IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 27, 2021, accepted April 30, 2021, date of publication May 7, 2021, date of current version May 17, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3078335

Microgrid Energy Management With Asynchronous Decentralized Particle Swarm Optimization

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This work was supported in part by the Fondo Sectorial Consejo Nacional de Ciencia y Tecnología (CONACYT)-Secretaría de Energía (SENER) Sustentabilidad Energética, in part by the Centro Mexicano de Innovación en Energía (CEMIE) Redes under Project PE-A-17, and in part by the Tecnológico Nacional de México (TecNM) Proyectos de Investigación Científica (TecNM/Scientific Research Projects) under Project 8335.20-P.

ABSTRACT Controlling distributed energy resources (DERs) in low voltage microgrids is a challenging task for operators. The simultaneous operation of independent small-scale DER owners could compromise the operator's hierarchical and centralized control to reach system stability and cost optimization. Recent Decentralized Energy Management (DEM) approaches provide flexibility for DERs control, but several existing solutions depend on powerful and expensive computer clusters and their ability to deal with a high burden of data in the communication channel. This work is motivated towards a DEM framework that involves independent DER owners while microgrid operator still maintains a hierarchical control philosophy. The framework must include a method to reduce the need of powerful computer clusters and depend on low bandwidth communications channel. Here, a multi-layered framework for every DER, consisting of physical, control, and agent layers for DEM is approached, where the agent layer participates in the energy management task. An Asynchronous Decentralized PSO (ADPSO) algorithm is proposed for the agent layer based on its primal characteristic: it can reach a consensus state between networked computing units by exchanging asynchronously only the state variable through the communications channel. The proposed solution allows the integration of DEM capabilities within the physical controller of the DERs, distinguishing it from other decentralized solutions. Easiness of implementation and low computational requirements are shown by performing DEM tests on single board computers. The tests show improved convergence rate, improved swarm diversity behavior and fast consensus reaching of DEM optimization.

INDEX TERMS Energy management, smart grids, optimization.

NOMENCLATURE

A. ACRONYMS

ALM	Augmented Lagrangian Methods.
ADMM	Alternate Direction Method of Multipliers.
ADPSO	Asynchronous Decentralized Particle Swarm Optimization.
AFSO	Artificial Fish Swarm Optimization.
CBPSO	Chaotic Binary Particle Swarm Optimization.
CSU	Communications Supervisor Unit.
DER	Distributed Energy Resource.
DGLDPSO	Dynamic Group Learning Distributed PSO.
DEM	Decentralized Energy Management.
EMS	Energy Management System.
FGU	Forecast Generation Unit.
GBMOHSA	Grid-Based Multiobjective Harmony Search Algorithm.
GWO	Gray Wolf Optimization.
MPPT	Maximum Power Point Tracker.
NRM	Newton Raphson Method.
PATS	Pattern Search.

The associate editor coordinating the review of this manuscript and approving it for publication was Salvatore Favuzza.

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PC Personal Computer.
PDM Primal-Dual Methods.
SPSO Synchronous Particle Swarm Optimization.
RMS Root Mean Squared.
SBC Single Board Computer.
SQS Sequential Quadratic Search.
TCP Transmission Control Protocol.

B. INDICES

g, h Index of an agent in a distributed environment.
i Index of a distributed energy generator on a microgrid.
j Index of a particle in an artificial swarm.
k Iteration index of a swarm optimization algorithm.
l Index of a power load on a microgrid.
m, n Index of electrical bus of a microgrid.
r Iteration index of a NRM solution.
t Index of a discrete interval of time.

C. VARIABLES

δ_m Voltage angle on the m-th bus.
$\delta(r)$ Estimated voltage angle matrix at iteration r.
$\varphi_1^j(t), \varphi_2^j(t)$ Cognition and social component for the swarm learning behavior respectively.
$\leftthreetimes(r)$ Power flow state variable at iteration r.
A_g, B_g, C_g Dynamical equations coefficient matrices for the g-th agent.
$b(X), c(X)$ Linear and non-linear constraint matrix for an optimization problem respectively.
$B_i(t)$ Generation tariff for the i-th DER at time t.
$B_{grid}(t)$ Power tariff for the utility grid at time t.
$B_{low}(t)$ Transitional low state tariff for the i-th DER at time t.
$B_{off}(t)$ Halt state tariff for the i-th DER at time t.
$B_{up}(t)$ Transitional up state tariff for the i-th DER at time t.
$Cost_t$ Cost of microgrid operation at time t.
$\delta_{j_{best}}(k)$ Distance between $x_{j_{best}}(k)$ and $g_{best}(k)$.
E Edge set corresponding to the underlying graph of a network.
$f(X)$ Objective function for an optimization problem.
$g_{best}(k)$ Best position achieved by local swarm of agent g up to iteration k.
$h_{best}(k)$ Best position achieved by the neighborhood set of agent g up to iteration k.
$h_{low}(t)$ Transitional low state for the i-th DER at time t.
$h_{off}(t)$ Halt state for the i-th DER at time t.
$h_{up}(t)$ Transitional up state for the i-th DER at time t.
$\mathbf{I}$ Injected currents matrix for a microgrid.
I_m Injected current at bus m.
$\mathbf{J}$ Computed Jacobian matrix.
$\mathbf{P}, \mathbf{Q}$ Active and reactive matrices of power injected on buses at iteration r.
$P_{grid}(t)$ Bi-directional Power Interchanged between microgrid and utility grid at time t.
$P_{grid_{max}}(t)$ Maximum power interface capacity limit for the utility grid at time t.
$P_{grid_{min}}(t)$ Minimum power interface capacity limit for the utility grid at time t.
$P_i(t)$ Power reference for the i-th DER at time t.
$P_{i_{max}}(t)$ Maximum power interface capacity limit for the i-th DER at time t.
$P_{i_{min}}(t)$ Minimum power interface capacity limit for the i-th DER at time t.
$P_{loss}(t)$ Power loss on a microgrid at time t.
R^o, R^p Real numbers set of size o and p respectively.
S_m Injected complex power at bus m.
u_g Input vector for the g-th agent's dynamical equations.
$\mathbf{V}$ Bus voltages matrix for a microgrid.
$\mathbf{V}(r)$ Estimated voltage magnitude matrix at iteration r.
$v_j(k)$ Velocity estimation of a virtual particle at iteration k.
$V_m(t)$ Voltage magnitude on the m-th bus at time t.
V_n, V_n^* Voltage of a node and its complex conjugate respectively.
$w(k)$ Inertial factor for velocity in the iteration k.
X State variable for an optimization problem.
X_g Vector state for the g-th agent's dynamical equations.
$x_j(k)$ Position estimation of a virtual particle at iteration k.
$x_{j_{best}}(k)$ Best position achieved by particle j up to iteration k.
$\mathbf{Y}$ Admittance matrix for a microgrid.
Y_g Output vector for the g-th agent's dynamical equations.
Y_{mn}, Y_{mn}^* Admittance matrix element and its complex conjugate.

