An energy management method for the food industry

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Abstract

This paper presents a method combining a top-down and a bottom-up approach, which has been developed to track energy saving opportunities. The top-down modelling method aims at correlating the energy consumption with the final products and the auxiliaries and at distributing the energy bill among major consumers. Based on the description of the thermodynamic requirements of the process operations, the bottom-up approach is used to define the energy requirements of these consumers. When compared with the measured consumptions, these energy requirements allow the identification of energy saving opportunities that are evaluated using thermo-economic modelling tools. The developed methodology has been applied in the food industry. It allowed identifying energy savings options ranging from good-housekeeping measures, optimised process operation to energy saving investments.

Key words: food industry, energy management, top-down, degree days

1 Introduction

The food industry is a non-intensive industry where energy is only a small part of the total cost of production (approximately 3%) (10; 16). However, it is one important energy consumers in the industrial sector. In 1998, food industry accounted for 4.4% of the energy consumption of the US industry

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sector. It was the fifth biggest consumer (out of 20 sectors) after petroleum and Coal products, chemicals, paper and primary metals (8). Thus, the potential energy savings achievable through an efficient energy management program can be quite significant. The facts that most of the saving opportunities can be 'repeated' from one production site to the other is an additional opportunities for corporations having a large number of production sites.

However, multiple barriers have to be overcome in order to put in place an efficient energy management program (4). The fact that energy is only a small part of the total cost of production makes that it is not considered as a 'core' business. Thus, it is not viewed as a priority in the daily management. It is only when an increase in energy costs is detected that an energy management program is set up. This initiative will often lead to short-term results that will once again relegates energy management to a position of secondary importance. Consequently, the energy costs will often increase once again and the cycle continues repeatedly. Energy management needs a constant attention to be effective. As a consequence, top management commitment is a necessary condition to lead an effective energy management program as stated in different best practices (5; 3). Another frequently encountered difficulty in energy management is the lack of resources for energy monitoring as well as for implementing energy efficiency projects. If resources allocated to energy management may appear as a cost, they should be viewed as an investment to increase the factory productivity. Another consequence of the secondary role played by energy, is the low level of energy metering and recording that is frequently found in the facilities. Moreover, The few information that are available are often spread all over the facilities and are not centralized due to the lack of human resources. Availability of reliable data is a key component of an energy management program.

Today, even if the food industry remains a non-intensive energy industry, higher energy prices and the Kyoto protocol have put an increased focus on energy efficiency. The set up of an energy management program involves many actors with different visions and expectations: the factory manager, the technical manager, maintenance and project engineers, production and utility operators. The goal of an energy management program is to monitor, record, analyse, critically examine, alter and control energy flows so that energy is always available and utilized with maximum efficiency (11). The needed knowledge to fulfill these goals includes engineering, economics, management, information technology.

In the field of engineering, a wide range of methods and tools are available to support energy management programs:

- Energy follow-up and monitoring tools
- Process modeling, simulation and optimisation tools

- Process integration
- Energy and exergy analysis
- Decision support tools: best practices, literature, etc.

The first one can be considered as a top-down approach while the three following ones are considered as bottom-up approach since they are focused on the process itself. The last point includes general conclusion and advice which comes out of the four first points. Often, only one of these two approaches is used when it comes to energy management. This paper presents an energy management method that combines a top-down approach - which offers a holistic vision of the energy consumptions in the factory - with a bottom-up approach - which determines the efficiency gaps between the thermodynamic requirements of the process operations and their technological implementation in production. Together with the best practices, this method will help in defining road maps towards energy efficiency.

2 Methodology

A typical factory representation can be found on figure 1. The system boundary includes the processes, the energy conversion units and the distribution systems, support to production and waste treatment. Horizontal transformations concern transformation of raw materials into products or by-product. They have to be maximised while minimising the vertical flows which include energy usage and waste generation.

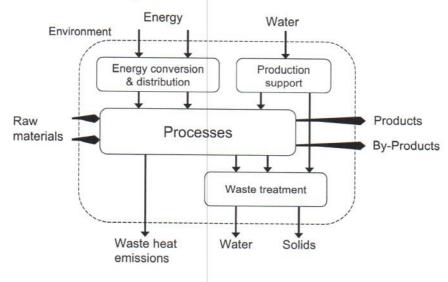


Fig. 1. Typical production setup.

