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COB-2021- 0130 - BICRITERIA OPTIMIZATION OF ENERGY SUPPLY SYSTEMS UNDER ECONOMIC UNCERTAINTY

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Abstract. *The economic benefit of introducing new sources and technologies in an energy supply system can be evaluated using optimization tools and data such as the consumer's energy demands, performance and cost of energy conversion and storage technologies, etc. If the goal is to minimize the environmental impact of the system, data regarding the life cycle emissions of equipment and energy sources must be used. Although in general both objectives are not aligned in the mathematical sense, multi-criteria optimization can be used to obtain trade-off solutions that meet additional criteria, which may be difficult to express as functions of economical or environmental variables. Thus, this work uses bicriteria optimization to design a combined energy production system for a hospital located in Joao Pessoa, northeast Brazil. The hospital energy demands include electricity, heating (hot water and steam) and cooling. The objective is to consider total annual costs and total greenhouse gas emissions under different future fuel prices. To this end, we combine multi-criteria optimization and parametric analysis to build synthesis solution maps, as well as the corresponding Pareto front. Results presented in this way help decision makers to evaluate the robustness of each solution to different price scenarios, and their flexibility to achieve the desired economic and environmental performance.*

Keywords: *MILP, multi-criteria optimization, life cycle assessment, polygeneration.*

1. INTRODUCTION

To reduce the emissions associated with energy systems, alternative sources and technologies must be considered. The design or synthesis of energy systems has been addressed in scientific literature using mathematical optimization approaches (a comprehensive review has been presented by Andiappan (2017), which incorporate information on the surroundings and particularities: energy demands, technologies available, energy utilities available, energy tariffs, legal constraints, to name a few. Optimization can be approached at three levels: synthesis (configuration), design (component characteristics), and operation, and for Frangopoulos (2018), perhaps the most challenging area within energy system optimization is optimization itself.

When there are no environmental constraints, the decision on the installation of an energy system relies on economic criteria – the minimization of costs has been the focus of optimizations carried out in mines (Carvalho et al., 2014), in Canadian (Romero et al., 2014), Spanish (Lozano et al., 2009) and Brazilian (Delgado et al., 2018) hospitals, in a residential complex in Iran (Ameri and Besharati, 2016), in a university campus located in Italy (Testi et al., 2019), in an industrial area in Italy (Buoro et al., 2014), and even in integrated ship energy systems (Sakalis and Frangopoulos, 2018). The consideration of environmental impacts at earlier stages of the traditional design and planning of energy systems has been reported by Theodosiou et al. (2015), and environmental data has already been implemented in the optimization of energy supply systems (Carvalho et al., 2011; Carvalho et al., 2016). However, the analysis of compromises and trade-offs is especially beneficial when considering economic and environmental objectives, which sometimes can result in divergent results.

Multi-objective optimization (MOO) is considered a powerful approach to address decision problems affecting the design and operation of energy systems, especially when opposite optimization criteria are implemented. Alarcon-Rodriguez et al. (2010) reviewed the state-of-the-art of multi-objective planning of decentralized energy systems, showing the growing penetration of evolutionary algorithms at the expense of more traditional linear programming (LP). Currently, however, most open source and commercial energy systems optimization tools are based on LP (Groissböck, 2019). Alarcon-Rodriguez et al. (2010) suggested that the relatively simple epsilon-constrained method (see Section 3) for MOO of LP should be restricted to problems with a low number of objectives, and whenever a priori knowledge of the problem is available. The epsilon-constrained method was used by Gebreslassie et al. (2009) to optimize cost and emissions, and

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more recently by Sedighizadeh et al. (2018) in combination with stochastic optimization for a mixed integer nonlinear programming (MINLP) problem. It can also be used with evolutionary algorithms (Alarcon-Rodriguez et al., 2010). An alternative to the epsilon-constrained method for MILP (and potentially MINLP) is the weighted sum method, used for example by Stadler et al. (2014) to illustrate economic and environmental trade-offs of different energy system's design and operational strategies.

The objective of the present study is to consider economic and environmental objective functions in the synthesis of a combined energy system. This study includes photovoltaic solar energy in the multigeneration superstructure and the legal scenario established by the Brazilian Electricity Regulatory Agency (ANEEL, 2012), which enables exports of self-generated electricity. Sugarcane bagasse is also considered as a locally available energy resource. The main contribution of this work is the combination of multi-criteria and sensitivity analyses with regards to utility price uncertainty to help decision makers in finding more resilient and more sustainable energy supply solutions, following a similar approach found in Haesen et al. (2006) for plotting MOO solutions with more than two objective functions.

