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Managing Networked Hybrid-Energy Systems: a Predictive Dispatch Approach

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Abstract: Energy source management in networked enterprises is one of the crucial tasks of recent times: different energy requests as well as distribution among node-enterprise due to variety of production loads and duties exchanges may in fact bring to un-optimal energetic balance of the network. The idea of optimal balancing of energy sources within a set of nodes of an enterprise network, even though temporarily cooperating, by endeavoring a systemic perspective is the rationale of the present paper. A methodology for the optimal dispatch of energy sources in hybrid as well as isolated energy systems has been devised to this aim. The core of the methodology is based on the formulation and solution of a non-linear discrete optimization problem aimed at optimizing input and output time trajectories for a set of combined power-generation and storage technologies. The proposed approach is general enough to be susceptible of implementation in any network of enterprises to optimize the energy dispatching.

Keywords: networked enterprises, energy hub, discrete optimal control, energy management systems, smart grids.

1. INTRODUCTION

Despite the industrial systems of the past tended to emphasize the independence and the competition between enterprises, nowadays the new concept of networking and interoperability is emerging as a new paradigm in a *glocal* perspective. Since industries are dependent on the local resources of their environment to ensure their productivity, but at the same time their production is pulled according to global market dynamics, it is evident the need to adopt a systemic view strategy to coordinate the network of enterprises in their operations. In the early times, the idea of industrial ecology was launched to promote a better interaction of industrial systems with the ecosystem they work in. Industrial ecology relied on a systems-oriented approach to integrate human economic activity and resource management into fundamental biological, chemical, and physical global system [Lowe,1995]. Amongst other, energy resources are critical to assure sustainability of Networked Enterprises or any industrial network.

Several studies have been developed so far on this concern for managing complex systems, such as networks of enterprises, to natural eco-systems [Coté, 1998]. Other interesting approaches have been developed according to this systemic view to help decreasing the emissions while at the same time guaranteeing resilience of energetic supply [Weber, 2011]. Undoubtedly, systemic studies either on the influence of the integration of large-scale renewable energy powered technologies in the current energy market [Goransson, 2009] or those devoted to set European energy policy [Dass,2013] both share the need to have a systemic perspective of the energetic issue.

The approach presented here shares this idea, which allows to be applied at any scale of industrial network complexity for optimal energy dispatching. In this paper, an application to Small-Medium Enterprises has been shown.

2. HYBRID SYSTEMS AND CONTROL ARCHITECTURE

Within the paper, in order to show the generality of the approach and its impact on sustainability, a reference will be made to a system composed of two renewable sources (photovoltaic generation and a cogeneration unit), two storage facilities (battery energy storage system or BESS, pumping-hydro station), and a back-up heat generator (gas boiler). Moreover, the possibility of shedding load is considered if production cost is higher than interruption cost. The system is modelled with a double single-bus scheme [Barley et al., 1996; Caisheng Wang et al., 2006] as shown in Fig. 1.

The presence of multicarrier energy systems can be suitably treated through optimal predictive control strategy [Adamek et al., 2014; Bozchalui et al., 2012]. This choice is also indispensable in the presence of multiple energy storage systems that might have different response in time, due to their storable capacity and charge/discharge speeds.

The optimal dispatch methodology proposed in this paper is based on forecasts of load and renewable generation over a reasonable observing time window. The general architecture of the proposed management scheme is shown in Fig. 2.

Optimal dispatch of all resources is obtained through the solution of a non-linear optimization problem aimed at minimizing overall cost of production, equipment wear (BESS) and load shedding. Interruptible loads and interruption costs are taken into account, embedding the cost of unserved load into the objective function [Dufo-Lòpez et al., 2007] and ensuring secure and adequate system operation. The optimality criteria adopted tend to assure sustainability of operating of the whole energy system in assuring longest life and optimal source utilization.

