Industrial Optimal Operation Planning with Financial and Ecological Objectives

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$_2$ Emissions.

Abstract: As energy transition is fundamental to have a chance to fight climate change, every stakeholder concerned by energy should be able to get a better knowledge of the consequences of these actions. However, it could be very complex to understand energy problematics without being an expert. This article focuses on giving the possibility to an energy intensive consumer of a district to make decisions about its energy planning while taking into account its specific operating constraints. A practical case has been studied in a heat recovery project to help the experiments planning of a research laboratory according to the thermal needs of the district. At first, the energy planning only aims to reduce its electricity consumption bill. In a second time, we consider re-using the thermal power from processes cooling. Then, two energy planning were realised: reducing district CO_2 emissions and reducing district supply cost. Finally, trade-offs between these two goals have been studied. The work is based on mixed-integer linear optimization models (MILP) gathered into a Python library to provide a modular decisions tool for energy stakeholders.

1 INTRODUCTION

More and more modeling approaches and tools emerge for the district-scale energy systems (Allegrini et al., 2015). However, district energy models focus more on simulation or design optimization (Schütz .et al., 2016) than on energy management optimization. Our objective was to develop an optimization tool to help energy stakeholders to make decisions about district energy management with technical, financial, environmental and social aspects.

Lots of the emerging district tools are based on a bottom-up methodology gathering thermal buildings models to create a district one (Lauster et al., 2014), (Jimeno et al., 2015) while we aim to create a single multi-energies representation with production, conversion and consumption.

Before the district scale, energetic optimisation has been studied at the urban level through lots of optimization techniques (Keirstead et al, 2012), (Z. Shi et al., 2017). Best et al. provide genetic optimization models for supply and demand of heating, cooling, and electricity (Best et al., 2015), while Shabanpour-Haghighi et al. use heuristic algorithm through the modified teaching–learning based optimization (MTLBO) in order to minimize the fuel cost in multi-carrier energy network (Shabanpour-Haghighi et al., 2015). Finally, a lot of them preferred a Mixed Integer Linear Programming (MILP) approach, as B. Morva et al. who optimized both design and operational aspects of an urban energy system (Morva et al, 2016).

In our study, several objectives will be presented: reducing an energy supply bill, reducing CO_2 emissions of a district and reducing the heating supply cost of a district. Therefore, the presented problems require a formulation of energetic, economic and CO_2 flux, what generates hundreds of variables. In order to easily deal with a large amount of variables, we are working on MILP formulation.

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2 INDUSTRIAL ENERGY PLANNING TO MINIMIZE ENERGY SUPPLY BILL

For industries and other energy intensive users, the energy bill strongly affects their operation. From simple operation schedules based on lower prices to energy management policies, planning the energy repartition to stay competitive becomes crucial.

In France, Energy Intensive Industries (EII) such as steel, chemical and microelectronics' industries or paper mills can be directly connected to the transmission system (Rte&Vous Le Mag, 2018). In this case, electrical access and supply are two separated contracts. With temporal repartition of prices at several scales, the associated pricing is more complex than a simple electrical cost for standard consumer (Clients.rte-france.com, 2018).

At its Grenoble site, the National High Magnetic Field Laboratory (LNCMI) offers static magnetic fields up to 36 T, thanks to several magnets supplied by a 24 MW electrical power station (LNCMI, 2017). The mean consumption during a day of experiment is 6 MW (one fourth of the maximum value), while the annual consumption for this laboratory is typically around 14 GWh leading to an important electricity bill. This should be taken into account when experiments on magnetic fields are planned, task which is currently handled manually.

Our study case focuses here on minimizing the electricity bill considering specific operating constraints and complex pricing structure.

2.1 Energy Pricing for Energy Intensive Industries

2.1.1 Pricing Structure for French Electrical Transmission System Access and Supply

As explained before, EIIs have direct access to the electrical transmission network. For those, electricity access is not included into the supply and requires subscribing two different contracts:

- The TURPE: French price for accessing the public transmission system of electricity
- An electrical supply contract

The TURPE pricing for LNCMI has an hourly-seasonal structure (price variations at different time scales: seasonal to hourly), which can be presented as follows (Table 1).