D. CONSTANTS

$\overline{\varphi}_1, \overline{\varphi}_2$ Maximum Cognition and Social component limits for the swarm learning behavior respectively.
Ω Set of agents in a distributed environment.
b_L, b_U Lower and upper limits for the linear constraint matrix.
c_L, c_U Lower and upper limits for the non-linear constraint matrix.

N	Total number of agents in a distributed environment.
N_{DER}	Total number of distributed energy resources on a microgrid.
m_δ	Threshold for stopping criteria.
N_g	Neighborhood set of agents for g-th agent.
N_{it}	Total iterations of a swarm optimization algorithm.
N_L	Total number of loads on a microgrid.
N_m	Total number of electrical nodes of a microgrid.
o, p, q	Dimensions of vectors.
p_δ	Percentage of swarm population employed for stopping criteria.
T	Total regular spaced intervals of time t.
$V_{m_{min}}$ $V_{m_{max}}$	Minimum and maximum allowed voltage at bus m respectively.
w_{max}, w_{min}	Maximum and minimum inertial factor limits respectively.
X_L, X_U	Lower and upper limits of the state variable X respectively.

I. INTRODUCTION

Microgrids are a paradigm of construction and operation of electric power systems where several distributed energy resources (DERs) are interfaced through power electronics converters and connected to a local grid [1]. By means of setting the controllable variables for each DER, an energy management system (EMS) achieves an efficient and optimal utilization of the local energy resources and to control the power flow between the nodes of the microgrid.

As microgrid technology has consolidated, the number of existing controllable DERs have increased and the optimization problem has become more complex to solve. Also, distinct operative scenarios have arisen and the interaction between different stakeholders on a microgrid operation is gaining attention. In this work, attention is given to this last case as it describes the complexity of allowing the participation of DERs of independent owners on energy management.

Multiple EMS paradigms have been explored and reported in the literature in the last years. In the centralized EMS paradigm, a single operator knows and manages the whole physical structure of the microgrid and its measurement data. This paradigm has the advantage of having all the microgrid information concentrated in a single processing place, but the volume of this information might become prohibitive in cases with frequent information exchange or large-scale microgrids. Within this paradigm, a first class of algorithms are characterized by approaching the optimization solution to be efficiently performed in a single central processing unit. The Grey Wolf Optimization (GWO) introduced in [2] to solve optimal power flow problems, the Chaotic Binary PSO (CBPSO) is developed for optimal DER scheduling in [3], the Grid based Multiobjective Harmony Search Algorithm (GBMOHSA) applied in [4] to reduce voltage deviations and power losses are some of the algorithms of this class. In some of these cases, the underlying complex models could be reformulated to reduce the number of variables and constraints to reduce the computational burden [5], but in general, these algorithms do not enable consumer participation in DEM.

A second class of algorithms comprises decentralization of the optimization problem in autonomous problems within zones or regions with smaller scope, this is typical in the multi-microgrid scenario. A twofold system whit autonomous microgrids performing demand-side management by linear programming and a trading center calculating time of use tariffs is used in [6] to solve the joint energy management and energy trading model among microgrids to maximize self-generation. In [7], the global operation cost between several microgrids trading energy with each other is minimized by proposing an iterative and scalable distributed algorithm that first addresses the problem decentralization and then solves the sub-microgrid problem as a second step. In [8], the total electricity cost minimization of multiple households with DERs is treated in a two-level optimization: load scheduling on a first level and energy storage scheduling on a second level. In [9] a hierarchical decentralized System of systems is proposed, and a bi-level optimization problem is formulated for a multi-microgrid system. These algorithms could enable consumer participation on energy management but could not enable DEM integration on DER controllers as they are more oriented to medium to large scale microgrids.

A third class of algorithms applies distributed computing techniques to parallelize processing between several high-performance processing units. These algorithms achieve promising performance and effectiveness for large-scale microgrids. The Augmented Lagrangian based Alternating Direction Inexact Newton Method in [10] is used to reformulate the power flow optimization problem to a distributed least-squares problem for rapid convergence. Additional results on Augmented Lagrangian Methods (ALM) and Primal-Dual Methods (PDM) are studied for the smart grid context in [11]. In [12], a distributed algorithm based on Alternating Direction Method of multipliers (ADMM) decompose the original optimal power flow problem into several subproblems to be solved by several distributed agents. An interesting approach to cloud workflow scheduling applications is presented in [13], where a Dynamic Group Learning Distributed Particle Swarm Optimization (DGLDPSO) with improvements is used for the development of an intelligent partitioning in distributed optimization algorithm for electric power systems. This class of algorithms shows high computational efficiency on large-scale microgrids managed with the centralized paradigm, but work needs to be done to reduce the dependency on powerful computer clusters and high speed communications channels.

The fourth class of algorithms considered here includes decentralization techniques based on the cooperation of several processing units distributed in different physical regions over the microgrid. In [14] an asynchronous distributed

TABLE 1. Comparison of energy management optimization approaches.

Reference	Oriented to large-scale grids	Communication Channel Required	Performed on low-processing units	Integration of DEM on DER controllers	Enable Consumer participation
Class 1 [2], [3], [4] [5]	✓	X	X	X	X
Class 2 [6], [7], [8], [9]	✓✓	✓	X	X	✓
Class 3 [10], [11]	✓✓✓	✓✓	X	X	X
[12]	✓✓✓	✓	X	X	X
[13]	✓✓	✓✓	✓	X	✓
Class 4 [14], [15]	✓✓✓	✓✓	X	X	X
[16]	✓	✓	✓✓	✓	X
[17]	✓✓	✓	✓	X	✓
[18]	✓	✓	X	X	✓
This work	✓	✓	✓✓	✓✓	✓✓

X: Not applicable,✓: Low, ✓✓: Medium, ✓✓✓: High

version of ADMM is proposed to solve optimization problems over a star computer network. In [16], an optimal power flow problem is formulated and solved by Distributed Control Units in a modular framework; the lack of need for powerful computers for these units is remarked. The adoption of a modular framework is also present in [17] where a PSO algorithm to solve general optimization problems cooperatively by sharing the optimization variable and performing a finite-time average consensus algorithm for each step is presented. In [15], a Neurodynamic-Based Distributed Optimal Control Algorithm is used for the distributed optimization of economic system operation in a multienergy system with combined heat and power, and conventional generators. In [18], an improved coordinate descent method algorithm is used by a multi-layered model that puts processing agents in the same physical place that power nodes. In this class, work has been done to reduce the need of powerful and expensive computers to enable DER integration on DEM. Also, the awareness for independent DER owners and their DEM participation needs is increasing.

