A detailed model for the optimal management of a multigood microgrid

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1. Introduction

The fulfilment of human needs in remote areas, as islands or small villages, is a challenging task which can be faced only with an economical and sustainable provision of electricity. In many cases, the main grid extension is not a cost-effective solution since it requires large investments and maintenance costs and generally the power demand is locally covered by Diesel Internal Combustion Engines (ICE) [1,2]. However, this solution is far to be economic and sustainable for the environment. The high fuel cost, strongly affected by transportation, leads to a relevant increase of the levelized cost of electricity and represents a barrier to social and economic development in rural regions [3]. Furthermore, an ICE locally releases air pollutants, as well as CO_2, and it requires a periodic maintenance to avoid malfunctioning and oil leakages. The possibility to install standalone systems together with the high availability of Renewable Energy Sources (RES) makes the renewable-based hybrid MGs (Microgrid) [4] a suitable and promising solution in most of these contexts, as confirmed by a large number of studies and publications about this topic [5–7].

In a standalone MG, the electricity (but same considerations can be addressed for the thermal energy or others) can be generated and consumed by a variety of units. A storage is usually present to level off the imbalances of electricity on the grid, to increase system flexibility and to limit energy losses or power shortages. MG stability requires large size and expensive storage systems especially if most of the electricity generated is coming from non-programmable units and if the demand is not concurrent with the generation. This effect is mitigated by the presence of programmable units which allow shifting in time the generation and/or the consumption of electricity, thus limiting the use and the size of the storage. The operation of programmable units and

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Nomenclature

α	auxiliary variable
δ	dumped
ϑ	self-discharge
μ	unmet
π	penalty term
φ	non-programmable contribution
y	on/off variable
b	intercept
c C	consumption
CC	cycle-charging
CHP	combined heat and power
EMS	energy management system
G	set of goods
U	set of units
ICE	internal combustion engine
LCOE	levelized cost of electricity
LF	load following
m	slope
M	big-M term
MG	microgrid
MILP	mixed integer linear programming
N	minimum running hours
on	start-up variable
ORC	organic ranking cycle
p P	production
PW	piecewise
PV	photovoltaic
RES	renewable energy source
SL	storage level
SOC	state of charge
SP	set point
WT	wind turbine
USD	United States dollar

Subscripts/superscripts

aux	auxiliary
p	producer/production
c	consumer/consumption
el	electrical
g	good
i	unit
min	minimum
max	maximum
0	initial condition

the methodology to determine their schedule, i.e. the Energy Management System (EMS) can strongly affect the efficiency, the operating cost, the electric storage life and the availability of the system.

The aim of this work is to propose a new and more general approach to the solution of the EMS problem starting from the state of the art methodologies in literature and adding new features. In the proposed approach, the MG operation is defined through an EMS model able to determine the schedule of each programmable unit to fulfil the community needs at the lowest operation cost. Unlike the current approaches, described in detail in the next section, the problem formulation allows considering different goods in the MG and multi-input and multi-output units. In literature there are different works in which the optimal planning of a MG takes into account the heat and cooling demand, as well as the electricity consumption [8,9]. However, this work goes beyond the current state of art investigating the possibility to include in the optimal planning each valuable asset requested by the community served by the MG. The possibility to consider explicitly goods easily storable (i.e. woodchips, potable water, heat) can play a relevant role in operating cost reduction and adds new degrees of freedom in MG scheduling. Formulating the problem with different goods, instead of considering them only as deferrable electric loads (a solution already adopted in other publications [10–12]), allows modeling units requiring more than one good during operation and taking into account their off-design performance, as well as technical operation constraints and start-up penalties. Furthermore, the management of complex systems including multi-input and multi-output units can be really optimized only considering the different good separately, as shown by the second test case results.

These features represent a consistent step ahead in the simulation of MGs, leading to a general, flexible and compact formulation of the problem and to the possibility to use multi-fuel generators and units requiring and/or producing more than one good during operation.

2. Relevant literature

The approach to face the EMS problem is not univocal and in literature different methodologies are proposed, from simple heuristic strategies to more advanced optimization methods.

Most of the studies on MG design rely on heuristic dispatch strategies where the operation of programmable units is pre-defined. These studies are generally focused on the design of standalone systems and calculations are carried out using HOMER (Hybrid Optimization Model for Electric Renewables), a commercial optimization software developed by NREL since 1995 [13] and based on heuristic strategies. It implements a large data bank of different components, i.e. wind turbines, photovoltaic panels, small hydro power, biomass fired engines, fuel cells and battery systems with referenced off-design performance maps. It works by simulating one year of operation for several combinations of generator sets and comparing them on the basis of the Levelized Cost of Electricity (LCOE). Each simulation is performed selecting a priori one of the two following heuristic dispatch strategies: the load-following (LF) and the cycle-charging (CC) [14]. These strategies are simple and effective tools for the management of an off-grid power system but they present some limits in the simulation of complex systems.

In LF strategy, whenever a programmable generator is on, it produces only enough power to cover the electricity demand. This means that the generator operates at part load for most of the time, thus increasing its variable cost due to the lower off-design efficiency. On the other hand, the use of the energy storage is limited, thus entailing economic benefits related to a longer life of the batteries [15]. In the CC strategy, whenever a generator is on, it runs at its maximum rated capacity and charges the battery bank with the energy excess. The generator runs until the battery is charged up to a certain level, called Set Point (SP). The main advantage is the more efficient use of the generators; on the other hand the sequence of charging and discharging process may damage the energy storage leading to a higher replacement cost.

In addition, HOMER can handle deferrable loads shifting in time a part of the electricity demand. This is an extremely relevant feature in systems with a high share of intermittent power sources as WT and PV plants [16]. HOMER treats programmable loads as tanks gradually depleted proportionally to the load demand [13]. The load is served when intermittent RES power is available and dispatchable power sources are used only if the tank is close to be empty. In this case the deferrable load is treated as a primary load. However, even in this case, the schedule of deferrable loads is not really optimized but it is the result of a greedy strategy, which may lead to non-optimal solutions.

The quality of the results obtained with these approaches depends on the value of input parameters assumed for the simulation, such as the storage set point or the battery minimum state of charge [14]. A first improvement to the standard heuristic methods is obtained with the optimization of these parameters which allows obtaining a consistent decreasing of the operation costs. This approach is implemented by Dufo-Lopez et al. [17] who proposed a novel dispatch strategy for off-grid hybrid systems. It is based on traditional heuristic dispatch strategies but each user-defined parameter is chosen solving an auxiliary problem with a genetic algorithm. Similarly, Zhao et al. [18,19] proposed an optimization model to define the schedule of a standalone MG in Dongfushan Island (China). The model takes into account generators and battery operating cost (using a battery lifetime model) to obtain the set of optimal parameters for the operation strategy. The problem is solved using a nondominated sorting genetic algorithm. Similarly, Urtasun et al. [20] proposed an energy management strategy for a hybrid PV-battery-diesel power system. In particular, three modes of operation and the conditions required to switch from one to another are investigated.

