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Multiagent-Based Optimal Microgrid Control Using Fully Distributed Diffusion Strategy

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***Abstract*—This paper proposes a multiagent-based optimal microgrid control scheme using a fully distributed diffusion strategy. A two-level cooperative optimization multiagent system is adapted for distributed energy resources economic dispatch. The lower level implements an adaptive droop scheme based on online no-load frequency adjustments. The upper level implements distributed communication using diffusion between neighboring agents for optimal microgrid management. The proposed control scheme enables peer-to-peer communication among the agents without the necessity of a centralized controller, and simultaneously performs resource optimization while regulating the system frequency. The results are compared with centralized and consensus-based optimization algorithms. We have concluded that the proposed algorithm is superior over consensus algorithms in terms of convergence speed and utilizes reduced communication infrastructure compared to centralized controllers. Simulation demonstrations were conducted along with experimental results from a hardware-based microgrid using an industrial multiagent framework. The simulation and experimental results show that the proposed method and the agent framework can be deployed in real-world microgrids and offer superior decision making on optimal microgrid control.**

***Index Terms*—Cooperative control, distributed control, diffusion strategy, multiagent, microgrid, optimization.**

I. Introduction

THE microgrid concept has been proposed to stimulate renewable energy penetration in existing power systems by improving reliability and resiliency [1], [2]. The future grid will be restructured as a cyber-physical system which has components not only to carry power flow, but also to transmit data for advanced distributed control capability [3], [4]. Legacy power grid control schemes rely mostly on power-line communications and Ethernet in order to collect and distribute information. However, resiliency requirements call for a redundant wireless communication architecture that can provide alternative data routes in case of link failures [5], [6]. In both wired and wireless communication infrastructures, during an outage, a microgrid can be isolated from the host grid and should be able to continue operation in standalone mode with indeterminate broken communication links and scarce generation resources. In such circumstances, fully distributed adaptive agent discovery methods are more favorable than centralized data acquisition methods in order to ensure resiliency.

Due to the low-inertia nature of microgrids, sophisticated control systems and optimization methods are required to effectively coordinate stochastic (non-dispatchable) and dispatchable distributed energy resources (DER). Thus far, a number of centralized methods have been proposed for optimal microgrid control. In [7], a model predictive control using support vector machines and mixed integer linear programming methods were used for microgrid optimization under time-varying operational constraints. A genetic algorithm-based multi-objective optimization methodology was applied for DC microgrid systems [8]. Another study reported a stochastic optimal operation of microgrids using chaotic binary particle swarm optimization [9]. Niching evolutionary algorithm was used for optimal dispatch of DERs and storage systems in islanded microgrids [10]. An adaptive predictive supervisory control concept using dynamic stochastic optimization was proposed to smoothen PV and wind generator intermittent output powers [11]. Resiliency [12], frequency control [13] and islanding-based optimization [14] methods were reported. An adjustable droop parameter based optimization was proposed in [15]. Although centralized optimization methods require less communicational bandwidth and computational burden, they are more susceptible to single point failures, which can easily jeopardize the resiliency in case of partial power outages and broken communication links.

In contrast to centralized controls, the emerging smart grid concept compels microgrids to adopt distributed cooperative methods as a result of the highly dynamic behavior of microgrids. Distributed control approaches intend to provide adaptive agent discovery through online peer-to-peer communication enabling neighbor negotiations. The implementation of distributed control is established using multiagent systems (MAS), which are composed of intelligent agents that cooperate to achieve a global or local objective function. Embedded decision-making algorithms and individual behaviors facilitate the benefit maximization of the agents. So far, a large number of microgrid distributed optimization methods have been proposed in the literature. In [16], a replicator dynamic theory-based multiagent system was introduced with the ability to reach the economic operating point of the microgrid. However, in this framework, a *dominant agent* was used to aggregate the cost functions of the DER agents, which still makes the system vulnerable to single point failures. A comprehensive distributed agent-based microgrid management was proposed in [17] without any optimization or communication method. A

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distributed consensus algorithm-based load-shedding was proposed to maintain microgrid frequency [18]. A network of dynamic fuzzy agents are incorporated through distributed consensus algorithm for voltage control of microgrids [19]. However, these studies do not consider optimal and economic operation of the microgrids; or in other words they do not include tertiary level control. System efficiency optimization with genetic algorithms was considered in [20] using dynamic droop control for a DC microgrid. Similar, but modified consensus algorithms were proposed in [21] and [22] for optimal DER management without considering primary level control.

Similar to a large scale bulk-generation power system, to deal with a complex microgrid operation, hierarchical control levels were proposed [23], [24]. The latest literature includes hierarchical microgrid control including primary and secondary levels, where the authors of [25], implemented a distributed multiagent architecture to maintain system frequency with droop controlled DERs. A continuous fast-acting distributed load control [26] and optimal decentralized primary frequency regulation was implemented [27]. Furthermore, a distributed cost minimization of droop controlled microgrid was proposed [28]. In [29], a short review of multiagent systems and in [30] microgrid optimization methods were presented. A fully distributed power dispatch method for frequency recovery was proposed [31]. However, so far most of the distributed solutions have implemented the well-known consensus method [32]-[33]. Diffusion strategy based optimization methods have not been exploited yet for microgrids [34]-[36].

In this paper, we propose a new fully distributed optimization method using diffusion strategy with a hierarchical approach to maintain frequency regulation and economic dispatch. The proposed control scheme employs peer-to-peer communication among the agents replacing the need for a centralized controller to maintain system frequency regulation and additionally performs optimal economic dispatch simultaneously. The results are compared with centralized and consensus-based optimization algorithms in a simulation platform. Furthermore, experimental results are obtained from a smart grid testbed implementing industrial MAS protocols. To the best of the authors' knowledge, this paper provides the following novel contributions:

- The proposed diffusion strategy outperforms consensus-based methods to *"diffuse"* or *"spread"* information faster by implementing an additional gradient term.
- The modification on the traditional diffusion-based optimization method, herein termed the *"nudge"* mechanism, provides a unique application of the diffusion approach fitted for the microgrid economic power dispatch optimization.
- A penalty-based convex function has been introduced considering the DER generation constraints, which has not been implemented in the microgrid context yet.
- A laboratory-based industrial multiagent framework has been introduced for real-time experimental verification of the proposed diffusion-based optimization method.

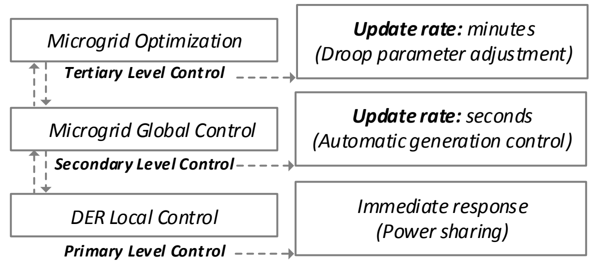

Fig. 1. Hierarchical control of a microgrid.