The remainder of the paper is organized as follows. The second section introduces the hospital and its energy demands, the available technological options and additional local data. Section 3 describes the multi-criteria optimization problem to be solved and the software used. Results are presented first for the simple Pareto front, and second for the price-sensitivity analysis. Finally, Section 4 summarizes the conclusions and presents some directions for future work.

2. MATERIAL AND METHODS

2.1 Energy demands

The consumer center under analysis is a university hospital located in Northeast Brazil (city: João Pessoa). It is a medium-size hospital, with 420 beds, and the energy demands are electricity, sanitary hot water, steam (for laundry and sterilization) and cooling. Because hospitals have a regular operation throughout the year, two representative days (weekdays and weekend/holidays) and six characteristic months are sufficient to characterize yearly operation. Each day encompasses 24 hours, resulting in 288 different operation periods throughout the year. Real electricity data was available. The calculation of hot water and cooling demands employed the degree-days method (Erbs et al., 1983) along with climate (Climaticus, 2005) and occupation (Nepote et al, 2009) data.

Table 1 shows the hospital utility demands (daily values) for a set of characteristic days, throughout the year. The set includes weekdays (1a, ..., 6a) and weekends (1b, ..., 6b). These represent statistically meaningful data, i.e., most likely operating conditions. Figure 1 presents the hourly profiles, where all days are plotted successively for convenience.

Table 1. Daily and annual demands of the university hospital (Delgado et al., 2018).

		Electricity	**Heating**	**Steam**	**Cooling**
Month	Days	[MWh/day]			
1a	20	8.538	3.543	0.465	5.961
1b	11	6.315	3.543	0.233	4.360
2a	19	9.696	6.436	0.465	6.472
2b	9	6.247	6.436	0.233	4.290
3a	20	9.861	6.436	0.465	8.013
3b	11	7.474	6.436	0.233	5.443
4a	20	9.949	6.436	0.465	7.071
4b	10	7.348	6.436	0.233	4.737
5a	20	8.901	6.436	0.465	7.895
5b	11	6.383	6.436	0.233	5.534
6a	19	7.489	5.032	0.465	7.768
6b	11	6.832	5.032	0.233	5.259

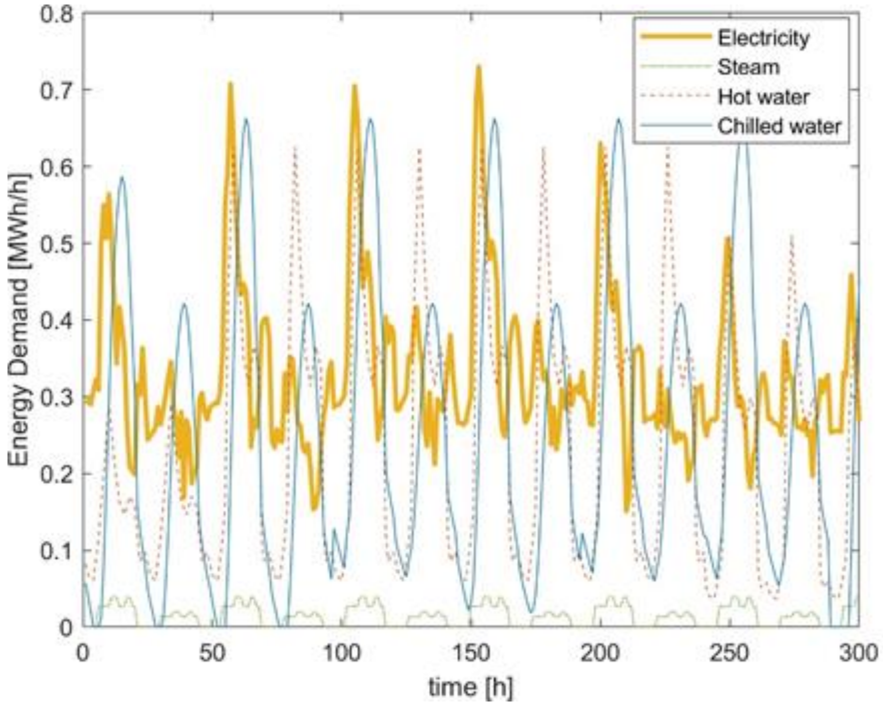

Figure 1. Hourly Energy Demands.