A further and consistent improvement can be reached facing the MG management as a Unit Commitment Problem [21,22]. In this approach, the schedule of each unit in the MG is defined solving an optimization problem using forecast of future generation and consumption of electricity. A relevant number of studies have been published in these years regarding the management of MGs connected to a main grid [23]. Bischi et al. [8] proposed a model for planning the operation of combined cooling, heat and power energy systems. The resulting non-linear problem is converted into a Mixed Integer Linear Programming (MILP) by piecewise linear approximation of the non-linear performance curves of the programmable units. A similar problem, applied to the specific case to the Savona Campus trigeneration microgrid, has been solved by Bracco et al. using both MILP [24] and nonlinear solvers [25]. In Parisio [26] a model predictive control in combination with MILP is tested on an experimental microgrid located in Athens. Morais et al. [27] described a dispatch strategy based on 24 h ahead forecast for a case study in Budapest Tech. The MG includes a fuel cell, photovoltaic panels, a wind turbine and a controllable load. The schedule of each controllable component is defined at the beginning of the day solving a MILP problem based on the minimization of the operating cost. This approach allows obtaining a smart units operation schedule but it does not take into account forecast errors. Wu et al. [28] presented a hierarchical framework to handle uncertainties during generation schedule. The upper level of the framework determines the optimal generation plan. The objective function includes operation cost of the dispatchable generators and the cost or revenue by purchasing or selling electricity with the main grid. The overall schedule is updated during each time step using more accurate available forecast. The problem is solved using genetic algorithm. The same approach of grid connected MG has been applied to autonomous power systems. Dai et al. [11] developed an Energy Management System (EMS) based on a rolling horizon strategy. The inner problem is solved using the MILP. The result is the optimal schedule of both the generators and the schedulable loads over the time horizon. The proposed approach is tested on two different off-grid systems, a household and an electric boat. In Palma-Behnke et al. [12], a detailed EMS is proposed and tested using real data sets from an existing MG in Chile provided with two Photovoltaic (PV) plants, a wind turbine (WT), a Diesel Internal Combustion Engine (ICE), a battery bank and a controllable load (water pump with storage). A rolling horizon strategy is adopted and, for each time step, a MILP problem is solved. The inner problem includes nonlinear constrains represented by piecewise linear models and binary variables. Hassan and Abido [29] proposed a dynamic economic dispatch of a MG provided by different DGs and loads, both controllable or not. The optimal scheduling is obtained minimizing the objective function using Particle swarm optimization. A similar problem has been solved by Marzband et al. [30] using multi-period gravitational search algorithm and the final results show a better performance in comparison with Particle swarm optimization.

3. Energy management system

The most important novelty introduced in this work is the concept of good, defined as every valuable asset in the MG which can be produced, consumed and possibly stored. Examples of goods are the traditional energy vectors (AC and DC electricity, heat, cooling) and material products (potable water, ice, woodchips). The purpose of the EMS is to properly manage the balance of each good in the MG in order to cover community needs with the minimum operational cost.

In our work, the EMS is based on a rolling-horizon strategy, including the solving of a Unit Commitment problem through Mixed Integer Linear Programming (MILP). The inner problem consists in finding the optimal schedule of each unit over a certain time horizon (T_h) considering all the operation constrains. Forecasts of the production and consumption of each good by non-programmable units over the whole time horizon are required to properly solve the problem. The objective function to be minimized includes the actual operation cost of each unit and penalty terms proportional to the unmet demand of each good.

The rolling horizon approach allows diminishing the effect of forecast uncertainties on the schedule errors [31]. In fact, the optimization results are followed only during the first time step, then the forecasts are updated and the inner problem is solved again and the schedule of each unit over the time horizon is re-optimized as shown in Fig. 1. In this way the actual schedule of the MG is always based on more recent and reliable forecast and forecast error impact is reduced. The advantages related to an hour-by-hour update of the optimal solution make this kind of strategy very useful and commonly adopted in many fields [12,32,33]. The use of robust programming, widely used in differ-ent application fields to further reduce the impact of error in fore-cast [34,35], is not implemented in this work.

In addition to the optimal schedule definition, the EMS has to ensure MG stability against unavoidable fluctuations in

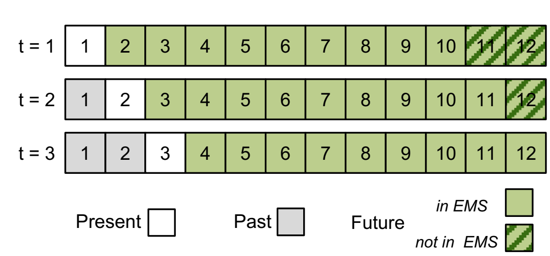

Fig. 1. Example of the rolling horizon approach with T_h = 10 h.

intermittent RES power and load consumption [36]. For this reason, during MG operation, a control strategy is needed to maintain frequency and voltage stability and guarantee power quality [37]. This level of control strategy is not discussed in this work, which is focused on the definition of the optimal hourly units operation, but a proper operating reserve constraint is considered to obtain a schedule feasible in real operation. The EMS takes into account that the available units have to face the worst-case scenario, where intermittent RES supply is not available and the highest load consumption in each time step is considered.

3.1. Problem statement

The solving of the EMS problem determines for each time step t in the whole time horizon T_h the schedule of each programmable unit and the storage level of each storable good, minimizing the overall operation cost and respecting all the operation constrains. The information required are: (i) the initial condition of storages and programmable units, (ii) the production and consumption of each good by non-programmable units for each time step, (iii) the performance curves, the start-up penalties and operations constrains of each programmable unit and (iv) the penalty for the unmet demand and the storage properties of each good.

Every good in the MG represents a subsystem. Each subsystem is composed by the storage (if present for that kind of good) and a set of units that produce or consume the good. In Fig. 2 the subsystem "Heat" is represented as example. The units which interact with this good are listed in two categories. First we have non-programmable units, whose production and operation cannot be modified by the EMS. Concentrating solar thermal collectors, as Fresnel or parabolic trough, are an example of non-programmable producers while the use of the heat by domestic and civil users can be considered a non-programmable load. The difference between production and consumption by non-programmable units is the gross aggregate balance of the good, a useful information to assess properly the programmable units schedule.

On the other hand, there are programmable units whose operation is defined by the EMS. For goods without storage, the EMS ensures the balance of production and consumption in each time step using the programmable units. If the storage is available, the excess of production in a certain time step can be stored and used in the future; otherwise the storage can be discharged to satisfy the good demand. In Fig. 2 two programmable producers are shown: a boiler which uses fuel to produce heat and a cogenerator that produces both heat and AC power. An example of a programmable consumer of the good "Heat" is the absorption chiller. The cogenerator and the absorption chiller are two examples of multi-input

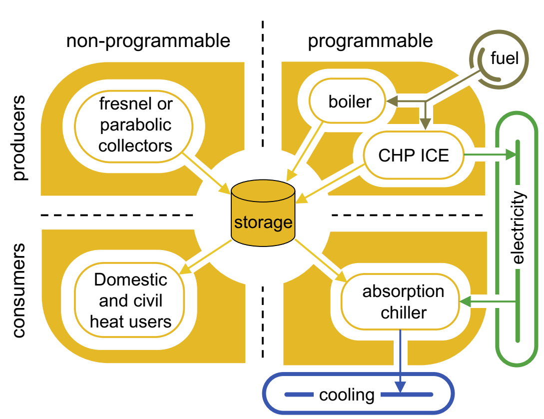

Fig. 2. Example of the subsystem framework for the good "Heat", including storage, producers and consumers (both programmable and not).

and multi-output programmable units respectively; these units can be simulated by the definition of a specific performance curve for each good consumed or produced.