The remainder of the paper is organized as follows: In section II, the hierarchical microgrid structure is outlined and the multiagent system under study is explained. Section III introduces the proposed diffusion strategy and the implementation methodology. Section IV provides the simulation and experimental results from an actual microgrid setup. Section V concludes the paper.

II. Multiagent System and Control Hierarchy

This section introduces how the proposed multiagent scheme is integrated in the control hierarchy.

A. Microgrid Control Hierarchy

In the literature, three distinct control hierarchies are introduced according to the response speed and communication infrastructure requirements [37]. Primary control adjusts the output power of each DER unit based on local measurements to maintain the system frequency and voltage. In general, depending on the control method (e.g. droop control), this control does not require distributed communication. This is because by definition primary control must act instantaneously and automatically, therefore it cannot be subject to communication delays. Secondary control adjusts the dispatchable assets shortly after frequency and voltage deviations to restore the system to nominal operating conditions. Tertiary control tracks the minimum global operating costs as DER costs fluctuate according to their output power, and state of charge in the case of energy storage systems. Fig. 1 shows the hierarchical microgrid control levels, update rates and possible applications. It is important to note that this hierarchy does not depend on a central entity, rather the control hierarchy is implemented within the agents themselves.

B. Multiagent Framework

In this study, as illustrated in Fig. 2, we adopted a microgrid consisting of 9 nodes including a utility grid, two conventional dispatchable synchronous generators, one battery storage, two stochastic (non-dispatchable) wind turbine and photovoltaic generation units, one industrial, one commercial and one residential load. The various load nodes possess different consumption profiles. Each node is assigned to a corresponding intelligent agent that controls the power generated/consumed and is able to communicate only with neighboring agents. The optimization process aims to minimize the total cost of the generation while maintaining the frequency regulation in the microgrid. Fig. 3 shows the communication and agent layers of the microgrid. The *device layer* is situated on the lowest layer of the agent platform, where the physical electrical connections components are located.

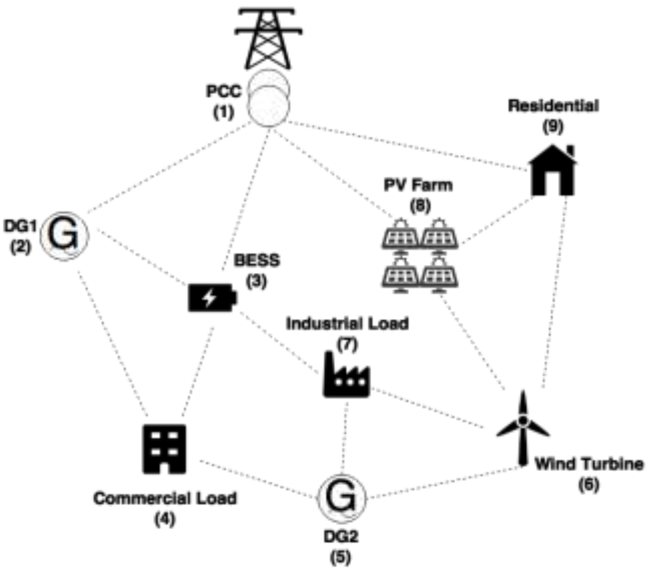

Fig. 2. Microgrid nodes.

The *primary control* is located in the middle layer directly controlling the power output of the corresponding devices. This layer mainly deals with the power being drawn or delivered for the load and stochastic generation units. Droop control is implemented in this layer for conventional synchronous generators and battery storage systems as the primary frequency control. The top level termed the *agent and communication layer* implements the diffusion strategy to provide secondary and tertiary control. Thus, the agent layer substitutes the centralized microgrid control structure.

Load agents and stochastic DER agents extract the power measurements from the device layer and diffuse the information to neighboring agents. The Point of Common Coupling (PCC) of the utility grid measures the delivered and drawn power of the microgrid and controls the islanding decision. For the dispatchable DERs, the agent layer operates to adjust the power levels of each unit in two separate time scales: (i) As secondary response, to adjust online adaptive no-load frequency shortly after the primary response; (ii) As tertiary response, gradually and continuously tracking the global optimal economic dispatch solution. The resulting operating points are informed through the control layer to the DER actuators located on the device layer, which adjust the corresponding device power output.

C. Agents Descriptions

Five types of agents are defined in the microgrid context. The cost and the marginal cost functions are used in the distributed optimization formulation in Section III-B.

Load Agents: They correspond to the industrial, commercial and residential load models. The consumed power cannot be precisely predicted as a result of stochastic consumer behavior. They measure and broadcast the instantaneous power requirements of their connected loads.

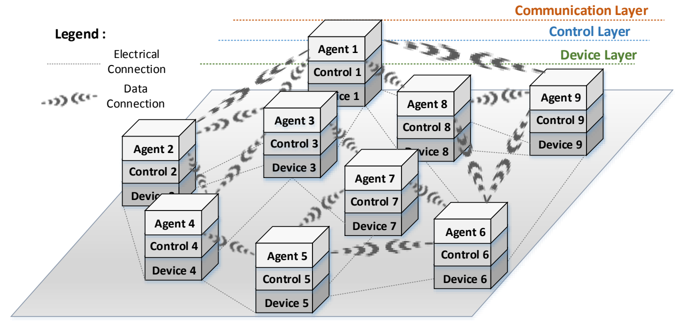

Fig. 3. Agent communication network.

Renewable DER Agents: This agent type is associated with stochastic (non-dispatchable) wind and solar DERs. Similar to load agents, the generation profiles cannot be accurately forecasted, therefore they are counted as negative loads. They measure and broadcast the instantaneous generated power.

Conventional DER Agents: This agent type is associated with dispatchable synchronous generators such as diesel or natural gas plants. They possess an ability to manage their output power. Each DER's corresponding cost function is not known by other agents. They broadcast their current marginal cost according to the typical quadratic cost functions:

$$F_{DG} = a + bP_{DG} + cP_{DG}^{\ 2} \quad (1)$$

$$\frac{dF_{DG}}{dP_{DG}} = b + 2cP_{DG} \quad (2)$$

$$P_{DG,\min} \le P_{DG} \le P_{DG,\max} \quad (3)$$

Where F_{DG} is the quadratic cost function for a fossil fuel distributed generator (DG). Constants *a*, *b*, and *c* are the quadratic coefficients, P_{DG} is the power level for the unit. The derivative of the cost function with respect to power is dF_{DG}/dP_{DG}, which is also known as the marginal cost function. The marginal cost function is used by the optimization diffusion algorithm to reach the economical dispatch point of DERs as will be explained in Section III.

