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Distributed operational management of microgrids: a second order dual update approach ⋆

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Abstract: This paper develops a Distributed Energy Management System (EMS) to optimally allocate electric and thermal power production in a polygenerative microgrid. The EMS problem is formulated as a multiperiod convex optimization problem and solved using AL-SODU, a new distributed algorithm based on the augmented Lagrangian method with second order dual updates. The proposed AL-SODU algorithm significantly outperforms state of the art algorithms employing first order dual updates, with 15-times speedup in convergence speed. A case study of the EMS based on AL-SODU is conducted on the Smart Polygeneration Microgrid (SPM) located on the Savona Campus of University of Genova (Italy). The EMS determines the optimal schedules for electric and thermal power plants every 15-minutes. This real time scheduling of the microgrid is enabled by the Al-SODU algorithm, which solves the scheduling problem in 1.86s.

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1. INTRODUCTION AND STATE OF THE ART

Microgrids (MG) can provide flexibility services for the distribution power grid at a small scale level by managing multiple generators/loads in a limited geographical area. In order to exploit the full potential of the MG infrastructures, Energy Management Systems (EMS) are needed. These EMS generally include an optimization-based dispatch algorithm within a system architecture that communicates with supervision tools (like SCADA) and in-field power plants (Delfino et al., 2019b; Touma et al., 2021; Zhou et al., 2021). For this specific reason, in the last decade, several research groups have developed new tools, models, methods, and technologies (see (Sen and Kumar, 2018) and references therein). The emergence of smart buildings, storage, and renewable generation introduce rapidly changing demand and generation patterns, for which new decision making paradigms are needed. These include real-time electricity markets at the distribution level, i.e. retail prices that are updated every 5 minutes (Haider et al., 2020). To solve such a market and dispatch resources every 5 minutes, new optimization algorithms that are fast and accommodate resource operating constraints are needed. Several papers propose distributed and decentralized methods for the optimal operation of MGs. However, very few of them deal with multiple kinds of demand (such as electric and thermal loads in polygeneration MGs) and local controllers which are managed by different owner/managers, which are typical of sustainable districts and medium/large MGs that serve real loads (Ding et al., 2020). This work proposes a distributed EMS to optimally allocate electric and thermal power production in a polygenerative MG, where resources have different ownership boundaries. To solve the EMS problem, a distributed algorithm is proposed. This algorithm, called AL-SODU, is based on an augmented Lagrangian method and uses second-order dual updates to significantly improve convergence speed. The EMS based in AL-SODU determines the optimal resource dispatch every 15-minutes over a whole day of operation. The EMS has been tested on a real case study of the Savona Campus Smart Polygeneration Microgrid (SPM) (Bracco et al., 2016) located at the University of Genoa (Italy), representative of a small district MG. The EMS optimization problem is based on a multi-agent framework, where each agent represents a resource in the MG (ex. power plant

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or storage system) and participates in a MG market to minimize costs and achieve electrical and thermal power balance. The distributed AL-SODU algorithm leverages local computing resources with minimal information exchange across agents to determine the optimal dispatch.

The survey paper (Sen and Kumar, 2018) provides a comprehensive review of EMS design for MGs. The decision-making approaches can be classified into two main categories: centralized and distributed. In a centralized architecture, the EMS needs to collect information from each resource, solve a centralized optimization problem, and send back the optimal dispatch of each resource (Delfino et al., 2019b), (Stluka et al., 2011). Centralized architectures are usually implemented when the area of the MG is limited, given the high communication and computational burden. In a distributed architecture, resources use local computing equipment to make their own dispatch decisions, with communication with neighboring agents or a central controller (Xin et al., 2014). A distributed approach has lower computational and communication burden (as compared to centralized approaches), and when designed well, can be robust to failure modes (unlike centralized approaches which have a single point of failure). A review on distributed control in MGs is reported in (Yazdanian and Mehrizi-Sani, 2014), and highlights some of the main techniques used for decision making (MPC, consensus, agent-based) in the different control levels of primary, secondary, and tertiary.