The penalty term is a function of the unmet demand of each good: depending on the penalty value, the EMS could decide to meet only partially the demand, if this avoids a huge increase of operation costs. In general, a high penalty term is related to a very high priority load, as for example healthcare appliances, and a low penalty term is related to interruptible load, as part of the public lighting.

3.2. Mathematical model

The core of the methodology proposed in this work is the MILP problem that allows the definition of the most cost effective schedule of each programmable unit over a certain time horizon. The rigorous formulation of the scheduling problem is a Mixed Integer Non-Linear Problem, but a conversion in MILP is obtained using linearization techniques [38]. Hence, near-optimality and fast convergence is ensured thanks to current MILP solvers [39].

The problem is implemented in AMPL and the algebraic formulation is here presented. First of all, we define the sets that allow describing the problem in a concise and clear formulation. The time steps considered in optimization model are defined with the set $T = \{1, 2, \ldots, T_h\}$ where T_h is the time horizon that is the number of hours which are taken into account in the schedule defining.

The set G includes each good present in the MG. The following subset is defined:

$G^{\text{storage}} \subseteq G$: set of goods that have storage.

The set U includes each programmable unit present in the MG. The following subsets are defined:

$U^{\text{minload}} \subseteq U$: set of units that have minimum production rate once they are on.
$U^{\text{startup}} \subseteq U^{\text{minload}}$: set of units that have start-up penalization.
$U^{\text{minN}} \subseteq U^{\text{startup}}$: set of units that have constraints on minimum running hours once they are switched on.

The following subsets describe relations between goods and units in terms of production and consumption:

G_i^p: set of goods that can be produced by the unit i, with $i \in U$.
G_i^c: set of goods that can be consumed by the unit i, with $i \in U$.
U_g^p: set of units that produce the good g, with $g \in G$.
U_g^c: set of units that consume the good g, with $g \in G$.
$\text{PW}_{i,g1,g2}$: set of linear inequalities that relate production of good $g1$ by unit i and the consumption of good $g2$, with $i \in U, g1 \in G_i^p, g2 \in G_i^c$.

3.2.1. Parameters

The parameters are constant values and they represent the inputs of the problem. Some parameters have a different value for each time step. The parameters used to goods properties definition are hereafter reported:

$\varphi_{t,g}$: production and consumption by non-programmable units of the good g during the time step t, $\forall t \in T, g \in G$.
$\varphi_{t,g}^{\text{reserve}}$: production and consumption by non-programmable units of the good g during the time step t in the worst case scenario, $\forall t \in T, g \in G$.
π_g: penalty related to the unmet demand of the good g, $\forall g \in G$.
$SL_g^{\min}$: minimum level of the good g that can be stored in the related storage, $\forall g \in G^{\text{storage}}$.

SL_g^{max}: maximum level of the good g that can be stored in the related storage, $\forall g \in G^{storage}$.

SL_g^0: amount of the good g stored in the related storage in the first time step, $\forall g \in G^{storage}$.

ϑ_g: self-discharge factor of the good g in the related storage, $\forall g \in G^{storage}$.

The parameters used to units properties definition are hereafter reported:

$P_{i,g}^{rate}$: maximum production rate of the unit i of each good g that can be produced by unit i, $\forall i \in U, g \in G_i^p$.

$P_{i,g}^{min}$: minimum production rate of the unit i of each good g that can be produced by unit i, $\forall i \in U^{minload}, g \in G_i^p$.

$c_{i,g}^{startup}$: start-up additional consumption of good g by the unit i, $\forall i \in U^{startup}, g \in G_i^c$.

N_i: number of minimum running hours of the unit i, $\forall i \in U^{minN}$.

N_i^0: number of residual minimum running hours of the unit i, $\forall i \in U^{minN}$.

on_i^0: state of operation of the unit i at the beginning of time horizon, $\forall i \in U^{startup}$.

$m_{i,g1,g2,pw}$: slope of the pw line that relates production of good $g1$ by unit i and the consumption of good $g2$, with $i \in U, g1 \in G_i^p, g2 \in G_i^c, pw \in PW_{i,g1,g2}$.

$b_{i,g1,g2,pw}$: intercept of the pw line that relates production of good $g1$ by unit i and the consumption of good $g2$, with $i \in U, g1 \in G_i^p, g2 \in G_i^c, pw \in PW_{i,g1,g2}$.

3.2.2. Variables

Variables are the quantities that are varied by the solver in order to reach the minimum of the objective function while respecting all the constraints of the problem. They are divided in real continuous variables and Boolean variables.

3.2.2.1. Continuous.

$SL_{t,g}$: storage level of the good g in the time step t, $\forall t \in T \cup \{T_h + 1\}, g \in G^{storage}$ and $SL_g^{min} \le SL_{t,g} \le SL_g^{max}$.

$\delta_{t,g}$: amount of the good g dumped in the time step t, $\forall t \in T$, $g \in G$.

$\mu_{t,g}$: unmet demand of the good g in the time step t, $\forall t \in T, g \in G$.

$p_{t,i,g}$: production of the good g by unit i in the time step t, $\forall t \in T, i \in U, g \in G_i^p$ and $p_{t,i,g} \ge 0$.

$c_{t,i,g}$: consumption of the good g by unit i in the time step t, $\forall t \in T, i \in U, g \in G_i^c$ and $c_{t,i,g} \ge 0$.

$p_{t,i,g}^{reserve}$: production of the good g by unit i in the time step t in the worst-case scenario, $\forall t \in T, i \in U, g \in G_i^p$ and $p_{t,i,g}^{reserve} \ge 0$.

$c_{t,i,g}^{reserve}$: consumption of the good g by unit i in the time step t in the worst-case scenario, $\forall t \in T, i \in U, g \in G_i^c$ and $c_{t,i,g}^{reserve} \ge 0$.

3.2.2.2. Boolean.

$y_{t,i}$: Binary variable related to off/on status of unit i in time step, $\forall t \in T$, $i \in U^{minload}$.

$\mathrm{on}_{t,i}$: Binary variable related to the switching on of unit i in the time step, $\forall t \in T$, $i \in U^{startup}$.

$\alpha_{t,i,g}$: Binary variable that avoids simultaneous production and consumption of the same good by the same unit, $\forall t \in T, i \in U, g \in G_i^p \cap G_i^c$.

3.2.3. Objective function

The objective function is to minimize the operative costs and the penalties related to unmet goods demand:

$$\sum_{t\in T} C_{t,money} + \sum_{t\in T} C_{t,money}^{startup} - \sum_{t\in T} P_{t,money} + \sum_{t\in T}\sum_{g\in G} \mu_{t,g} \cdot \pi_g \tag{1}$$

where $C_{t,money}$ denotes the operation cost of all the units in time step t, $C_{t,money}^{startup}$ denotes the start-up cost of all units in time step t and $P_{t,money}$ denotes the total revenue in time step t (only if a unit in the MG can produce the good 'Money'). They are defined similarly for each generic good:

$$C_{t,g} = \sum_{i\in U_g^c} c_{t,i,g} \qquad \forall t \in T, g \in G \tag{2}$$

$$C_{t,g}^{startup} = \sum_{i\in U_g^c \cap U^{startup}} \mathrm{on}_{t,i} \cdot c_{i,g}^{startup} \qquad \forall t \in T, g \in G \tag{3}$$

$$P_{t,g} = \sum_{i\in U_g^p} p_{t,g} \qquad \forall t \in T, g \in G \tag{4}$$

The last term of Eq. (1) is the penalization related to the unmet demand of each single good over the whole time horizon. In this case we consider only money as good whose consumption has to be minimized, but, if requested, other goods (as for example pollutants emission) can be considered similarly.