Energy Storage Agents: The storage agent is also a dispatchable type, which has the capability to transfer power bidirectionally; either charging or discharging. The battery storage agents should ideally charge when the rate of electricity (or marginal cost) is low, and oppositely discharge when high. In accordance to our literature review, we have concluded that there is a lack of agreement of what the cost function of a storage system should be. In [38], a function is presented that takes into consideration the rate of charge or discharge, the number of cycles and the depth of discharge. These factors are too specific for battery storage systems. In this work, a more general cost function is proposed that is technology-agnostic:

$$F_B = x + y(P_B + 3P_{B,\max}(1-SOC)) + z(P_B + 3P_{B,\max}(1-SOC))^2 \quad (4)$$

$$\frac{dF_B}{dP_B} = y + z(2P_B - 6P_{B,\max}(SOC-1)) \quad (5)$$

$$-P_{B,\max} \le P_B \le P_{B,\max} \quad (6)$$

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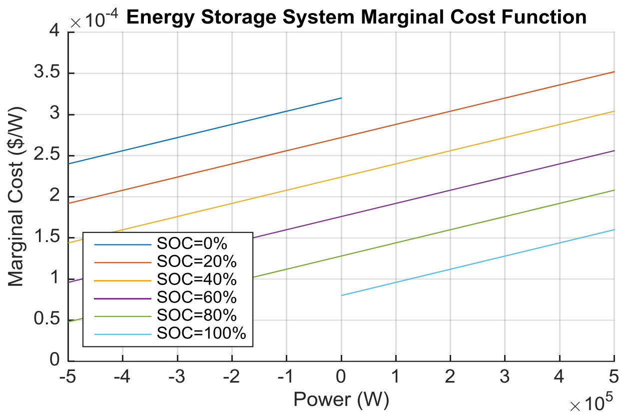

Fig. 4. Energy storage system marginal cost function.

Where F_B is the cost of the power, P_B, being charged or discharged from the storage, $P_{B,max}$ is the maximum charge or discharge rate, *SOC* is the current state of charge, and *x*, *y* and *z* are the quadratic coefficients similar to those in (1). The marginal cost dF_B/dP_B is proportional to the power drawn and inversely proportional to the SOC, meaning the marginal cost will be lower as SOC approaches 100%. The relationship between power, SOC and marginal cost is illustrated in Fig. 4.

This cost function is formulated in such a way that the energy storage systems automatically charge when the microgrid's marginal cost is low, and discharge when it is high. In this way, the storage asset automatically performs in a cost effective way by maximizing the energy arbitrage potential with the distributed optimization signal as described in Section III. The energy storage cost function will be further demonstrated in the simulations results in Section IV.

Utility Grid Agent: This agent is active when the microgrid is operating in grid-tied mode. The utility grid agent is of a dispatchable type. It monitors the delivered and received power to the microgrid. It broadcasts the current electricity rate being offered by the utility, which can be assumed as a constant marginal cost.

$$F_G = r_u \cdot P_G \tag{7}$$

$$\frac{dF_G}{dP_G} = r_u \tag{8}$$

Where F_G is the cost of the power, P_G is the power delivered or received and r_u is the current electric rate being charged or offered by the utility grid. Thus, the cost is a linear function of the power, and the marginal cost dF_G/dP_G is a scalar value equal to the electric rate.

There are two main modes of operation; islanded and grid-tied mode. In the former, the optimal (economic dispatch) operation of the dispatchable agents is at the point where every asset's marginal cost function is equal to the others while maintaining the net power demand. This is known as the Lagrangian point (λ). When grid-tied, all the dispatchable agents converge to the point where all marginal costs are equal to the electric rate given as a constant marginal cost.

$$\frac{dF_1}{dP_1} = \frac{dF_2}{dP_2} = \ldots = \frac{dF_n}{dP_n} = \lambda (= r_u) \tag{9}$$

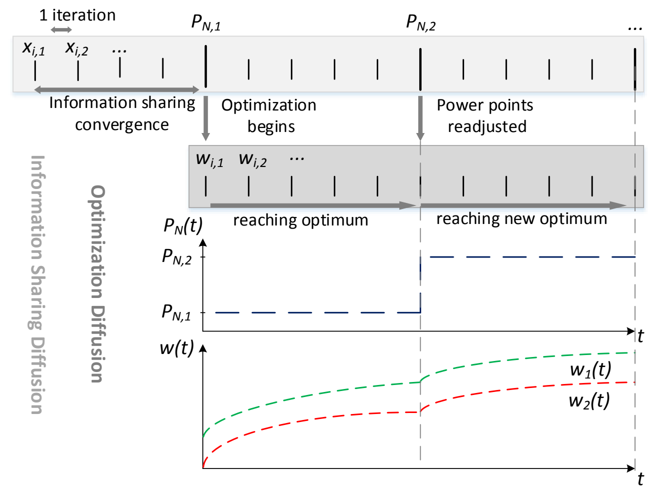

Fig. 5. Diffusion strategy.

III. Diffusion Strategy and Implementation

Traditionally, the distributed information sharing between neighboring agents is established through consensus [20]-[22]. The diffusion strategy includes a stochastic gradient term to expedite the process and reach convergence much quicker. Additionally, by including the gradient of the cost function in the formulation, diffusion can reach the economic dispatch point through distributed optimization. In this study, as shown in Fig. 5, two separate diffusion processes are implemented: (i) Information sharing diffusion; (ii) Optimization diffusion.

The information sharing diffusion is formulated to broadcast the instantaneous stochastic power consumed by the load agents and generated by non-dispatchable renewable DER agents plus network losses. This process continuously updates the network's net power demand to be supplied by the dispatchable DER agents.

$$P_N = \Sigma P_{LA} - \Sigma P_{RA} + \Sigma P_{Loss} \tag{10}$$

Where P_N is the net power demand, which is defined by the addition of all load agents (P_{LA}) minus all intermittent renewable DER output (P_{RA}) plus the network losses (P_{Loss}). As described in [39], we assumed the resistance R_{ij} of each distribution line is known. Thus, each agent calculates their local contribution to the network losses, and this value is included in the information sharing diffusion process as described in the next sub-section.

As shown in Fig. 5, the information sharing process restarts after a certain precision level (acceptable residual convergence error) has been reached among all agents. Programmatically, this can be implemented with a system of flags that are communicated among neighboring agents to assure all agents in the network have reached convergence.

After the first convergence, the net power demand of the network is known, thus the economic dispatch is initiated as explained in Section III-B. The optimization diffusion is used to adjust the dispatchable DERs to their economic dispatch point on a continuous basis as the optimal solution is approached after every iteration. When the information sharing converges once again, the economic dispatch points are shifted, and the optimization begins converging to the new optimal points. These two complementary processes continue indefi-

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nitely tracking the net power demand, and the economic dispatch solution.

