Multi-Carrier Energy Systems: Optimization Model based on Real Data and Application to a Case Study

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Abstract

Multi-carrier energy systems are increasingly used for a number of applications, among which the supply of electricity, heating and cooling in buildings. The possibility of switching between different energy sources is a crucial advantage for the optimal fulfillment of the energy demand. The flexibility of these systems can benefit from the integration with smart grids, which have strong variations in time during their operation. The energy price is the parameter that is usually considered, but also the primary energy factor and the greenhouse gases emissions need to be accounted. This paper presents an example of application of an optimization method for the operation of a multi-carrier energy system, based on real data-driven model and applied to different countries. The generation plant of a hospital is considered as case study, coping with multiple energy needs by relying on different conversion technologies. The optimal operation of the system shows a wide range of variability, depending on the chosen objective function, the hour of the day, the season, the country. The results are affected mostly by the energy mix of the electricity supplied from the power grid, which has a direct influence on the primary energy consumption and the greenhouse gases emissions, and an indirect influence on the electricity prices.

Keywords: Energy conversion, Optimization model, Operation, CHP, Data analysis

1. Introduction

The whole energy sector is dealing with an important transition: many countries are promoting policies related to the energy efficiency, the use of renewable energy sources (RES) and the reduction of greenhouse gases (GHG) emissions. In this framework, energy consumption and production are facing consistent variations in economic, energetic and environmental parameters. In particular, a higher penetration of non-programmable RES in power networks and other energy systems (e.g. district heating networks) calls for the need of a complex matching of demand and supply.

The increase of electricity production from non-programmable RES has led to strong oscillations in the hourly production mix, and consequently consistent variations of the electricity stock prices. The possibility for RES power plants to produce at zero marginal costs has lowered the average prices, but the impacts on price volatility is still unclear [1, 2]. However, the high penetration of RES in electricity markets is currently leading to variable energy mixes throughout the day and the year. The energy mix has also a strong influence on the primary energy factor of the electricity (i.e. the primary energy consumed for the electricity production) and its specific GHG emissions.

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The natural gas sector is following a similar behaviour, with natural gas being more and more traded at gas hubs rather than with long-term contracts. The variation of natural gas prices appears to be no more related to oil price, but rather to market competition and in some cases also to the electricity market [3]. The high variability of electricity and gas prices is currently limited to the energy markets, as final consumers are usually paying a rather constant price. The unexpected variations of most final prices are generally limited to monthly variations. However, some larger consumers are already facing strong energy price variations, such as district heating (DH) networks operators and large industries or commercial/tertiary sector buildings. The availability of multiple energy conversion technologies in the same site (eg. natural gas boilers, heat pumps, CHP, etc) leads to multi-carrier energy systems [4], where consumers can choose to switch among different energy supply systems based on the optimal conditions, e.g. cost of gas and electricity. Optimization tools are now being applied by some district heating utilities in order to balance the variations caused by RES [5]. However, increasing prices variations could lead other consumers to use optimization tools to optimize their energy supply (e.g. industries, large commercial buildings, hospitals). These users are generally dealing with multiple energy vectors (e.g. electricity, heating and cooling at different temperature levels), while DH systems are generally limited to heating and, in some cases, cooling. Complex systems need to be able to optimize their whole energy supply, including all the different energy carriers they require.

The optimization of the energy supply can be based on day-ahead market forecasts and consumption plans, but it needs to be able to switch to real operation conditions, especially concerning demand fluctuations. Thus, any optimization tool needs to be connected to real-time data on market prices in order to perform the best choice in any given condition. Moreover, if the objective function includes primary energy or environmental goals, additional information on the electricity mix is necessary. These data are already available in different countries at national level, while information at local level could be probably obtainable in the future.

Multi-carrier energy systems have been thoroughly considered in the last decade in the literature, focusing on multiple scales and with different perspectives [6, 7]. Their applications to the energy demand of buildings have been investigated by several authors [8, 9]. Multi-carrier energy systems have a fundamental importance for the development of smart grids [10], as they become energy hubs where the optimal dispatch strategy needs to be implemented [11]. While electricity grids are traditionally considered, also other networks such as district heating systems can be of interest [12, 13]. Moreover, these optimization models may need to take into account also other aspects such as demand side management [14, 15] and integration with variable RES [16, 17]. The possibility of exploiting multiple resources is a key aspect in increasing the reliability of the supply system [18], thanks to their flexibility and the available redundancy. The widespread diffusion of multi-carrier energy systems is strictly related to the development of interconnected smart grids. Shariatkhah et al. [19] point out the importance of considering the dynamic behaviour of the thermal loads rather than using constant approximations. Many authors propose different models for optimizing the multi-carrier energy hubs, and some of theme propose advanced algorithms for solving highly non-linear problems (e.g. by using Evolutionary Algorithms [20, 21], Dynamic MOPSO Algorithm [22], Genetic Algorithm [23] or Gravitational Search Algorithms [24]). All the works agree on the importance of an integrated optimization of hybrid systems, which allows increasing the economic and energetic performance of the each system.