In our study, only the three major components of the price have been modeled: the power part (subscription), the energy part and the taxes (see equations 1, 2 and 3 below).

$$\text{Power\_part} : b_k = b_1 * Ps_1 + \sum_{k>1} b_k (Ps_k - Ps_{k-1}) \quad (1)$$

$$\text{Energy\_part} : c_k = \sum_k c_k E_k \quad (2)$$

$$\text{Total electricity cost} = \text{Power\_part} + \text{Energy\_part} + \text{Taxes} \quad (3)$$

Moreover, according to the TURPE, the subscribed power has to respect the following rule: $Ps_k \leq Ps_{k+1}$. (Clients.rte-france.com, 2018)

Table 1 : TURPE 4 pricing structure.

Time period	b_k [€/kW/y]	c_k [c€/kWh]	Monthly period	Day type	Hour range
k=1	9.24	3.01	Dec., Jan., Feb.	Working	9:00-10:59 / 18:00-19:59
k=2	8.5932	2.73	Dec., Jan., Feb.	Working	7:00 - 8:59 / 11:00 – 17:59 20:00 - 22:59
k=3	6.6528	2.26	March, Nov.	Working	7:00– 22:59
k=4	5.1744	1.59	Dec., Jan., Feb.	Working	0:00 - 6:59 / 23:00 – 23:59
				Non-working	0:00 – 23:59
k=5	4.2504	1.22	March, Nov.	Working	0:00 – 6:59 / 23:00 – 23:59
				Non-working	0:00 – 23:59
k=6	3.696	1.37	Ap., May, June, Sept., Oct.	Working	7:00– 22:59
k=7	1.9404	0.86	Ap., May, June, Sept., Oct.	Working	0:00 - 6:59 / 23:00 – 23:59
				Non-working	0:00 – 23:59
k=8	0.924	1.08	July, August	All	0:00 – 23:59

Where:

- b_k: Price for the capacity defined by time interval k and the tariff version
- Ps_k: Subscribed power for time interval k
- c_k: Price for the energy for time interval k and the tariff version concerned
- E_k: Active energy extracted over the year during time interval k, expressed in kWh

Energy supply prices are based on electrical consumption forecasts for each price period (same pricing repartition as TURPE). This contractual commitment forces the LNCMI to estimate its electrical load repartition by time period one year ahead explaining the energy planning need for an entire year. As mentioned before, this work is realised by a member of the LNCMI, who could benefit from the developed tool.

2.1.2 Operation Constraints

Each big consumer has its own operating constraints: some industries cannot ever stop their process, whereas some others can only operate on working days for instance. Understanding and being able to describe these particulars needs is very important to get a plausible energy planning. Therefore, a part of our work was to translate common constraints into easy Python objects and thus enrich the possibilities of the decision tool.

As an industry, LNCMI has operating constraints. In its case, it is estimated that it cannot handle experiments more than 16 hours per day (considering for instance the time required between experiments). Moreover, the laboratory is closed several days per year (two weeks starting at Christmas' Eve) and should be working all other days.

On the other side, quality of life at work is currently taken into account without being strictly formalized, by avoiding too many nights and weekends of work. To do so, the current planning is created with energy limits on the corresponding time periods. For instance, maximum values are fixed for some time periods including nights and non-working days as k=4, k=5 and k=7.

In our study, to avoid an experiment planning only focused on electricity prices, these current energy limits will be directly translated into optimization constraints (see equations 5 to 8).

2.2 Optimization Problem Formulation

2.2.1 Daily Steps Model

For a yearly study, an hourly step could lead to heavy formulations due to the amount of decision variables. To avoid computational issues in case of complex problems, we went for a daily step when we aim to optimize an annual energy planning.

