A Matheuristic Approach for Resource Scheduling and Design of a Multi-energy System

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Abstract: Modern energy system are evolving due to the opportunities and challenges that new technologies pose in the energy sector. These changes create the requirements of decision tools able to effectively sustain the processes of design and retrofit of energy systems. In this paper a multi-energy system management problem is taken into account and a mixed integer linear programming (MILP) formulation is proposed to model both the design and the resource scheduling of energy districts. However, since the size of the formulation restricts its applicability to small cases far from the application of interest, a matheuristic based on constraint relaxations and variable fixing has been designed. Preliminary computational results show that the proposed solution strategy is able to achieve good solutions (i.e., solutions with small optimality gaps) on restricted random instances, and to solve in reasonable times instances derived from a real case study.

1 INTRODUCTION

The push towards a more rational and sustainable use of primary energy resources is increasing worldwide and many countries and organization take concrete actions and commitments in addressing such challenges, e.g. (European Commission, 2012), (BNEF, 2017). Among those actions, a common commitment is to adopt higher shares of renewable energy generation technologies into the energy mix to satisfy the users demand for energy and/or other commodities. Moreover, several studies as (European Commision, 2017) and (ISE, 2015) predict in the near future a strong reduction of the purchase cost of such technologies that would induces a dramatic change, with relative challenges, in existing energy distribution infrastructures. Most of renewable energy generation technologies are in-fact characterized by an intermittent and non-dispatchable electric generation capacity, making the integration with current national and local distribution grids challenging (California ISO, 2012).

A possible solution lies in regional large centralized energy storage systems, such as pumped hydro, compressed air and large battery storage systems. Such approach has been followed both in many studies and actual projects (Jülch, 2016). Another emerging approach to address such challenging integration resides in decentralization with the aid of microgrids (Speer et al., 2015). While microgrids are already a well established solution to accommodate the needs of rural off-grid communities, their deployment in already urbanized contexts of developed countries is also gaining attention from researchers (Enea, 2017), (Center for Climate and Energy Solutions, 2017).

The basic idea behind microgrids is strictly related to electric energy management, but their potential to handle and optimize the employment of renewables and primary energy resources greatly improves in multi-energy systems (MES), that is systems in which multiple energy vectors (i.e., carriers of energy as electricity) are concurrently considered (Mancarella, 2014). To capture the potential opportunities for efficient energy use (polygeneration, (Jana et al., 2017)), MES models have to explicitly consider the interactions across different energy vectors, in accordance with the real scenario under analysis, e.g. a comprehensive assessment of users demanded commodities such as heat, cooling and electric energy. In order to exploit all the potential energy savings opportunities, such cross vector interactions have to be taken into account since the design phase of both new energy systems and the retrofit of already exist-

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ing settings. Thus, MES models must preferably be adapted to represent such opportunities and have a correct assessment of what high integration of renewables might imply.

In this paper a mixed integer linear programming (MILP) formulation is proposed to model the design of MES, where the optimal investment choices are performed by evaluating also the required commodities from the exogenous energy networks. Specifically, the formulation aim at minimizing the set-up, maintenance and procurement costs by taking into account all the operational constraints, i.e., the scheduling of the operation performed by the available technologies in order to convert energy vectors. Due to the inner complexity of the addressed problem and the size of the mathematical programming formulation, a matheuristic scheme based on fixing integer variables and relaxing constraints is designed to produce good sub-optimal solutions in a reasonable amount of time. To the best of our knowledge such scheme has only been applied by (Triadó-Aymerich et al., 2016) for energy systems related problems, where the optimal design for a rural electrical microgrid is evaluated using different heuristic approaches, among which a fix-and-relax strategy. In the last few years the optimal design and operation management of distributed MES has been addressed by means of several methods (Singh and Sharma, 2017). The problem has been formalized with both single or multi-objective functions, and solved by techniques that can be mainly classified into single monolithic and decomposition approaches. With respect to the former, (Mehleri et al., 2012) and (Omu et al., 2013) exploit MILP formulations to compute the optimal design of a small district needing electricity and heat; the same is done in (Bischi et al., 2014) where the demand of cooling power is also considered. For the latter, decomposition approaches rely on keeping the planning phase, that is the decision to purchase and deploy, separated by the operational phase. In (Elsido et al., 2017) a mixed integer non linear programming (MINLP) formulation is presented and solved by a two phases approach, where the first is handled by means of two evolutionary algorithms and a discrete variable relaxation technique, while the second is solved by exploiting a linearized MILP. In (Li et al., 2017) the design of an hydrogen based microgrid is performed by using a genetic algorithm to determine the size of the systems, while the operational variables are set by solving a MILP. A similar technique is described in (Sachs and Sawodny, 2016), where the same framework is applied for a multi-objective variant of the problem.