The focus of this paper is on tertiary control, i.e the optimal dispatch of power sources in the MGs over a daily time horizon, using a distributed architecture. Recent work on distributed control of polygenerative MGs are (Mohamed et al., 2020) and (Nudell et al., 2022). The work in (Mohamed et al., 2020) focuses on smart islands considering coupling between multi-polygenerative MGs, but the coupling between power and thermal production are not modelled. In (Nudell et al., 2022) a transactional framework denoted as Dynamic Market Mechanisms (DMM) is presented, to determine the optimal schedule of a polygenerative MG using market prices. The DMM is a distributed algorithm which can distribute dispatch resources in a multi agent framework; however, the algorithm is limited to strictly convex cost functions and exhibits slow convergence to the optimal solution. In this regard, the AL-SODU algorithm presented in this paper can handle any convex function (including those that are non strictly convex), and the SODU feature provides significant acceleration in convergence. These results are shown in a case study of the Savona SPM, representative of a small district MG.

The main contributions of the paper are the following:

- A new EMS for polygenerative MGs based on the distributed AL-SODU algorithm. The EMS models coupling between electrical and thermal production. The EMS is used for real time scheduling of the MG resources, enabled by the AL-SODU algorithm. Our results show that AL-SODU outperforms first order dual update algorithms (converges faster) and can handle general convex objective functions typical of power plants in the SPM.
- The validation of the EMS on the Savona SPM, representative of a small district MG, thus ensuring a practical value to the developed methodology.

The organization of this paper is as follows. Section 2 introduces the optimization problem and models of each component of the MG. Sections 3 and 4 derives the SODU method and the AL-SODU algorithm for the distributed EMS respectively. Section 5 presents a case study of the EMS on the SPM and compares the performance of the AL-SODU with a first order update algorithm. Section 6 provides conclusions and directions for future work.

2. THE MICROGRID MODELLING

This section describes the mathematical modelling of a multi-agent MG in which each resource participates in determining the optimal resource dispatch. Both thermal and electrical energy resources powering the MG are included.

2.1 Definition of agent types

The Proposed EMS optimally schedule all thermal and electric units in the MG over a time horizon $T = \{1, ..., K\}$, defined as the set of the time intervals. The units (or agents) in the MG are classified as:

- $\mathcal{S}$: Storage system (e.g. batteries);
- $\mathcal{C}$: Cogenerative plants;
- $\mathcal{H}$: Thermal plants (e.g. boilers);
- $\mathcal{B}$: Smart building units;
- $\mathcal{P}$: Market coordinator at the point of common coupling (PCC)

Collectively, the set of all agents is denoted as $\mathcal{A} \triangleq \mathcal{S} \cup \mathcal{C} \cup \mathcal{H} \cup \mathcal{B} \cup \mathcal{P}$. We assume all agents participate in the market negotiation. We assume that forecasts of electrical and thermal load are available and a priori known for the whole optimization interval. We do not model the electrical or thermal network constraints. This modeling assumption is valid when the MG covers a small geographic area, such that losses are negligible. This assumption holds for the microgid we consider in this paper. We use x^T to denote the transpose of vector x, and overbar $\overline{x}$ and underbar $\underline{x}$ notation to denote the upper and lower limits of a variable x.

2.2 Storage systems model ($\mathcal{S}$)

The storage systems are represented by the following discrete-time first order integrator model:

$$SOC^S_{t+1} = SOC^S_t + \frac{P^S_t}{CAP}\Delta \quad t \in T \tag{1}$$

$$\underline{SOC^S_t} \leq SOC^S_t \leq \overline{SOC^S_t} \quad t \in T \tag{2}$$

$$\underline{P^S_t} \leq P^S_t \leq \overline{P^S_t} \quad t \in T \tag{3}$$

$$\overline{P^S_t} = \begin{cases} \overline{P^S_t} & if \quad SOC^S_t \leq a \\ cSOC^S_t + d & if \quad SOC^S_t \geq a \end{cases} \tag{4}$$

where SOC^S_t is the state variable representing energy stored in the storage system, P^S_t is the active power injected/absorbed by the storage unit, CAP is the storage capacity, while Δ is the discretization step. A peculiar characteristic of this model is constraint (4) that approximates the nonlinear behavior of the storage systems during the charging phase (Delfino et al., 2019a) (a, b, c and d are p).