However, as the price may change during the day, we expressed the daily energy consumption as consumption at a fixed equivalent power and deducted the equivalent operating hours, according to equation 4.

$$op_h(t) = e_{in}(t) / p_{eq}(t) \quad (4)$$

This deduction of an equivalent number of operating hours is fundamental to evaluate the consumption cost of the day, taking intra-day prices variation into account. Indeed, LNCMI expenses are calculated as follows:

$$expense_{lncmi}(t) = p_{eq} \sum_k c_k * op\_h_k(t) \quad (5)$$

$$\sum_k op\_h_k(t) = op_h(t) \quad (6)$$

Where:

- $e_{in}(t)$: Electrical consumption for the day t
- p_{eq}: Equivalent power of the LNCMI (6MW)
- $op_h(t)$: Equivalent number of operating hours for the day t
- $op\_h_k(t)$: Number of operating hours at price c_k for the day t

2.2.2 Translation of Operating Constraints into Energetic Constraints

According to the use of the magnets, each experiment led in the LNCMI consumed a different amount of electricity. By knowing by advance the experimentations planned on the following year, it becomes possible to evaluate the annual electrical consumption to come. For the year 2107, it has been estimated at 14 GWh, leading to equation 7:

$$\sum_t e_{in}(t) = 14000000 \text{ for t in } \{0; 364\} \quad (7)$$

As written before, the LNCMI closes annually for two weeks, but the installation is working all the others days with a minimal value of 0.5 hours per day, leading to the equations 8 and 9. The minimal value of 0.5 daily operating hours has been set from an energetic point of view, forcing the installation of consuming at least 3MWh per day (see equation 4).

$$e\_in_{lncmi}(t) = 0 \text{ for t in annual closure} \quad (8)$$

$$op\_h_{lncmi}(t) \geq 0.5 \text{ for t not in annual closure} \quad (9)$$

Finally, the next equations translate LNCMI choices to avoid high electricity prices, while considering the quality of life at work. Indeed, the equation 9 expresses the fact that no power subscribing was taken for time periods tp_1 and tp_2, in order to limit energy costs and avoid a bill increase. In the other hand, as explained in 2.1.2, quality of life at work is considered into the energy planning. Limits are fixed in terms of energy minimums or/and maximums for some pricing time periods and are based on the LNCMI experience. If we call tp_k the time period corresponding to the TURPE period at price c_k, the constraints are expressed as follows in equations 10, 11, 12 and 13.

$$\textstyle\sum_t e_{in}(t) = 0 \text{ for t in } tp_1 \text{ and } tp_2 \quad (10)$$

$$\textstyle\sum_t e_{in}(t) \leq 2000 \text{ for t in } tp_4 \quad (11)$$

$$\textstyle\sum_t e\_in_{lncmi}(t) \geq 500 \text{ for t in } tp_3 \quad (12)$$

$$\textstyle\sum_t e_{in}(t) \leq 1500 \text{ for t in } tp_5 \quad (13)$$

$$\textstyle\sum_t e_{in}(t) \leq 6600 \text{ for t in } tp_7 \quad (14)$$

2.2.3 Objective Formulation

In this case study we aim to reduce the LNCMI electricity bill by optimizing its consumption planning under specific constraints. The expressions of these constraints were expressed above, so that the objective formulation is:

$$\text{Minimize} \left(\textstyle\sum_t expense_{lncmi}(t) \right) \quad (15)$$

With $expense_{lncmi}$ expressed in equation 5.

2.3 Results

2.3.1 Optimal and Previous Planning Comparison

The current LNCMI energy planning is based on a compromise between consuming low prices electricity and avoiding too many working nights and weekends. To allow a comparison between optimal and usual planning (created manually), values chosen for the 2017 year are shown in the second column of Table 2. The energetic values are expressed in MWh, while the electricity prices have been normalised regarding to the maximal value for a confidentiality purpose.

Table 2: Comparison between current and optimized LNCMI energy planning.

Time period	Elec. price [pu]	2017 Planning	Optimization Results Constraints		Results without constraints
1	1.00	0	= 0	0	0
2	0.98	0	= 0	0	0
3	0.83	180	≥ 500	500	0
4	0.65	1 200	≤ 2000	234	234
5	0.56	1 420	≤ 1500	714	183
6	0.67	250	None	0	0
7	0.48	6 600	≤ 6600	6600	9648
8	0.55	4 350	None	5952	3935

As a first approach, we considered the optimization problem as a minimization of the electricity bill under constraints. Energetic planning for this optimization can be found in the fourth column next to the energetic constraints taken into account (equations 9 to 13). We can notice that some of the constraints are reached (see values in red), so that we can hope to get better results in terms of electrical bill reduction if we relax the constraints.

These results led us to the second approach, without the energetic constraints put in place manually, but not corresponding to a real constraint of the installation, in opposite to the annual closure for instance. Results of this optimization are shown in the last column of Table 2 and Figure 1.