The rest of the paper is structured as follows: in Section 2 the approach to the energy hub and technologies modeling is described, in Section 3 the problem is formalized and the mathematical model is presented. Section 4 describes the matheuristic used; in Section 5 preliminary computational results are presented, based on both randomly generated instances and a real case study. Finally in Section 6 conclusions and future perspectives are presented.

2 ENERGY HUB AND TECHNOLOGY MODELLING

In this section the concept of energy hub and the specific setting related to the case study in §5.2 are described. Furthermore, the technologies that are considered within the energy hub and their general function are depicted.

2.1 The Energy Hub

Among the suitable tools for the management of MES, a relevant option can be found in energy hub (Mohammadi et al., 2017). An energy hub can be thought as an integrated unit within which the conversion and storage of different energy carriers is undertaken in order to satisfy different commodities demanded by an user. The energy hub can get some of such energy vectors from outside of its boundaries, as for example the withdrawal of electric energy or natural gas from the respective national energy distribution infrastructures. Then, within the boundaries of the energy hub such vectors can be transformed in order to meet the demand of users, this provided that the technology needed to operate the conversion is installed. Such technologies can either be already available or be deployed within the energy hub by sustaining the relative purchase and maintenance cost. Thus, the choices regarding which kind of technologies to deploy within an energy hub have to be assessed by considering both the monetary investment needed to purchase such technologies and how such systems will work, providing the needs of the community of users tied to the energy hub.

Energy hub is then a general scheme that can be adapted to various settings and the case study presented in §5.2 reflects the structure presented in Figure 1. It serves a community consisting in buildings of the tertiary sector, which will need to properly function electric energy, space heating for the winter and cooling for the summer. It has access to both the natural gas network and the national electric energy grid; also has access to a solar resource to be used to power the district.

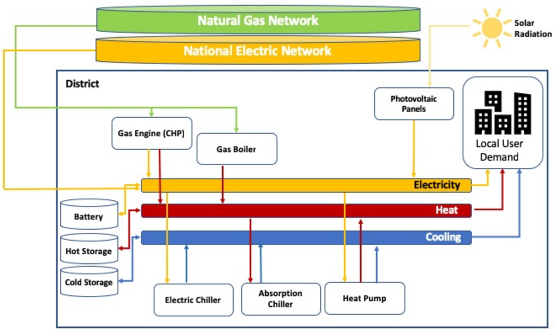


Figure 1: Proposed energy hub model.

2.2 Technologies Modeling

The technologies deployed in the energy hub convert energy among the different vectors, or store it for a later use. The technologies considered in this study include the majority of the most mature ones available on the market for small urban districts. These can be listed as:

- **Natural Gas Engine** (CHP): operates in combined heat and power (CHP) mode, thus producing electricity and simultaneously recovering the waste heat, using natural gas as fuel;
- **Natural Gas Boiler** (GB): production of heat from natural gas;
- **Electric Chiller** (EC): conversion of electric energy in cooling power;
- **Absorption Chiller** (AC): conversion of heat in cooling energy;
- **Heat Pumps** (HP): allows the conversion of electric energy into (alternatively) cooling energy or heat, based on the required output;
- **Photovoltaic Panels** (PV): production of electric energy from solar radiation;
- **Batteries** (EES): storage of electricity;
- **Hot Thermal Storage** ($HTES$): storage of heat;
- **Cold Thermal Storage** ($CTES$): storage of cooling energy.