A. Information Sharing Diffusion

The communication between neighboring agents is bidirectional. The nonnegative communication coefficient from agent i to agent j is defined as a_{ij}, with n number of agents. Coefficient a_{ij} can be assumed as a trust factor that each agent places on the other. The coefficients do not need to be symmetric, i.e. $a_{ij} \neq a_{ji}$. They must satisfy the following conditions:

$$a_{ij} \geq 0, \sum_{i=1}^{n} a_{ij} = 1 \text{ and } a_{ij} = 0, \; if \; j \notin N_i \tag{11}$$

Where N_i represents the neighborhood, or a group of agents within communication reach, of agent i. As a condition for convergence and stability of the diffusion algorithm, the adjacency matrix of weights $A=[a_{ij}]\in\mathbb{R}^{n*n}$ must be a left-stochastic matrix satisfying $A^T\mathbb{1} = \mathbb{1}$, where $\mathbb{1}$ is an $n*1$ vector of all ones.

$$a_{ij} = \begin{cases} \dfrac{1}{\max(n_i, n_j)}, & i \in N_j \setminus \{j\} \\ 1 - \sum\limits_{i \in N_j \setminus \{j\}} a_{ij}, & i = j \end{cases} \tag{12}$$

The Metropolis rule (12) is applied to construct a symmetric and doubly stochastic (right and left) A matrix, where n_i is the number of connections out of the node i [40]. Metropolis weights guarantee stability, good performance and the ability to adapt to changing topologies. Adaptability via automatic agent discovery is crucial for altering topologies as a result of incoming or outgoing agents in the network.

The Metropolis rule depends only on the local information available to each agent, and that of its neighbors. The adjacency matrix can be constructed on the fly through the number of neighbors each agent has. Reference [39] provides an elegant solution in the process of addition and removal of nodes, and the tracking of the total number of agents participating in the agent framework, n. This is realized by assigning a unique ID to each node and communicating this ID, along with the iteration number, among the neighbors to create a local database of the global agent network.

The diameter of the network, d, is defined as the maximum shortest path from any node to another. After d iterations, all nodes achieve a global knowledge of the node population in the microgrid network. Likewise, if a node stops communicating, this node is dropped from the local database after d iterations, and the Metropolis weights are recalculated. In the real-time experimental study, we have implemented agents in the Java agent development framework (JADE) [41]. This framework supports automatic agent discovery by assigning a unique serial number for each agent in the network.

The Combine-Then-Adapt (CTA) diffusion strategy is implemented for information sharing. CTA employs a gradient term in an intermediate step which is disseminated to neighboring agents. This allows for information to "*diffuse*" more quickly beyond the neighborhood of any given agent:

$$CTA_{Diffusion}: \begin{cases} \phi_{i,k-1} = \sum\limits_{j \in N_i} a_{ij} x_{j,k-1} \\ x_{i,k} = \phi_{i,k-1} - \mu_i \hat{s}_{i,k}\left(\phi_{i,k-1}\right) \end{cases} \tag{13}$$

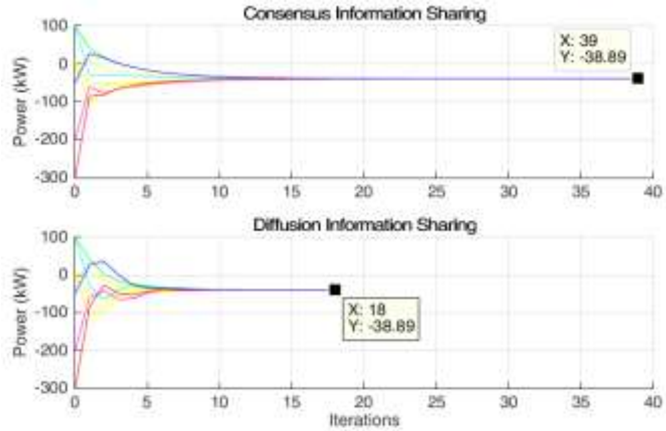

Fig. 6. Consensus vs diffusion information sharing (9-Node).

Where $x_{i,k}\in\mathbb{R}$ denotes the state of agent i at time k, $\phi_{i,k}$ is the intermediate variable for agent i at time k, μ_i is a nonnegative updating parameter of agent i, and $\hat{s}_{i,k}(\phi_{i,k-1})$ is the stochastic gradient for agent i of the intermediate state ϕ at time k. The stochastic gradient is simply calculated on the difference of ϕ from one iteration to the other; thus, each agents keeps track of its gradient and updates the combination of all its neighbors accordingly.

In our microgrid control scheme, (13) is used to broadcast P_N to all agents in the network. Because the purpose of the information sharing is to know the net power demand, only the stochastic agents (load and renewable DER) communicate their current power status; dispatchable agents only communicate their contribution to the network losses. Then, P_N is used for the distributed optimization of the diffusion strategy. To compare the performance of diffusion versus consensus, we take a hypothetical scenario using the microgrid shown in Fig. 2. Suppose the commercial, industrial and residential loads were consuming 200kW, 300kW and 50kW, respectively; and the wind and solar farm were producing 100kW each. Taking these as starting points for our convergence analysis (the dispatchable nodes being at zero), we get the performance shown in Fig. 6.

As observed in Fig. 6, diffusion reaches the same level of precision in less than half the iterations needed for consensus (18 vs 39). This is clearly a substantial improvement that can be used for more precise tracking of microgrid conditions for faster frequency response. The value reached, -38.89kW is the average of the net power requirement. When multiplied by the number of nodes n in the network, P_N is obtained: *-38.89kW * 9 = -350kW = 100kW + 100kW - 200kW - 300kW - 50kW.*

Although for small scale systems a centralized method would outperform diffusion since no iterations are needed, the proposed method foregoes any communication infrastructure and is therefore valuable for any system that extends beyond one single agent. The scalability of the diffusion method is tested with the well-known IEEE 14-Note Test System [43] and IEEE Reliability Test System-1996 [44], which has 73 nodes. Table I shows the results of applying the proposed method to these layouts and comparing the performance of the diffusion algorithm versus consensus. The same Metropolis weights (12) were used, taking the electrical connections as the edges of the graph, and the starting points were randomized within ±400kW.

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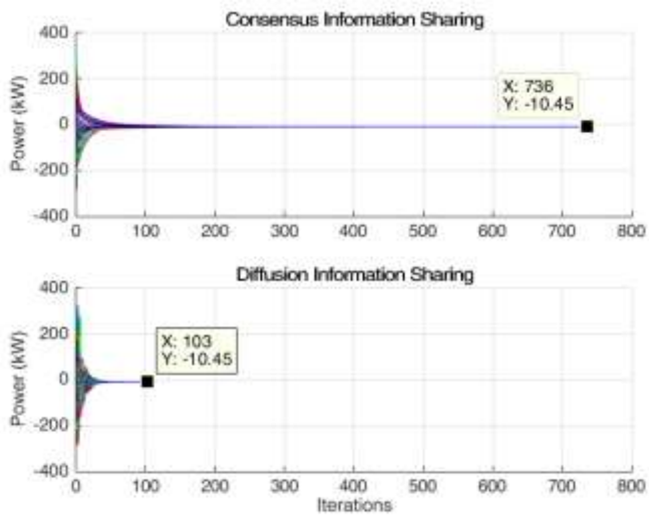

Fig. 7. Consensus vs diffusion information sharing (73-Node).

