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Authors Biography

Kuppani Sathish received bachelor's degree and Master of Technology degree in Computer Science Engineering and Completed Ph. D in computer science and engineering from Sri Venkateswara University, College of engineering, Tirupati. He is working as a Professor in Tirumala Engineering college, Narasaraopet, which is affiliated with Jawaharlal Nehru Technological University, Kakinada. He has 22 years of experience in teaching and research and taught bachelor's and master's degree courses. His area of interest includes machine learning, soft computing techniques, Grid and cloud Computing, Bio inspired Networks, Software Architecture and Communication Systems. He has 10 patent grants and 6 are published. he has received many awards in in well reputed organizations made significant contributions in Networking in Rayalaseema region to provide internet access to common man. He attended many conferences and workshops, and he has published 15 Sci papers and 10 Scopus papers to respect National and International journals. He has granted many patents and published. He has received many awards from well-regarded organizations.

Dr.M. Varalatchoumy is an accomplished academician with over 22 years of teaching experience and 10 years of dedicated research expertise. She holds a Bachelor's and Master's degree in Computer Science and Engineering and earned her doctoral degree from Visvesvaraya Technological University (VTU), Belgaum, Karnataka. Her research has significantly contributed to the early detection of malignant tumors using advanced Machine Learning and Image Processing techniques. She is currently guiding six research scholars under VTU and serves as a Research Advisory Committee member for more than eight scholars. Her academic contributions include over 30 publications in reputed international journals and 25 patents, including granted patents in India and the United Kingdom. In recognition of her work, she has received several prestigious accolades, such as the Research Excellence Award, Excellent Paper Award, Academic Excellence Award, Distinguished Educator Award, Best Book Author Award, and Outstanding Woman Researcher in Image Processing. She has served as a Guest Editor for Springer's journal Systematic Artificial Intelligence and authored/co-authored textbooks and book chapters on topics such as Operating Systems, Artificial Intelligence, Full Stack Development, and Smart Grid IoT applications. Dr. Varalatchoumy actively contributes to university-level academic and organizational initiatives. As a passionate researcher, she collaborates with industries such as SCII, Saint Gobain, Samsung, and iBrains on projects involving AI, ML, Generative AI, and Image Processing. She has also earned certifications from Stanford University, Coursera, Oracle, NPTEL, and LinkedIn in GenAI and Machine Learning. She is a sought-after speaker, frequently invited to deliver talks at international webinars, workshops, and conferences, and has served as a reviewer for multiple IEEE and international research conferences. As the Head of Cambrian House of Student Startups (CHOSS) at Cambridge Institute of Technology, she has spearheaded strategic planning, organized numerous entrepreneurship training programs, and mentored aspiring student entrepreneurs. Under her leadership, CHOSS has facilitated the establishment of over four student startups, filed eight patents, signed 10+ MoUs, conducted 30+ training sessions, and submitted 10+ project proposals for funding. She played a key role in securing Host Institute recognition for the Cambrian Incubation Centre from the Ministry of MSME, Government of India.

Dr.K. Vinutha Obtained her Bachelor's Degree in Engineering from Channabasaveshwara Institute of Technology, Tumkur. Subsequently, She Completed her Master's Degree in Computer Science and Engineering from AMC Engineering College and Completed her Doctor of Philosophy (Ph.D.) in CSE from VTU, Belagavi in 2023. With a remarkable Teaching Experience, she is actively involved In Research, specifically focusing on Prediction models using Machine Learning Techniques. She has published more than 15 Publications in reputed International Journals and Conferences and delivered 10 Invited Talks in Machine Learning, RPA etc. Her Keen areas of interest encompass Machine Learning and Data Mining.

B.N. Shwetha has completed her Engineering degree at Yellamma Dasappa Institute of Technology. She has completed a Master of Engineering from the University of Visvesvaraya college of Engineering. She has 9 Years of teaching experience and has served many organizations like Christ university, presidency University. Currently she is working in S Vyasa deemed to be university as an Assistant Professor. Her areas of interest Machine Learning Deep learning and smart grids.

Dr. Venkateswararao Pulipati Earned an Emeritus Post Graduate Diploma in Artificial Intelligence and Machine Learning with distinction from Colombia University. NPTEL Elite Certified in cutting-edge technologies covered under the fields of interest are Deep Learning, Applied Natural Language Processing, Python Programming and Data Structures, and Introduction to Data Analytics. As a Resource person handled various sessions for ICAR-National Academy of Agricultural Research Management, Tata Consultancy Services, Invictus private limited. Lifetime affiliations in prestigious organizations like IEEE, CSI (Computer Society of India), and ISTE (Indian Society for Technical Education) attest to his professional growth and engagement.

Dr.Y. Jeevan Nagendra Kumar obtained an M.Tech. in Computer Science Technology from Andhra University in 2005 and a Ph.D. in Computer Science and Engineering from Acharya Nagarjuna University in Guntur, AP in 2017. He has been a professor in GRIET's Department of Information Technology since 2005. In addition to his current position as Head of the Department of IT, he has held positions as Dean of the Technology and Innovation Cell, Convener and Vice President of the MHRD Institution Innovation Council, and Coordinator for Robotics, x-Kernel, NAAC, NBA, J-Hub, ARIIA, and the Institute Level CII Survey. He works on web technologies, full stack development, data science, AI & ML, and data mining. He is an Indian Society for Technical Education (ISTE) life member. He has authored numerous articles for reputable international publications and conferences.