A small database of purchasable devices is considered for each of such technologies, distinguished by size. Then for each particular model, parameters representing costs and performance are specified. The performance of conversion devices is described by the energy conversion efficiency for each available size, whereas the relevant parameters for the storage devices are the efficiency of both charge and discharge phases. Besides, conversion devices are enforced to work above a fixed threshold value for a certain timespan, this to represent a lower bound of partialisation (i.e., the minimum output power) for the technology. The only exception concerns the photovoltaic panels, whose produced electric energy is directly dependent by the total panel surface and the solar exposition. Hence, in absence of solar radiation the output of the photovoltaic can be zero.

Regarding the cost, each model of technology is characterised by its own purchase cost related to its size and performance. Such cost has to be sustained in order to make use of the technology for a representative lifetime in years, after which the purchase cost has to be re-sustained. Moreover, additional costs related to the maintenance operations are considered. In this way, all of the costs related to purchasing and operating phases of a certain technology are taken into account. Finally, further costs sustained within the energy hub are given by the possible withdrawal of energy from the two national infrastructures. The withdrawal is priced with a fixed cost per kWh of purchased energy, different for natural gas and electricity.

3 PROBLEM DEFINITION AND MATHEMATICAL FORMULATION

The problem can be summarized as follow: an energy district has to be designed and managed (by selecting an equipment of technologies and by controlling the relative operations) in order to satisfy the demand of different energy vectors (commodities). Decisions have to be performed such that the total costs sustained by the energy district within a certain time horizon are minimized, both in the planning and operational phases. We assume that the time horizon is cyclically repeated to describe the optimal dynamic of a fully operational energy district, satisfying requests that (hopefully) follow periodical patterns.

Let K be the set of commodities, with a fixed unit purchasing and storing price, that is respectively c_k and h_k. Then, let us define Q as the set of technology models that can be deployed in the district, e.g. heat pump 170kW or electric chiller 120kW. Moreover, let $S \subseteq Q$ be the subset of all the storage systems and $S^k \subseteq S$ that of models that store the commodity k. Parameters v_i are defined for each $i \in Q$, stating the costs for buying, installing and maintaining the i-th appliance type. This cost is normalized along the considered period: indeed, the approximated profile of the demand of each commodity is reported for a discrete time horizon $T = \{1, \dots, \tilde{T}\}$ with intervals of one hour; namely d_t^k is the demand of the commodity $k \in K$ at time $t \in T$.

Therefore, the matrix $\mathbf{v}$ is normalized in this way: given the purchasing and installing cost (IC), maintenance cost per year (MCY) and estimated lifetime (expressed in year and hours respectively as ELY and ELH), each element of $\mathbf{v}$ is defined by:

$$v_i = \frac{IC_i + MCY_i \times ELY_i}{ELH_i} \times \tilde{T}$$

Although fixed costs should be fully sustained in the same moment, the definition of v_i includes only the portions of hourly costs related to the considered time horizon T. Hence, the ratio between fixed and variables costs (e.g. c_k) is contained, while the objective function weights the total cost associated to the life cycle of each device.