However, few papers focus on the relationship between multi-carrier energy systems and the current high variability of the energy networks operation conditions. While multiple methodologies provide precise optimization results, a real multi-carrier energy system would need to address the problem of facing strongly variable conditions in the parameters used by the optimization functions. These variations are both time-based (with seasonal and daily cycles) and space-based (with relevant differences among countries and regions).

The main purpose of this study is to investigate the optimal conditions of a multi-carrier energy system through real data. A decision tool is proposed, that is able to perform a global nonlinear optimization of a multi-carrier energy system, by considering multiple energy needs and calculating the optimal system configuration with the given generation units. The peculiarity of the model is its integration with variable parameters throughout the year: while variable energy needs are widely addressed in the literature, other aspects are usually considered as constant, or with limited variability (i.e. energy price, primary energy factors, emission factors). However, the variable conditions of the external networks may have an impact on the optimal solution as high as the one of the variable energy needs of the users.

For this reason, the optimization model has been applied to a complete year with an hourly time step, and it takes as input real values of energy prices and electricity generation mixes in different EU countries.

2. Methodology

2.1. Optimization model

The optimization algorithm presented in this paper has been developed in R, an open source programming language and software environment for statistical computing [25]. One of the main advantages of this choice has been the opportunity of dealing with all the tasks required by the simulation, including the data acquisition, cleaning and elaboration. The model performs a nonlinear optimization with constraints, by using an Augmented Lagrangian Minimization Algorithm for optimizing smooth nonlinear objective functions [26].

The optimization algorithm is based on an energy balance of the conversion plant, where m units are producing or consuming n different energy carriers (see equation 2, or equation 1 in compact form).

$$\overline{E_s} = A\overline{L} + \overline{E_d} \tag{1}$$

$$\begin{bmatrix} E_{s,1} \\ E_{s,2} \\ \vdots \\ E_{s,n} \end{bmatrix} = \begin{bmatrix} -a_{1,1} & -a_{1,2} & \cdots & -a_{1,m} \\ -a_{2,1} & -a_{2,2} & \cdots & -a_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ -a_{n,1} & -a_{n,2} & \cdots & -a_{n,m} \end{bmatrix} \begin{bmatrix} L_1 \\ L_2 \\ \vdots \\ L_m \end{bmatrix} + \begin{bmatrix} E_{d,1} \\ E_{d,2} \\ \vdots \\ E_{d,n} \end{bmatrix} \tag{2}$$

The vector of Energy supply $\overline{E_s}$ is computed by the sum between the vector of final demand of the users $\overline{E_d}$ and the energy conversions resulting from the operation conditions of the energy plant. Each unit has a defined conversion factor $a_{i,j}$, which is positive if the energy is produced and negative if it is consumed. In a complex energy plant, with different units able to match the energy requirements of the users, the calculation of the loads factors $\overline{L}$ of the m units has multiple solutions.

The optimization algorithm is designed to find the solution that minimizes a specific objective function. Usually the functions of interest are including the minimization of the operation cost of the system, the maximization of the conversion efficiency or other aspects such as the share of renewable energy sources, the use of local resources or the limitation of greenhouse gases emissions. The objective functions considered in this study are described in paragraph 2.2.4.

The optimization tool needs to fulfill a number of constraints. The loads of each unit must be included in the range [0,1], and some additional limitations may be valid for some specific units, e.g. minimum operational load. Moreover, in the vector of Energy supply only some energy types can be positive, i.e. the energy that can be actually supplied to the system (in this case-study natural gas and electricity). A negative value means a form of energy exiting the system: it can be possible for excess electricity produced by an engine and supplied to the grid, or an excess heat that needs to be dissipated from units that have a simultaneous production of multiple carriers. In some cases additional limits can be set by regulation laws (such as the restriction on heat dissipation).

2.2. Case study

2.2.1. General description

The optimization model described in the previous section has been applied to a hospital as a case study. This choice has been performed in order to find an energy consumer able to match multiple criteria: (1) simultaneous need of multiple energy vectors; (2) high variability of energy loads caused by multiple parameters (season, hour, weekday, etc.); (3) user size that allows for a complex energy plant with different technologies and (4) common application with consumption patterns comparable to other users.

The hospital considered in this study has around 500 beds, and a gross surface of about 85,000 m^2. The hospital is located in northern Italy, in a site with 2,800 degree days. The annual energy demand of the building is around 9.3 GWh of electricity, 16 GWh of heating (including high-temperature and low-temperature water and steam) and 6.8 GWh of cooling. The analysis has been performed on a reference year, considering hourly energy consumption in different scenarios.

2.2.2. Consumption profiles

The energy consumption of the hospital considered in this paper is related to multiple energy carriers:

- Hot Water at 80°C for high-temperature heating;
- Warm Water at 45°C for low-temperature heating and air handlers re-heating;
- Steam for operating theater humidification;
- Chilled water for ambient cooling;
- Electricity for hospital appliances, lighting, offices, etc.