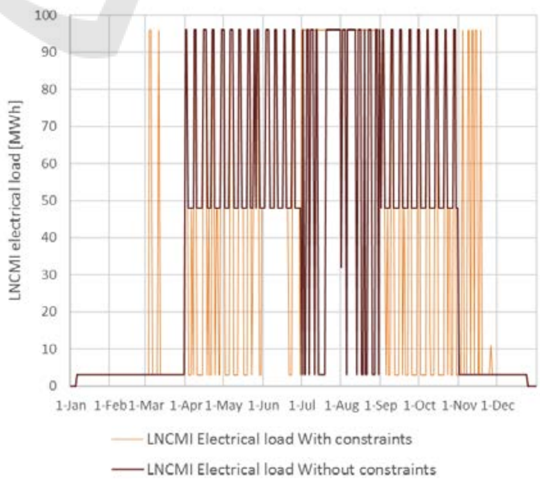

Figure 1: LNCMI electrical consumption from optimization results.

These values complete results from the first approach, by giving several indications as:

- As suspected, forcing the electrical consumption to zero for the first two price periods is not necessary because of high prices.
- Relaxing the two periods where limits are reached can significantly change the energy repartition.

For a better understanding of the impact of the relaxation of energy limitations, we will focus on the objective, which is the LNCMI electricity bill reduction.

In the first approach, the bill reduction with the new energy planning is estimated of 0.4%. Even if this diminution seems low, we have to keep in mind that our problem is more constrained than the current energy planning. Indeed, it has been wished that at least 500 MWh would be planned during the fourth time period, while only 180 MWh are currently planned. In the second approach, the bill reduction reaches 4.6%, but the impact on working conditions is not taken into account, as we relaxed the associated constraints.

2.3.2 Conclusion and Prospects

The energy planning of an EII allows us to use its consumption flexibility to adjust its operation. Moreover, it could also help the consumer to identify which constraints are the more restrictive from an economic point of view. However, it is important to keep in mind what impact could have the relaxation of restrictive constraints (less working quality in our case).

It has been shown that this first modeling could be used to minimize the energy bill with a defined pricing, but we can also imagine using it to compare financial gains associated with different energy supply contracts. Nevertheless, these two applications have as sole goal to serve economical interest of one particular actor, while we could imagine considering other goals.

A prospect for this decision tool could be to explicitly quantify the social impact of energy planning to realise multi-objectives optimizations and to help to choose a compromise between these two interests. Another one would be to use this flexibility into more ambitious projects and serve general interest at district scale.

3 COMBINED OPTIMIZATION OF ENERGY CONSUMPTION AND DISTRICT HEATING

On the one hand, for lots of energy experts, energy efficiency will be one of the keys of a successful energy transition (Smartgrids-CRE, 2017), so that energy losses reduction becomes more and more important. On the other hand, Joule losses in industrial processes can lead to temperature problems and lots of EIIs are forced to put in place cooling installations to evacuate generated heat. One way of reducing our total energy consumption consists in the heat losses re-use to supply heating demand instead of simply trying to evacuate it.

Well-known examples are datacenters (ADEME, 2015), but it could be achieved on the LNCMI installation with its annual consumption of 14 GWh and its cooling installation (which evacuates almost 12 GWh of heat). Therefore re-using calories from LNCMI magnets cooling to complete the heat supply of a district (annual load of 21GWh) instead of dissipating it into the neighbour river is studied in the project Valocal (C. Pajot et al., 2017).

3.1 Carbon Footprint for Heating Supply

Our first case study aims to reduce the carbon footprint of a district by minimizing the CO_2 emission generated to cover the heat load of buildings connected to a heating network. This reduction of greenhouse gases emissions will be realised thanks to the choice to solicit either the electrical network or the heating network offer by re-using LNCMI Joule losses.