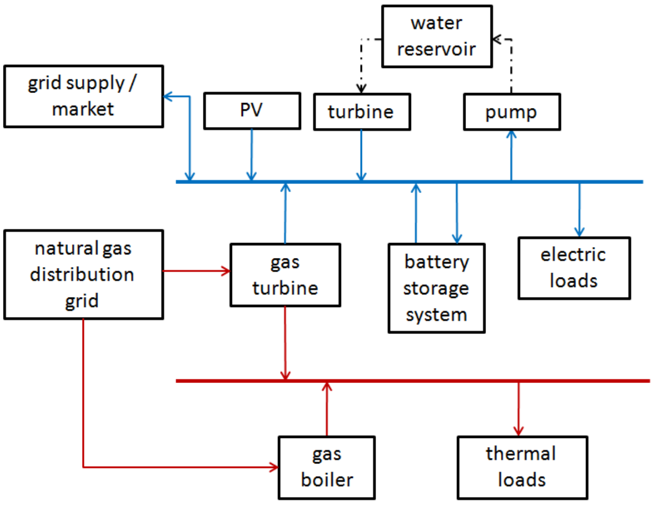

Fig. 1. Schematic representation of the proposed hybrid system

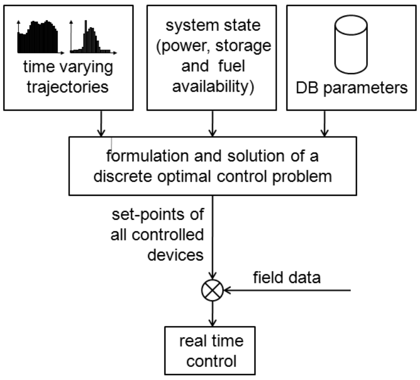

Fig. 2. Main scheme of the control architecture

The optimization approach is supposed to be applied recursively: set-points are recalculated each time a new operating state and new forecasts are available (for example every hour or whenever system parameters have changed). Optimal set-points are fed to the real time control layer (Fig. 2) that can be based on conventional control loop controllers and few overriding rules. Overriding rules are necessary in order to provide local non-optimal control whenever the optimization algorithm should fail to produce feasible solutions or sudden unavailability are experienced (for example loss of interconnection, component fails, excessive deviation from forecasts). Anyway, any sudden variation in the system structure can be taken into account updating the parameter database represented in Fig. 2.

2.1 *Mathematical formulation*

The optimization problem aims to minimize operative costs along a selected time window *T*. The cost function to be minimized is a non-linear function of power inputs and outputs:

$$\min_{\boldsymbol{p}} \int_{t=0}^{T} \sum_{x} c_x\left(p_x(t)\right) \cdot \mathrm{d}t \qquad (1)$$

where x refers to the generic power source/demand, p_x is the instant injected or demanded power, and $\boldsymbol{p}$ is the vector of control variables collecting all p_x. In general functions c_x are non-linear.

Many variables in the optimization process can constrained by equality and inequality constraints. The first two constraints are given by the energy balancing equations which derive from a single bus representation of the electric network [Barley et al., 1996; Caisheng Wang et al., 2006] and from the thermal energy balancing equation:

$$\left.\begin{array}{l} \sum_{x} ke_x \cdot p_x(t) = 0 \\ \sum_{x} kt_x \cdot p_x(t) = 0 \end{array}\right. \quad \forall t \qquad (2)$$

where coefficients ke_x and kt_x assume different values according to variables' weight in the energy balance of electric and thermal load, respectively. These coefficients can assume positive or negative sign depending on the direction of the power flow (usually positive for injected and negative for demanded power).