2.3 Cogenerative plants model ($\mathcal{C}$)

Cogenerative power plants (i.e. combined heat and power, microturbines) are able to produce both electric power $P_t^{C,el}$ and thermal power $P_t^{C,th}$ at the same time. The optimization model for this agent is given by:

$$\min_{P_t^{C,th}} \quad \Delta \sum_{t \in T} C^{\mathcal{C}} P_t^{C,pe} \tag{5}$$

subject to:

$$P_t^{C,pe} = \mu_t P_t^{C,el} \quad t \in T \tag{6}$$

$$P_t^{C,th} = \overline{\mu}_t P_t^{C,el} \quad t \in T \tag{7}$$

$$\underline{P_t^{C,el}} \leq P_t^{C,el} \leq \overline{P_t^{C,el}} \quad t \in T \tag{8}$$

where $P_t^{C,pe}$ is the primary fuel used to feed the cogenerative unit, $P_t^{C,th}$ is the thermal production, and μ_t and $\overline{\mu}_t$ are conversion parameters that depend on time-varying external air temperature. The overall goal of the Cogenerative units is to minimize the overall consumption of fuel as expressed in (5) that is weighted by the cost $C^{\mathcal{C}}$ related to taxation policies for the primary fuel regulation and the CO_2 emission factors .

2.4 Thermal plants model ($\mathcal{H}$)

In this work, thermal plants include boilers. The model is similar to that of the cogeneration unit $\mathcal{C}$ described above. The optimization model for the thermal plant is given by:

$$\min_{P_t^{B,th}} \quad \Delta \sum_{t \in T} C^{\mathcal{B}} P_t^{B,pe} \tag{9}$$

subject to:

$$P_t^{B,pe} = \eta_t P_t^{B,th} \quad t \in T \tag{10}$$

$$\underline{P_t^{B,th}} \leq P_t^{B,th} \leq \overline{P_t^{B,th}} \quad t \in T \tag{11}$$

where $P_t^{B,pe}$ is boiler's thermal production, $P_t^{B,pe}$ is boiler's primary fuel and η_B is boiler's efficiency. As regards the objective function of the thermal plants (9) it concerns the minimization of the operational costs of the primary fuel.

2.5 Smart building model ($\mathcal{B}$)

The smart building includes three main components: a geothermal heat pump, thermal storage, and fan coil circuit. The objective of this agent is to track the thermal storage operating temperature T_S^*, and the comfort temperature $T_{R,h}^*$ in each room in set H. The thermal behavior of the building is simulated through an equivalent RC circuit model described as follows:

$$\min_{Q_{h,t}^{RM}, P_t^{HP}} \sum_{t \in T} \left(T_t^{ST} - T_S^*\right)^2 + \sum_{t \in T} \sum_{h \in H} \left(T_{h,t}^{RM} - T_{R,h}^*\right)^2 \tag{12}$$

subject to:

$$T_{t+1}^{ST} = T_t^{ST} + \left(Q_t^{HP} - \sum_{h \in H} Q_{h,t}^{RM}\right) \frac{\Delta}{C^{ST}}, t \in T \tag{13}$$

$$P_t^{HP} = \frac{Q_t^{HP}}{COP}, \quad t \in T \tag{14}$$

$$T_{h,t+1}^{RM} = T_{h,t}^{RM} + \left(\frac{\left(T_t^A - T_{h,t}^{RM}\right)}{R_h^{E,RM}} + Q_{h,t}^{RM} + Q_{h,t}^{IG} + \sum_{k \in K^h} \frac{\left(T_{k,t}^{RM} - T_{h,t}^{RM}\right)}{R_{k,h}^{I,RM}} \right) \frac{\Delta}{C_h^{RM}}, \quad t \in T \; h \in H \tag{15}$$

$$\underline{T^{ST}} \leq T_t^{ST} \leq \overline{T^{ST}}, \quad t \in T \tag{16}$$

$$0 \leq P_t^{HP} \leq \overline{P^{HP}}, \quad t \in T \tag{17}$$

$$\underline{T^{RM}} \leq T_{h,t}^{RM} \leq \overline{T^{RM}}, \quad t \in T \; h \in H \tag{18}$$

$$Q_{h,t}^{RM} \leq \varepsilon^{fc} m_{h,t}^{air} cp^{air} \left(T_t^{ST} - T_{h,t}^{RM}\right), \quad t \in Th \in H \tag{19}$$