As previously mentioned, each device can require and supply different types of commodity, according to his features. For example a Gas Engine uses gas and can supply heat or electricity, whereas an Electric Chiller needs electricity to work and supply cool. A parameter ω_i^{hk} is then defined only for conversion technology $i \in Q \setminus S$, expressing the unitary conversion multiplier to convert commodity h into commodity k by means of appliance i. Some devices, such as solar panels or wind farms, have a base production that exploits renewable resources and are dependent by weather conditions at a certain time. Thus, parameter b_{it}^k states the base production for commodity $k \in K$ produced by the equipment $i \in Q \setminus S$ at time t. The amount of output k produced by the conversion device i at each time t ranges within the maximum rated power U_i^k and the lower bound L_i^k.
Regarding the storage technologies, each device $i \in S^k$ is able to collect commodity k up to a fixed capacity C_i^k, with a common efficiency ϕ_k.
We define non-negative variables $\mathbf{r}$ and $\mathbf{p}$ to model the flow of commodities converted by conversion devices: at each time instant t, variable $r_{it}^{hk} \in \mathbb{R}^+$ expresses the amount of commodity h converted into commodity k by device $i \in Q \setminus S$; on the other hand, variable $p_{it}^k \in \mathbb{R}^+$ models the output commodity k resulting by the conversion operation related to r_{it}^{hk} and alternative base productions b_{it}^k (e.g. solar energy). Furthermore, for each $k \in K$ and $t \in T$ we define variables l_t^k and f_t^k, to describe for the time t respectively the total amount of commodity k stored within the district, and the quantity of k acquired by the exogenous supplier. By assuming that each technology has an estimated lifetime much larger than $\tilde{T}$, we can use binary variables $y_i \; \forall i \in Q$ to model the selection of devices, i.e. $y_i = 1$ if and only if the district is provided with equipment i since the beginning of T. Finally, for conversion technologies $i \in Q \setminus S$ and for each $t \in T$, variables $z_{it} \in \{0,1\}$ are further employed to describe the operation of device i at time t through $z_{it} = 1$.

The proposed MILP formulation reads as follow:

$$\min \sum_{t\in T}\sum_{k\in K}(c_k f_t^k + h_k l_t^k) + \sum_{i\in Q} v_i y_i \tag{1}$$

$$d_t^k + l_t^k + \sum_{i\in Q\setminus S}\sum_{\substack{h\in K:\\ h\neq k}} r_{it}^{hk} = \phi_k l_{t-1}^k + \sum_{i\in Q\setminus S} p_{it}^k + f_t^k \quad \forall k\in K, \forall t\in T \tag{2}$$

$$p_{it}^k = \sum_{\substack{h\in K:\\ h\neq k}} \omega_i^{hk} r_{it}^{hk} + b_{it}^k y_i \quad \forall i\in Q\setminus S, \forall k\in K, \forall t\in T \tag{3}$$

$$L_i^k z_{it} \le p_{it}^k \le U_i^k z_{it} \quad \forall i\in Q\setminus S, \forall k\in K, \forall t\in T \tag{4}$$

$$\sum_{t\in T} z_{it} \le |T| y_i \quad \forall i\in Q\setminus S \tag{5}$$

$$l_t^k \le \sum_{i\in S^k} y_i C_i^k \quad \forall k\in K, t\in T \tag{6}$$

$$l_0^k = l_{\tilde{T}}^k \quad \forall k\in K \tag{7}$$

$$l_t^k, f_t^k \ge 0 \quad \forall k\in K, \forall t\in T \tag{8}$$

$$p_{it}^k \ge 0 \quad \forall i\in Q\setminus S, \forall k\in K, \forall t\in T \tag{9}$$

$$r_{it}^{hk} \ge 0 \quad \forall i\in Q\setminus S, \forall h,k\in K : h\neq k, \forall t\in T \tag{10}$$