3.2.4. Constraints

The goods without storage must respect the balance between consumption and production in each time step as shown in Eq. (5). Note that the parameter φ is positive if the difference between non-programmable units production and consumption is positive and negative is the consumption exceeds the production.

$$\varphi_{t,g} + P_{t,g} + \mu_{t,g} = C_{t,g} + C_{t,g}^{startup} + \delta_{t,g} \qquad \forall t \in T, g \in G\ C\ G^{storage} \tag{5}$$

Goods with storage can be stored if there is excess of production to be exploited when there is an excess of consumption, as shown in following equation:

$$SL_{t+1,g} = SL_{t,g} \cdot (1 - \vartheta_g) + \varphi_{t,g} - \delta_{t,g} + \mu_{t,g} + P_{t,g} - C_{t,g} - C_{t,g}^{startup} \qquad \forall t \in T, g \in G_{storage} \tag{6}$$

Relation between consumption and production of good by each unit are expressed through a set of linear inequalities:

$$c_{t,i,g2} \ge m_{i,g1,g2,pw} \cdot p_{t,i,g1} + b_{i,g1,g2,pw} \cdot y_{t,i} \qquad \forall t \in T, i \in U, g1 \in G_i^p, g2 \in G_i^c, pw \in PW_{i,g1,g2} \tag{7}$$

The last term, present only for units with on/off binary variable, disables the constraint when the unit is switched off. This formulation requires that performance curve to be linearized has to be convex; if it is not, piecewise linearization techniques are used [38]. This approximation introduces error in performance curve representation which can be partially reduced increasing the number of intervals of piecewise linearization at the expense of an increment of computational time [8]. In the configurations studied in this work, only the battery life loss is modeled with a non-convex relation. This is because in the weighted-Ah model [40] used in this work, the life loss of the battery (and so money consumption) is not a linear function of the state of charge and the actual energy throughput.

$$c_{t,battery,money} = f(p_{t,battery,DC}, SL_{t,battery}) \qquad \forall t \in T \tag{8}$$

Maximum production by a unit is expressed with Eq. (9). For units that have minimum load constrains, two additional constraints have to be considered:

$$p_{t,i,g} \le P_{i,g}^{rate} \qquad \forall t \in T, i \in U \tag{9}$$

$$p_{t,i,g} \leq y_{t,i} \cdot P^{\text{rate}}_{i,g} \qquad \forall t \in T, i \in U^{\text{loadmin}} \tag{10}$$

$$p_{t,i,g} \geq y_{t,i} \cdot P^{\text{min}}_{i,g} \qquad \forall t \in T, i \in U^{\text{loadmin}} \tag{11}$$

The variable related to the start-up of a unit is defined through the following constraint:

$$\text{on}_{t,i} \geq y_{t,i} - y_{t-1,i} \qquad \forall t \in T, i \in U^{\text{startup}} \tag{12}$$

Note that this constraint allows to consider $\text{on}_{t,i}$ as a continuous variable because $y_{t,i}$ is boolean. Some units can be affected by technical limit as minimum running hours once the unit is switched on. This is taken in to account through the following constraints:

$$y_{\tilde{t},i} \geq \text{on}_{t,i} \quad \forall i \in U^{\text{min}N}, t \in T, \tilde{t} \in T : t \leq t1 \leq t + N_i \tag{13}$$

$$y_{\tilde{t},i} = 1 \qquad \forall i \in U^{\text{min}N}, t \in T : t \leq N^0_i \tag{14}$$

Eq. (14) takes into account the minimum number of residual hours of operation if the unit is already operative at the beginning of the time horizon. Some auxiliary constraints are added for those units that can produce and consume the same good. This is the case of the bidirectional inverter than can produce and consume both DC and AC power depending on the way it is working. In order to avoid a simultaneous production and consumption of the same good the two following constraints are considered:

$$p_{t,i,g} \leq \alpha_{t,i,g} \cdot M_{4,i} \qquad \forall t \in T, i \in U, g \in G^p_i \cap G^c_i \tag{15}$$

$$c_{t,i,g} \leq (1 - \alpha_{t,i,g}) M_{5,i} \qquad \forall t \in T, i \in U, g \in G^p_i \cap G^c_i \tag{16}$$

where the parameters $M_{4,i}$ and $M_{5,i}$ are large enough to enable or disable the respective constraint.

In off-grid systems where a significant amount of power is supplied by intermittent RES, the operating reserve is needed to guarantee system stability even if forecasts are inexact. The EMS has to ensure that the running units can cover the goods demand if the supply by intermittent RES is not available and the real load consumption is higher than the forecasted one. The parameter $\varphi^{\text{reserve}}_{t,g}$ is similar to $\varphi_{t,g}$ but it describes the worst-case scenario, where intermittent RES supply is omitted and highest feasible good consumption is considered.

$$p^{\text{reserve}}_{t,i,g1} \leq P^{\text{rate}}_{i,g} \qquad \forall t \in T, i \in U \tag{17}$$

$$p^{\text{reserve}}_{t,i,g1} \leq y_{t,i} \cdot P^{\text{rate}}_{i,g} \qquad \forall t \in T, i \in U^{\text{loadmin}} \tag{18}$$

$$p^{\text{reserve}}_{t,i,g1} \geq y_{t,i} \cdot P^{\text{min}}_{i,g} \qquad \forall t \in T, i \in U^{\text{loadmin}} \tag{19}$$

$$c^{\text{reserve}}_{t,i,g2} \geq m_{i,g1,g2,pw} \cdot p^{\text{reserve}}_{t,i,g1} + b_{i,g1,g2,pw} \cdot y_{t,i} \qquad \forall t \in T, i \in U, g1 \in G^p_i, g2 \in G^c_i, pw \in PW_{i,g1,g2} \tag{20}$$

$$\varphi^{\text{reserve}}_{t,g} + P_{t,g} + C_{t,g} + \mu_{t,g} \geq 0 \qquad \forall t \in T, g \in G\ C\ G^{\text{storage}} \tag{21}$$

$$\varphi^{\text{reserve}}_{t,g} + (SL_{t,g} - SL^{\text{min}}_g) + P_{t,g} + C_{t,g} + \mu_{t,g} \geq 0 \qquad \forall t \in T, g \in G_{\text{storage}} \tag{22}$$

Eqs. (17)–(20) define the production and consumption by programmable units in the scenario with $\varphi^{\text{reserve}}_{t,g}$ in place of $\varphi_{t,g}$. The constraints defined by Eqs. 21, 22 have the same structure of Eqs. 5, 6 and guarantee that the available units, moduling the production and consumption, can face the worst case scenario. In addition to the units production, goods provided with a storage, can use an amount of previously stored good to meet the operating reserve constraint (see Eq. (22)).

4. Results and discussion

In this section the proposed approach is tested with two different configurations. They differ in both the units installed and the goods produced and consumed.