Constraint (13) represents the dynamic behavior of the thermal storage internal temperature T_t^{ST} by considering the thermal storage capacity C^{ST}, with thermal flow input Q_t^{HP}, and thermal flow output $Q_{h,t}^{RM}$. The input Q_t^{HP} is expressed in (14) as a function of the active power P_t^{HP} and its coefficient of performance COP. The output $Q_{h,t}^{RM}$ is the thermal power extracted by the fan coils circuit for each room. Constraint (15) defines the dynamic behavior of the internal room temperatures $T_{h,t}^{RM}$ by considering: the heat flow given from the difference of temperature between the room and the external environment both through the wall and the windows, the heat exchange between adjacent rooms ($R_h^{E,RM}$ are thermal resistances between the room's internal air and the external air, whereas $R_{k,h}^{I,RM}$ is the thermal resistance between two adjacent rooms), the heat supplied through the fan coil circuit within each room $Q_{h,t}^{RM}$, and the internal heat gains $Q_{h,t}^{IG}$ given by the occupants, the electronic devices and the solar radiation gain considered as known a priori. The control variable $Q_{h,t}^{RM}$ is the fan coil in each room, upper bounded in (19) as a function of the room temperature and the temperature of the storage tank, where ε^{fc} is the fan coil efficiency, cp^{air} is the specific heat capacity of the air, and $m_{h,t}^{air}$ is the maximum mass flow rate of the air that passes through the fan coil. Other constraints represents bounds on the decision variables.

2.6 Market coordinator at PCC model ($\mathcal{P}$)

The PCC represents the electrical and thermal balance node of the MG. This agent represents the MG coordinator and aims to minimize the overall electrical cost, i.e., the electrical power purchased P_t^G at the point of exchange with the medium-voltage grid. It is assumed that the thermal system in the MG can supply all heating loads, and does not have to purchase thermal energy from any external sources. The optimization model for this agent is given by:

$$\min_{P_t^{C,th}} \quad \Delta \sum_{t \in T} C^{\mathcal{G}} P_t^G \tag{20}$$

subject to:

$$P_t^{NL} + P_t^S = P_t^G + P_t^{C,el} + P_t^{HP}, \; t \in T \tag{21}$$

$$P_t^{C,th} + P_t^{B,th} \geq P_t^{D,th}, \; t \in T \tag{22}$$

$$\underline{P_t^G} \leq P_t^G \leq \overline{P_t^G}, \; t \in T \tag{23}$$

The overall MG electrical power balance is given in (21), that is the sum of all the generation/load, and the net load P_t^{NL} which is the net sum of MG's non-controllable power generation and local load. Constraint (22) denotes the thermal energy balance, with any excess heat output being dispersed into the atmosphere by the cogeneration units.

3. SECOND ORDER DUAL UPDATE (SODU)

A key contribution of this paper is a new distributed optimization algorithm that is based on Second Order dual Update (SODU). The use of SODU allows for faster convergence to the optimal solution, thus allowing MG dispatch to occur at very fast time scales (e.g. every 5 minutes). To introduce SODU, we first consider a general convex optimization problem of the form:

$$\begin{aligned} \min_x \quad & f(x) \\ s.t \quad & Ax = b \end{aligned} \tag{24}$$

where A and b are the constraint matrix and vector, and $f(x)$ is a general convex objective function. The corresponding Lagrangian function of (24) is:

$$\mathcal{L}(x,\nu) = f(x) + \nu^T (Ax - b) \tag{25}$$

where the constraint has been dualized with dual variable ν. The resulting Lagrangian function can be solved as an unconstrained optimization problem with various iterative primal-dual and dual-ascent algorithms. Current state of the art optimization algorithms generally carry out the dual update as a gradient step of the dual function as:

$$\nu[\tau+1] = \nu[\tau] + \rho(Ax[\tau+1] - b) \tag{26}$$

where ρ is the step size.

We propose an alternative dual update which employs Newton's method to solve the Lagrangian system in (25) (Bertsekas, 1997):

$$\begin{aligned} \nu[\tau+1] = \nu[\tau] + & \left[A^T (\nabla_{xx} f(x[\tau+1]))^{-1} A\right]^{-1} \\ & \left[-A^T (\nabla_{xx} f(x[\tau+1]))^{-1} \nabla_x \mathcal{L}(x[\tau+1], \nu[\tau]) \right. \\ & \left. + Ax[\tau+1] - b\right] \end{aligned} \tag{27}$$