Inequality constraints take into account technical limitations such as technical minimum power output and maximum rated power:

$$p_{\min x} \le p_x(t) \le p_{\max x} \quad \forall t, \forall x \qquad (3)$$

The presence of storage units requires the introduction of state variables referred to the quantity of energy stored. If s denotes the generic storage system, and q_s the energy stored, the following differential equations and constraints must be added to the formulation:

$$\dot{q}_s = f_s(\boldsymbol{p}(t), q_s(t)) \quad \forall s \qquad (4)$$

with $$q_s(0) = Q_s^0$$

and $$q_{\min s} \le q_s(t) \le q_{\max s} \quad \forall t, \forall s \qquad (5)$$

where Q_s^0 is the initial charge and f_s is a generally non-linear function that associates power inputs and outputs to energy stored, taking also into account conversion and standby losses. Inequality constraints (5) take into account the limitations on storing capability. The minimum charge level can be zero or, as for BESS, can be kept above a given threshold.

The optimization problem (1)-(5) can be solved through discretization, by assuming that along the generic time step *i*, state and control variables remain constant. The size of a single time step is denoted in the following as Δt, whereas n_T is the overall number of time steps. If storage efficiency is assumed independent of state and control variables, equation (4) can be easily solved through discretization. Consequently, the energy stored for system *s* at the end of time step *i,* is reformulated as follows:

$$Q_s^i = Q_s^0 + \sum_{k=1}^{i} \boldsymbol{F}_s \cdot \boldsymbol{P}^k \cdot \Delta t \quad \forall i, \forall s \tag{6}$$

where $\boldsymbol{P}^k$ is the set of all power inputs and outputs during the time step *k*, Q_s^i is the energy stored at end of time step *i*, $\boldsymbol{F}_s$ is a constant matrix that, through efficiencies and the coupling relations due to the single bus assumption, associates stored energy to charging and discharging power.

Under such hypothesis and through discretization the overall problem is therefore formulated as:

$$\min_{\boldsymbol{P}_x} \sum_{i=1}^{n_T} c_x(P_x^i) \tag{7}$$

subject to (6) and to:

$$\begin{aligned} &\sum_x ke_x \cdot P_x^i = 0 \\ &\sum_x kt_x \cdot P_x^i = 0 \end{aligned} \quad \forall i \tag{8}$$

$$p_{\min x} \le P_x^i \le p_{\max x} \quad \forall i, \forall x \tag{9}$$

$$q_{\min s} \le Q_s^i \le q_{\max s} \quad \forall i, \forall s \tag{10}$$

This formulation of the problem is characterized by a non linear objective function, whereas all equality and inequality constraints can be expressed under the linear form $\boldsymbol{A} \cdot \boldsymbol{P}_x \le \boldsymbol{b}$, where $\boldsymbol{P}_x$ denotes the set of power inputs P_x^i discretized at the *i*-th time step. Please note that other inequality constraints, such as slew rates, can be easily formulated adding to $\boldsymbol{A} \cdot \boldsymbol{P}_x \le \boldsymbol{b}$ the constraints $\boldsymbol{A}_{SR} \cdot \boldsymbol{P}_x \le \boldsymbol{b}_{SR}$, with $\boldsymbol{A}_{SR}$ being a bi-diagonal matrix which takes into account the link of a constraint at the *i*-th time step with preceding states at the (*i*-1)-th time step.

The formulation of equations (6)-(10) is given in the following subsections.

2.2 Grid supply

The generic industrial network can be considered as connected to electric distribution system for two basic reasons: to avoid any possible power failure buying energy from the grids and to keep the possibility to sell electric energy to the grid itself while the district generation exceeds power demand. We also assume that a natural gas distribution system is available at the industrial site under consideration.

The system acquires through smart meters price signals from the market and then decides if is less expensive to generate or buy power. If c_{gen} is the generic generation cost and c_{grid} is the market price, the algorithm will decide to:

- buy energy from the grid when $c_{gen} > c_{grid}$;
- sell energy to the grid when $c_{gen} < c_{grid}$

2.3 RES generating units

Since RES production is characterized by a negligible marginal price, the power produced by PV is considered costless. This means that the optimizer will exploit renewable generation as much as possible.