The energy consumptions considered above are not including the operation of the energy conversion units, which are computed by the optimization model.

The energy consumption profiles of the case study have been built by combining heating and cooling design simulations with available electricity profiles of a real hospital. The electricity load profile is quite related to business hours, as a number of rooms and offices are used only at specific times. Therefore, the occupation pattern has been used also to correct the heating and cooling profiles, especially by scaling holiday patterns due to lower actual energy consumption. Figure 1 presents an example of the energy demand of the building during one day of operation (the 15$^{\text{th}}$ January has been considered).

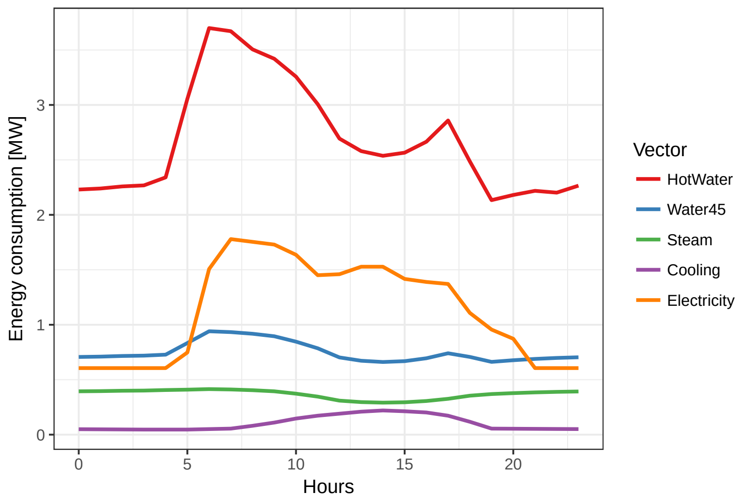

Figure 1: Example of energy consumption in winter (15th January)

The simulations presented in this paper consider four different countries (see paragraph 2.2.4). The energy profiles are related to a location in Northern Italy. Heating and cooling demand could have some variations considering locations in other countries, resulting in slightly different annual energy demand. However, varying the energy demand would not allow to analyse comparable results. Therefore, for the purpose of this paper, the same energy profiles have been applied to each scenario, neglecting the differences in weather conditions.

2.2.3. Energy plant layout

The energy plant layout of the case study is shown in Figure 2, while the main characteristics of the units are summarized in Table 1. In some cases multiple units with the same size have been installed, mainly for reasons related to backup in case of failures and higher efficiency at partial loads.

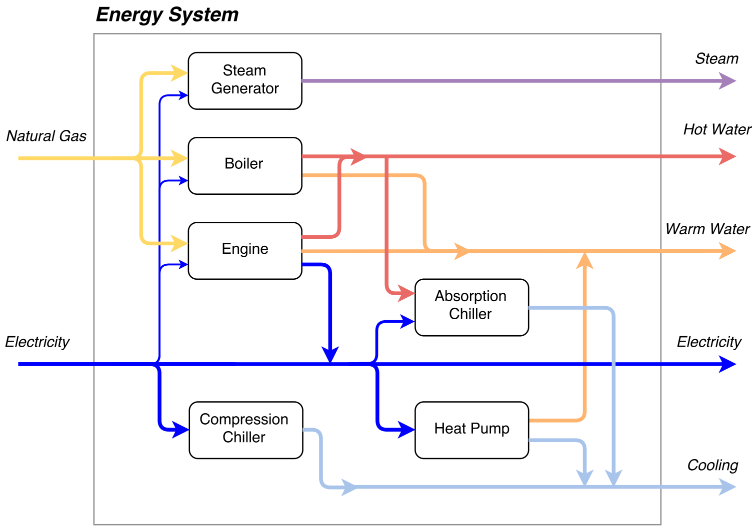

Figure 2: Layout of the Energy System

Table 1: Units input and output power at nominal load (inputs are shown as negative values)

	# of units	Output and input power for each unit [kW]					
		Water $80°C$	Water $45°C$	Steam	Cooling	Electricity	Natural Gas
Boiler	2	2,500	300			-10	-2,700
Steam generator	1			500		-4	-560
CHP Engine	2	920	60			760	-1,940
Compression chiller	2				2,500	-650	
Absorption chiller	1	1,840			1,200	-130	
Heat Pump	1		820		640	-180	

The nominal powers of the units have been chosen from commercial datasheets, and their sizing has been based on usual design parameters. Considering their operation, a lower limit has been set on 25% of nominal load for the absorption chiller and 50% for each engine. No limit has been considered for the other units, which are usually more flexible at partial loads. A heat exchanger for the production of warm water from hot water has been added to the simulation, in order to provide a backup possibility for matching warm water demand in some particular conditions.