To derive the dual update in (27) we consider the nonlinear system of equations in x and ν:

$$\nabla f(x) + \nabla \nu^T (Ax - b) = \nabla \mathcal{L}(x,\nu) = 0 \tag{28}$$

We then apply Newton's method to solve (28):

$$\nabla^2 \mathcal{L}(x,\nu) = -\nabla \mathcal{L}(x,\nu) \tag{29}$$

Therefore we obtain

$$\nabla_{xx} f(x)\Delta x + A\Delta\nu = -\nabla_x \mathcal{L}(x,\nu) \tag{30}$$

$$A^T \Delta x = -Ax + b \tag{31}$$

By multiplying (30) by $A(\nabla_{xx} f(x))^{-1}$, ad using (31) we have:

$$\begin{aligned} & -Ax + b + A^T (\nabla_{xx} f(x))^{-1} A\Delta\nu \\ & = -A^T (\nabla_{xx} f(x))^{-1} \nabla_x \mathcal{L}(x,\nu) \end{aligned} \tag{32}$$

Finally, since the dual update is given by

$$\nu[\tau+1] = \nu[\tau] + \Delta\nu \tag{33}$$

by solving (32) with respect to $\Delta\nu$ we obtain (27).

4. THE AL-SODU ALGORITHM

This section will state the AL-SODU algorithm employed to solve the optimization problem (1)-(23). The overall EMS problem can be easily rewritten in the form of (24) by using positive slack variables z. The resulting optimization problem will be of the form:

$$\begin{aligned} \min_{y,z} \quad & f(y) \\ s.t \quad & \begin{bmatrix}\hat{A} & I\end{bmatrix} \begin{bmatrix} y \\ z \end{bmatrix} = b \\ & z \geq 0 \end{aligned} \tag{34}$$

where y is the vector of decision variables and $\hat{A}$ is the constraint matrix of the EMS problem (1)-(23).

4.1 Statement of the algorithm

The AL-SODU primal update is based on an augmented Lagrangian which uses a proximal term to have a strongly convex problem:

$$\mathcal{L}^A = \mathcal{L}(x,\nu) + \frac{1}{2\rho}\|x - x[\tau]\|_2^2 \tag{35}$$

The general form of the AL-SODU algorithm with the dual update of (27) is stated as follows:

$$x[\tau+1] = \underset{x\in\mathcal{X}}{\operatorname{argmin}} \left\{ f(x) + \nu^T[\tau](Ax - b) + \frac{1}{2\rho}\|x - x[\tau]\|_2^2 \right\}, \tag{36}$$

$$\begin{aligned} \nu[\tau+1] = \nu[\tau] + & \left[A^T \left(\nabla_{xx} \mathcal{L}^A (x[\tau+1])\right)^{-1} A\right]^{-1} \\ & \left[-A^T (\nabla_{xx} f(x[\tau+1]))^{-1} \nabla_x \mathcal{L}^A (x[\tau+1], \nu[\tau]) \right. \\ & \left. + Ax[\tau+1] - b\right] \end{aligned} \tag{37}$$

where $x = \begin{bmatrix} y & z \end{bmatrix}^T$ is the whole decision vector including slack variables and $A = \begin{bmatrix}\hat{A} & I\end{bmatrix}$. The positivity constraint in (4) is subsumed in the primal update of (36), where the slack primal variables $x[\tau+1]$ belongs to the set $\mathcal{X}$, where $\mathcal{X}$ is the positive orthant $\mathbb{R}^+$.

4.2 Distributed AL-SODU for EMS

We propose a distributed EMS architecture to solve (1)-(23) using AL-SODU. In this section, we discuss the *decomposition* of the overall problem such that it can be solved in a distributed way.

The EMS objective function is the sum of the objectives of each agent, i.e. $f(x)$ =(5)+(9)+(12)+(20). Note that the objective function at the PCC, (20), can be re-written as a linear combination of decision variables owned by the other agents, $\mathcal{A} \setminus \mathcal{P}$. Further, the constraints coupling the actions of the different agents are located only at the PCC agent, $\mathcal{P}$, in Eq. (22) and (23). In this way, the EMS optimization problem of (1)-(23) can be distributed amongst each agent. Correspondingly, the primal update of the AL-SODU algorithm can be re-written as:

$$x_i[\tau+1] = \underset{x\in\mathcal{X}}{\operatorname{argmin}} \left\{ \frac{1}{2} x_i^T Q_i x_i + q^T x_i + \left[\nu^T[\tau](Ax - b)\right]_i \right.$$