Common points to both configurations are: (i) the presence and the size of non-programmable RES producers, namely a PV plant and a WT (both of them have a nominal power of 100 kW_{el}) and (ii) the AC loads for domestic consumption. The trends of the electricity generated and consumed by non-programmable units is reported in Fig. 3.

Simulations are carried out on a 48 h timespan and it is possible to notice that the first day is characterized by a large production by RES, in fact the PV plant reaches its nominal power output and the WT operates with a high average power. On the other hand, the second day is representative of a cloudy day with a low wind speed. The AC loads are higher in the morning and during the night because of public lighting and domestic appliances use. The grey shaded area represents the resulting aggregate energy flux through the battery (φ) if programmable units are not used. Minimizing the extent of these fluxes allows reducing the battery wear and the energy losses in charging/discharging process and it is implicitly accounted for by the objective function of the EMS problem.

The properties of all the other units considered in the two test cases are reported in Table 1 and Fig. 4.

All the simulations have been performed by an i5 2.6 GHz desktop computer with 8 GB RAM, using Gurobi [41] as solver for MILP problems. Each step of the rolling horizon strategy requires in average 2.7 s for the first test case and 4.2 s for the second one. Because in real management the solver is called only once an hour, the computational time are fully compatible with practical implementation. The heuristic strategies are implemented in MATLAB environment [42] and they require less than 1 s because based on if-then constructs.

4.1. Comparison with heuristic dispatch strategies

The first test case aims to compare our methodology with the heuristic dispatch strategies commonly used to manage standalone hybrid MG. Fig. 5 shows the diagram of the MG, goods present on the grid are described in Table 2.

Two identical programmable generators are available: the first one (ICE) is used as primary generator while the auxiliary one (ICE_{aux}) is switched on only to avoid battery depletion or power shortages. The wear cost of lead-acid battery is related to the operative SOC level and two different cost of supplied energy are considered: 0.09 USD/kW h if the SOC is over 50% and

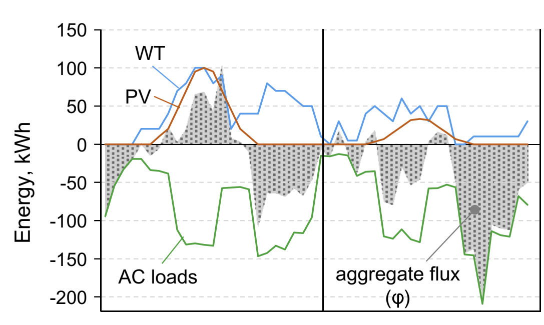

Fig. 3. Hourly contribution of non-programmable units (PV, WT, AC loads) and the resulting aggregate net flux used in the simulations.

Table 1
Properties of programmable units considered in this study.

Unit	Produced good		Hourly production			Consumed good		$c^{\text{start-up}}$	Hourly consumption	
			P^{min}		P^{max}				$C\,(P^{min})$	$C\,(P^{max})$
Battery	DC/$DC_{storage}$	kW h	0	–	200	$DC_{storage}$/DC	kW h	–	See Fig. 4a	
Boiler	Heat	kW h	400	–	800	Woodchips	kg	190	100.64	193.24
						Money (fuel)	USD	5.7	3.02	5.8
						Money (O&M)	USD	3.3	1.46	
Chipper	Woodchips	kg	500			AC	kW h	0	5	
						Money (O&M)	USD	1	1	
ICE	AC	kW h				Money (fuel)	USD	3.68	See Fig. 4b	
			50	–	100	Money (O&M)	USD	2.62	1	
Icemaker	Ice	kg	250			AC	kW h	9.5	37.5	
						Water	m^3	0	0.28	
						Money (O&M)	USD	0.1	0.1	
Inverter	AC/DC	kW h	0	–	250	DC/AC	kW h	–	0	260
ORC	AC	kW h	50	–	100	Heat	kW h	400	See Fig. 4c	
						Money (O&M)	USD	1.25	1.25	
Osmosis plant	Water	m^3	3.5	–	7	AC	kW h	–	14	28
						Money (O&M)	USD	0.7	0.7	

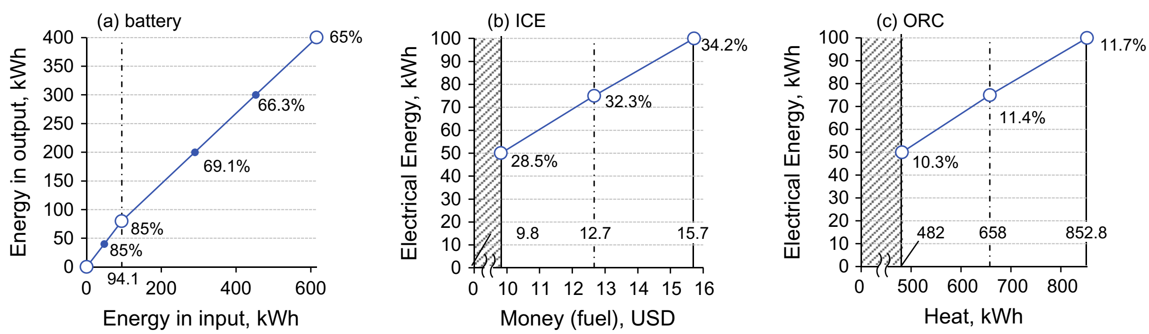

Fig. 4. Off design performance curves for the battery (a), the ICE (b) and the ORC (c).

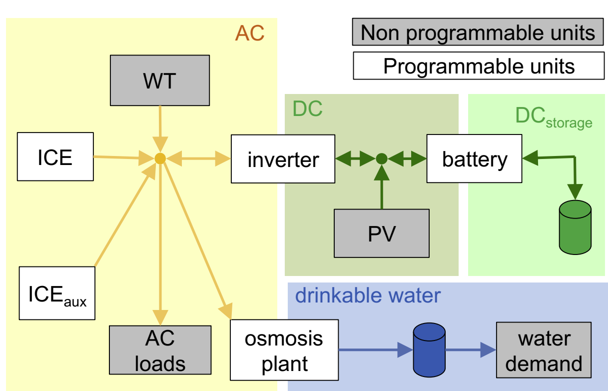

Fig. 5. MG framework in first test case.

Table 2
Properties of goods in test case 1.

Good		Storage	SL(t = 0)	SL^{min}	SL^{max}	ϑ (%)
AC	kW h	No	–	–	–	–
DC	kW h	No	–	–	–	–
$DC_{storage}$	kW h	Yes	250	40	400	0
Water	m^3	Yes	12	0	60	0

0.14 USD/kW h otherwise. The rolling horizon strategy is based on a 24-h time horizon with an exact forecast. A sensitivity analysis on the forecast error is presented at the end of this section.

The operation cost to be minimized by the EMS problem is formed mainly by three terms: (i) ICE operation cost due to O&M the fuel and (ii) the battery wear due to the charging and discharging fluxes. In addition, a penalty term proportional to the difference between a reference storage level (SL) and the actual SL at the end of day has been added. We assume that the reference SL is equal to the maximum one among the different strategies. The monetary value of the energy stored in the battery is set equal to 0.2 $/kW h, which is the price of a kW h of electricity generated by Diesel ICE working in nominal condition and stored in the battery. This additional term allows a proper comparison between dispatch strategies having different SL at the end of the simulation and it is required only for short-term simulations. In fact, if a whole year is considered the effect of different final battery levels on the overall solution is negligible. Finally, the comparison between the different dispatch strategies have been carried out under two different assumptions: (i) neglecting the start-up penalizations and (ii) considering them as an additional cost the first hour of operation. In the start-up cost two terms are considered: (i) a consumption of the input goods without any useful effect and (ii) a monetary cost due to component wear and O&M.