2.2 Superstructure

Figure 2 shows the superstructure of the multigeneration system for the consumer center described above, following the scheme created by Carvalho and Millar (2012). The optimization methodology adopted herein relies on a predefined superstructure that includes all possible processes and connections, allowing several redundant possible alternatives for each process.

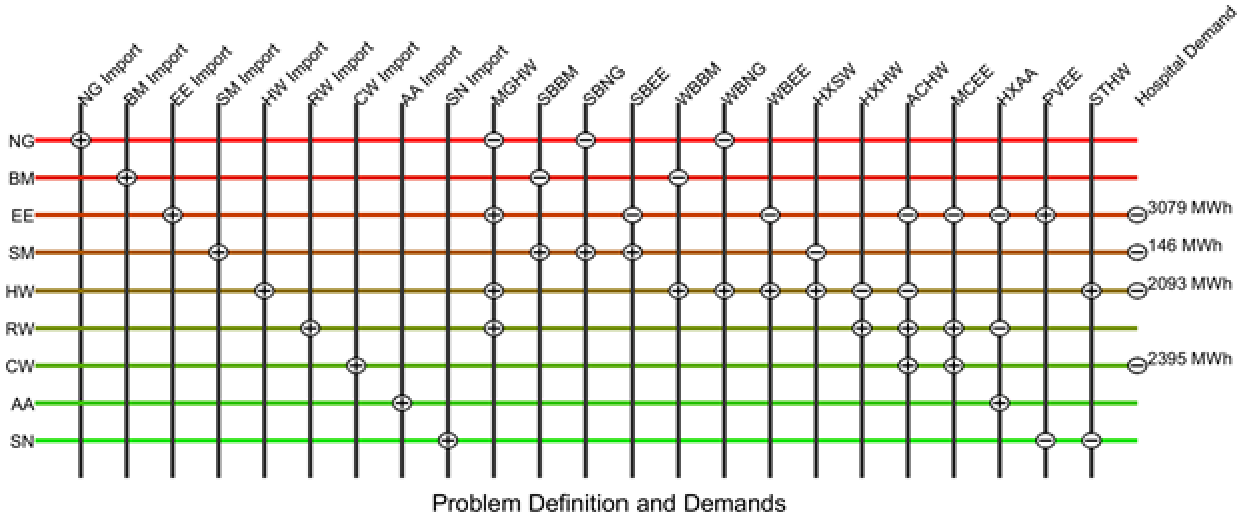

Figure 2. Superstructure representation with imports, utilities, technologies and demands.

The utilities present are electricity (EE), diesel (DI), biomass (BM), natural gas (NG), steam (SM, 180ºC), hot water (HW, 90ºC), cooling water (RW, t0 + 5ºC), ambient air (AA), chilled water (CW, 5ºC), and solar irradiation (SN). The horizontal bars represent the types of energy available on site, to which different technologies (vertical bars) are connected. A positive node means the production or supply of energy, and a negative node means the consumption of this energy form.

A positive node denotes supply/production of energy and a negative node denotes consumption. The horizontal lines represent the energy forms considered at the site, to which the equipment (vertical lines) are connected to consume or produce energy. In general, all utilities could be purchased from the market, thus the Import vertical line. However, this work assumes that only electricity, diesel, biomass and natural gas can be imported.

2.3 Technical, economic and environmental data

Table 2 shows the production/consumption coefficients for the technologies available on site. The main utility, which defines the technology, is represented by 1 (in bold). All energy flows have been normalized to the main utility.

Table 2. Technology Conversion Matrix

Technology	Abbrev.	NG	BM	EE	SM	HW	RW	CW	AA	SN
Gas engine	MGHW	-2.66	0	**1**	0	1.1	0.45	0	0	0
Steam boiler	SBBM	0	-1.4	0	**1**	0	0	0	0	0
Steam boiler	SBNG	-1.18	0	0	**1**	0	0	0	0	0
Steam boiler	SBEE	0	0	-1.15	**1**	0	0	0	0	0
Hot water boiler	WBBM	0	-1.25	0	0	**1**	0	0	0	0
Hot water boiler	WBNG	-1.22	0	0	0	**1**	0	0	0	0
Hot water boiler	WBEE	0	0	-1.11	0	**1**	0	0	0	0
Heat exchanger 1	HXSW	0	0	0	-1.1	**1**	0	0	0	0
Heat exchanger 2	HXHW	0	0	0	0	-1.1	**1**	0	0	0
Absorption chiller	ACHW	0	0	-0.01	0	-1.32	2.32	**1**	0	0
Mechanical chiller	MCEE	0	0	-0.21	0	0	1.21	**1**	0	0
Cooling Tower	HXAA	0	0	-0.02	0	0	-1	0	**1**	0
Photovoltaic panel	PVEE	0	0	**1**	0	0	0	0	0	-6.67