3.1.1 Energetic Model

Indeed, from an energetic point of view, the LNCMI could be considered as a conversion unit between electricity and heat with a conversion rate depending of temperature conditions. To simplify the problem and focus on power flows only, we modeled the LNCMI process with a fixed electrical to thermal conversion rate of 85% (mean value of thermal losses observed in real conditions).

$$e\_out_{LNCMI}(t) = 0.85 * e\_in_{LNCMI}(t) \tag{16}$$

The previous operating constraints were kept and a thermal dissipation model was added as a flexible consumption (see Figure 2). Heating power provided by the LNCMI can be either dissipated through this flexible consumption unit or exported to the heating network as expressed in equation 16:

$$e\_out_{\,lncmi}(t) = e_{dissip.}(t) + e_{export}(t) \tag{17}$$

e_{export} : export to the district heating network
e_{dissip}: the variable dissipated heat

The energy networks (heating and electrical) were modeled as production units with limitations on maximal power delivered corresponding to network maximal power flux.

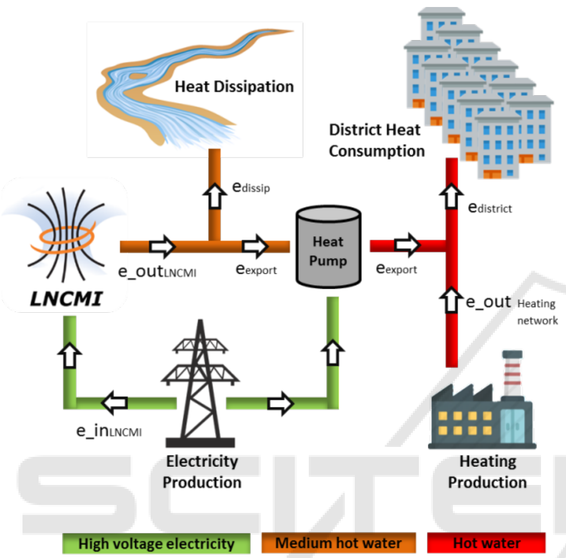

Figure 2 : Schematic diagram for district energetic model.

In our study case, we don't consider the possibility of load variations (load shifting, load reduction, etc.), so that the district heating consumption was modeled as a fixed load corresponding to a representative year.

3.1.2 Environmental Model

3.1.2.1 French Electrical Emissions

The French electrical system is well known for its low CO_2 emission, due to its high share of nuclear power (72% of the 2016 electrical production (RTE, (2016)). Moreover, this massive nuclear power integration into the electrical mix has affected the heating sector with one of the highest electrical heating share among European countries, so that fossil fuel production units are only started to provide supply for load peaks (see French electricity network CO_2 emission during a year in Figure 3). That is why we decided to study the subject of energy carbon footprint from a dynamic point of view (ADEME, 2014).

For both of the production units modelling energy networks, a dynamic CO_2 emission rate was defined corresponding to the daily mean value (see 'Electricity' and 'Heat' curves on Figure 3).

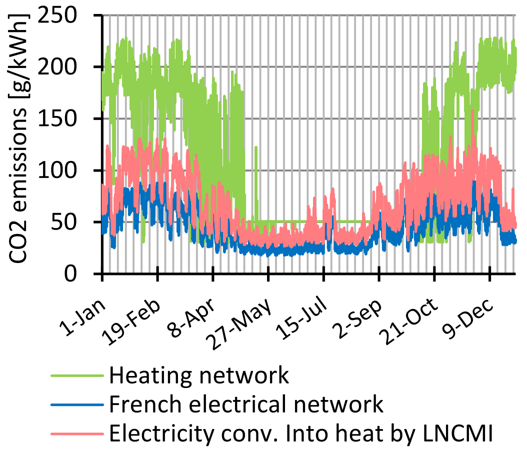

Figure 3: Dynamic CO_2 emission from energetic (electrical and heat) production.

3.1.2.2 Additional emissions

Moreover, temperature levels need to be increased to reach those of the heating grid. Therefore, the resulting electrical consumption increase needed to feed a heating pump was also considered. As before, we consider temperature variations to be negligible and make the hypothesis of a constant ratio. After a technological benchmark realised in the Valocal project, the heat pump was chosen with a coefficient of performance equal to 3.25.

Therefore, if we consider the CO_2 emissions related to the entire conversion chain of electrical consumption into heat production, we have to add the CO_2 emission from the electrical consumption of the heat pump to the electrical consumption to the LNCMI electrical consumption converted into heat and exported into the heating network.