The power input from PV, namely P_{PV}^i, is constrained only by maximum available power output, as forecasted. It is assumed that whenever RES production exceeds load plus storage charging power, generation can be curtailed or dump loads can be activated. Equation (9) is given by

$$0 \le P_{PV}^i \le P_{PV\,max}^i \tag{11}$$

2.4 Gas turbine and gas boiler

In the proposed eco-district system (Fig. 1) the presence of a gas turbine is assumed. Clearly, the formulation is general enough to be extended to any other generator. The power output of the gas turbine P_{GT} is limited in (9) considering the existence of technical-economical feasibility limits:

$$P_{GT}^i = \begin{cases} \overline{P}_{GT}^i & \text{if} \quad P_{GT\,min} \le \overline{P}_{GT}^i \le P_{GT\,max} \\ \text{otherwise}\, 0 \end{cases} \quad \forall i \tag{12}$$

Costs have been associated to natural gas consumption and are modeled considering the non-linear dependence of efficiency with respect to electrical power output. Such dependence can be formulated by interpolating efficiency/power output data found in technical sheets. Having fixed the cost of natural gas c_{gas} and said η_{GT} the efficiency as a function of power output, cost in (7) is calculated as

$$c_{GT}(\,P_{GT}^i\,) = c_{gas} \cdot \eta_{GT}(\,P_{GT}^i\,) \cdot \Delta t \tag{13}$$

Further variable costs, such as O&M costs, can be also added.

The amount of thermal energy produced through co-generation is considered having a linear relation to the electric energy produced by the gas turbine. The boiler thermal output is limited by its rating

$$0 \le P_{Bt}^i \le P_{Bt\,max}^i \tag{14}$$

whereas gas consumption costs are easily derived considering the efficiency η_{Bt} of the boiler.

2.5 Battery

The quantity of power exchanged with the BESS at each time step is here described with two variables: P_{CB}^i and P_{DB}^i that represent respectively BESS charging and discharging power. Each variable is limited by maximum charge and discharge power.

$$0 \le P_{CB}^{i} \le P_{CBmax} \tag{15}$$

$$0 \le P_{DB}^{i} \le P_{DBmax} \tag{16}$$

Charge-related inequality constraints are aimed at limiting the State Of Charge (SOC) of the battery. Roundtrip efficiency is adopted, accordingly to the assumption of a single bus model [Barley et al., 1996].

Under these assumptions equations (6) and (10) are

$$Q_B^i = Q_B^0 + \sum_{k=1}^{i} \left(\eta_{B\,rte} \cdot P_{CB}^i - P_{DB}^i \right) \cdot \Delta t \tag{17}$$

$$q_{\min B} \le Q_B^i \le q_{\max B} \tag{18}$$

where $\eta_{B\,rte}$ is the BESS round trip efficiency and Q_B^0 is the initial charge of BESS.

Knowing the maximum rated BESS capacity $Q_{B\,max}$, the two charging limits in (18) can be derived having fixed a minimum and maximum SOC:

$$\begin{aligned} q_{\min B} &= \mathrm{SOC}_{\min} \cdot Q_{B\,max} \\ q_{\max B} &= \mathrm{SOC}_{\max} \cdot Q_{B\,max} \end{aligned} \tag{19}$$

The maximum and minimum SOC can be set so that the lifespan of the battery is maximized and a good level of reserve is always kept during real time operation. Usually, minimum SOC sets an expected life number of cycles $n_{life\ cycles}$.

From these quantity, it is possible to calculate what is defined battery throughput and represents the expected value of energy that will be cycling through the battery, completing a charge/discharge cycle, before the battery has to be substituted [Lambert et al., 2006]. BESS life throughput can be conservatively evaluated as:

$$Q_{tpB} = Q_{B\,max} \cdot (1 - \mathrm{SOC}_{min}) \cdot n_{life\ cycles} \tag{20}$$