TABLE I
DIFFUSION VS. CONSENSUS CONVERGENCE COMPARISON

Test System	*Consensus Iterations*	*Diffusion Iterations*	*Diffusion Time to Converge vs Consensus*
9-Node	39	18	46%
IEEE 14-Node	106	34	32%
IEEE RTS-96 (73 Node)	736	103	14%

Fig. 7 illustrates the significant performance improvement for the RTS-96 system from 736 iterations with consensus to 103 with diffusion. It is important to note that μ in (13) is a key parameter for the convergence of the information sharing diffusion and affects the performance of the algorithm. In these test cases a trial-and-error method was used to select the most effective parameter for each case. Also, a 73-node network would be considered as a bulk-generation power system, and even in such a vast electrical structure the diffusion algorithm shows promise in distributed control.

In intermittent-dominant microgrids that include mostly stochastic loads and non-dispatchable units, the frequency regulation would be more challenging due to the low inertia of the system. Therefore, in such microgrids, the performance improvements are essential to maintain the system frequency at nominal levels. With modern communication technologies, the iterations can actually run in the milliseconds, so even for the 73-node case, convergence could realistically be reached in a few seconds. As the number of dispatchable units' increases, the frequency regulation is also easier due to the increase in inertia and/or droop support.

B. Optimization Diffusion

The previous diffusion formulation includes a stochastic gradient in the information sharing (also known as estimation) problem. However, in optimization diffusion, the marginal cost functions of the DERs are used instead. First the global problem is defined:

$$J_{glob}\left(w\right)=\sum_{i=1}^{n} J_i\left(w\right) \tag{14}$$

$$\min_{w} J_{glob}\left(w\right) \tag{15}$$

Where J_i is the cost function of agent i defined over the real-valued vector of arguments $w\in\mathbb{R}^n$, representing the power output of each dispatchable agent. Therefore, the objective is to minimize the global cost J_{glob}, which is the sum of all the individual cost functions. The cost functions do not need to be the same for each agent, as is the case for the microgrid where each agent has its own cost function.

All J_i need to be *convex* and differentiable, and at least one J needs to be *strongly convex* in order for J_{glob} to also be strongly convex, meaning there is only one global minimum solution [35]. Although assuming convex functions is a simplification of the DG cost functions due to the valve-point loading effect, multiple fuel options, and prohibited operating zones, non-convex distributed optimization is beyond the scope of this work and the reader is referred to [34] and [45].

In our study, the cost functions of the DERs are all strongly convex with the exception of the utility grid agent which is only convex (linear functions are both convex and concave). The conventional DER agents' and energy storage agents' cost functions are strongly convex since they are positive quadratic functions. Thus, J_{glob} is also strongly convex and can reach a global minimum through optimization.

Similar to CTA diffusion for the estimation problem (13), CTA can be used for distributed optimization by adopting the gradient of the cost function instead of the stochastic gradient:

$$CTA_{Optimization}:\begin{cases}\phi_{i,k-1}=\sum_{j\in N_i} a_{ij}w_{j,k-1}\\ w_{i,k}=\phi_{i,k-1}-\mu_i\nabla_{w^T}J_i\left(\phi_{i,k-1}\right)\end{cases} \tag{16}$$

Where $w_{i,k}$ is the i^{th} agent's estimate of w at time k, and $\nabla_{w^T}J_i\left(\phi_{i,k-1}\right)$ is the gradient of agent i*'s* cost function calculated with the intermediate variable ϕ_i; all other parameters are the same as (13). The weights also remain the same Metropolis values as with information sharing. Convergence of the diffusion strategy for information sharing and distributed optimization given the pre-conditions described has been extensively proven and the readers are referred to [34]-[36] for more in-depth analysis.

During the optimization, not all agents necessarily need to be *informed*, or have an associated cost function. Only conventional DER agents, utility grid agents and energy storage agents have a gradient for the second term of (16). All other agents are *uninformed*. However, these uninformed agents still have a purpose in disseminating the information across the network by implementing the first term of (16).

The vector of arguments w has an entry for each of the agents in the network, however only the dispatchable DERs have a nonzero value. All other nodes on the network remain at zero and are not updated. Since each agent has unique knowledge of its own resource, the cost function (17) and gradient (18) for dispatchable agent i are only defined for the i^{th} element of vector w. All other elements remain at zero.

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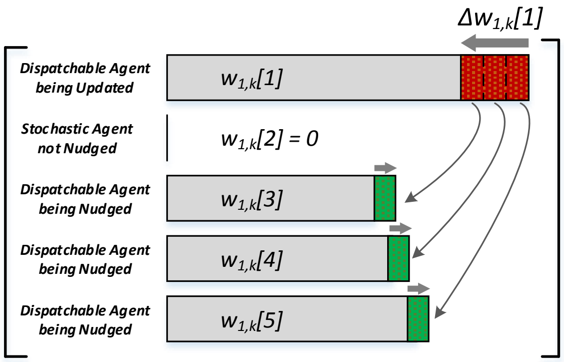

Fig. 8. Nudge methodology.

$$J_i\left(w_i\right) = F_i\left(w_i[i]\right) \tag{17}$$

$$\nabla J_i\left(w_i\right) = \nabla F_i\left(w_i[i]\right) \tag{18}$$

Thus, the gradient update step in the second term of (16) only affects the agent's own power level (if such a gradient exists). Through CTA optimization, each dispatchable agent's gradient term converges to the economic dispatch or Lagrangian point. However, an additional step in the updating procedure must be included for the microgrid optimization system. This is explained as the *nudge methodology* in the next section of modified optimization diffusion.

C. Modified Optimization Diffusion

The net power demand must be supplied among the dispatchable agents. This is where the information sharing and optimization diffusion methods are merged. The net power is included in the optimization formulation in the following way:

$$\sum_{i=1}^{n} w[i] = P_N \tag{19}$$

To keep the equality in (19), after the gradient update by the dispatchable agents in (16), a *nudge* by the agent being updated gets added to the other dispatchable agents plus any deficit compared to the net power:

$$\Delta w_{i,k}[i] = -\mu_i \nabla_{w^{\mathrm{T}}} J_i\left(\phi_{i,k-1}\right) \tag{20}$$

$$\sum_{j=1}^{n} \Delta w_{i,k}[j] = P_N - \Sigma w_{i,k-1} - \Delta w_{i,k}[i] \tag{21}$$

where $j \neq i$ and $j \in$ dispatchable

Where $\Delta w_{i,k}[i]$ is the so called "gradient nudge" of (16). Equation (21) and Fig. 8 describe how the nudge is distributed among the other dispatchable agents to maintain the net power demand. Intuitively, if one of the DER's marginal cost is greater than the rest, by decreasing that particular unit's power level, and increasing the others by the same amount in a collective way, a lower total cost is reached since the former unit is "*nudged down*" in cost a greater amount than the others are "*nudged up*". Because the $w_i[i]$ of stochastic units always stays at zero, the dispatchable units will know which other nodes are also dispatchable to distribute the nudge to them. This is how the economic dispatch point is reached in a distributed way, and is the key variance of the proposed modified diffusion method in this study to other existing diffusion methods in the literature. The power levels would drift to each agent's minimum cost and the power balance would not be maintained unless this methodology is used.