Two approach can be considered when it comes to modeling energy consumption in the perspective of energy efficiency: top-down and bottom-up approach.

Based on the energy bills, the top-down approach aims at allocating the consumption among the different users in the factory. It helps identifying the main energy drivers. in that perspective, multiple linear regressions can be used to define relationships between dependent variables, such as energy consumptions, and independent variables, such as production volumes, ambient temperature, etc. Experience shows that a linear model is accurate enough in most of the cases (9). Unlike the top-down approach that is based on the global energy consumption of the factory (i.e. the utility bills), the bottom-up approach aims at thermodynamically modelling the energy consumptions of the different process operations in order to recalculate the global energy consumption by summing up their different contributions. This technique is modelling community and offers an excellent basis for pinch analyses (6) given the large amount of information that is made available. Methods suggested by (7) can be used to simplify the process integration analysis.

Both approaches have been applied to chemical batch plant. The efficiency of each methods will mainly depends on the variability of the products as shown in (1; 2). Besides its applicability, both methods have their advantages and disadvantages which are presented in table 1. A more detailed discussion can be found in (9).

Table 1 Advantages and disadvantages of the top-down and the bottom-up approaches

	Advantages	Disadvantages		
Top-down	• Low cost	• Require statistical expertise		
	• Simple model	• Require data history		
	• Easy monitoring	 No efficiency assessment 		
	• Easy forecasting	• High level modeling		
	• Flexible			
	• Minimal maintenance			
Bottom-up	• Based on equipments	• High level of metering needed		
	• Good accuracy	• Time-consuming study		
	• Clear picture of energy usage	• High data entry requirement		
	• No data history required	• Forecasting is difficult		
	• Efficiency assessment	• High cost of using/maintenance		

Due to its characteristics, the top-down is more adapted to quickly identify the main energy drivers of a factory which can be the base for a more detailed study in a specific area. The bottom-up approach requires a lots of efforts in terms of time, people, metering and model updating but it gives a clear and precise picture of the energy usage. It makes it difficultly applicable in industries where the resources dedicated to energy management are limited. In our approach, the bottom-up approach is used as a complement rather than as an alternative to the top-down approach in order to analyse the main energy drivers identified in a first phase. It is applied locally not for the whole site as done in the perspective to recompute the energy bill.

3 Top-down approach: fuel modeling

For the sake of demonstration, this technique has been applied in a Nestlé factory in Switzerland. The factory produces three main products $(n_p = 3)$. The selected independent variables to estimate the monthly fuel consumptions y_i are the monthly production volumes $v_{i,p}$ of each product p together with the heating degree days. The database built up for this study covers a period of 36 months $(n_{month} = 36)$ from January 2000 to December 2002. Assuming that no major process modifications have occurred during this period, the problem is solved using the least square principle and is formulated as follow:

$$\min_{a_p,h,k} \left(\sum_{i=1}^{n_{month}} \epsilon_i^2 \right) = \min_{a_p,h,k} \left(\sum_{i=1}^{n_{month}} [\hat{y}_i - y_i]^2 \right)$$
 (1)

with

$$\hat{y}_i = \sum_{p=1}^{n_p} a_p \cdot v_{i,p} + h \sum_{j=1}^{n_{days_i}} HDD(T_{i,j}) + k \cdot n_{days_i}$$
(2)

where a_p , h and k are the regression coefficients, ϵ_i is the random error of month i and n_{days_i} is the number of days in month i. Heating degree days $(HDD(T_{i,j}))$ are used to characterize the heating requirements as a function of the ambient temperature $T_{i,j}$ of the day j in the month i. In Switzerland, they are computed according to a norm (18):

$$HDD(T_{i,j}) = \begin{cases} T_{room} - T_{i,j} & \text{if } T_{i,j} \leq T_{lim}; \\ 0 & \text{if } T_{i,j} > T_{lim}. \end{cases}$$

$$(3)$$

 T_{room} and T_{lim} are respectively the indoor temperature and the limit heating temperature respectively, set to 20 and 12°C. The average ambient temperature of day i in month j ($T_{i,j}$) has been obtained from a meteorological station located nearby the factory. The results of the least square estimation are presented in table 2. The validity of the model is tested using the following hypothesis:

 $H_0: \beta_j = 0 \ \forall j$ vs. $H_1:$ at least one $\beta_j \neq 0$ with $\beta_j \in \{h, k, a_1, ..., a_{n_p}\}$

The test is performed using the F statistic which is computed as follows:

$$F = \frac{(n_{month} - m - 1)R^2}{m(1 - R^2)} \tag{4}$$

$$R^2 = \frac{\hat{Y}^T \hat{Y} - n_{month} \bar{Y}^2}{Y^T Y - n_{month} \bar{Y}^2} \tag{5}$$

with

$$\bar{Y} = \frac{1}{n_{month}} \sum_{i=1}^{n_{month}} y_i \tag{6}$$

where \hat{Y} and Y are respectively the array of the estimate \hat{y}_i and the measured consumptions y_i and m is the number of independent variables excluding the constant. The F statistic has a F distribution with m, $n_{month}-m-1$ degrees of freedom. The test is performed by comparing the F statistic with the critical F-value of a table at a given level of significance. It can be seen on table 2 that the computed F-value (equation 4) is higher than the table value (2.68) at 0.05 level of significance and (4,31) degrees of freedom. As a consequence, the null hypothesis (H_0) can be rejected. This result could have been expected given the high value of the coefficient of determination R^2 (equation 5), which intervenes in the computation of the F-value.

Table 2 Results of the regression ($T_{lim} = 12^{\circ}\text{C}$ and $T_{room} = 20^{\circ}\text{C}$)

	k	a_1	a_2	a_3	h	\mathbb{R}^2	Computed F -value
Unit	$\frac{GJ}{day}$	$\frac{GJ}{t}$	$\frac{GJ}{t}$	$\frac{GJ}{t}$	$\frac{GJ}{HDD}$		
β coefficients	61.48	1.56	1.71	-0.31	4.18	0.950	147.13
Computed t -value	6.61	3.57	2.64	0.68	19.08		
Table t -value	2.04				Table .	F-value	2.68

After testing the relevance of the model, the validity of each of the model parameters is verified by testing the following hypothesis:

$$H_0: \beta_j = 0$$
 vs. $H_1: \beta_j \neq 0 \ \forall j$

The t-value of a coefficient can be obtained with the following equation (12):

$$t = \frac{\hat{\beta}_j}{\sqrt{c_{jj} \cdot MSE}} \tag{7}$$

where $\hat{\beta}_j$ is the coefficient estimate. MSE is the error mean square and is computed according to the following formula:

$$MSE = \frac{\sum_{i=1}^{n_{month}} \epsilon_i^2}{n_{month} - m - 1} \tag{8}$$

 c_{jj} is the jth diagonal element of matrix $C = (X'X)^{-1}$ where X is the m-by-(m+1) matrix containing all the independent variables including the constant. The constant is represented by a column of 1 in the first column of matrix X.

The t statistic has a Student's t distribution with $(n_{month} - m - 1)$ degrees of freedom. The test involves comparing t-value with the critical t-value of a table at a given level of significance. From the results presented in table 2, the null hypothesis for coefficient a_3 can not be rejected because the computed t-value is lower than the table value of 2.04 at 0.05 level of significance and 31 degrees of freedom. As a consequence, a model without the product 3 variable $(v_{i,3})$ should be used for further analysis. With the aim of improving the model, the sensitivity of the T_{lim} and T_{room} value in equation 3 has been studied. The results are presented in table 3. All the 9 restricted models in this table did satisfy the two tests with 3 independent variables $(v_{i,1}, v_{i,2}, HDD)$ except for the model with $T_{lim}=14^{\circ}\text{C}$ and $T_{room}=22^{\circ}\text{C}$, in which the test on the significance of the coefficients showed that product 2 had also to be excluded. It can be seen that T_{room} has fewer impacts on the coefficient of determination R^2 than T_{lim} and that shifting from $T_{lim} = 10^{\circ}\text{C}$ to $T_{lim} = 8^{\circ}\text{C}$ reduces significantly the regression quality. According to the results of table 3, T_{lim} =10°C and $T_{room} = 22$ °C is the most appropriate value for computing heating degree days for this example. The estimates of the coefficients as well as the results of the tests obtained with these values can be found in table 4. The resulting estimated monthly fuel consumptions are then compared with the measured consumptions on figure 2. The figure shows as well the contribution of the different independent variables. It can be noticed that more than half of the fuel consumption (62%) is not directly correlated with the production and that the base load represents 39% of the consumption. This relatively high base load can be explained partially by the fact that the production only takes place 5 days a week, while some pieces of equipment are kept hot during the whole period. However, such base load stresses the need for changing operation practices during process stand-by periods.