The BESS throughput is used in order to asses wear costs of the battery. Wear cost is simply formulated as the ratio between the substitution cost of batteries and the total throughput. In the proposed model, wear cost is associated to the discharge phase only, so that battery charge has no cost and it is always maximizes. The cost function appearing in (7) is formulated as:

$$c_B = \frac{\text{BESS substitution cost}}{Q_{tpB}} \cdot P_{DB}^i \cdot \Delta t \tag{21}$$

2.6 *Water pumping storage system*

Pumping storage system is formulated very similarly to the BESS. Pumped and generated powers are limited by pump and hydroelectric turbine requirements:

$$0 \le P_{CW}^{i} \le P_{CW\,max} \tag{22}$$

$$0 \le P_{DW}^{i} \le P_{DW\,max} \tag{23}$$

In the pumping system, the role of the maximum SOC is played by the maximum level of water storable in the reservoir. Roundtrip efficiency is also introduced, taking into account losses in pump, pipes, and turbine. Constraints in (6) and (10) can be written as:

$$Q_W^i = Q_W^0 + \sum_{k=1}^{i} \left(\eta_{W\,rte} \cdot P_{CW}^i - P_{DW}^i \right) \cdot \Delta t \tag{24}$$

$$q_{\min W} \le Q_W^i \le q_{\max W} \tag{25}$$

where $\eta_{W\,rte}$ is the pumping storage round trip efficiency and Q_W^0 is the initial charge. Minimum and maximum storable energy is expressed as function of minimum and maximum volume of storable water and geodetic drop.

As done before, a cost c_W associated to the sole discharging phase is defined. This cost can be estimated considering the average number of working hours before a major maintenance intervention is necessary.

2.7 *Loads and interruptible loads*

In the methodology proposed, chronological load curves (i.e. P_L^i at each time step *i*) are assumed as inputs of the optimization problem. It is also assumed that load is known at each time step and that a certain quantity of such load (P_{Lint}^i) is characterized by lower interruption costs. The amount of load to be shed (P_{LS}) is a control variable limited by the actual total demand at a specific time. Interruption costs can vary according to the quantity, interruption duration, and typology of curtailed load. A simple, but not limiting, hypothesis consists in assuming that interruptible and firm loads have two different constant interruption costs. More complex, non-linear, relationships between the overall amount of load shedding and interruption costs, or time dependent formulation of interruption costs, can be assumed. It is clear that more complex formulations are credible only if a fine and detailed knowledge on the nature and distribution of loads is available. The problem formulation is general enough to adopt any interruption cost formulation.

$$0 \le P_{LS}^{i} \le P_{L}^{i} \tag{26}$$

$$c_{LS} = \begin{cases} c_{Lint} & \text{if } 0 \le P_{LS}^i \le P_{Lint}^i \\ c_{L\,firm} & \text{if } P_{Lint}^i \le P_{LS}^i \le P_L^i \end{cases} \tag{27}$$

3. IMPLEMENTATION AND TEST RESULTS

Having formulated the dispatch problem as above, it is general enough to be applied to any network of energy supply but at the same time it has a particularly suitable form for numerical solution. In fact, its constraints are linear and non-linearities are confined in the objective function, allowing to implement the solver on general purpose optimization platforms. Only constraints in (12) are non-linear, but these are treated by means of relaxation technique.

Tests were performed by considering a small-medium enterprise, equipped with a hybrid power supply system, as a node of a network configuration. Test results presented here shows the feasibility of the approach for the system schematized in Fig. 1 during a random day of operation under normal conditions. The optimization period can be modified and set from one hour to one week. RES production and demand were calculated adapting historical time series extracted from the Italian TSO (Terna) database.

Calculation figures are drawn from a real hybrid system implemented for the project performed. Demand and production series were scaled considering a 180 kW peak demand and a 140 kW PV generation peak.

It was assumed that a 100 kWh BESS system with a charge/discharge time of 4 hours, a 50 kWh pumping storage unit with a charge/discharge time of 5 hours and a 100 kWt gas boiler are present.