A. MOTIVATION

Distributed computing algorithms (third class) show promising benefits, particularly in large-scale medium voltage microgrids. However, distributed computing infrastructure could be too expensive for a small group of DER owners [19]. DEM paradigm and algorithms of the fourth class could help to raise social awareness and interest in energy management before making any investment. Also, decentralization maintains a level of hierarchy similar to the microgrid operator/owner centralized philosophy and their sense of ownership is preserved. As shown on the comparison Table 1, this work is intended to take further steps in avoiding powerful computers for the distributed processors, and to integrate DEM capabilities on DER controllers. These DEM-enabled DER controllers could allow owner and consumer participation in the energy management of a microgrid.

B. CONTRIBUTIONS

In this paper, the decentralization of a low voltage microgrid EMS based on a multi-layered framework for DER control is approached. An Asynchronous Decentralized PSO (ADPSO) algorithm is proposed for DEM optimization. This solution is similar to [14] as it allows a system supervisor to coordinate distributed controllers over a star communications network to cooperate in the solution search. The modular distributed framework exists in [16], [17]. In ADPSO, the solution search requires only the exchange of the state variable between agents and the supervisor completely in asynchronous manner [20], meaning that there is no need for synchronization between distributed controllers and the supervisor does not need to wait for every controller to progress in order to update the state variable. This distinguish this work from other works where at least one algorithm variable must be kept synchronized across all agents [11], [12], [15]. Moreover, the collaborative operation of ADPSO algorithm allows the reduction of the swarm population on each computational agent, which implies lower function evaluations in that agent. This implies a potential lack of need of powerful computers similar to [16], but different to the majority of DEM algorithms. With this, the integration of DEM on DER controllers is expected.

The contributions and features are summarized as follows:

1) An asynchronous and decentralized algorithm based on particle swarm optimization (ADPSO) is proposed to solve optimization of energy management problems. The algorithm only needs the global state variable to be exchanged individually between a processing agent and a communications supervisor to reach a consensus state between the agents.
2) The proposed algorithm has low complexity and is easy to implement with reasonable efficiency on limited computing power processors.
3) The multi-layered framework for decentralized EMS could lead to integrate energy management capabilities into the DER controllers of the microgrid.
4) An experimental setup to test ADPSO in the agent layer of the multi-layered framework for decentralized EMS is performed. The algorithm is implemented in an IEEE 802.11 network of single board computers (SBCs) optimizing an active power scheduling and optimal power flow problem for a microgrid. This experimental setup shows easiness of implementation and low computational requirements of the proposal. The DEM tests show improved convergence rate, improved swarm diversity behavior and fast consensus among SBCs.
5) In its current formulation, the power flow constraint evaluation is the main drawback of the proposal due to its long processing steps and time.

The paper is organized as follows: Sect. II presents the decentralized architecture, the management problem definition, the optimization algorithm and the complete EMS solution proposed; Sect. III presents the agent layer simulations where a decentralized EMS is developed and simulated by single-board computers and a PC and Sect. IV presents conclusions of the work.

II. DECENTRALIZED EMS FOR A GRID CONNECTED AC MICROGRID

A. DECENTRALIZED EMS ARCHITECTURE

Similar to related work, the proposal is based on a multi-layered framework. Our reference framework is depicted on Fig. 1. In this framework, it is assumed that each DER has a modular controller consisting of three layers: a component layer referring to the physical component interface to the microgrid, a control layer where the operation of the previous is controlled (e.g. governors, MPPT devices, charge controllers, etc.) and an agent layer where reference control signals are locally used to manage the control layer. Within this framework, each local DER controller performs energy management functions. The decentralized agent layer

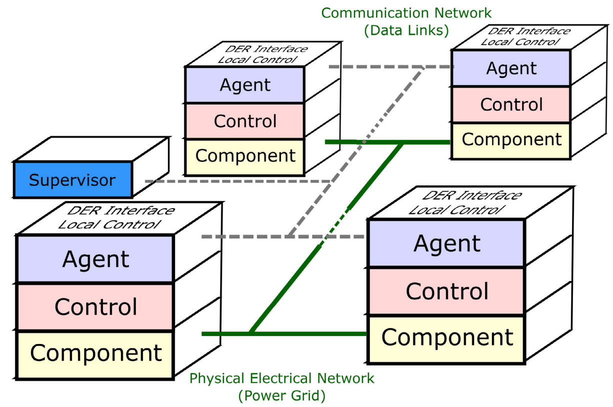

FIGURE 1. Reference of a multi-layered framework for decentralized EMS.

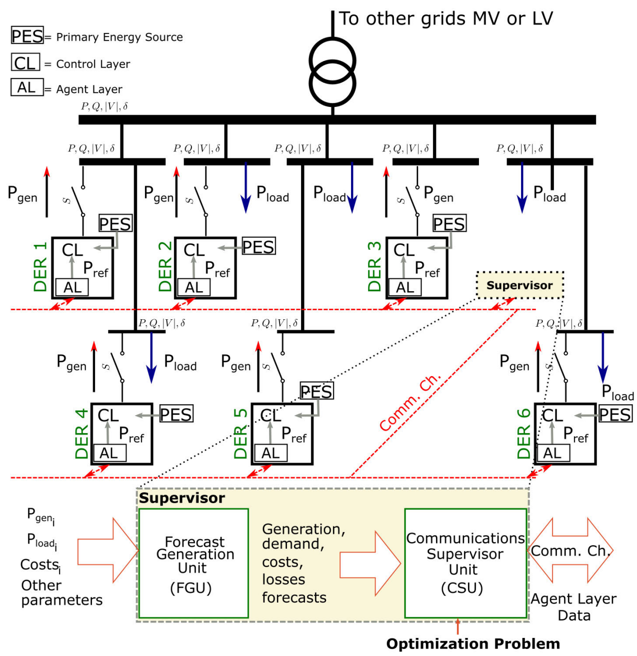

FIGURE 2. Concept of a microgrid with a decentralized EMS framework.

provides the overall management for the microgrid, supervised by a central supervisor unit.