The design parameters of each unit have been fixed, in order to focus on the comparison of different operation logics. However, the choice of different technologies and/or sizing can lead to an additional degree of freedom for the model, which has not been considered in this paper, mainly for computational time. A partial analysis on the design choices will be discussed in the results, based on the utilization factor of each unit.

2.2.4. Scenarios and objective functions

The optimization model has been applied to the case study by considering multiple scenarios, that have been defined by varying the external energy framework and the objective function.

As discussed above, the main indicators that have been considered for this study are the energy prices, the primary energy factors (PEF) and the specific CO_2 emissions. These parameters could have been varied in a continuous range in order to perform a number of sensitivity analyses. However, a more realistic approach has been chosen by considering actual data of four European countries: France, Germany, Italy and Sweden. These countries have been selected as representative of both different electricity mixes and price ratios between electricity and natural gas.

The objective functions reflect three different approaches, by minimizing:

- the operation cost of the energy plant;
- the primary energy needed to supply the building needs;
- the CO_2 emissions related to the energy consumption of the building.

The economic objective function aims to minimize the running cost of the system, as described in equation 3:

$$\mathcal{F}_{COST} = \bar{E}_s \cdot (\bar{E}_s > 0) \cdot \bar{C}_{BUY} - \bar{E}_s \cdot (\bar{E}_s < 0) \cdot \bar{C}_{SELL} + c_{O\&M} \tag{3}$$

with $\bar{C}_{BUY}$ being the vector of prices for energy supply cost and $\bar{C}_{SELL}$ the vector of prices for energy sold back to the grid (usually applied to electricity only). Moreover, $c_{O\&M}$ takes into account other non-neglectable running costs related to maintenance of some units (e.g. engines).

The second objective function aims at minimizing the primary energy associated with the energy supply, as described in equation 4:

$$\mathcal{F}_{PE} = \bar{E}_s \cdot \bar{P}_{PEF} \tag{4}$$

being $\bar{P}_{PEF}$ the vector of primary energy factors for each energy carrier supplied to the system. This factor is usually quite variable for electricity, being strongly related to the mix of generation sources and technologies. In some cases also other carriers can show variable factors over time (e.g. heat from a district heating with different generation units).

The third objective function has been built on CO_2 emissions related to the energy supply of the system, as described in equation 5:

$$\mathcal{F}_{CO2} = \bar{E}_s \cdot \bar{P}_{CO2} \tag{5}$$

being $\bar{P}_{CO2}$ the vector of emission factors for each energy carrier supplied to the system. The emissions show a similar behaviour to primary energy, but with significant differences in some particular technologies.

All these objective functions are optimized for each hour of operation of the system, in order to find the best operational layout matching the variability of the energy demand and on the conditions of the energy network supplying the system under analysis. Each objective function has been used to build a different scenario. These scenarios have been compared with a reference scenario, where only the standard technologies have been used, i.e. natural gas boilers and compression chillers.

2.2.5. Economic parameters

The main economic parameters that have been considered in this application are the natural gas and electricity prices. The only other cost that has been accounted is the O&M cost of the CHP units, which has been set to a fixed cost of 19.4 €/h per unit (calculated from real data), including the maintenance, lubricating oil and urea consumption for the SCR flue gases cleaning system.

The natural gas price has been taken from Eurostat Database [27], by considering the gas price for industrial consumers excluding VAT (first and second semester 2015).

The electricity price has been split into a variable part (energy cost) and a fixed part (taxes and levies). The variable part has been defined by considering the hourly spot prices of each country in 2015 (see Figure 3), while the constant part has been calculated by subtracting the average spot price from the average price reported in Eurostat Database [28]. The energy prices used in the study are reported in Table 2.

It can be observed that the selected countries show a wide range of prices, which are related to a number of causes. Italy has the highest electricity price and the lowest gas price, while Sweden shows the opposite situation. France and Germany lay in the middle.