$$y_i \in \{0,1\} \quad \forall i\in Q \tag{11}$$

$$z_{it} \in \{0,1\} \quad \forall i\in Q\setminus S, \forall t\in T \tag{12}$$

The objective function (1) aims to minimize the total cost given by the cost related to deployed technologies, the cost of acquiring external commodities from public suppliers and the expense for storing surpluses for further use. Constraints (2) are stock-balancing constraints and state that the commodity k demanded, stored and required by devices is equal to the summation among the previously amount of commodity k stored at time $t-1$, the total one produced by all deployed technologies and the quantity acquired from external networks. The set of constraints (3) defines the variables $\mathbf{p}$, for each conversion technology $i \in Q \setminus S$, as the summation between the required commodity h necessary to produce commodity k and a base production without consumption. This is due to the feature of green technologies, such as photovoltaic and wind farm, to produce commodities without consuming other resources. The bounds of variables $\mathbf{p}$ are given by the set of constraints (4): if binary variable z_{it} is equal to 1, the corresponding variable p_{it}^k is limited between values L_i^k and U_i^k. The link among variables $\mathbf{z}$ and $\mathbf{y}$ is coherently modelled by the set of constraints (5). Constraints (6) limit the stored quantity of commodity $k \in K$ at any time $t \in T$ to the total sum of capacities of the storage systems in S^k installed. In order to translate the cyclicality of the selected time horizon, the quantities of commodities stored in the first timestep ($t = 1$) are balanced in (2) with the quantities stored in the last timestep ($t = \tilde{T}$) by means of equality (7). It is worth noting that whenever an appliance i is not able to convert a certain commodity h into k, the corresponding parameter ω_i^{hk} is null. In all such cases, $\forall t \in T$ variables r_{it}^{hk} are fixed to zero as a preprocessing phase. Moreover, $\forall t \in T$ variables f_t^k are set equal to zero for any commodity $k \in K$ that is not purchasable by external suppliers.

4 MATHEURISTIC APPROACH

Computational experiments showed that the mathematical formulation proposed in §3 cannot be exploited to solve real-size instances in a reasonable amount of time by means of standard solvers. This can be (partially) related to the size of the formulation, as the number of constraints is $O(|Q||K||T|)$ and the number of binary variable is $O(|Q||T|)$, whereas continuous variables are $O(|Q||K|^2|T|)$. Therefore, we design a matheuristic algorithm to approach instances that are meaningful in real context.

The matheuristic used to solve the proposed MILP is based on relaxing integrality constraints and fixing subsets of variables, similarly to the *Fix & Relax* scheme formalized in (Escudero and Salmeron, 2005). Starting with the linear relaxation of the mathematical formulation, the idea is to restrict it by restoring the integrality conditions only for a subset of the original integer variables. Then, the restricted linear relaxation is solved and the integer variables are fixed to their values in the resulting solution; hence, the number of variables is reduced and the space of research shrunk. This process is iterated until a feasible integer solution for the original problem is found.

A common challenge for this kind of approach is to find an equilibrium between the algorithm efficiency and quality of the solution. Indeed, while the former usually requires to proceed by small subset of variables, the latter could be compromised by such scheme as the first steps can bring the current solution far from the optimum. Moreover, a robust strategy is one that can avoid the convergence to an unfeasible solution, or is able to efficiently backtrack whenever this occurs.

The matheuristic approach is actually a customization of the *Fix & Relax* scheme for the energy district design and management problem, obtained by specifying the strategy of selection and fixing of the subset of variables. In particular, the subsets of binary variables are obtained by separating the corresponding technologies for their capacity of converting or storing commodities. Indeed, each technology rarely produce (store) more than one commodity, thus creating a natural separation between the relative variables. Moreover, as detailed below the fixing policy is defined to allow a certain grade of flexibility to the matheuristic and to reduce the possibility of reaching unfeasible states.

The scheme can be summarized as follow. Let us consider the mathematical formulation proposed in §3 as $\mathcal{M}$. Let V_y and V_z be the sets of variables in $\mathcal{M}$ for which the binary condition holds, related respectively to $\mathbf{y}$ and $\mathbf{z}$. In a similar way, let us define V_y^r and V_z^r as the subsets of variables whose integrality is relaxed in $\mathcal{M}$. Finally, let K_r be an auxiliary set initialized as K and collecting all the commodities.