A microgrid with a decentralized EMS framework is shown on Fig. 2. According to Fig. 2 electrical parameters are measured over the microgrid electrical buses (i.e. magnitude and frequency of voltage, active and reactive power) and transmitted to a Forecast Generation Unit (FGU) which in turn builds estimated profiles for DER generation, load demand, microgrid losses, and other information [21], [22]. These profiles are then transmitted by a Communications Supervisor Unit (CSU) to the agent layer module in each DER controller. As mentioned, the data exchanged corresponds to the state variable of the energy management problem which will be subsequently treated as control layer power references. Thus, each agent layer module will generate power references for its corresponding control layer module. These power references will be optimized to accomplish a prescribed optimization objective, subject to the availability described by the estimated profiles and the safe and reliable operation constraints of the microgrid.

Implementation of a FGU usually involves different statistical or artificial intelligence techniques and its methods and complexity validate its execution on a central single or multi-threaded processing unit [23], [24]. The CSU could be a variable complexity data server using an open or private communications protocol over a physical network [25]. In this paper a decentralized solution to the optimal schedule and power flow will be formulated and solved.

B. DECENTRALIZED EMS FORMULATION

The algorithm described in this section is inspired on the algorithm of [26], [27], which was proposed towards consensus seeking of solutions to complex problems in distributed environments. Start by assuming a set of agents $\Omega = \{g = 1, \ldots, N\}$, where N is the number of agents, the dynamical equations of each agent is given by:

$$\begin{aligned} \dot{X}_g &= A_g X_g + B_g u_g \\ Y_g &= C_g X_g, \end{aligned} \tag{1}$$

where $X_g \in R^o$ denotes the state vector, $u_g \in R^p$ is the input vector, and $Y_g \in R^q$ is the output vector of agent $g \in \Omega$. Variables o, p and q denote the dimensions of vectors. By concatenation of all the vectors, the entire set of vectors are given by:

$$\begin{aligned} X_{N\times o} &= \left[(X_1)^T \ldots (X_N)^T\right]^T \\ u_{N\times p} &= \left[(u_1)^T \ldots (u_N)^T\right]^T \\ Y_{N\times q} &= \left[(Y_1)^T \ldots (Y_N)^T\right]^T \end{aligned} \tag{2}$$

Cooperation and coordination require that each member of Ω has to be aware of the output state vector, thus each member have to communicate with each other. By calling neighborhood set N_g to the set of agents from which agent g can interchange information, two agents named g and h are nodes connected to each other in the network graph and have a direct or indirect link to transfer their status and state vectors. This is expressed by:

$$\begin{aligned} &\forall g = 1, \ldots, N, \\ &N_g = h = 1, \ldots, N | g \neq h; (g, h) \in E, \end{aligned} \tag{3}$$

where E is the edge set that corresponds to the underlying graph of the network. When agents cooperate to solve a problem, they reach consensus when their output vectors converge to the same value or consensus state. Then the main goal of the proposed algorithm will reach a consensus state for each agent layer module in the DERs of the microgrid.

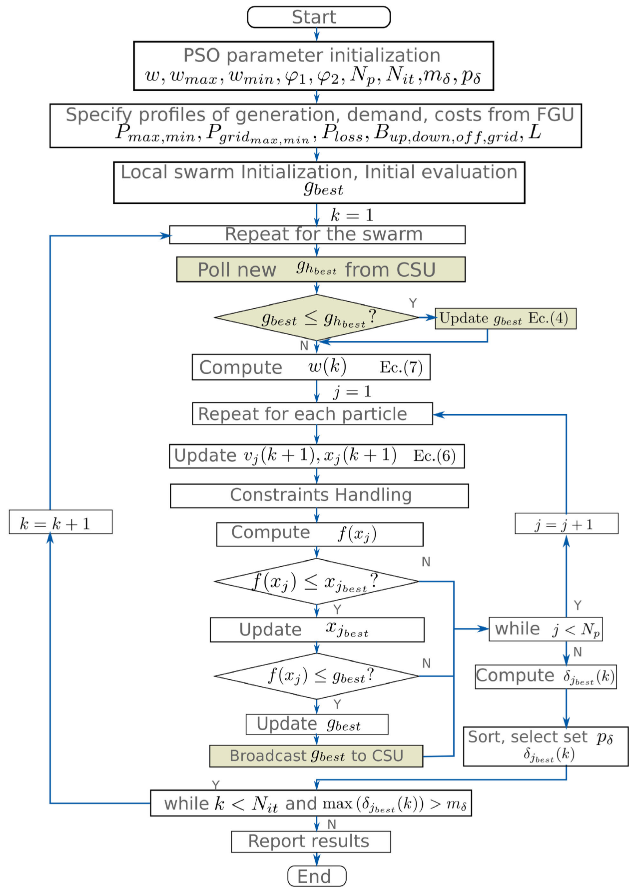

FIGURE 3. Asynchronous decentralized PSO algorithm operational flow.

C. ASYNCHRONOUS DECENTRALIZED PSO ALGORITHM

PSO algorithm is a well-known optimization algorithm and different implementations are found on literature regarding EMSs optimization. In the usual implementation of PSO, the algorithm runs on a single computer which is well suited for centralized EMS operation. As the EMS optimization problem grows, PSO requires modifications to reach an adequate optimization result and to avoid increments in the computational processing and in the time consumed (i.e. using a considerable large particle swarm population, changes on dynamic update functions). In this paper, a simultaneous cooperative implementation of the algorithm is proposed as it seems advantageous to reduce those increments. The simultaneous cooperative execution on several computers could improve the optimization search and could allow to build a decentralized EMS optimization. The operational flow of an asynchronous decentralized PSO shown on Fig. 3 is proposed.