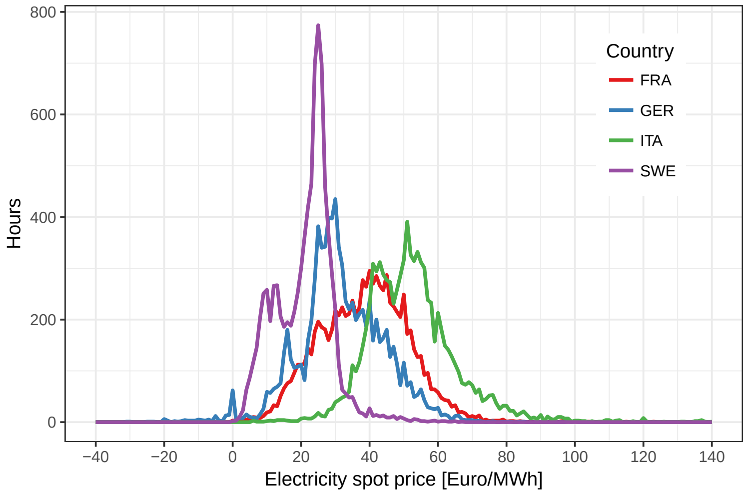

Figure 3: Spot prices of Electricity in 2015 for selected countries

Table 2: Natural gas and Electricity prices in the selected countries

Energy Prices [€/MWh]	2015-S1				2015-S2			
	FRA	GER	ITA	SWE	FRA	GER	ITA	SWE
Natural gas	37.7	39.5	35.4	44.9	36.7	37.7	31.9	41.8
Electricity	100.8	150.9	160.8	62.2	94.9	149.3	159.7	59.0
- of which variable part (mean)	38.8	30.2	49.8	24.3	38.2	33.0	54.7	18.1
- of which fixed part	62.0	120.7	111.0	37.9	56.7	116.3	105.0	40.9

2.2.6. Primary energy factors

There are different methodologies to calculate the primary energy factor of the electricity mix of a given country. Since there is currently no standard methodology, one of the possible approaches has been chosen and described below. The simulation model can however be applied also with the other approaches.

A primary energy factor has been calculated for each hour of operation, based on the specific energy mix available for that hour. An average conversion efficiency has been chosen depending on the type of primary energy:

- for thermoelectric plants, some standard efficiencies have been considered: 0.35 for coal-fired plants, 0.40 for oil-fired plants and 0.48 for natural gas-fired plants [29].
- the conversion efficiency for biomass source has been set to 0.30, since no detailed information is available about conversion technologies and kind of biomass (e.g. wood, biogas, bio fraction of wastes, etc.) [29];
- the conversion efficiency for geothermal has been set to 0.1, in accordance with [30];
- the efficiency of nuclear power stations has been set to 0.33 [29];

- all other RES technologies (i.e. hydro, wind and solar) have been considered with a 100% efficiency.

The use of average conversion efficiencies is an approximation, which is due to the unavailability of information on the real hourly conversion efficiencies of all the power plants in the network. In the future this information could eventually be available and will therefore be integrated into the model. Renewable primary energy has been included into the calculation, in order to assess the actual primary energy consumption. Other approaches may limit the analysis to fossil primary energy consumption. However, the author believes that energy efficiency and RES production should be considered separately: energy efficiency should be a specific target, regardless of the availability of RES.

The hourly data of electricity production by source that have been used for the calculations refer to the year 2015 [31, 32, 33, 34]. A more detailed approach would have required detailed data of actual conversion efficiencies of the power plants in operation in each country, but no complete data is currently available.

The primary energy factor for natural gas used directly at the site has been chosen equal to one, i.e. the transport consumptions have been neglected (in coherence with fuel consumption calculation in power plants).

2.2.7. CO_2 emissions

The CO_2 emissions have been calculated using the primary energy computed from hourly data and the IPCC2006 emission factors for stationary combustion [35]. According to the common approach, emissions from biomass plants have been neglected, due to their closed CO_2 emissions cycle. For municipal solid waste plants the renewable share has been set to 33%, thus neglecting a part of CO_2 emissions. The emission factor for the natural gas consumed at the case study site has the same value considered for power plants (equal to 56,100 $kgCO_2/TJ$).

In some countries this parameter provides similar results with the above-mentioned primary energy factor: RES have in general low energy factors and zero emissions, while in fossil plant natural gas is better than coal in both indicators. A notable exception is nuclear power: while having a low conversion efficiency it has no CO_2 emissions, thus making a difference in countries where it represents a significant share of the electricity mix.

3. Results

The results of the application of the model to the different scenarios are represented in Figures 4, 5 and 6. Each Figure shows one of the indicators that have been used for the scenarios definitions.

3.1. Specific Cost

From Figure 4 it is possible to observe the variability of the operation cost depending on the scenario and the country. The cost has been expressed as specific cost (with respect to the entire energy demand of the user), in order to provide results that can be compared with other situations. The average specific cost of the energy is in the range 40 - 80 €/MWh, and for each country any optimization scenario provides lower costs than the reference scenario. As expected, the lowest cost happens for the economic scenario, however, in the case of Sweden the Emissions scenario provides an identical result. The costs are generally higher for Italy and Germany, with Sweden showing the lowest cost, mainly because of the very low cost of electricity (see Table 2). However, under the economic scenario, Italy show a lower cost than France.

It has to be noted that all the economic costs are limited to operational costs, i.e. investment costs are not taken into account in the calculations. A detailed economic assessment would therefore require a careful evaluation of the investments, which can show significant differences between countries for some technologies.