For each thermal kWh exported, 1/0.85 electrical kWh was consumed by the LNCMI and an extra 1/3.25 electrical kWh was consumed by the heat pump leading to an equivalent CO_2 emission rate (see 'Electricity conv. into heat by LNCMI' on Figure 3) expressed as follows:

$$co_{2eq\ rate}(t) = co_{2elec\ rate}(t) * (1/0.85 + 1/3.25) \tag{18}$$

For reminder, the objective in this case study is to reduce the carbon footprint of the district by minimizing the CO_2 emission of the heating network. To simplify, we introduced an equivalent CO_2 emission rate (equation 16) for thermal energy provided by LNCMI cooling system, so that objective can be formulated as:

$$\text{Minimize} \quad \sum_t CO_{2district}(t) \tag{19}$$

$$\text{Where:} \quad CO_{2district}(t) = co_{2eq\ rate}(t) * e_{export}(t) + co_{2heat\ rate}(t) * e\_out_{heating\ network}(t) \tag{20}$$

3.1.3 Results and Prospects

As before, we studied two different approaches: with and without LNCMI energy limitation constraints. We reached a reduction of CO_2 emission of 28% in the first case and 35% in the second case.

Unlike the energy bill reduction problem, we can notice that energy limitations are less restrictive in order to minimize CO_2 emission. However, the energy repartition changes a lot between optimizations with or without energy limitations (see Figure 4 and Figure 5).

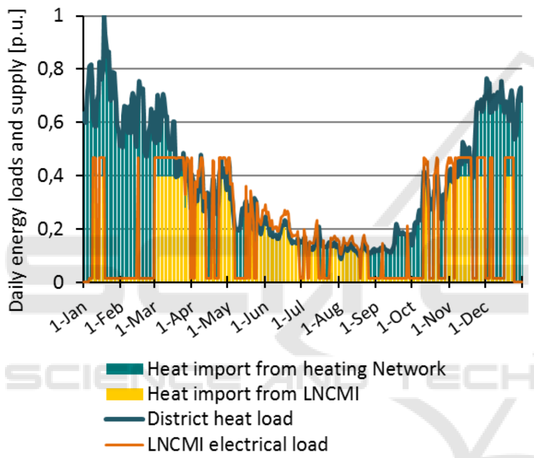

Figure 4: District energy flows repartition with LNCMI constraints taken into account.

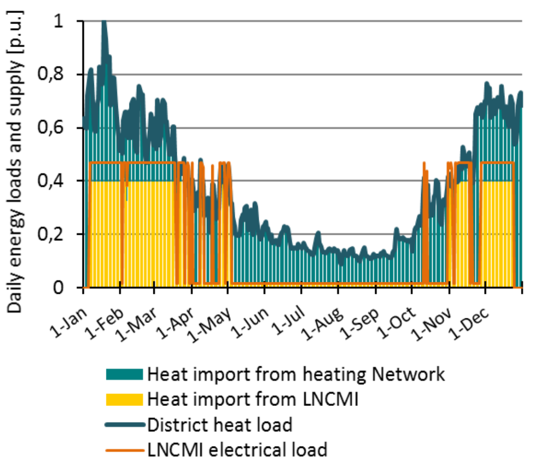

Figure 5: District energy flows repartition without LNCMI constraint.

In section 2, we optimized energy planning in order to reduce the electricity bill and demonstrated that the currently used energy planning was already a good optimization as we reduced the bill with and without energy constraints of respectively 0.4% and 4.6%. This first case aimed to help a single stakeholder, while we focused on the global interest through an ecological optimization in 3.1.

Nevertheless, we can now wonder how the LNCMI is impacted by these ecological considerations. In the first case, the electricity bill of the LNCMI increases by 21% and reaches 39% of raise when we remove the LNCMI energy limitations. In these cases, why would the LNCMI be the one to pay the CO_2 emissions reduction? Moreover, the electricity cost to feed the heat pump was not included into the increases, while some stakeholders would have to pay for it.

These results raise an issue: how to guarantee no economic effect on the heating consumer bill, while guaranteeing no LNCMI electricity bill increase either?

3.2 Reduction of a District Heating Supply Cost

One of the main issues in energy transition is to mitigate our environmental impact without leading to an uncontrolled raise of energy prices for the consumer. How to do so, when we have the possibility to produce at low price with energies as coal with a strong impact on global warming for instance?