As in PSO algorithm, ADSPO is based on the expression of movement in k iterations of virtual particles represented by their positions and velocities. Let $x_j(k)$ be the position estimation of the j-th particle on iteration k and let $x_{j_{best}}(k)$ be the best position achieved by a particle j from the beginning of the execution to current iteration; on the other hand, let $g_{best}(k)$ be the best position achieved for the local swarm of agent g. The value of $g_{best}(k)$ is given by:

$$g_{best}(k) = arg\min\{f\left(g_{best}(k-1)\right), \\ f\left(x_{j_{best}}(k)\right), h_{best}(k)\}, \quad (4)$$

where:

$$h_{best}(k) = \min\left[g_{best}(k)\right]_h, \quad h \in N_g, \quad (5)$$

is the best position of the neighborhood set for agent g up to the k-th iteration. Eq. (4) states that the current best position of the local swarm, $g_{best}(k)$, is the minimum value between the previous iteration best, $g_{best}(k-1)$, the j local particle best position, $x_{j_{best}}(k)$, and the current best position in the neighborhood, $h_{best}(k)$. In this scheme, the dynamic update of particles is given by:

$$\begin{aligned} v_j(k+1) &= w(k)v_j(k) + \varphi_1^i(k)\left(x_{j_{best}}(k) - x_j(k)\right) \\ &\quad + \varphi_2^j(k)\left(g_{best}(k) - x_j(k)\right) \\ x_j(k+1) &= x_j(k) + v_j(k+1) \end{aligned} \quad (6)$$

Coefficient $w(k)$ in (6) represents an inertial factor for speed in the k-th iteration, here updated in a linearly decreasing fashion between w_{min} and w_{max} limits:

$$w(k) = w_{max} - \frac{w_{max} - w_{min}}{N_{it}} \times k. \quad (7)$$

To represent the cognition and social components of the swarm behavior, coefficients $\varphi_1^j(t) \in \left[0, \overline{\varphi}_1\right]^n$ and $\varphi_2^j(t) \in \left[0, \overline{\varphi}_2\right]^n$ in (6) are learning coefficients for each particle and the swarm, respectively.

Diversity in the swarm population is considered as stopping criteria in this work. If diversity is low, i.e. the individual particles are close to each other, then it is assumed that convergence has been obtained. A maximum distance criterion is used. First, the distance between each particle objective function value and the objective function value resulting from the neighborhood best position:

$$\delta_{j_{best}}(k) = f\left(x_{j_{best}}(k)\right) - f\left(h_{best}(k)\right). \quad (8)$$

Then, the particles are sorted by distance and a p_δ set of the closest particles is selected. The optimization is stopped if the maximum distance from the set is below a threshold m_δ. As a note, p_δ must not be chosen too low for a reliable detection of convergence nor too high to avoid wasting of computational resources. As mentioned, in ADPSO the swarm population of each agent share the term $h_{best}(k)$, which gives the same stopping criteria for all agents without any agent been aware of the other agents individual particle positions.

In other words, ADPSO decentralized nature is based on the interaction of a communications supervisor unit (CSU) with the agent layer module in each DER. Here, the main role of the CSU is to set the start of the optimization algorithm execution, to store $h_{best}(k)$ obtained during execution and to receive/send that global best result from/to any of the requesting agents. Agent layer module's role is to perform the dynamic position and velocity update of their internal swarm and to request/provide an updated global best to CSU.

According to Fig. 3, the mentioned interaction is performed at two moments in the operational flow. The first moment occurs at the beginning of each dynamic update of the swarm, when each agent polls the global best position stored in the CSU and if this value is better than its local best then updates its local value. The second moment of interaction is performed whenever any local particle in any agent finds a new local best. At this moment, the performing agent updates its local best asynchronously and in this same asynchronous manner the agent sends a broadcasting message with the new local best to CSU to update the global best. As a result, all the state vectors of $X_{N\times o}$ converge to the same value and the dynamic solution of the optimization problem is achieved. In other words, a consensus state is achieved using ADPSO for the cooperative participation of various agent layer modules at microgrid DERs.

With this approach, a contribution to the energy management of small scale microgrids is obtained. The characteristics of the ADPSO algorithm exposed is simple to implement and several agents could converge to a consensus state in this scheme. Also, the algorithm is of low complexity and require low computational resources thus could be implemented in limited processing power processors. In the next Section a management problem definition will be presented to apply ADPSO in an EMS context.

D. MANAGEMENT PROBLEM DEFINITION

As mentioned earlier, an optimal schedule and power flow energy management solution searches for an optimal set of power references for every DER in the microgrid. In this sense, in the very deep, the solution of the EMS is the solution of an optimization problem. Start by formulating the general optimization problem as follows:

$$\begin{aligned} &\min_X f(X) \\ &\text{s. t.: } X_L \le X \le X_U, \\ &\qquad \mathbf{b}_L \le \mathbf{b}(X) \le \mathbf{b}_U, \\ &\qquad \mathbf{c}_L \le \mathbf{c}(X) \le \mathbf{c}_U. \end{aligned} \quad (9)$$

where $f(X)$ is the objective function on which a minimization of its value should be achieved, X_L and X_U are the lower and upper limits of the state variable X, respectively; $\mathbf{b}(X)$ and $\mathbf{c}(X)$ are the linear and nonlinear constraints matrices and their corresponding lower and upper limits $\mathbf{b}_L, \mathbf{b}_U, \mathbf{c}_L$ and $\mathbf{c}_U$.

1) OPERATIVE COST MINIMIZATION

For the EMS problem treated in this paper, the objective is to get the lowest operational cost of the microgrid in a daily basis. For this objective, operative costs in a microgrid include: generation costs, start/stop transitional costs, halt costs and cost for selling/buying energy to external grids. All these costs must be accumulated on a daily basis. Accumulating costs on a total of T regularly spaced intervals, the operational cost of a microgrid over a day could be defined as the sum of the generation costs, start/stop transitional costs, halt costs and cost for selling/buying of energy to external grids at each t interval. Considering variable $X = [P]_{N_{DER} \times T}$ as the matrix of power references for the total of N_{DER} DERs at each interval and assuming in this approach that $N_{DER} = N$, the cost function is expressed as follows:

$$\begin{aligned} f(X) = \sum_{t=1}^{T} Cost_t = \sum_{t=1}^{T} \Big\{ & \sum_{i=1}^{N} \big[P_i(t) B_i(t) \\ & + h_{up_i}(t) B_{up}(t) + h_{down_i} B_{down}(t) \\ & + h_{off_i} B_{off}(t) \big] \\ & + P_{grid}(t) B_{grid}(t) \Big\} \end{aligned} \quad (10)$$

where $P_i(t)$ is the power reference for the i-th DER and $B_i(t)$ is its corresponding generation tariff at ordinal interval t; $P_{grid}(t)$ is the bi-directional power interchanged between the microgrid and its external grid. $B_{grid}(t)$ is the corresponding tariff at interval t for the purchase or the selling of $P_{grid}(t)$, according to $P_{grid}(t)$ flow direction. Moreover, $h_{up_i}(t)$, $h_{down_i}(t)$ and $h_{off_i}(t)$ are the operative transitional states for the i-th DER and the halt state and $B_{up}(t)$, $B_{down}(t)$ and $B_{off}(t)$ are the cost associated with those states, respectively. It must be observed that those parameters considered in (10) could be simplified, i.e. considering full time operating DERs thus transitional states are not required to be considered, or more detailed, i.e. by considering fuel consumption costs, solid or gasses waste generation costs. A review of additional control models and variants are provided in [28]–[31].