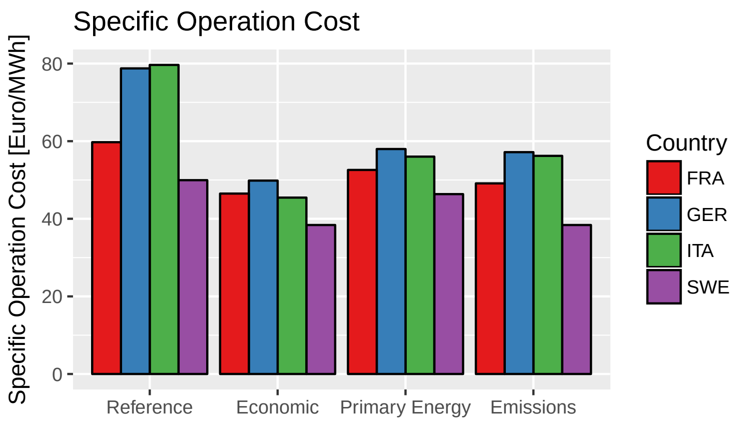

Figure 4: Specific Operation Cost with reference to total energy demand

3.2. Primary Energy Factor

Figure 5 shows instead the average Primary Energy Factor of the energy demand of the user, i.e. the amount of primary energy required to produce a unit of energy demand. The main parameter influencing the PEF is the electricity mix, and there are some marked differences among countries. The reference scenario shows always a PEF larger than one, reaching almost 1.5 in the worst case (France). On the other hand, the optimization scenarios have always values lower than one, regardless of the type of optimization (with the exception of Emissions scenario for France). The minimization of PEF provides similar results among countries, between 0.88 for Sweden and 0.94 for Germany. This result shows that optimizing the PEF is possible for each country, but with slightly different costs (see Figure 3).

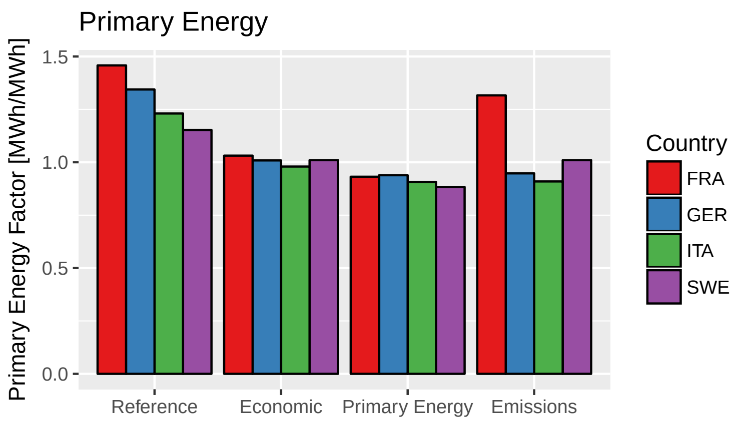

Figure 5: Primary Energy Factor of the Energy System

3.3. CO_2 Emissions

Finally, Figure 6 compares the specific emissions generated from the supply of the energy required by the hospital. In this case the differences among countries are more significant than for the others indicators, as the specific emissions are ranging from 92 g/kWh to 273 g/kWh. Sweden and France have significantly lower electricity emission factors thanks to their generation mix, mostly based on nuclear and hydro. However

France has much more nuclear, resulting in higher PEF when lowering the emissions and vice versa. Sweden has much more hydro energy, resulting in lower differences among scenarios. Italy and Germany have more fossil-based electricity mixes, resulting in emission factors never lower than 175 g/kWh (Italy) or 185 g/kWh (Germany).

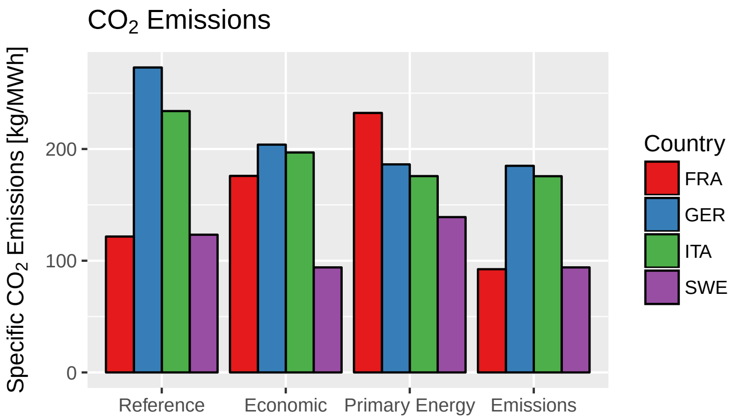

Figure 6: Specific CO_2 emissions of the Energy System

3.4. Natural Gas and Electricity supply

The results discussed above are caused by different electricity mixes of the selected countries, but also on the share of Electricity and Natural Gas in the total energy supply to the system (see Figure 7). These shares are a result of the choices of the Optimization Model, depending on the other parameters and the objective functions. In the reference scenario the energy plants requires natural gas for heat and steam production, and electricity for the hospital's power demand and for the cooling production. In the minimum cost scenario, Sweden is the only country where electricity is preferred (due to a low electricity price and a high natural gas price), while in other countries natural gas usage is maximised, especially in Italy. In the Primary Energy scenario, Germany and France go for natural gas, and France is even selling electricity to the grid, due to the high PEF of nuclear-based electricity production. Finally, in the emissions scenario only Germany is strongly dependent on natural gas, due to the high emission factor of its electricity mix, including a considerable share of fossil fuels, and coal in particular.