Table 3 shows the economic and environmental data for the technologies. The GHG emissions for each piece of equipment were obtained using data from Carvalho et al. (2016) (implemented within Simapro 8.4.0.0 software (2019) with Ecoinvent 3.3 (2017), and using the IPCC 2013 GWP 100y (2013) impact assessment method. The carbon footprint groups greenhouse gas (GHG) emissions in a common metric, CO_2-eq.

Table 3. Technology Costs and Carbon Footprint.

Technology	Investment (R$)	O&M Cost (R$/MWh)	Nom. Power (MW)	Carbon footprint kg CO_2-eq
MGHW	4.63E+05	15	0.41	3.53E+02
SBBM	5.10E+04	8	0.25	2.73E+06
SBNG	4.79E+04	2	0.3	2.22E+06
SBEE	4.25E+04	2	0.15	2.22E+06
WBBM	6.25E+04	8	0.17	2.73E+06
WBNG	4.93E+04	2	0.3	2.22E+06
WBEE	2.82E+04	2	0.15	2.22E+06
HXSM	8.90E+03	2	0.4	1.50E+03
HXHW	7.40E+03	2	0.4	1.47E+03
ACHW	5.40E+05	10	0.49	3.04E+05
MCEE	2.17E+05	4	0.27	5.23E+03
HXAA	2.80E+04	10	1	9.71E+03
PVEE	3.61E+05	2	0.025	7.86E+04

Information regarding the PV system was obtained from the manufacturers of the panels (Kyocera, 2018) and inverters (Santermo, 2018). The lumped cost of the PV system is R$2202/m^2 (including the cost of panels, inverters, installation, transportation, and assembly). The area of each panel is 1.64 m^2, with annual maintenance costs of R$25/m^2. Historical hourly radiation data (W/m^2) is available from Climaticus (2005). Electricity storage is not considered in this work due to its still relative high cost, good irradiation conditions, and simultaneity of PV production and electrical demand.

Electricity presents different tariffs for peak (R$ 298.00/MWh between 18h and 21h) and off- peak (R$ 190.00/MWh) periods. The generation mix of the Northeast electric grid is hydro 36.21%, thermoelectrical (oil) 40.85%, and wind 22.94% (Brazilian National Electric System Operator - ONS, 2017), yielding 0.605 kg CO_2-eq/kWh.

Natural gas (R$ 293/MWh - Companhia Paraibana de Gás, 2017) and diesel (R$ 290/MWh) present flat rates, with associated GHG emissions of 0.254 kg $_{CO2}$-eq/kWh and 0.333 kg $_{CO2}$-eq/kWh, respectively. Due to the location of João Pessoa, which counts with several sugarcane-ethanol plants, the biomass considered was sugarcane bagasse, at R$ 52,00/MWh. LHV of bagasse (15.4 MJ/kg dry matter) and dry matter content (0.787kg DM/kg fresh bagasse) were considered along with the assumption that 1% of dry mass was converted into ash, resulting in 0.099 kg $_{CO2}$-eq/kWh.

The multigeneration system can export selfgenerated electricity (from photovoltaic and natural gas) to the electric grid, following the Brazilian Electricity Regulatory Agency – ANEEL (2012, 2015). The electric grid stores the extra electricity, and the consumer receives electricity credits, which are valid for 60 months. The GHG emissions associated with imported and exported electricity is the same – this leads to a GHG emission offset scheme. Emissions are avoided because instead of consuming electricity from the grid (with higher emissions) there is selfgenerated electricity available at lower emission rates.

2.4 Optimization framework

The problem consists of establishing the configuration of the system (type of equipment and power installed) and their operation profiles for each time interval defined. Due to the extraordinary size of the solution space, an optimization method based on mathematical programming (MILP) is used to efficiently seek the most convenient configuration and operation modes for power systems. The optimization problem was implemented in LINGO 15.0 (2019), a solver that combines branch and bound and simplex methods. Equipment models and their connectivity, along with the operational constraints, utility balance constraints, etc., are incorporated into the mathematical model. For further information regarding the constraints of the optimization problem, the reader is referred to Romero (2016).