2) POWER BALANCE AND LIMITS CONSTRAINT

Power balance between power generation and demand is a main constraint in this optimization problem formulation. The total power generated/supplied from DERs plus the power interchanged with utility grid minus distribution power losses must be equal to local load demand. Local load demand is an estimated profile provided by an FGU (according to Fig. 2) and the power from DERs, the power interchanged with the utility grid and losses will be determined by the optimization process. The power balance at the t-th interval of the day is given by:

$$\sum_{i=1}^{N} [P_i(t)] + P_{grid}(t) - P_{loss}(t) = \sum_{l=1}^{N_L} L_l(t) \qquad t = 1, 2, 3, \ldots, T \quad (11)$$

where $L_l(t)$ is the power demanded by the l-th load, N_L is the total number of loads and P_{loss} are the power losses. Also, each DER has its own power generation limits, given either by the limits expressed in the estimated generation profiles provided by FGUs, or by its respective minimum and maximum power interface capacity. Respective limits also apply to $P_{grid}(t)$. Both limits are expressed by:

$$\begin{aligned} P_{i_{\min}}(t) \le P_i(t) \le P_{i_{\max}}(t) \\ P_{grid_{\min}}(t) \le P_{grid}(t) \le P_{grid_{\max}}(t) \end{aligned} \quad (12)$$

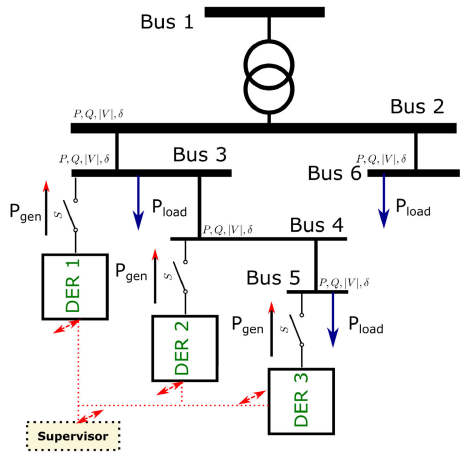

FIGURE 4. Small scale low voltage microgrid used in simulations.

3) POWER FLOW CONSTRAINT

The microgrid DER generation must be constrained in order that voltage at buses does not exceed the existing limits established in regulatory standards, i.e. ANSI C84.1. Therefore, a voltage deviation constraint could be defined as:

$$V_{m_{\min}} \le V_m(t) \le V_{m_{\max}} \quad (13)$$

where $V_{m_{\min}}$ and $V_{m_{\max}}$ are respectively the minimum and maximum allowed voltage on the electrical bus m and $V_m(t)$ is the bus voltage expected at time t. Thus, the knowledge of these expected voltage values on every bus of the microgrid is key for evaluating this constraint. This problem, known as the power flow problem, involves the computing of the voltage magnitude $|V_m|$ and angle δ_m on each bus m of a power system given power generation and load demand. In this context a radial microgrid is considered and the voltage on the buses are estimated by a power flow analysis solved with the Newton-Raphson method (NRM) [32].

For this power flow constraint, the relation between the injected currents $\mathbf{I}$ and bus voltages $\mathbf{V}$ is described by the admittance matrix $\mathbf{Y}$:

$$\mathbf{I} = \mathbf{Y}\mathbf{V}, \quad (14)$$

the injected current at bus m, I_m, could be written as:

$$I_m = \sum_{n=1}^{N_m} Y_{mn} V_n, \quad (15)$$

and the power flow problem formulation is given by:

$$S_m = V_m \sum_{n=1}^{N_m} Y_{mn}^{*} V_n^{*}, \quad (16)$$

where S_m is the injected complex power at bus m, Y_{mn}^{*} and V_n^{*} are the complex conjugate of the admittance matrix element Y_{mn} and the complex conjugate of voltage at node n, V_n, respectively. Expression (16) represents a set of nonlinear system of equations where all variables are in complex form.

TABLE 2. General characteristics of hardware employed in simulations.

Role	Type	Freq./Memory (GHz)/(GB)	PSO parameters
CSU	PC (i7)	3.2/12	—
Agent 1	BBG (Cortex-A8)	1/0.512	$N_p = 6$
Agent 2,3	rPi4 (Cortex-A72)	1.5/2	$N_p = 28$
All agents	$N_{it} = 36$	$p_\delta = 66\%$	$m_\delta = 25$

The Newton-Raphson method linearizes the problem of finding the magnitude and phase of the voltage with an iterative process. By defining:

$$\leftthreetimes(r) = \begin{bmatrix} \delta(r) \\ \mathbf{V}(r) \end{bmatrix}, \tag{17}$$

as the power flow state variable at iteration r and by using a square Jacobian matrix $\mathbf{J}$ equation, the process involves the iterative numerical computation of:

$$\mathbf{J} \begin{bmatrix} \Delta\delta(r) \\ \Delta\mathbf{V}(r) \end{bmatrix} = \begin{bmatrix} \Delta\mathbf{P}(r) \\ \Delta\mathbf{Q}(r) \end{bmatrix}, \tag{18}$$

to compute the next iteration value, $\leftthreetimes(r+1)$ as follows:

$$\leftthreetimes(r+1) = \begin{bmatrix} \delta(r+1) \\ \mathbf{V}(r+1) \end{bmatrix} = \begin{bmatrix} \delta(r) \\ \mathbf{V}(r) \end{bmatrix} + \begin{bmatrix} \Delta\delta(r) \\ \Delta\mathbf{V}(r) \end{bmatrix}. \tag{19}$$

The steps are continuously processed until convergence is obtained, i.e. until continuous values of $\leftthreetimes(r)$ are practically equal up to a certain level of accuracy.

In the context of EMS problem formulation, the power flow analysis is used to estimate the resulting voltage at the buses for given active and reactive power managed in every bus of the microgrid. If voltage parameter at any bus does not complies with the standard voltage limits, then another combination of active and reactive power references for DERs must be evaluated until voltage limits be satisfied in all microgrid buses. Expressions (10) to (13) represent the optimization problem of the form of (9) and is proposed to be solved with the ADPSO algorithm implemented in a star network of SBCs.

III. SIMULATION

The algorithm of the previous section is used on the decentralized EMS architecture of Fig. 2 to solve the optimization problem of the cost function stated in (10) subject to power balance, power limits and power flow constraints in (11)- (13). In order to validate the performance of this approach, a simulation of an optimization scenario of a small-scale low voltage microgrid with three DERs (Fig. 4) is performed.