3.5. Hourly analysis

The analyses reported above are limited to a summary of the annual conditions, and the range of variation over the year is not emerging. Figure 8 shows together all the hourly values simulated in the three scenarios, by comparing the Specific cost, the Specific emissions and the Primary energy factor. France shows the larger variability, especially considering emissions. Further distinctions can be made by analyzing the effect of the single scenarios (see Figure 9) or also the electricity exchange with the grid (see Figure 10).

This last approach underlines that some linear tendencies (especially in France and Sweden) are caused by the use of CHP units to sell electricity to the grid, which can help in some cases to match specific objective functions under some particular conditions. In the case of France, the Primary Energy Scenario needs to face an average high PEF for national electricity: as a result the system decides to sell back to the grid the excess of electricity produced locally with a lower PEF (as the CHP engines have higher efficiency than the nuclear power). However this phenomenon is associated with a considerable heat dissipation, resulting in higher specific emissions and also in higher costs. For that reason, a multi-objective decision function could provide a best solution.

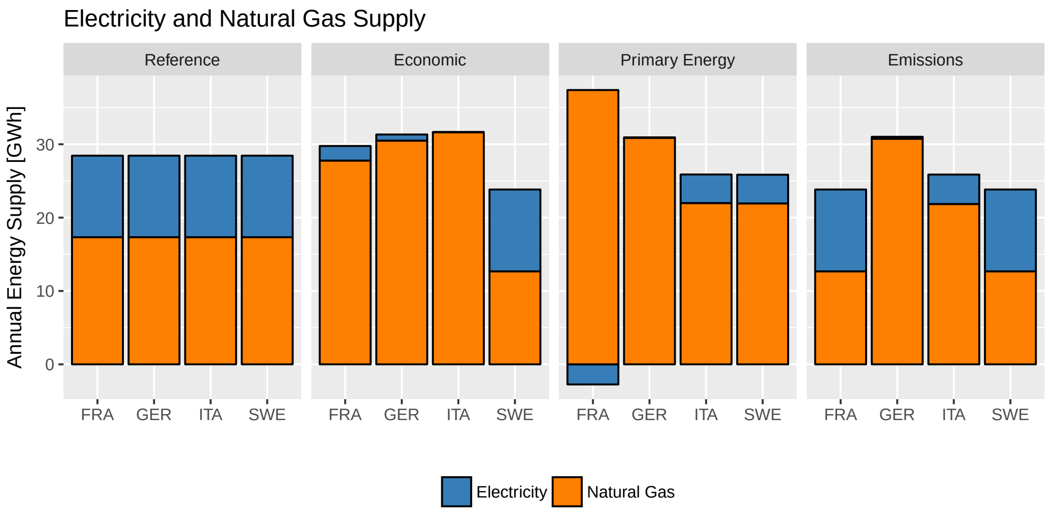

Figure 7: Electricity and Natural Gas Supply in different scenarios and countries

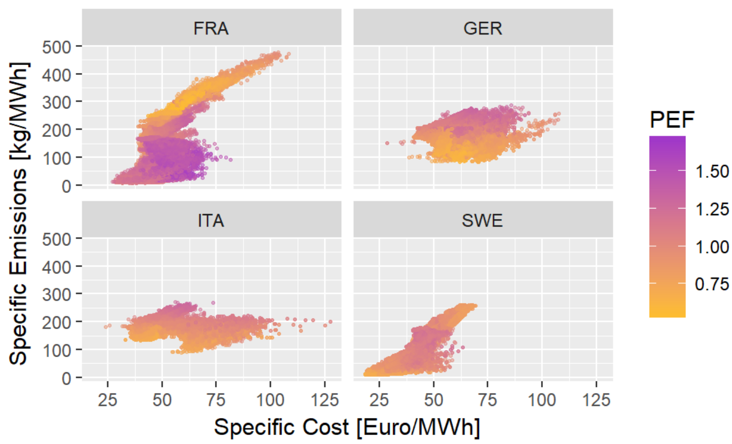

Figure 8: Hourly analysis: Specific costs, Specific emissions and Primary energy factor

4. Discussion

4.1. Main findings

The results presented for the case study show the importance and the effect of the variability of energy demand as well as decision parameters. In this particular application the highest variability was related to the electricity supply from the network: the simultaneous variation of the electricity price and the generation mix creates virtually unique conditions in each hour of operation. Moreover, matching these parameters with the energy demand of the users could prevent from finding two hours that have the same features, even if some recurring cycles lead to a number of comparable situations.

Since the optimization of a single parameter can lead to results that lower the performance of the other optimizations, it is possible to define advanced solutions that aim to find an optimum which considers multiple objective functions with appropriate weights, i.e. a multi-objective optimization. Although the model can perform such a simulation, this approach has not been considered in this study.