Additional to the net power constraint, the dispatchable agents have unique constraints on the minimum and maximum power of their corresponding resource, (3) and (6). As in [46], a *barrier* or *penalty* function is included around the feasible region. The penalty method is preferred, as it maintains the continuity of the cost function and can converge to a solution even if the initial or intermediate states fall beyond the constraints. The objective described by (15) becomes:

$$\min_{w} \; J_{glob}\left(w\right) + \eta \sum_{i=1}^{n} \delta_i(w_i) \tag{22}$$

$$\delta_i(w_i) = \begin{cases} 0 & w_{i,\min} \le w_i \le w_{i,\max} \\ \alpha(w_i - w_{i,\max})^2 & w_i > w_{i,\max} \\ \alpha(w_i - w_{i,\min})^2 & w_i < w_{i,\min} \end{cases} \tag{23}$$

Where η is a parameter which dictates the importance of obeying the constraints, and δ is the penalty function defined for each element in w according to its inequality constraints. Equation (23) describes a simple addition to the cost function of the squared deviation from the constraint tuned by scalar α. The penalty is designed so that the cost function maintains its convexity; in fact, in the case of the quadratic cost functions for the DERs, the function remains strongly convex.

D. Implementation Methodology

The proposed methodology implements an online no-load frequency adjustment method in the lower level as the primary control. A continuous distributed optimization through the diffusion strategy is implemented in the upper level as combined secondary and tertiary controls.

Droop control represents a simple yet powerful solution to the microgrid primary control problem. DERs adjust their power output according to the no-load speed setting with respect to the system frequency. By changing the no load frequency upwards or downwards, the power output for any given system frequency can be controlled. The no-load frequency of a given generator can be set to obtain any desired power output according to its droop slope R.

$$f_{NL} = P(f_{NL} - f_{FL}) / (P_{\max} - P_{\min}) + f_{sys} \tag{24}$$

$$f_{NL} = -P \cdot R + f_{sys} \tag{25}$$

Here, R is typically formulated with the maximum and minimum power outputs of the DG, P_{max} and P_{min}, respectively. The no-load and full-load frequencies, f_{NL} and f_{FL} respectively, are normally chosen as the bounds which the system frequency must not cross. The secondary and tertiary optimization level controls adjust the no-load frequencies as shown in Fig. 9. For the energy storage systems, the no-load frequencies can be set below nominal to absorb power (charge) or above nominal to inject power (discharge). In the upper level control, the main functions of the stochastic and dispatchable agents are illustrated in Fig. 10. Assuming agent i is stochastic, the device layer reads the current power (P_i) being demanded or produced by its associated device

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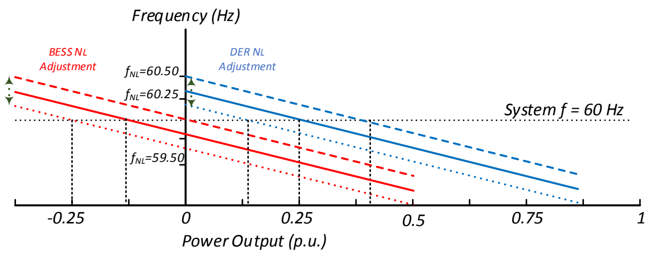

Fig. 9. Droop no-load frequency adjustments.

The information sharing (IS) diffusion takes this information (x_i) and transmits it to its neighbors and receives the same from them (x_j). Convergence is achieved once a certain precision level has been achieved, at which point the net power (P_N) required by the microgrid is known.

Each net power update is used by the dispatchable agents according to (21). However, optimization diffusion is continuously running and all agents participate in disseminating the w_i estimates across the microgrid. The data packets (p_i) are a combination of the IS and optimization diffusion data points which are sent and received among the neighborhood of agents. After each iteration, the no-load frequency of the droop control for dispatchable agents is updated to track the optimum as described in Fig. 5. Therefore, the upper level control is setting the output power points of the DERs at their optimum levels by manipulating the droop curve. In turn, this adaptive droop scheme inherently takes care of primary frequency control in an instantaneous and autonomous way.

Since reactive power cannot be billed in the traditional way active power is, voltage regulation was not considered within the optimization problem. Both in simulation and experimental studies, we have implemented conventional synchronous generators and energy storages as (V-f) control. Synchronous generators are equipped with automatic voltage regulators. Energy storage inverter-based DERs implement reactive power compensation for the local bus. DERs regulate the bus voltage control while maintaining the frequency regulation with the earlier described distributed control method.

IV. Simulation and Experimental Results

A. Simulation Results

The 9-node microgrid depicted in Fig. 2 was built in the Matlab Simulink Simscape Power Systems™ simulation platform. The stochastic load demand and renewable generation output were programmed into the model according to real-world profiles. The two conventional DERs and an energy storage system (ESS) are controlled through the described adaptive droop strategy and the diffusion communication algorithms were implemented in the model. The coefficients for these DERs corresponding to (1) and (4) are specified in Table II, they were analytically selected to approximate real-world conditions.

TABLE II
DER Coefficients for Simulation

DER	Parameters		
DG1	a_1=30	b_1=4e-8	c_1=6e-11
DG2	a_2=20	b_2=5e-8	c_2=10e-11
ESS	x_1=20	y_1=8e-5	z_1=8e-11

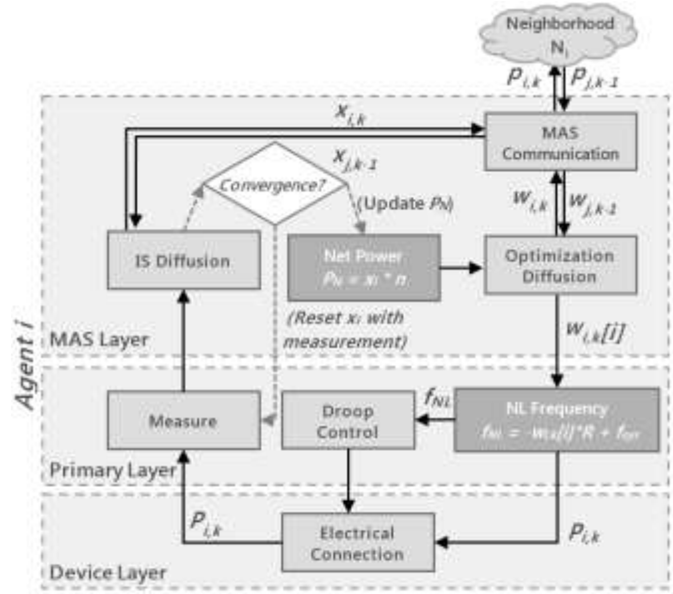

Fig. 10. Agent operation flow.