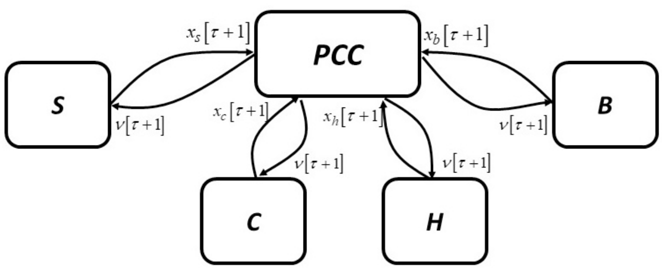

Fig. 1. The AL-SODU algorithm

$$+ \frac{1}{2\rho} \left\| x_i - x_i\left[\tau\right] \right\|_2^2 \Big\} \, i \in \mathcal{S} \cup \mathcal{C} \cup \mathcal{H} \cup \mathcal{B} \tag{38}$$

where the agents' objective functions are written as general quadratic functions $\frac{1}{2} x_i^T Q_i x_i + q^T x_i \; i \in \mathcal{A}$.

Each agent $\mathcal{A} \setminus \mathcal{P}$ carries out a parallel update of its primal variables $x_i \;\forall\; i \in \mathcal{A} \setminus \mathcal{P}$ using (38). Next the agents communicate their updated primal variables to the PCC, which as the market coordinator collects the primal variables and updates the dual variables using (37). The updated duals are communicated back to each agent to complete the algorithm iteration. This concept is shown in Figure 1.

5. SIMULATION STUDIES

This section presents the validation of the proposed EMS using experimental data from the SPM at the University of Genoa. To show the effectiveness of the proposed AL-SODU algorithm a comparison with a first-order dual update has been performed.

5.1 Application to the Savona Campus SPM

The SPM is a cogenerative low-voltage MG that has been operating since February 2014 on the Savona Campus of University of Genoa. The SPM is funded by the Italian Ministry of Research, and it is the first MG in Italy at the Campus scale being inserted in the National Plan for Research Infrastructures. The SPM has two cogeneration units (indicated as CHP and CHP2 in the following and characterized by a rated electrical power of 65 kW); one NaNiCl2 battery storage system rated at 141 kWh capacity; one boiler system rated at 1000 kW thermal power; and a photovoltaic power plant rated at 80 kW peak power. Note that the PV power plant is a non-dispatchable unit with no controllable parameters; the output of the PV unit is included in P_t^{NL}, the net sum of the MG's load in (21). The Campus distribution grid is also connected to the national distribution grid employing a dedicated transformer at the PCC. A schematic representation of the SPM layout is provided in Figure 2. From an ICT point of view, the SPM is characterized by local controllers for each plant. As regards other nameplate values of each component (e.g. efficiencies, coefficient of performances) of the SPM we refer to (Delfino et al., 2019b).

The EMS developed in this paper has been tested in a winter scenario (with high thermal load) with the EMS re-scheduling every 15-minutes for a 24 hours period. The optimal electric and thermal dispatch schedule is obtained