The algorithm starts by considering the linear relaxation of $\mathcal{M}$, that is $V_y = \emptyset$ and $V_z = \emptyset$. Firstly, the demands and costs for acquiring external resources are used to define a priority among the commodities $k \in K$. Specifically, at each iteration the commodity $s \in K_r$ is selected accordingly to the following rule:

$$s = \underset{k \in K_r, t \in T}{\operatorname{argmax}} \{d_t^k / c_k\} \tag{13}$$

That is, the commodity chosen is that one with the largest cost required to satisfy its own demand peak through the external supply. Commodity s is then removed from K_r and the integrality is restored for the variables $y_i \in V_y^r$ modeling appliances able to convert (store) the commodity s. In other words, for all the conversion technologies $i \in Q \setminus S$ such that exists $\omega_i^{hs} > 0$, with $h \in K : h \neq s$, the binary condition for y_i is restored, that is y_i is removed from V_y^r and added to V_y; the same is done for the storage systems $i \in S$ with positive C_i^s. Formulation $\mathcal{M}$ is then solved and for each variable y_i just added to V_y, its value is fixed to one if and only if $y_i = 1$ in the resulting solution. Furthermore, only for conversion devices $i \in Q \setminus S$, the value of y_i is set equal to zero if $y_i = 0$ currently holds. By excluding the variables related to the storage devices, the flexibility of the current solution is partially preserved. In fact, if in a later iteration related to $h \neq s$ the requests r_{it}^{sh} increase due to deployment of different appliances, then storage devices of s are still valid options to avoid the increment of f_t^s. For each y_i currently fixed to 1, all the corresponding z_{it} in V_z^r are fixed to one if $z_{it} > 1 - \varepsilon$ (with ε reasonably small), and moved from V_z^r to V_z. This process is iterated until K_r is empty.

Afterwards, the integrality for all the variables left in V_y^r and V_z^r is restored and all the subsets are coherently updated. In order to reduce the number of binary variables in V_z, a further fixing step is performed. For each $i \in Q$ and $t \in T$, let $\bar{z}_{it}$ be the values of variables z_{it} obtained in the last solution. Each $\bar{z}_{it}$ is compared with a threshold $\theta \in [0,1]$ and fixed to one if $\bar{z}_{it} \geq \theta$, then $\mathcal{M}$ is solved. If the current state is unfeasible, θ is incremented by a small step α and all the z_{it} for which $\bar{z}_{it} < \theta$ are unfixed; then $\mathcal{M}$ is solved again. This is done until $\mathcal{M}$ is feasible or it results unfeasible for $\theta = 1$, case in which the algorithm ends with an unfeasible state. Although possible, during computational experiments no unfeasibility state has been reached and a feasible integer solution is achieved for the starting value of θ. It is worth noting that for each commodity $k \in K$ that is not purchasable by an external supplier, $c_k = \infty$ is assumed to preserve the consistency within (13). Moreover, selecting those commodities in later steps help to prevent unfeasibility, as variables f_t^k are enforced to be zero and cannot balance the possible increment of requests r_{it}^{kh}, due to the selection of device i in further steps of the algorithm.

5 PRELIMINARY EXPERIMENTS

The code was implemented in AMPL v.20180308 (MS VC++ 10.0, 64-bit) and experiments were performed on a Intel® Core i7-7500U 2.90 GHz with 16Gb RAM. All the MILP were solved by IBM® CPLEX® 12.8.0.0.

The matheuristic performance were tested on two instances derived from a real case study and five randomly generated instances, all based on the energy hub scheme depicted in §2: 4 energy vectors uniformly measured in kWh are taken into account, and a database of 37 conversion appliances and 18 storage devices are considered. For conversion technologies, the lower bound of partialisation is set equal to 30% of the maximum rated power. Parameters were set to $\varepsilon = 0.1$, $\theta = 0.7$ and $\alpha = 0.1$.

5.1 Random Instances

The five random instances were generated by considering a time horizon T of 48 time steps, simulating the requests of commodities within a period of two days. The values of demands were randomly chosen within [0, 250] kWh for each time unit $t \in T$, whereas solar radiation was derived by a real profile.

Table 1 shows the results obtained by the matheuristic ($\mathcal{H}$) with respect to the optimal solution provided by CPLEX after exactly solving the MILP formulation ($\mathcal{M}$). In all the instances the percentage optimality gap is smaller then 1%, with an average value of 0.65%; then the CPU time required by $\mathcal{H}$ is reasonable and exceeds two minutes only in one case, while being widely smaller than directly solving $\mathcal{M}$ on the mean.