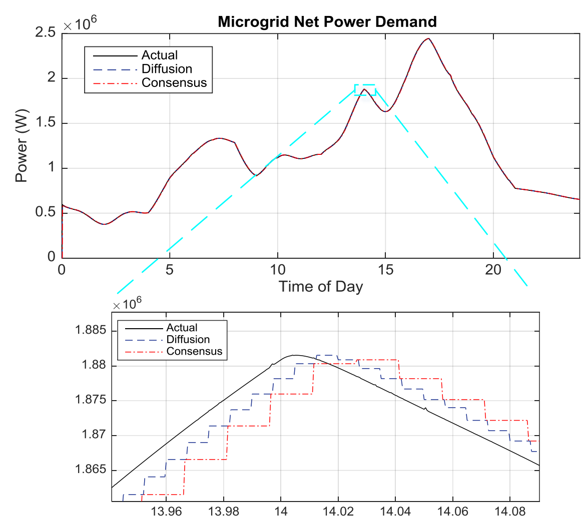

Fig. 11. Information sharing performance comparison.

Delays were also considered to simulate the communication lags. IS performance of the diffusion strategy was evaluated and compared to the consensus-based control. As illustrated in Fig. 11, the microgrid net power P_N is being diffused through the 9 node network. The net power profile is similar to the residential load profile, due to large solar and wind power outputs around noon, which compensate for a big portion of commercial and critical loads. Both diffusion and consensus closely track the actual net power demand. However, in the zoomed figure, it is clearly seen that the diffusion strategy is approximately twice as fast to converge as consensus, which agrees with the earlier performance comparison of Fig. 6 and Table I.

TABLE III
Total Cost Comparison

Control Scheme	Total Cost
Centralized	$ 4,917.60
Distributed MAS	$ 4,922.80
Difference	*0.11%*

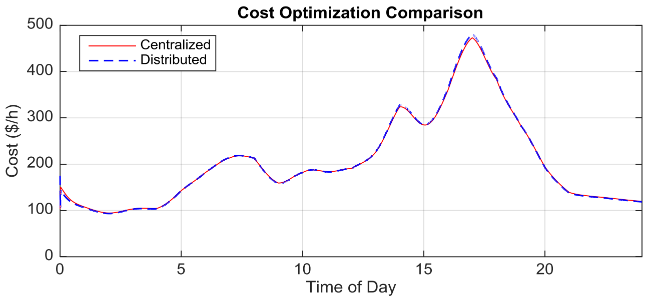

Fig. 12. Cost optimization comparison (Centralized vs Diffusion).

Although the units in the x-axis correspond to the hours of the day, the whole simulation was ran in 48 seconds, with iteration steps of 5e-4s, which would correspond to about one iteration per second in real-time. As previously mentioned, modern peer-to-peer communication technologies can achieve very high speeds of transmission. Given the low data payload necessary for the messages in the proposed framework, the tracking of the net power and economic dispatch points would be much more accurate than presented in simulation results.

The optimization of the cost functions are compared versus a centralized solution in Fig. 12. As can be seen, the cost directly corresponds with the net power demand shown in Fig. 11. It is also shown how the total cost of the distributed control scheme closely tracks that of the centralized scheme (which represents the absolute optimum given system-wide conditions and cost knowledge). Table III presents the aggregated costs over a 24-hour period for an islanded microgrid. The proposed distributed optimization scheme is validated as the total cost is only 0.11% above the centralized solution.

To provide some real-world context, the average cost per MWh for this scenario is $171/MWh or $0.171/kWh (with an average load of around 1.2MW and total energy requirement of 28.7MWh). This is high compared to current electrical rates in the US markets, however this would be an islanded microgrid that would not benefit from bulk-generation economies of scale.

To scrutinize the performance of the proposed control, the most drastic event, an unintentional islanding, was demonstrated. In grid-tied operation, the net power demand was low and the DERs were operating at their optimum points considering the constant marginal cost of the utility electric rate.

Initially, the microgrid was exporting power to the external grid and the energy storage had already reached an equilibrium on its state of charge due to the fixed marginal cost. As shown in Fig. 13, exactly at 2 AM, the PCC of the utility grid is opened and the power export was terminated. As the lower level control, the droop controllers act immediately by reducing the outputs of both DERs and the storage system started to absorb some amount of the power into the battery system. Then, as the upper level control, the diffusion strategy takes over by adjusting the no-load reference points of the DERs. First the secondary response recovers the nominal frequency after the grid agent drops out of the w vector and the remaining DERs need to maintain the net power demand balance. Then, the optimization process continues adjusting the assets to their economic dispatch points according to the changing net power demand within the microgrid.

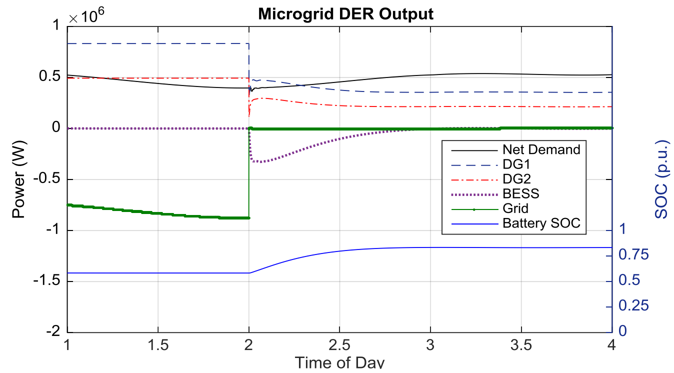

Fig. 13. Microgrid islanding DER power output and battery energy storage system state of charge.

Since the net power demand was relatively low at this time, the marginal cost of the microgrid (optimal λ point) was also low (lower than the utility rates). Therefore, as also shown in Fig. 13, the battery not only absorbs power due to the droop controller, but continues to charge until finding a new equilibrium SOC that moves with the net demand. This course of action corresponds to the behavior designed into the energy storage cost function as described in Section II-C.

Due to the extra power being generated during the islanding event, the frequency of the system rises to 60.3 Hz as shown in Fig. 14. The primary droop control suppresses the initial frequency rise by immediately dropping the power outputs of all dispatchable assets to protect the system from going beyond acceptable conditions as seen in the zoomed-in Fig. 14.

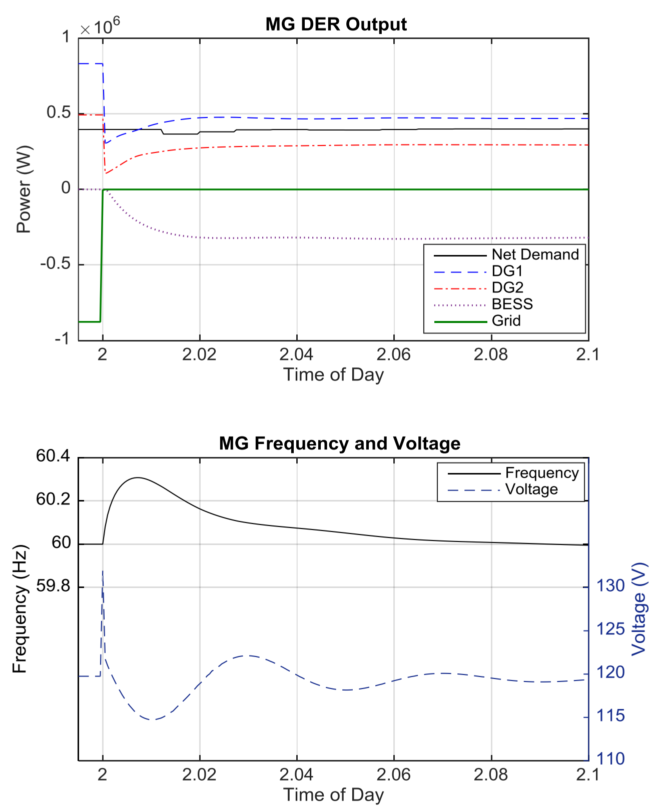

Fig. 14. Microgrid islanding transient analysis.