The gas turbine is rated 100 kW. The minimum power output of the cogeneration unit is 30% of rated power, whereas efficiency is 0.6 of maximum efficiency at 25%, 0.9 at 50%, 1.0 at 75%, and 1.0 at 100%. It was also assumed that for each kWh of electricity produced by the gas turbine, 1.5 kWht are co-generated. Other efficiencies are $\eta_{B\,rte}=0.8$, $\eta_{W\,rte}=0.5$. The assumption of representing storage efficiency with a fixed round trip value is coherent with the formulation of (6) as a linear equality constraint.

For the BESS a 30% SOC_{min}, a total number of 2400 cycles before substitution and a wear cost of about 0.12 €/kWh were hypothesized. Other substitution costs are negligible with respect to BESS wear cost. Interruption costs were set at 0.5 €/kWh for interruptible and 2.5 €/kWh for firm loads. It was assumed a 0.8 €/Nm^3 gas cost.

The results of the discrete optimal control approach are shown in Figs. 3-7: no load curtailments were experienced throughout the day. Storage units are set at minimum capability at the starting hour of simulation (12 A.M.) and managed in such way that they are charged even in late afternoon, when renewable PV power is not available. This strategy allows to minimize the quantity of imported energy in the last hours of the day (Fig. 5).

Electric power is exported only during one time step: from 11 a.m. to 12 p.m. Export is due to the fact that the PV peak is higher than the sum of electric load and storage maximum charging power. It should be noted how cogenerator is kept running through the whole late afternoon/evening in order to avoid the use of the bolier and store some energy for later.

Total costs (marginal cost plus wear costs) are equal to 266 €. The low value is due to optimization and to the fact that relevant contribution to generation is given from renewable sources. Investment and long term marginal costs are not considered since the management framework is the one of system operation and not system planning.

The computational time was about 80 seconds using an ordinary desktop PC. Clearly these timings can vary considerably depending on the observing time window and the selected time grid. The choice of this time window should be consistent with charge/discharge cycle periods of storage systems (for example a single day time span is not sufficient for optimizing water stored in large reservoir). In [Bruno et al., 2014] this issue was explicitly addressed and it was shown how, for storage technologies similar too ones adopted in this study, excellent results can be obtained running every hour the proposed optimization algorithm and adopting a 8-12 hours time window.