The MILP based strategy has been investigated under two different assumptions: the first one can use the two generators, while in the second one only the primary ICE is available. This approach is compared with the five different heuristic dispatch strategies considered: the LF and four CC strategies with different battery Set Point levels. The minimum SOC level of the battery is a parameter of great influence since the same battery operation at a lower

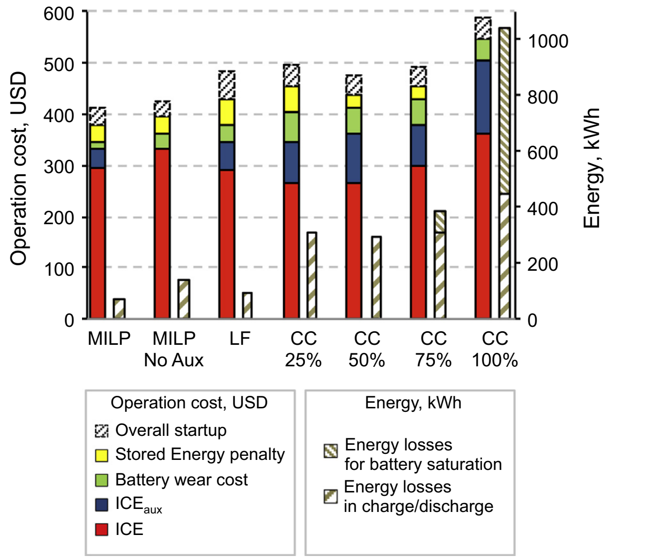

Fig. 6. Comparison of cost and energy losses over the two-day simulation between the dispatch strategies under consideration.

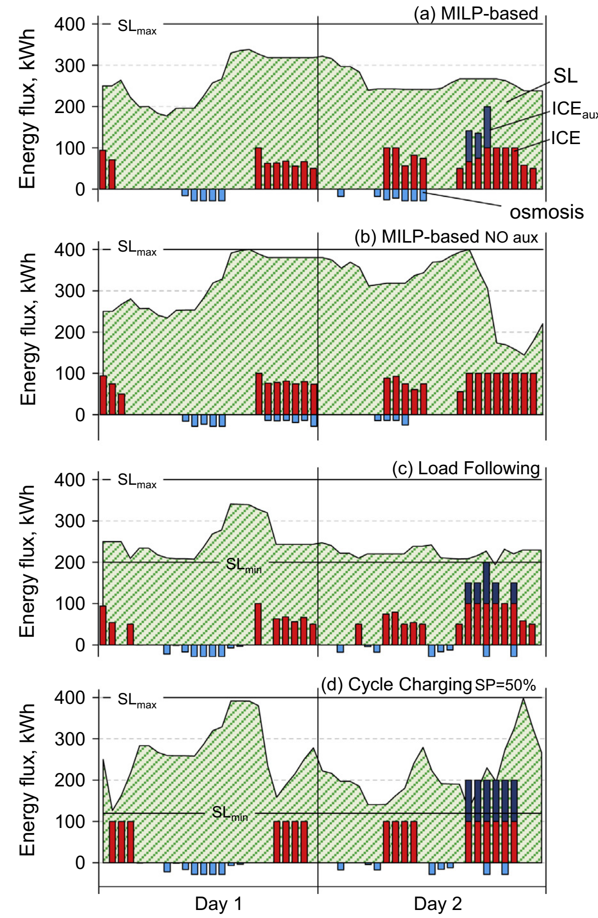

Fig. 7. Hourly contribution of programmable units (ICE, ICE$_{aux}$, osmosis plant) and battery SL for the dispatch strategies under consideration.

storage levels results in higher wear cost. On the other hand, working at high SOC may lead to battery saturation and energy dumping. For each heuristic strategy, the minimum SOC is optimized with a relevant operational cost decrease, especially for the LF approach, which tends to manage the battery close to the minimum SOC level.

The operative costs for all the investigated strategies are reported in Fig. 6 where it is possible to appreciate the cost reduction attainable with MILP based strategies. Without considering start-up penalization of the components, the MILP-based strategy reaches a cost reduction of 9.61% in comparison with the most cost effective heuristic dispatch strategy (LF strategy).

Considering start-up penalizations, the cost saving of MILP-based strategy increases to 13.09% in comparison with the CC-SP = 50% strategy which becomes the most cost effective among the heuristic dispatch strategies. In fact, the start-up impact is higher in LF because of the high frequency of start/stop affecting ICE schedule.

These results can be explained considering the differences of unit scheduling and battery use for the different strategies. Results are reported in Fig. 7 for the two MILP-based strategies, for the LF and for the best CC among those investigated.

The following observations can be addressed:

- Both the MILP-based strategies (with and without auxiliary ICE respectively) and the CC approach limit the number of start-ups and shutdowns for the ICE generator. The LF approach requires seven start-ups instead of four and three times the generator is operated for just one hour leading to high overall start-up costs.
- The MILP strategy is the only one able to fulfil the electricity demand without using the auxiliary ICE. In this case, the EMS is able to modify the schedule to cover the demand with a slight cost increasing (3.2% addressable to a higher wear of the battery the second day). The battery is charged to a higher SL since the first hours of the days to satisfy the operating reserve. During the last hours of the second day the ICE is switched on and it runs close to its nominal load even if the battery SOC is about 100%. This allows storing energy in the battery during the evening to be released during the nocturnal hours when the ICE generator is not able to cover the whole demand. This farsighted operation cannot be scheduled by any of the heuristic dispatch strategies, because it requires the use of forecasts of future power production and consumption. For this reason, besides obtaining a not negligible cost saving during operation, the MILP-based strategy leads to investment cost reduction during the design and the sizing of MG. In fact a better use of the available units avoids the need to oversize the power generation set or the battery system.
- CC strategies work always at full load and the average ICE efficiency is equal to 34.2% (the nominal one). In load following the average efficiency is lower (30%) because of the frequent part load operation of the generator. In MILP-strategy, instead, where the ICE load in each hour is the result of an optimization process, the average efficiency is equal to 32.3%. A value slightly higher is attainable if no auxiliary ICE is available because the generator is operated at full load for a longer number of hours.
- The auxiliary ICE (if available) is used by all the strategies at the end of the second day to avoid the total discharge of the battery. The CC strategy since it cannot control the generators power output operates the generator at its nominal load for six hours until the battery is full. LF is able to reduce the number of hours of operation but it entails two start-ups. Finally, he MILP based configuration runs the ICE$_{aux}$ for only three hours at reduced loads with evident economic benefits;
- Battery state of charge trend changes appreciably from one case to the others. The trend of the energy fluxes trough the battery is reported in Fig. 8 for three different strategies with the respective curves of cumulative absolute energy handled by the battery. In CC strategies, the battery wear cost is on average

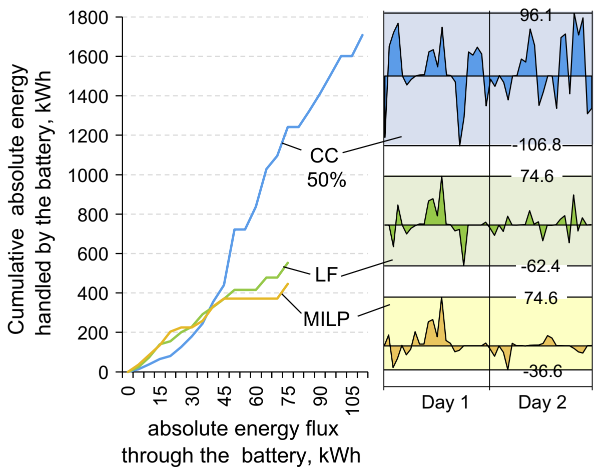

Fig. 8. Cumulated energy processed by the battery under a certain energy rate.