Table 1: Solutions for random instances.

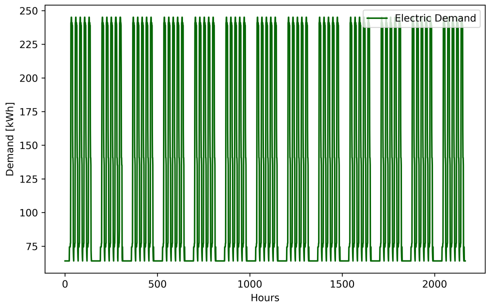
Instance	gap%	$CPU_{\mathcal{H}}$	$CPU_{\mathcal{M}}$
d_1	0.93	62.22	807.48
d_2	0.79	128.46	1592.91
d_3	0.36	83.45	1052.86
d_4	0.82	18.60	1481.12
d_5	0.37	65.42	2017.73
Average	0.65	71.63	1390.42

5.2 Case Study: Tertiary Urban District

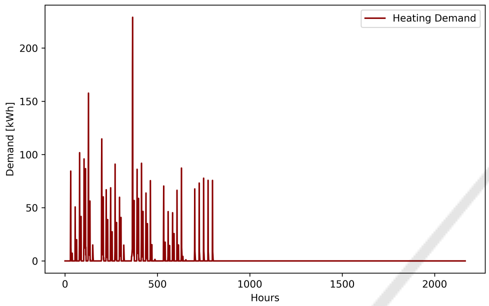
In order to validate the proposed method, the data describing the needs of an existing urban district is used to derive realistic instances. Simulated data based on building energy consumption models is used to obtain the demands of a district composed of tertiary use buildings, specifically ten offices and a school. Demands are distinguished in three commodities: electricity, space heating and cooling. The user demands are computed as if the buildings were situated in Italy, specifically in Rome, for a timespan of one year with a resolution of one hour. The building models are prototypes developed by the U.S. Department of Energy (U.S. Department of Energy, a) which are then simulated by means of the software Energy Plus (U.S. Department of Energy, b). The solar radiation is also given as an input by referring to an average year obtained from historical data. While the withdrawal of electric energy or natural gas from the respective national infrastructures comes with no limit in terms of maximum capacity, this is not the same of the radiation resource. The availability of this resource is then represented by realistic data with the same hourly resolution as for the commodities demanded.

5.3 Realistic Instances

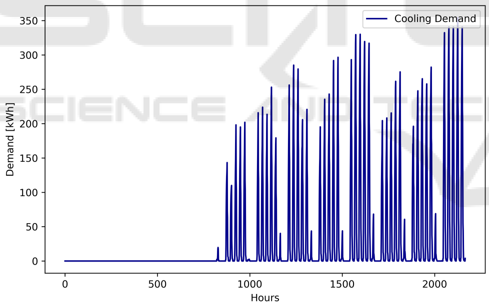
Given the scenario depicted as case study, two realistic instances are derived. The former instance r_1 counts 2160 hour as time horizon of simulated demands, corresponding to three months of data that cross the first two quarter of the year and have requirements linked to both the winter and summer period. The detail of the simulated demands is shown in kWh in Figure 2; the availability of the solar resource for a surface with an inclination of 30° in kW/m^2 is shown in Figure 3. The latter instance r_2 is based on the yearly demands aggregated within a daily resolution, so that the time horizon is translated into 365 days. This is done in order to keep manageable the size of the MILP, while obtaining a reasonable coarse-grained description of the urban district annual behaviour. To preserve the coherence, all technical parameters of systems are scaled within r_2. While solving r_1 and r_2, the relative optimality gap tolerance of CPLEX was set to 2%.



(a) Electric demand



(b) Heating demand



(c) Cooling demand

Figure 2: Three-month energy demands of the district.