Table 3 Effect of T_{lim} and T_{room} on the coefficient of determination \mathbb{R}^2

	$T_{lim}=8^{\circ}\mathrm{C}$	$T_{lim}=10^{\circ}\mathrm{C}$	$T_{lim}=12^{\circ}\mathrm{C}$	$T_{lim} = 14^{\circ}\mathrm{C}$
$T_{room} = 22^{\circ} \text{C}$	0.932	0.954	0.946	0.932
$T_{room}=20^{\circ}\mathrm{C}$	0.930	0.953	0.949	0.944
$T_{room}=18^{\circ}\mathrm{C}$	0.923	0.950	0.950	0.947

Table 4 Results of the regression ($T_{lim}=10^{\circ}\text{C}$ and $T_{room}=22^{\circ}\text{C}$)

	k	a_1	a_2	a_3	h	R^2	Computed F -value
Unit	$\frac{GJ}{day}$	$\frac{GJ}{t}$	$\frac{GJ}{t}$	$\frac{GJ}{t}$	$\frac{GJ}{HDD}$		
β coefficients	56.68	1.42	2.46	-	3.77	0.954	223.61
Computed t -value	8.59	3.50	4.14	-1	24.49		
Table t-value	2.04				Table	F-value	2.90

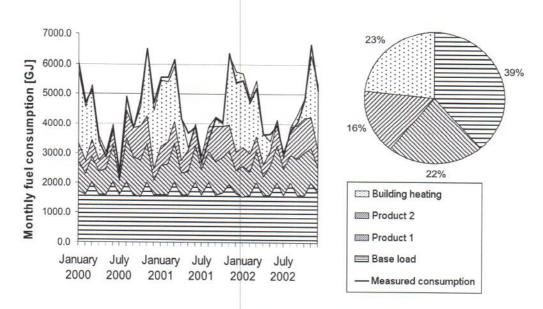


Fig. 2. Measured fuel consumption compared to estimation from the model and share of independent variables.

4 Top-down approach: electricity modeling

A similar model is used to estimate the monthly electricity consumption \hat{y}_i :

$$\hat{y}_i = \sum_{p=1}^{n_p} a_p \cdot v_{i,p} + h \sum_{j=1}^{n_{days_i}} CDD(T_{i,j}) + k \cdot n_{days_i}$$
(9)

The independent variables are the same as for the fuel model except for the climate contribution which is characterized with cooling degree days $(CDD(T_{i,j}))$. Since all the refrigeration unit use electricity as the driving energy (mechanical chiller), the hotter the outside temperature, the bigger the electricity consumption. The commonly used function to model this behaviour is given in equation 10 here below:

$$CDD(T_{i,j}) = \begin{cases} T_{i,j} - T_{room} & \text{if } T_{i,j} \ge T_{room}; \\ 0 & \text{if } T_{i,j} < T_{room}. \end{cases}$$

$$(10)$$

 T_{room} is usually taken as 18°C (17).