The simulation case is a simplification of the mathematical formulation of (10) - (13). For illustrative purposes: the $B_{up}(t)$, $B_{down}(t)$, and $B_{off}(t)$ costs were neglected; load demand and DER generation profile, $P_i(t)$, of the three DERs were assumed to be provided by a FGU (shown on

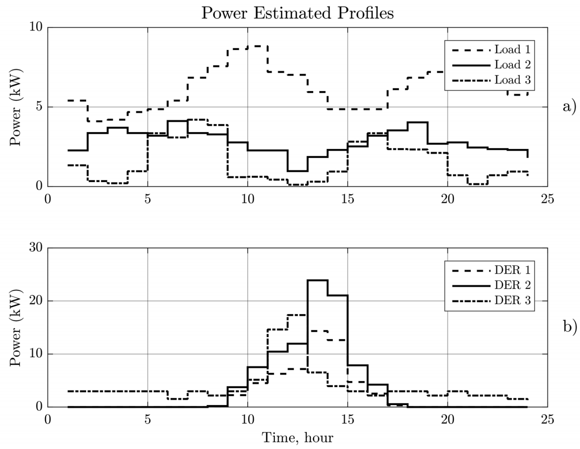

FIGURE 5. a) Load demand and b) DER generation forecast profiles used in simulations.

Fig. 5); P_{grid} power profile is not determined but is assumed to lie in the limits of $[-30, 30]$ kW; and the voltage at buses is required to be in the $[0.87, 1.06]$ p.u. limits. With these simplifications, the simulation problem takes the form of (20).

A. DEM-ENABLED DER CONTROLLER

An experiment of agent layer emulation for simulated DEM-enabled DER controllers for the problem (20) was performed. For this experiment, a simple TCP socket-based server was implemented using Python programming to play the role of a CSU and was deployed in a personal computer (PC). For the purpose of emulating the role of agent layer module in a DER, a client was also written in Python and deployed in single board computers (SBCs) for every one of the three DERs in this microgrid.

$$\begin{aligned} \min_X f(X) = \sum_{t=1}^{T} \Bigg\{ \sum_{i=1}^{N} \big[P_i(t)B_i(t)\big] \\ + P_{grid}(t)B_{grid}(t) \Bigg\} \\ \text{s.t.}: \sum_{i=1}^{N} P_i(t) + P_{grid}(t) = \sum_{l=1}^{N_L} L_l(t) \\ 0 \le P_i(t) \le P_{i_{max}} \text{ [kW]}, \\ -30 \le P_{grid}(t) \le 30 \text{ [kW]}, \\ 0.87 \le V_m(t) \le 1.06 \text{ [p.u.]}. \end{aligned} \tag{20}$$

The server and those clients were connected over a common IEEE.802.11 TCP network. In this setup communications were only allowed between each agent and the CSU, according to ADPSO. The SBCs used (two Raspberry 4 Model B+ [33] units [rPi4], and a BeagleBone Green [34] unit [BBG]) have similar computational resources. These resources are limited when compared with those of the PC used for CSU (see Table 2) or when compared with distributed computing clusters.

TABLE 3. SPSO vs. ADPSO results comparison.

Algorithm	Optimized Cost ($)	Time Consumed (s)	Averaged RMS Error ($)	Convergence rate	Multi-round optimization
SPSO	4574	415.5	114.9	Lower	X
ADPSO	4085	394	45.4	Improved	✓

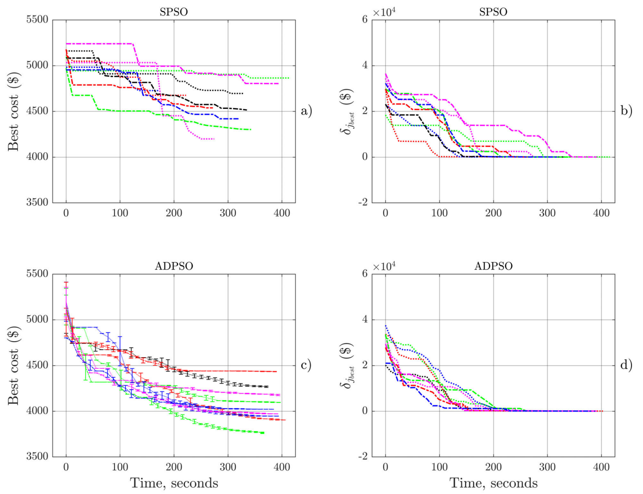

FIGURE 6. a) Several runs of cost functions against time and b) Swarm diversity ($\delta_{j_{best}}$) against time, for SPSO; c) Function cost against time and d) Swarm diversity, for ADPSO.

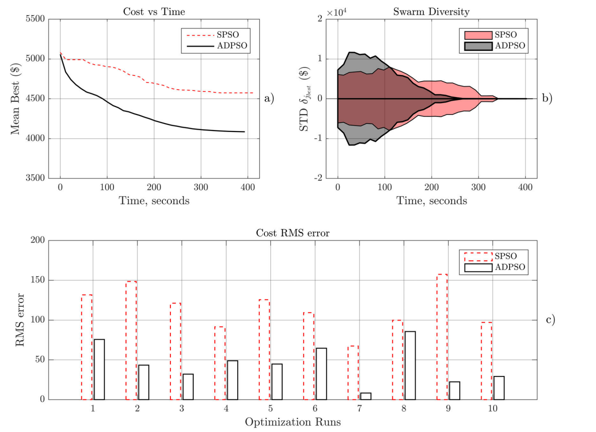

FIGURE 7. a) Averaged function cost optimization profiles; b) Standard deviation of variabilities ($\delta_{j_{best}}$) against time; c) Function cost RMS error.

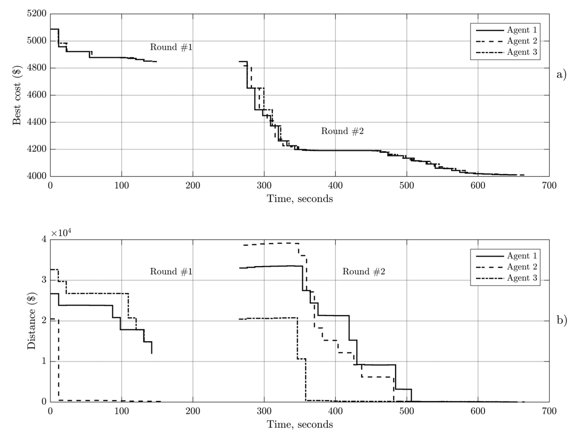

FIGURE 8. Recursive application of ADPSO, a) function cost behavior and b) variability.