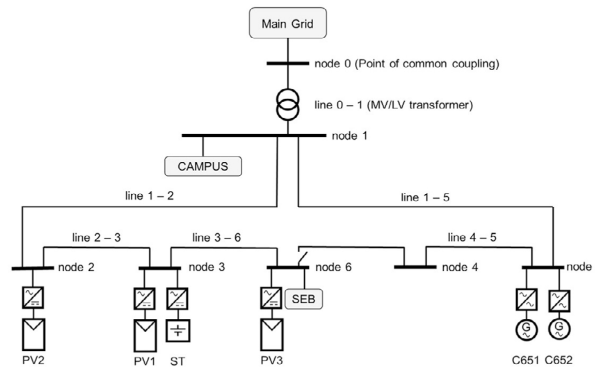

Fig. 2. One-line diagram of the SPM at Savona Campus

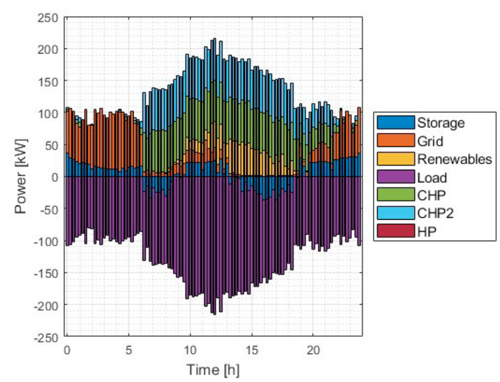

Fig. 3. Optimal electrical plant dispatch

by solving the optimization problem (1)-(23) with the AL-SODU algorithm. The dispatch results are presented in Figures 3 and 4. The MG is able to supply 85% of electrical load using local resources, relying heavily on cogerative units and PV during the day (6am to 7pm). Notably, the storage unit is able to charge during hours of higher PV production (1pm to 4pm) and discharge overnight to limit the amount of power drawn from the external grid. Further, the CHP microturbines are able to supply the thermal and electrical loads without exceeding thermal balance constraints. The total operational costs for this scenario is 405.48€. The distributed EMS algorithm was run on MATLAB 2021a, using the YALMIP interface (Löfberg, 2004). A PC Intel core i7 machine is used, with a run time of 1.86s. It is noteworthy this very short run time allows the EMS to have real time dispatch scheduling and support real time energy prices.

5.2 Comparison of AL-SODU with first order dual update

In order to show the effectiveness of the AL-SODU algorithm we compare it against a variant of the algorithm which uses the primal update in Eq. (36) and replaces Eq. (37) with a first order dual update in Eq. (39).

$$\nu\left[\tau+1\right] = \nu\left[\tau\right] + \rho\left(Ax\left[\tau+1\right] - b\right) \tag{39}$$

Both algorithms have been implemented using the distributed architecture presented in Fig. 1. The convergence of both algorithms is given in Figure 5. The plot shows that the first order update requires almost 60 times the number of iterations as compared to AL-SODU (180 iterations versus less than 5) to achieve the same precision. The run

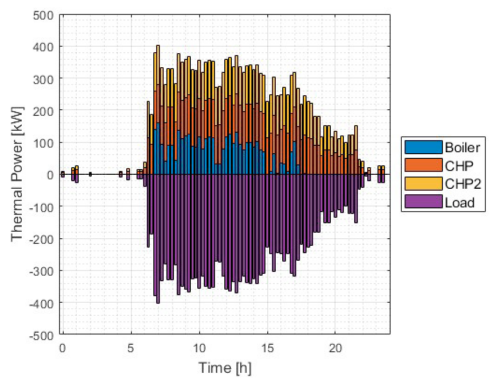

Fig. 4. Optimal thermal plant dispatch

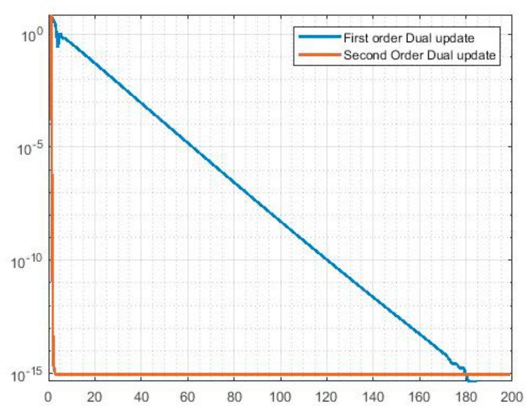

Fig. 5. Comparison first order update and SODU.

time for the first order variant is 35.16s, as compared to AL-SODU which requires only 1.86s. Thus the proposed AL-SODU is able to effectively combine the benefits of distributed computations with the speedup afforded by second order methods.

6. CONCLUSIONS AND FUTURE DEVELOPMENTS

In this paper, a distributed EMS for the daily optimal operation of polygenerative MGs is proposed. The developed algorithm is based on a second order dual update (SODU) approach and can improve the performances of current first order algorithms that are widely used in literature. The proposed AL-SODU algorithm is a dual descent algorithm using a augmented Lagrangian primal step, and second order Newton method update for the dual step. The distributed EMS has been tested on a real case study of the Savona Campus SPM obtaining fast convergence (approximately 3 iterations taking 1.86s). The proposed EMS allows for more frequent rescheduling of the power plants and can incorporate the nowcasting of non-dispatchable resources. Future developments will concern the inclusion of new elements of the MG like electric vehicles, controllable photovoltaic plants, and power-to-hydrogen modules, and the development of a Model Predictive Control architecture.

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