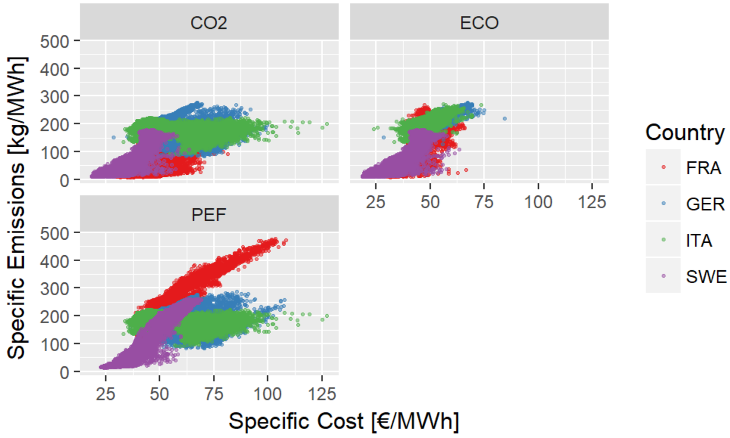

Figure 9: Hourly analysis: the effect of the objective functions

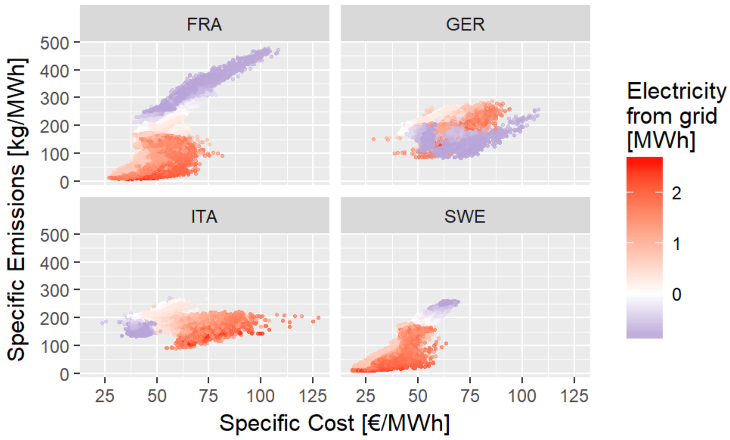

Figure 10: Hourly analysis: the effect of electricity grid exchange

4.2. Perspectives

Multi-carrier energy systems need to have enough flexibility to handle the variations over time of the parameters that affect the objective functions. The variability seen in the case study for electricity is the more usual, but other carriers are already having some considerable variations (e.g. district heating systems with multiple sources, natural gas networks including biomethane, etc.). In this perspective, the availability of decision models able to handle multi-carrier systems are important for better operation of the conversion units.

The optimization tool has been presented with historical data, but one of the most interesting applications is the possibility of defining a system configuration in advance. For this application, however, it is important to have reliable forecasts of all the parameters needed for the optimization. This is usually not a problem for economic parameters (electricity is usually sold and bought at day-ahead prices), while precise information on actual generation mix is not always easy to define. Moreover, while some users can have a quite predictable energy demand profile, in other cases a day-ahead prediction of the users' consumption can be non-trivial.

A future development of this optimization tool can lead to a live optimization, but this model has been built considering stationary conditions. A control system used for transients would need to be more accurate and complex, including detailed information about the technical features of the conversion units and the piping, etc. Moreover, an online optimization would need a data infrastructure providing detailed information from a number of different sources, which is currently not always available. However, live data availability is at the base of the smart grids development, as information is unavoidable for the management of energy grids with distributed generation and prosumers. Grids are now balanced by power plants auction systems, but future smart grids will need to be able to balance continuous load variations depending on a higher variability both at the supply side and at the demand side.

5. Conclusions

This paper presents an optimization tool that is able to optimize the operation of a multi-carrier energy system by using available data on user's energy demand and parameters related to the energy carriers (cost, primary energy factors, emission factors). The optimization model has been applied to a hospital as a case study, comparing different objective functions and implementation in different European countries.

The results show the importance of different parameters in identifying the optimal solution. In the scenarios considered in this study, the characteristics of the national electricity generation mix and the price ratios between electricity and natural gas are the two factors with the highest impact. Each country shows peculiar results, related to the characteristics of their energy context. The flexibility of the model allows considering multiple objective functions, and each approach leads to different operation logics. In some cases a single-objective optimization has lead to low performance on other aspects, therefore a multi-objective optimization could in some cases be considered. However, a multi-objective function would need a careful choice of the weights of each goal, as it is not trivial to compare economic, energetic and environmental aspects.

The optimization tool that has been described can be the basis for further developments, in order to define a data-driven control strategy for multi-carrier energy systems, both for forecasting schedule and for live tracking of the system operation. The increasing complexity of the energy systems needs to be faced by keeping a parallel increase of the available information, to guarantee that multi-carrier energy systems are always operating in the optimal configuration.

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