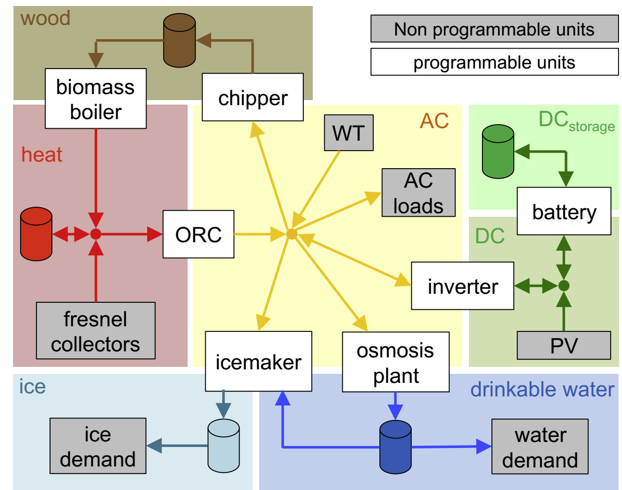

Fig. 9. MG framework in second test case.

higher than in all the other cases because it is frequently used with a total processed energy three times higher than in the other cases leading to a relevant loss in charging/discharging process. Furthermore, the average hourly absolute flux is close to 35 kW h entailing a high wear of the battery compared to LF and MILP showing an average value of 11 and 9 kW h respectively. This problem is reduced in both the MILP and the LF strategies where the usage of the battery is reduced and a small part of energy is lost in the charging/discharging process.

Finally, the difference of operation cost between MILP and the best heuristic strategy becomes less marked considering errors in forecast. For this example, we assumed that errors on the aggregate power are a linear function of time with an exact forecast in the first hour of the time horizon and a ±75 kW h error at the last (24th) hour. If always positive errors are added to the actual aggregate power the MILP operation cost is 433.1 USD, while, if only negative errors are considered, a value of 436 USD is obtained with a money saving respectively of 9.03% and 8.42%, in comparison with the CC-SP = 50% strategy. It is important to point out that these examples are the most critical ones since the presence of unilateral errors appreciably modifies the overall power forecast over the time horizon and induces the EMS to take wrong choices. In real cases where random errors are considered this effect is less marked and it could not affect deeply the optimal solution. These examples demonstrate that the MILP-based strategy, thanks to the rolling horizon approach, could be still advantageous even in presence of relevant errors on the forecast.

4.2. Advanced configuration test

The second test case is focused on a more complex MG whose diagram is reported in Fig. 9. This configuration could be used to cover the demand of a rural village located in a remote area. The power supply is provided by a WT, a PV plant and an ORC which produces AC power consuming medium temperature heat [43]. The thermal power can be produced by both Fresnel collectors and a biomass boiler: the Fresnel collectors produce heat when direct solar radiation is available while the biomass boiler is a programmable unit and the only constraint is the availability of a sufficient amount of woodchips. Woodchips can be previously produced by the chipper and stored in a dedicated tank. The ORC is the only controllable unit producing AC power and it guarantees in each time step the grid power balance with the assistance of the Lead-acid battery, connected to the DC bus. A thermal storage

Table 3
Properties of goods in test case 2.

Good		Storage	SL ($t = 0$)	SL^{min}	SL^{max}	ϑ (%)
AC	kW h	No	–	–	–	–
DC	kW h	No	–	–	–	–
$DC_{storage}$	kW h	Yes	300	35	350	0
Water	m^3	Yes	14	0	25	0
Heat	kW h	Yes	1500	0	3000	1
Ice	kg	Yes	150	0	1000	2
Woodchips	kg	Yes	1800	0	3000	0

allows decoupling heat and AC power production increasing the flexibility of the EMS. Respect to the previous case, the community requires water and ice blocks which are produced by an icemaker, consuming water and AC power during its operation. The goods properties are described in Table 3. The assumptions for the Lead-acid battery are the same of the previous test case.

In this case is not possible to make a comparison with other approaches since none of the heuristic strategies proposed in literature is able to manage a grid with several goods, a variety of programmable units and multi input/output components. Hence, the analysis is limited to the optimal operation of the whole system obtained using the proposed MILP strategy. We adopt a time horizon equal to 18 h and we assume that the forecasts are exact. The optimal operation of all the units over two-days is reported in Fig. 10.

The first day is sunny and windy and the PV plant, the WT and the Fresnel collector supply a large amount of power, while in the second day most of the power is provided by the biomass combustion.

In the first day, the ORC is immediately switched on because of the fixed AC consumption for public and domestic uses. The battery is slightly discharged during the following hours but the SL level remains above the minimum threshold (35 kW h) avoiding excessive storage depletion. Forecast information about the Fresnel contribution during the day and the trend of fixed AC loads are available and the EMS runs the ORC only for two hours exploiting the available stored heat without switching on the biomass boiler. During the central hours of the day the Fresnel collector produces a large amount of thermal power and the ORC is switched on again to avoid heat storage saturation and energy dumping.

The programmable AC loads are scheduled in those hours to shave the energy flux to the battery. The battery is filled by