As for the objective function, this can be formulated as a linear combination of the decision variables to reflect the system's total annual cost, total annual emissions, or a weighted sum of both. The epsilon-constraint (E-constraint) method (Gebreslassie et al., 2009) is used herein, developed for multi-objective problems, and consists of solving a problem of the following form.

$$\begin{aligned}
&\text{Minimize } f_2(x) \\
&\text{subject to } f_1(x) \leq E_{j\,,\,I} = 1, \ldots, m \qquad (1)\\
&Lim_{inf} \leq E_j \leq Lim_{sup}
\end{aligned}$$

where f2(x) is the economic objective function and f1(x) is the environmental objective function. This method is theoretically able to reach any Pareto point of a non-convex problem. However, an issue with this approach is that it is necessary to preselect the objective to minimize and the consequent Ej. The original optimization problems are solved individually to obtain the minimal economic and minimal environmental solutions (Lim_{inf} and Lim_{sup}], i.e., the extreme limits of E_j), and then the interval between the extremes is divided to obtain different E_j values, for which the economic optimization model is repeatedly solved with different environmental constraints. In practice, a small value of points (m in (1)) is needed to accurately draw the Pareto front.

3. RESULTS AND DISCUSSION

3.1 Economic and GHG emissions multiobjective optimization

The optimization model was solved, minimizing separately the economic and environmental objective functions. Each single-objective MILP problem involved 130,272 total variables, 2333 integer variables and 86,441 constraints, with an average solution time of 21 seconds (Intel Core i5, 1700 MHz and 4GB RAM).

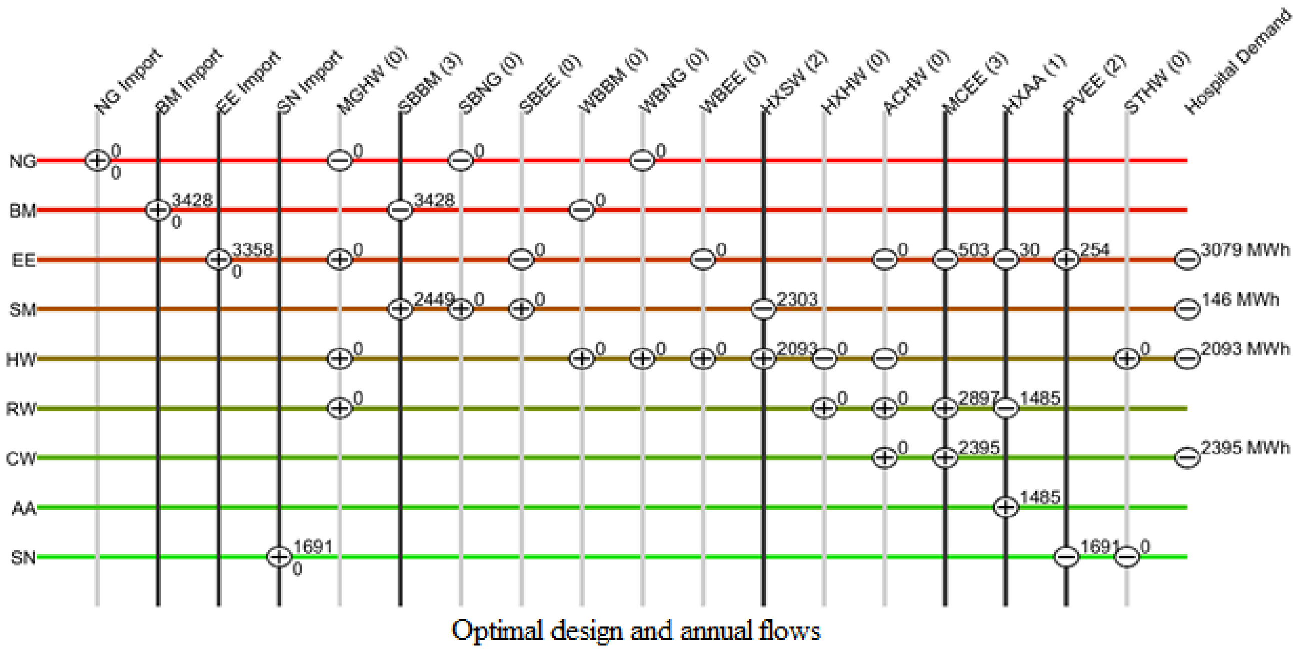

Figure 3. Economic Optimum.