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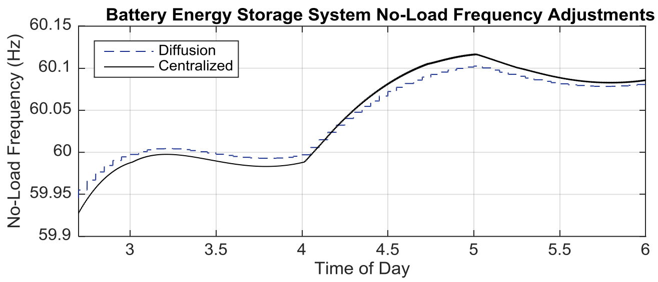

Fig. 15. Battery energy storage system no-load frequency adjustments.

Once the frequency is suppressed, the secondary control kicks in through the MAS to mitigate the residual error and put the system back to the nominal frequency value. The voltage shoots up further around 10% up to 132V as a transient, but is kept within safe levels. Diffusion then keeps the frequency very close to the nominal as the net demand fluctuates.

To compare the diffusion strategy with a centralized solution, the adaptive droop no-load frequency adjustments were compared side by side. The centralized solution implements the adaptive droop adjustments to operate the asset at the exact economic dispatch point given global power system knowledge. In Fig. 15, the slight differences are observed. Although the diffusion adjustments fall a little behind, the accuracy was still 99.9% at the worst points.

B. Experimental Results

To demonstrate the capability of the proposed control strategy in real-time, an experimental study has been performed on the reconfigurable power system at Florida International University as shown in Fig. 17. [47], [48]. The industrial agent framework developed by authors [41], [42] was used as the cyber-physical platform to implement hardware-in-the-loop agents. Information sharing is implemented by reading the power being drawn or injected by loads and generators through intelligent electronic devices (IED). An OPC UA middleware framework was implemented to map measurements in JADE Java agent platform as shown in Fig. 16. Each agent communicates to the others through the JADE and OPC UA middleware to reach convergence on the net power requirement of the microgrid. Here, the implemented agent framework simulates the peer-to-peer communication infrastructure that we envision in a real-world scenario. Consequently the power points of the DERs are adjusted to their economic dispatch points through the diffusion optimization. Both information sharing and optimization diffusion is sent in the same data packet as described in Fig. 10.

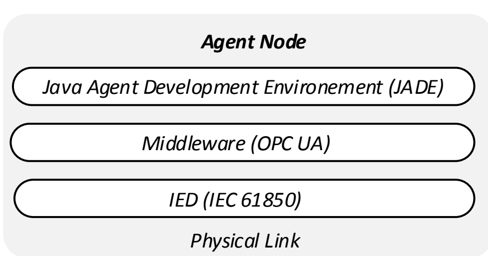

Fig. 16. Agent node architecture.

Fig. 17. Agent platform and laboratory setup at FIU.

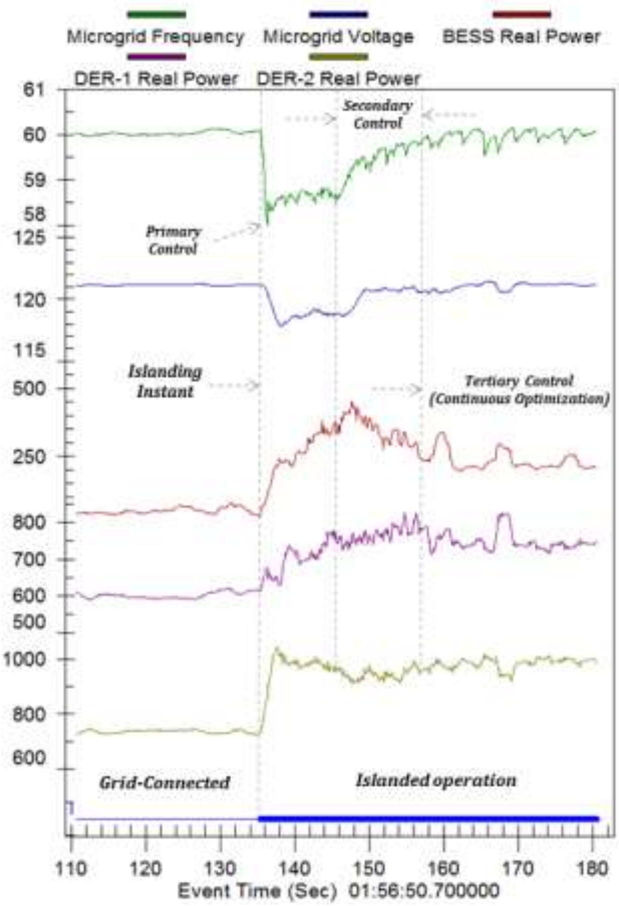

Fig. 18. Experimental islanding – distributed optimization performance.

Fig. 18 illustrates the experimental performance of the proposed diffusion strategy under the islanding event. In this scenario, we defined a 9 node microgrid network as initially importing power from the utility grid. The islanding event is established by opening the PCC circuit breaker. The primary control was taken immediately by all dispatchable DERs to recover system frequency and voltage. Once the system frequency was settled, the secondary control moved in to perfectly mitigate the residual frequency error and put system frequency back to nominal value.

In Fig. 18, the islanding event can be seen happening at around 135s. Primary droop control immediately takes action by injecting more power from the DERs and Battery Energy Storage System (BESS); this happens in less than a second and the frequency is prevented from collapsing. Then, secondary control recovers the frequency to the nominal 60 Hz by adjusting the no-load frequency parameters of the droop curves for each asset. Secondary frequency recovery is accomplished around 155s. Subsequently, the tertiary control economic dispatch is continuously adjusting the assets to their optimal levels.

It should be noted that the system frequency is more stable in grid connected operation, whereas minor frequency oscillations were observed in islanded operation mode due to the particularly low inertia of the experimental microgrid. Afterward, the tertiary control continuously adjusts the operating points until the optimum is reached.

V. Conclusion

The distributed diffusion strategy and its great potential value to the microgrid optimization problem have been discussed. The proposed method was applied to a 9 node microgrid network including stochastic and dispatchable DERs. An experimental study was also performed at FIU Smart Grid Testbed. It has been shown that the fully distributed multiagent systems based on the diffusion strategy can be easily applicable for microgrid optimization. The results show that in comparison to developed agent-based diffusion strategies and consensus-based methods, the new microgrid optimization scheme presents a desirable performance. It has been concluded that the proposed strategy can be successfully implemented in actual power systems offering a superior decision making and improved performance on optimal microgrid control.

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