That is the problem we address in this last case study at a district scale. Our aim is to add a financial modeling to our previous case study to find compromises between ecologic and economic points of view.

3.2.1 Financial Model

We found previously that LNCMI electricity bill could increase when we reduced the CO_2 emission. However, we did not define any economic model to compensate this bill augmentation.

Here, we decided not to model the financial transactions between the heat supplier and the LNCMI to keep all types of remuneration possible. To do so, we considered the LNCMI as a heating production unit with an energy production cost.

The production cost of 1 thermal kWh is estimated as the electrical consumption cost of the heat pump added to the increase of LNCMI bill regarding to the current one. LNCMI expense model is usable for any energy unit connected to the transmission grid under the condition of providing an equivalent power of consumption. Nevertheless, applying this particular point to the heat pump could lead to an over-estimation of its electricity consumption cost. We preferred here an average approach as studied on the ecological study case, with a mean dynamic cost of electricity.

3.2.2 Which Trade-off between Divergent Interests?

Optimization focused on district energy heating cost only can lead to a reduction of 8.3% with the LNCMI energy limitations. This result seems to say that we get a margin to lower the CO_2 emission of the district without increasing energy cost for the consumer. Our last case study aims to verify this assumption.

For this purpose, we combine financial and ecological objectives into a single one as follows with a coefficient α to weight the objectives:

Minimize:

$$\alpha \sum_t CO_{2district}(t) / CO_{2max} + (1-\alpha) \sum_t Ct_{district}(t) / Ct_{max} \tag{21}$$

Results obtained with α-values in [0; 1] showed that with great use of LNCMI flexibility, we could achieve both of the goals previously set: CO_2 emission reduction and heating supply cost reduction (see the Pareto diagram Figure 7).

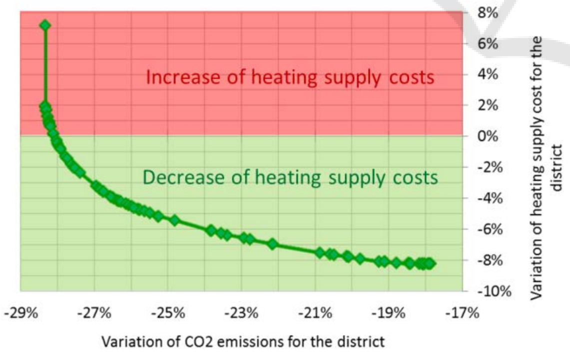

Figure 6: Pareto diagram for CO2 emission and heating supply bill reduction.

The abscissa shows the impact on CO_2 emission compared to the current estimation, while the y-axis represents the financial objective with the variation of heating supply cost (positive values when cost increases and negative ones when it decreases). We can observe on the Figure 6, the two extreme points corresponding to each objective. When alpha equals 0, the optimization is only financial and we reach the 8.3% of savings announced before. In the other hand, when alpha equals 1, we recognized the 28% of CO_2 emission reduction from the environmental optimization in 3.1.

If we consider only the results leading to supply cost decreases, we can see that reducing CO_2 emissions is possible without increasing the energy supply and can even lead to supply savings. However, these savings do not consider the investment costs to re-use the LNCMI thermal losses. That is why one of the outlooks for the use of this decision tool could be the study of return of investment in the case of heat recycling.

4 CONCLUSIONS

To summarize, we have shown that the developed decision tool could serve several needs:

- Reducing its energy supply bill under operation constraints
- Reducing the CO_2 emission of a district
- Reducing the heating supply cost of a district

With the defined energy limitations, the LNCMI optimal planning can only reduce by 0.4% the amount of the energy bill, while this decrease reached 4.8% when relaxing these limitations.

A multi-objective approach could be studied to take into consideration both of the financial and working quality aspect, by adding a social modeling. Moreover, the LNCMI energy planning could serve more ambitious projects than only bill reduction as the Valocal project, which aims to re-use LNCMI heat losses for building heating.

In this scenario, two goals have been studied (financial and ecological). Regarding the ecological optimization, the reduction of CO_2 emissions can reach 35% and heating supply cost can decrease by 8.8% for a financial optimization. Finally, we have seen that both goals could be achieved by merging the two objectives into one.

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