1) ADPSO PERFORMANCE COMPARISON

Initially several rounds of SPSO were performed on a single SBC to solve the same optimization problem and data, to be used as performance reference. After that, several rounds of ADPSO were performed on the hardware setup described. In reference to parts a) and c) of Fig. 6, a repeatable best function cost profile and the lowest cost is obtained in ADPSO. The small error bars in part c) of Fig. 6 indicate the small variations between the three agents working in the optimization with ADPSO, which shows the expected consensus achievement. On the right, in parts b) and d), the depiction of swarm diversities is shown for both SPSO and ADPSO. It is shown that ADPSO diversity is higher initially, when the initial search for a solution is needed, and it quickly reduces as the best solution is found between the three agent units. As expected, a consensus solution and algorithm convergence are achieved by sharing only the state variable.

The averaged behavior of both algorithms for a series of ten runs are shown on Fig. 7. Parts a) and b) shows better performance in the optimization profile and a low swarm diversity for ADPSO. The lower time for convergence needed in ADPSO is important in this work as it translates in avoiding unnecessary wasting of computational resources, which are limited in the context referred. In part c) of Fig. 7, the RMS error of the observations are shown. RMS error is lower in ADPSO, there are still some effects of randomness in the optimized results of ADPSO. Techniques to reduce these unwanted variations, probably by learning coefficients self-adaptation, should be further investigated. Results are summarized on comparison Table 3.

An example of the flexibility of the DEM-enabled DER controller solution using ADPSO is shown on Fig. 8. A multi-round optimization run was performed, and its best cost solution and swarm diversity were plotted. On part a) of Fig. 8, the interactions and reactions of the agent modules are observed when they share their best values. These interactions allowed better optimization after restarting algorithm execution. The diversity of each agent swarm population is shown on part b) of the same Fig. 8. Diversity re-initialization for the second round of the optimization run is the responsible for

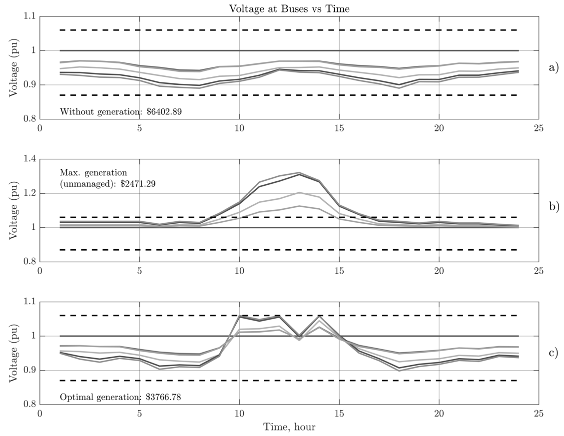

FIGURE 9. Power flow test scenarios and their corresponding operational cost.

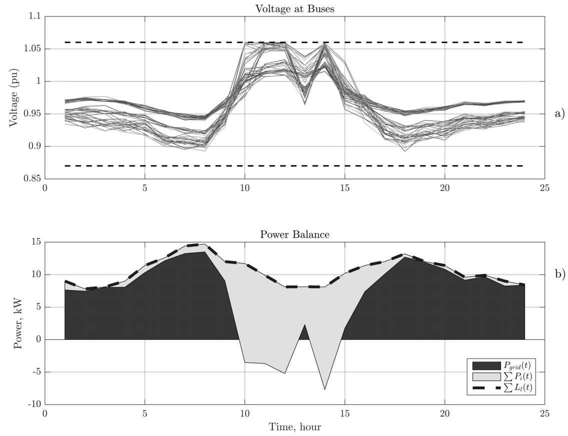

FIGURE 10. a) Voltage at buses and b) Power vs Load balance after DEM optimization.

the improved convergence rate in this case. Besides the flexibility exemplification, diversity re-initialization in a single round of ADPSO could be desirable to reduce the unwanted randomness mentioned before. The possible uses of learning coefficients and inertial weight self-adaptation, in this decentralized context, should be further investigated.

2) EMS RESULTS

On Fig. 9 three power flow test scenarios are shown. The first scenario, in part a), considers there is not DER generation. Voltage limits violation are not expected in this case but, with the test data, a high operational cost is obtained. The scenario of part b) considers DER power references to be maximum, e.g. to be equal to the values of DER generation profiles of Fig. 5. The operational cost is very low due to the high amount of energy sold to other grids, but the power flow solution shows severe non-compliance to voltage limits which makes this scenario impractical. The optimized DER power references obtained by ADPSO algorithm are shown on part c) of Fig. 9. DER generation is balanced with the power flow solution to reach the lowest operational cost in full compliance with the voltage limits specified.

Voltage at distribution buses and the power balance after DEM optimization are shown on Fig. 10 for several optimization runs. As expected, full compliance on voltage limits is achieved (part a)). The power balance constraint of (11) is accomplished, as noted on part b). As shown, power flow and power balance constraints were achieved using DEM-enabled DER controllers and the decentralized framework approach.

There are two remaining aspects to be noted. Regarding to simulation results, it is not clear if there must be an agent layer module in every DER controller or if there must be modules only in certain DERs. Unreported tests shown lower RMS error and better convergence characteristics when an agent module per DER was considered but the relation of these results with our case and optimization problem could be misdirecting and do not allow to generalize a conclusion. On the other hand, the selected Newton-Raphson method for the grid power flow solution contributions on the EMS performance was not fully evaluated. In its present form, the algorithm performs local evaluation of the power flow constraint and results suggest that this evaluation could be easily very time consuming and hard to run for SBCs. This limitation does not allow the use of the proposed EMS in its current form for real-time dispatch problems.

IV. CONCLUSION

A multi-layered framework for DEM optimization is approached by proposing ADPSO algorithm for the agent layer of the framework. The proposed ADPSO algorithm is characterized for linear deceleration, asynchronous local best updating, asynchronous global best broadcasting, global best polling operations and swarm diversity measurement as convergence criteria. It was shown that a consensus reach among agent layer modules is achieved by exchanging only the state variable through the communications channel. Each agent communicates only with a CSU in a series of broadcast and polling transactions. With the implementation over a computing network of single board computers, our results suggest ADPSO is a low complexity algorithm, easy to implement without needing powerful computers. To our consideration, this decentralized EMS solution could be in the interest of creating integrated EMS capabilities within DER controller units. Further research must be done on the local power flow constraint evaluation to improve efficiency.

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