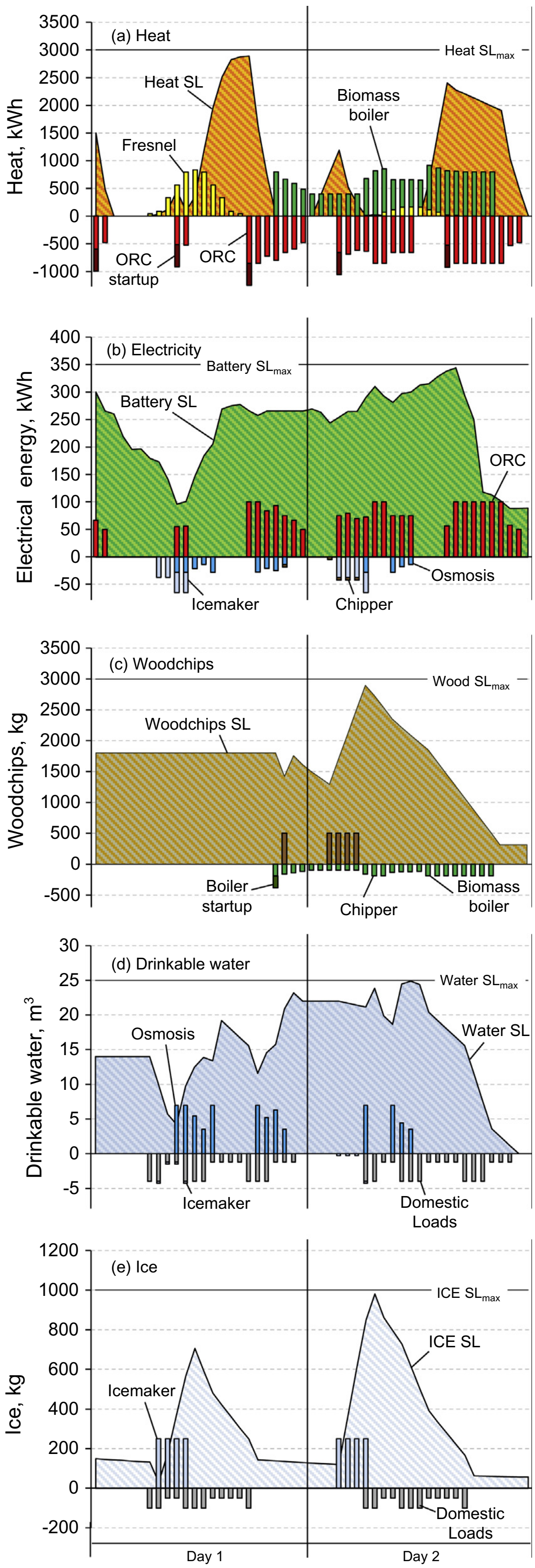

Fig. 10. Hourly trend of the SL for each storable good in addition with the production and consumption by all units related to that good. In electricity diagram (which includes AC, DC and $DC_{storage}$ goods), non-programmable units contribution is omitted (see Fig. 3).

intermittent generators PV and WT production up to 80%. At this point the EMS discharges the heat storage to operate the ORC with the aim to minimize the energy fluxes through the battery and to limit its wearing.

The heat stored during the day is not sufficient to fuel the ORC during the nocturnal hours and the biomass boiler is switched on the 21th hour. This unit runs almost until the end of the two days, minimizing the number of start-ups and working, when it is possible, at partial load with a higher efficiency. During the biomass operation the woodchips are gradually consumed and the chipper is switched on to fill the tank again.

In the second day the energy supplied by intermittent energy sources is not relevant and the biomass boiler runs the whole day to provide heat to the ORC. Both the biomass boiler and the ORC modulate their power to follow the load and limiting the use of the battery. Consequently, the heat storage remains almost empty until 14th hour when the EMS starts to increase the boiler load because it is aware of the future forecast. The small contribution of WT in the nocturnal hours of the second day results in the necessity of filling both the heat storage and the battery. In this manner, the EMS is able to guarantee a sufficient available energy in the following hours when the AC loads are higher and the biomass boiler is not enough to satisfy the thermal load of the ORC.

The scheduling of the osmosis plant and the icemaker highlights the advantages related to the multigood approach. In fact, considering the two goods separately and not as a singular deferrable electric consumption, allows decoupling the icemaker and osmosis plant operation. The EMS exploits this possibility, scheduling these two units in different hours in the central hours of day in order to shave diurnal power peaks and to obtain an operational cost reduction.

The operating costs resulting from the optimized management of the MG are reported in Fig. 11a (hourly data) and b (aggregate cost over two days). Pattern shaded and solid fill data refer to start-up and operation costs respectively. Table 4 reports numeri-cal results.

More than 60% of the total cost is related to the boiler operation because the wood consumption cost is allocated to the biomass boiler instead of the chipper. This assumption is due to numerical

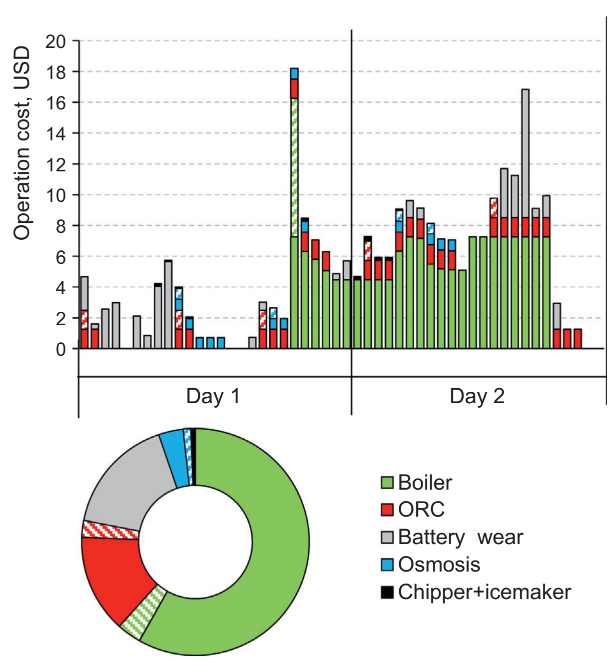

Fig. 11. (a) Hourly trend of monetary cost related to operation (solid fill) and start-up (pattern shaded) of each programmable unit. (b) Cost share over the whole timespan.

Table 4
Total costs for the two-day simulation.

	Operation	Startup	%
Boiler	150.94	9.00	61.67
Osmosis	9.10	2.80	4.59
ORC	36.25	6.25	16.39
Chipper	0.50	0.20	0.27
Icemaker	0.80	0.20	0.39
Battery wear	43.31		16.70

reasons and it allows finding the solution with a reduced computational time and without any effect on the veracity of the results. Finally, Fig. 10a highlights as the battery wear cost is extremely low for many hours during the two-days simulation proving the capability of the proposed approach in limiting the fluxes through this component.

5. Conclusions

In this paper, we presented a novel strategy for the definition of the optimal management of a multigood standalone MG integrated with RES. The optimal schedule, obtained solving a MILP problem, is frequently updated according to the rolling horizon strategy. The approach is tested on two problems highlighting the capabilities of this strategy to reduce the operational cost and to manage complex systems.

The first test case shows that a significant cost reduction can be reached using the proposed approach in place of the most commonly adopted heuristic strategies. In particular, the farsighted operation of programmable units allows a better exploitation of the RES and a limited wear of the battery. The advantage is greater if start-up penalties are considered because, in our test case, partial load operation of programmable units is more advantageous than their intermittent use.

In the second test case, an innovative configuration of the MG is proposed. The most interesting components are (i) the ORC that can be powered both by the Fresnel collector and the biomass boiler and (ii) the icemaker, modeled as a multi-input unit which requires water and AC power during operation. The management of such MG is not trivial and cannot be faced neither with common heuristic strategies or other formulations proposed for independent MG scheduling.

One of the main aspects is that the analytical formulation is extremely flexible and it is able to describe any MG since any type of components can be modeled including information on real operation constraints representing the first step to have an exhaustive and holistic approach to properly manage complex systems. Thanks to its features, the proposed method is a valuable option for the solution of two tasks. First it can be used to determine the optimal scheduling of programmable unit in an existing MG instead of using greedy approaches. In this case, it allows for a reduction of both operational cost and components wear and it avoids power shortages thanks to the possibility to exploit forecasts. On the other hand, it can be used for design purpose and in particular for the selection of generators and storages size leading to the lowest LCOE. Once the input data for a specific location are obtained, different power producer sets can be tested over one year of operation, highlighting the most cost effective solutions able to satisfy the goods demand without oversizing the system components.

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