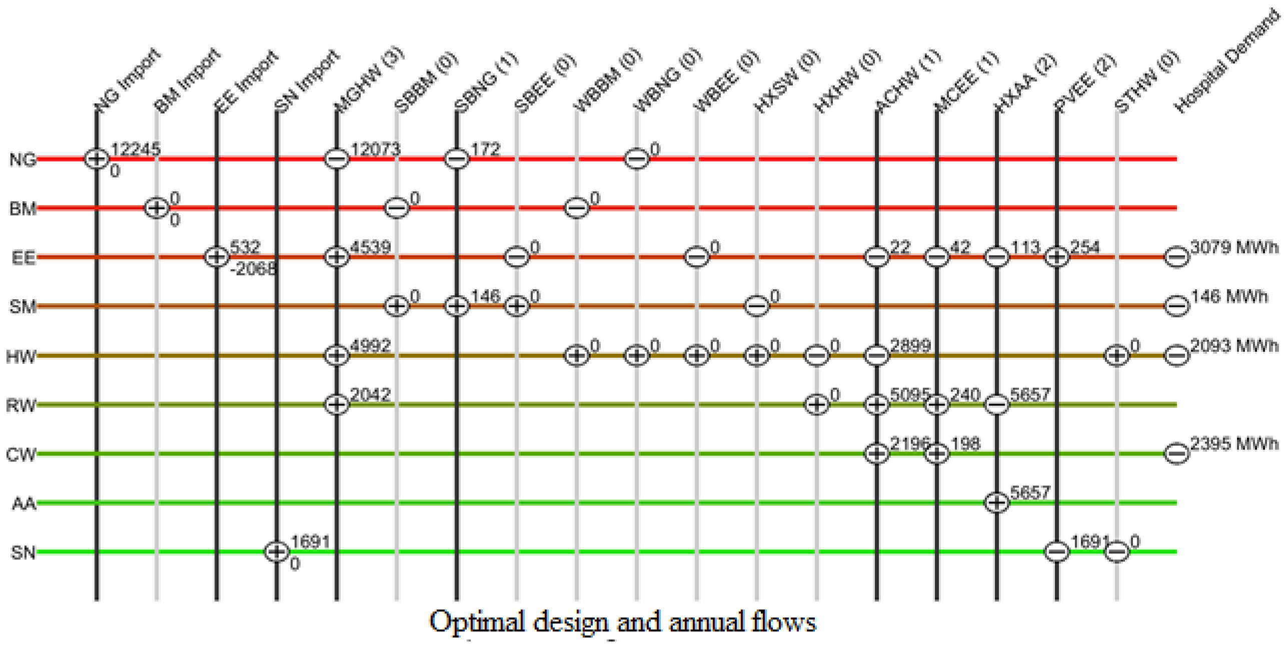

Figure 4. Environmental Optimum.

The solution of each individual optimization set the extreme limits for the bicriteria problem: Lim_{inf} = 2,624,099 kg CO_2-eq/year (environmental optimal) and Lim_{sup} = 3,464,730 kg CO_2-eq/year (economic optimal). Figures 3 and 4 show the configurations obtained for these limits, in addition to the annual flow values. The number in brackets that accompanies each technology indicates the number of equipment installed and the power. Vertical lines in grey indicate zero import/export of the allowed utilities and zero units installed for each technology considered. The environmental optimal solution presented GHG emissions that were 24.3% lower than the economic optimal, but with annual costs that were 307% higher. A significant increase in the annual costs embedded was required to obtain a moderate reduction in the total annual emissions.

Table 4. Annual Cost [MR$/year], Emissions [kT CO_2-eq/year], and Solution Topology.

Solution	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Cost	1.154	1.186	1.19	1.271	1.293	1.565	3.531	3.916
Emissions	3.35	3.318	3.299	3.067	3.026	2.738	2.6	2.593
MGHW	0	0	0	1	1	1	2	3
SBBM	3	2	1	2	1	1	0	0
SBNG	0	0	0	0	0	0	1	1
SBEE	0	0	0	0	0	0	0	0
WBBM	0	0	1	0	1	0	0	0
WBNG	0	1	1	0	0	0	0	0
WBEE	0	0	0	0	0	0	0	0
HXSW	2	2	1	2	1	1	0	0
HXHW	0	0	0	0	0	0	0	0
ACHW	0	0	0	0	0	0	1	1
MCEE	3	3	3	3	3	3	1	1
HXAA	1	1	1	1	1	1	2	2
PVEE	2	2	2	2	2	2	2	2

Table 4 shows the resulting configurations and primary and secondary objective values. For each configuration, the number beside the equipment specifies the items installed. The solutions shown are all the different resulting topologies when the emissions are constrained starting from 3.5×10^6 kg CO_2-eq per year and then decreased in steps of 5×10^4 kg. Here, only the transition points from the technological viewpoint are shown.