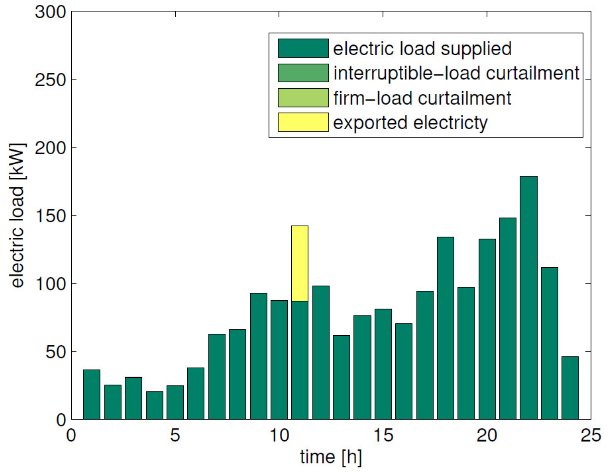

Fig. 3. Electric power supplied/sold

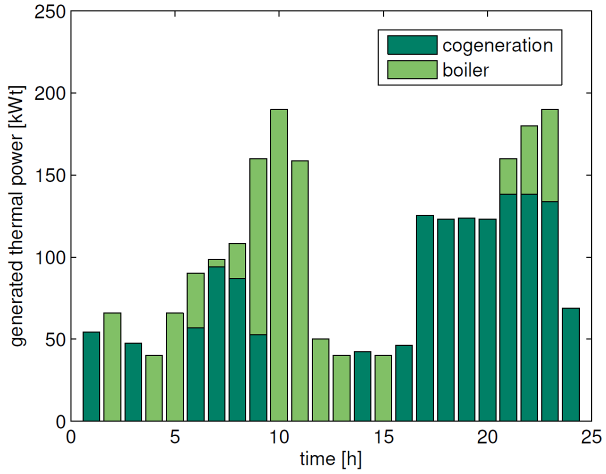

Fig. 4. Generated thermal power

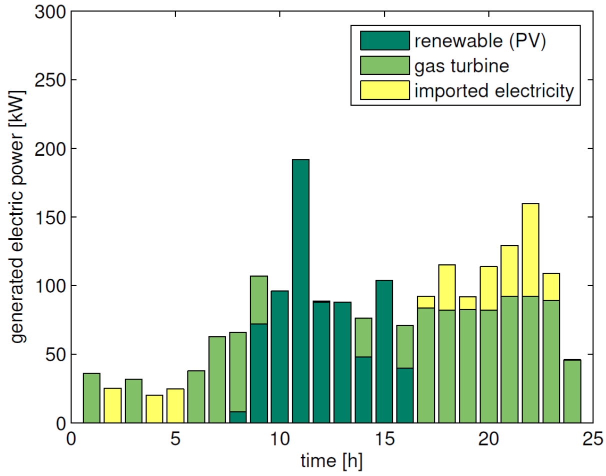

Fig. 5. Generated electric power

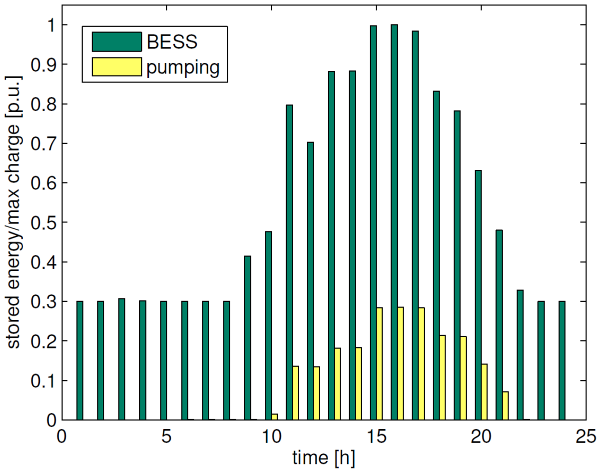

Fig. 6. Stored energy

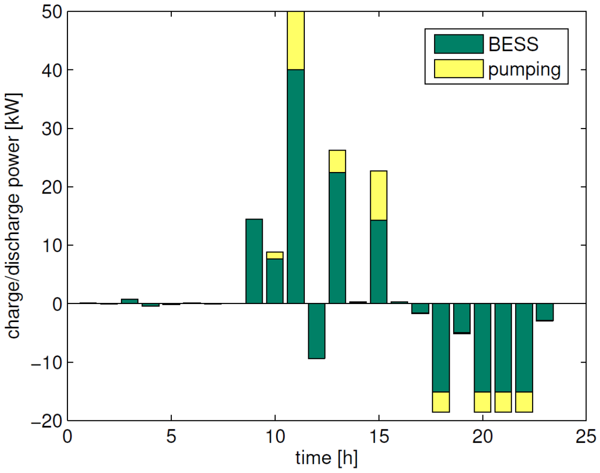

Fig. 7. Charge/discharge power of storage systems

4. CONCLUDING REMARKS

Energy source management is a crucial task for those networked enterprises that will be sharing energy control resources. The availability of multiple dispatching options requires the adoption of optimal control routines aimed at optimizing overall technical and economical objectives.

In this paper, a methodology for the optimal dispatch of energy sources in interconnected hybrid systems (as well as isolated energy systems) has been devised to this aim. The methodology has been tested based on implementation results of the project in the acknowledgment, which was aimed at building an innovative hybrid energy system.

The methodology presented is general enough to be implemented in any distributed network of enterprises in order to manage energy sources. The next steps of the research is to implement the approach to test it on a wider network to assess the stability of the solution proposed at the increasing of the complexity of the system.

5. ACKNOWLEDGMENT

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