Table 2 summarizes the results obtained by the matheuristic. For the two instances, the total cost Ω and the CPU time (in seconds) are reported; moreover, column $\overline{gap}\%$ reports the percentage gap obtained by comparing the heuristic integer solution with the lower bound resulting by the solution of the MILP in the first step of $\mathcal{H}$; that is the linear relaxation of M restricted only by the integrality of the variables y_i related to the technologies that convert (store) the first selected commodity. In Table 3 the list of appliances deployed in each solutions is reported, with subscripts specifying the maximum rated power of the models (or rated capacity, in case of storage devices). The matheuristic was able to achieve an integer solution for the instance r_1 in a CPU time of 5804.09 seconds. This solution has a total cost of 22185€, with a $\overline{gap}\%$ of 12.90%. For the instance r_2 the heuristic solution has total cost of 74356€found in 432.18 seconds, with a $\overline{gap}\%$ of 11.51%. Given the dimension of the instances and the size of the MILP on which the matheuristic is based (e.g., only the binary variables in instance r_1 are 79975), the time required to solve the problem is reasonable and the values of $\overline{gap}\%$ obtained testify that the maximum distance from the true optimal solution is not excessive.

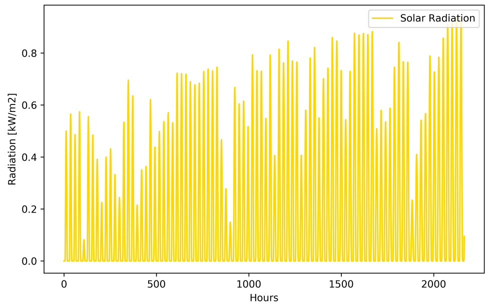


Figure 3: Three-month solar radiation.

Table 2: Solutions for realistic instances.

Instance	Ω	$\overline{gap}\%$	$CPU_{\mathcal{H}}$
r_1	22185	12.90	5804.09
r_2	74356	11.51	432.18

Table 3: Selected devices of realistic instance solutions.

Instance	Devices
r_1	$CHP_{140}, EC_{39}, EC_{52}, EC_{70}, EC_{120}, EC_{160}, HP_{160}, HP_{240}, PV_{2000}$ $HTES_{1000}, CTES_{500}, CTES_{1000}$
r_2	$CHP_{140}, EC_{39}, EC_{70}, AC_{83}, HP_{160}, HP_{240}, PV_{500}, PV_{2000}$ $HTES_{500}, CTES_{500}$

6 CONCLUSION AND FUTURE STEPS

In this paper a MILP formulation is described for the optimal design of energy hubs, aimed at modeling the energy systems of modern urban districts. The proposed model wishes to represent the possible interactions among different energy vectors, with the goal of meeting the multiple commodity demands of users. However, due to the size of the formulation, it is possible to directly exploit the MILP only to solve small instances. In order to efficiently solve instances of more relevant dimension, a matheuristic scheme relying on the MILP has been designed. The strategy behind the matheuristic is based on fixing the values of subsets of binary variables while other integrality constraints are relaxed, iteratively moving up to a feasible integer solution. Preliminary experiments on a restricted group of instances show that the matheuristic is able to solve instances with limited time horizon in restricted time, providing a solution with strict optimality gap. Moreover, two instances derived from real case scenario were solved in reasonable time with a limited gap from the best lower bound.

The matheuristic presented in this paper can be seen as a first promising step in approaching a challenging problem as the management of MES, with a strategy that can be customized in different ways. Indeed, elements of a MILP can be divided into subblocks following several criteria. Further work will be dedicated to refine the proposed framework based on variable separation and fixing, whereas alternative methodology (e.g., the decomposition into linked subblocks of constraints) will be explored. Concerning the formulation, future efforts could aim to include a more accurate modeling of the technology function, as for example switching from a performance based on a single constant efficiency value to a piecewise linear efficiency-load curve. Finally, the problem could be further extended by considering the existence of multiple separated districts, thus evaluating the deployment of technologies for connecting different districts and modeling the energy exchange.

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