3.2 Sensitivity analyses dealing with uncertain price environments

The total annual costs and emissions of the explored solutions is presented in Figure 5, where the line with square markers indicate the optimal value for each emission constraint with nominal price values, and is thus equal to Table 4 values. The circle markers are obtained for every combination of fuel prices and emission constraint (see sub-figures title). Figure 6 shows that eleven (11) different topologies exist according to the optimal solution for each combination of biomass and natural gas price. The prices were progressively increased from 50 and 200 R$/MWh respectively, in steps of 20 R$/MWh, a grid of 10x10 elements was obtained.

The procedure was carried out four times, each instance reducing the admissible total annual emissions in the interval [3.5×10^6, 2.5×10^6]. The design of each numbered topology is described in Table 5.

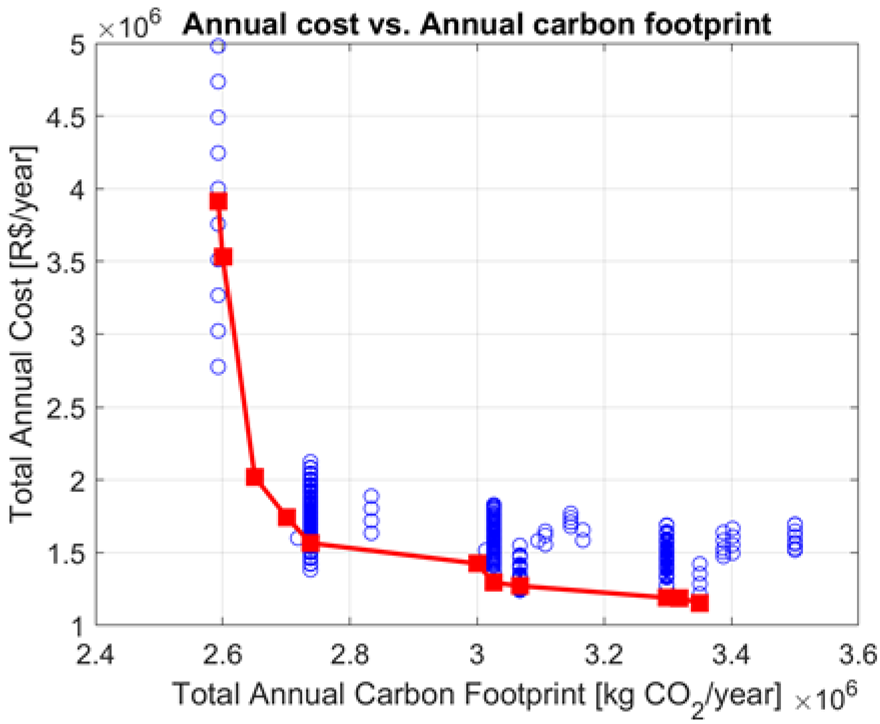

Figure 5. Pareto front: annual cost and carbon footprint with price sensitivity.

Table 5: Solutions obtained by sensitivity analysis to biomass and natural gas prices.

Solution	1	2	3	4	5	6	7	8	9	10	11
MGHW	0	0	0	1	1	1	1	1	1	1	3
SBBM	3	1	0	1	2	1	0	0	1	0	0
SBNG	0	0	1	0	0	0	1	1	0	1	1
SBEE	0	0	0	0	0	0	0	0	0	0	0
WBBM	0	1	1	1	0	1	1	0	0	0	0
WBNG	0	1	1	0	0	0	0	1	0	0	0
WBEE	0	0	0	1	0	0	0	0	0	0	0
HXSW	2	1	1	1	2	1	1	1	1	1	0
HXHW	0	0	0	0	0	0	0	0	0	0	0
ACHW	0	0	0	0	0	0	0	0	0	0	1
MCEE	3	3	3	3	3	3	3	3	3	3	1
HXAA	1	1	1	1	1	1	1	1	1	1	2
PVEE	2	2	2	2	2	2	2	2	2	2	2

Considering that the price status quo is 52 R$/MWh for biomass and 293 R$/MWh for natural gas, topology 1 (Table 5) remains resilient under natural gas price increase without emissions constraint 6(a). Topology 4 is with the highest cost the only one using cogeneration in this first map, and can be located in Fig. 5 with the extreme points (circles) at the right hand side. At those high prices, it makes more sense economically to use electricity from the grid; however, the limitation in annual emissions involves a counter-intuitive change in topology from 3 to 4.

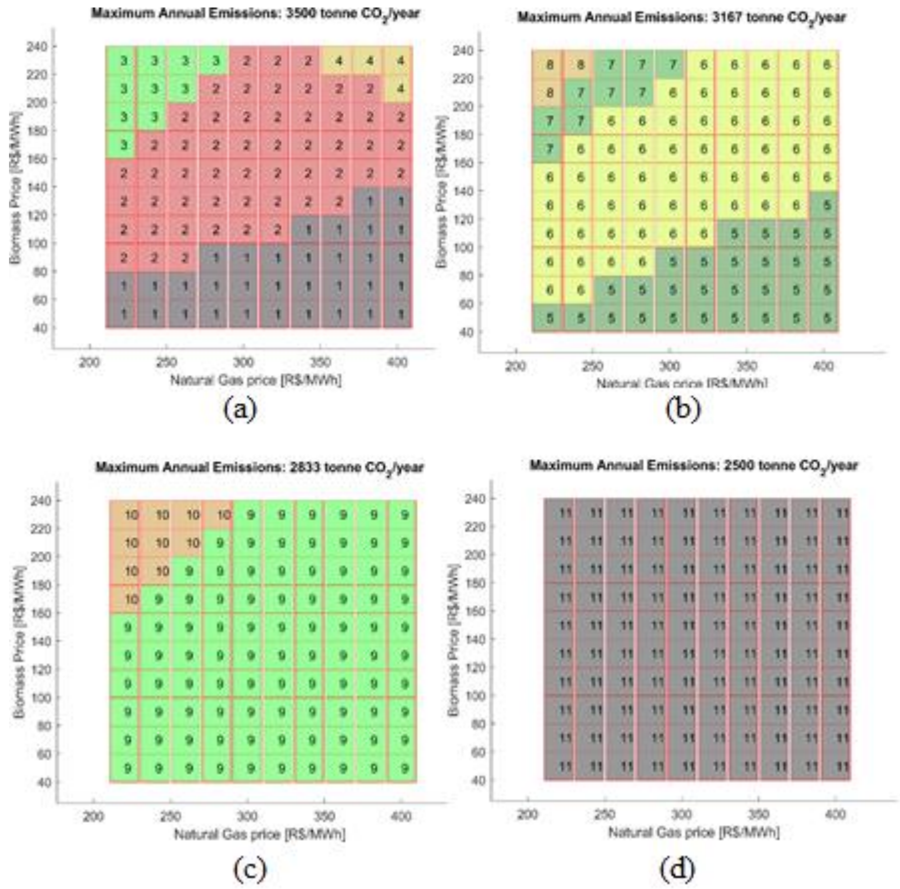

Figure 6. Solution maps for different maximum $_{CO_2}$-eq constraints.

Further constraint of emissions lead to a more intensive use of cogeneration, even for high natural gas prices. Finally, below approximately 2.7 x 10^6 kg $_{CO_2}$-eq, the annual cost tends to the asymptotic limit of the environmental minimum, cogeneration taking the dominant role, and absorption chiller assuming a share of the cooling load (Fig. 6(d)).

4. CONCLUSIONS

This study focused on the problem of minimizing the cost and GHG emissions associated with the installation and operation of a multigeneration system, designed to meet the energy demands of a Northeast Brazil hospital. The solution of the resulting MILP problem provided different sets of Pareto optimal design alternatives, highlighting the trade-offs involved regarding costs and emissions, and emphasizing the importance of expert decision-makers in using their specialized judgment.

When comparing the optimal economic and environmental topologies, these are clearly different. Significant reductions in GHG emissions can be obtained if economic costs are compromised. Furthermore, some configuration options presented a higher degree of resilience against fuel prices variability. This can be observed by means of conveniently designed resilience maps, although statistical data of the price distribution probabilities could be used, if available, to quantitatively determine the resilience or robustness of the solutions using, for example, Monte Carlo simulation.

5. ACKNOWLEDGEMENTS

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