The two tests presented for the fuel model are also implemented in this case. The best result for the electricity model for the same period as the fuel model (January 2000 to December 2002) is presented in table 5. It can be observed that, once again, product 3 variable has to be taken out of the model. More surprisingly, the climate does not have an impact on the electricity consumption according to the model. This could have been explained by the value of T_{room} that has been selected. Indeed, as stated in (17), this value has to be carefully chosen. However, the fact that the same result is observed with $T_{room}=10^{\circ}\text{C}$, 12°C, 14°C, 16°C and 20°C leads to the rejection of this assumption. Table 5 also points out that the quality of the model, which has a coefficient of determination of 0.872, is lower than for the fuel model. However, from the daily measurement made at the factory, we can see that the model predicts quite well the base load consumption as shown in figure 3. The black line on the figure represents the base load consumption as identified by the model (coefficient XXX) which is 81 GJ/day = 22639 kWh/day. It predicts quite well the electricity consumption in non production periods (week-end and holidays). It has to be noticed that during the holidays (April and December) the consumption is somewhat smaller because some additional equipment are turned off.

The monthly electricity consumption predicted by the model as well as the share of the independent variable is presented in figure 4 where it is compared to the measured value. It can be seen that the values obtained for November

Table 5
Results of the regression for the electricity

	k	a_1	a_2	a_3	h	R^2	Computed F-value
Unit	$\frac{GJ}{day}$	$\frac{GJ}{t}$	$\frac{GJ}{t}$	$\frac{GJ}{t}$	$\frac{GJ}{CDD}$		
β coefficients	81.50	1.67	3.03	_	-	0.872	112.63
Computed t -value	13.69	4.19	5.12	-	-		
Table t-value	2.04				Table	F-value	3.28

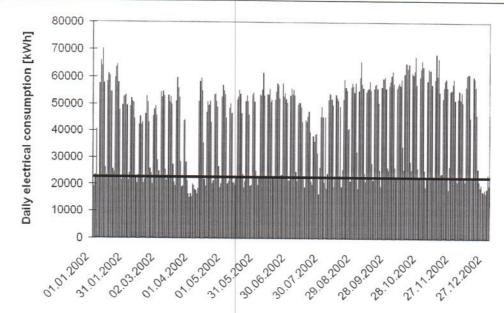


Fig. 3. Measured base load consumption versus model prediction for the year 2002

2001 and November 2002 clearly under-predict the measured consumption. The reasons for that gap was not clearly identified but some assumption can be made such as the temporary change of process operation.

Similarly to the fuel consumption, it can be seen in figure 4 that the share of the base load in the total consumption is important. According to the model, it represents 55% of total electricity consumption. Clearly, it is one of the point to take into consideration when using the bottom-up approach to identify energy savings opportunities.

4.1 Top-down approach: breakdown of electricity consumption

The same approach can be used inside the factory to correlate the consumption of converted energies such as chilled water with independent variables. The only requirement is to have a data history for that energy. As an example,

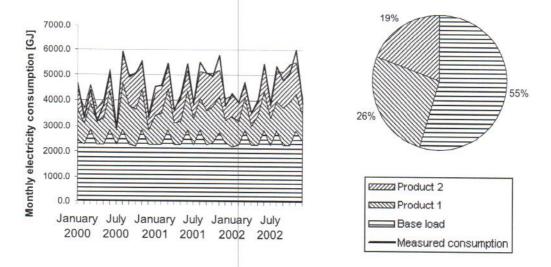


Fig. 4. Measured electricity consumption compared to estimation from the model and share of independent variables

we look more into details at the main refrigeration unit which is supposed to be an important consumer due to its installed power. The unit is a single stage NH₃ unit with 2 screw compressors that cools down a mixture of glycol and water from 6°C to 0°C. The goal is to model the electricity consumption of the chiller in function of the independent variables. Since the only data history on the refrigeration plant is the distributed energy through the chilled water, a procedure to link it to the electricity consumption of the chiller is implemented. It is presented in figure 5.

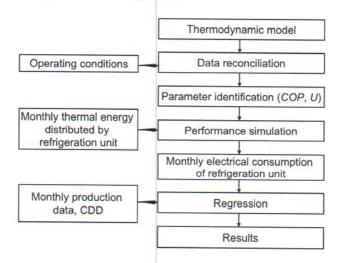


Fig. 5. Procedure applied when using a thermodynamic model

In a first step a thermodynamic model of the unit is developed. From the measurements of the operating conditions, the model allows for identifying the main parameter through a data reconciliation. In this example, the more

important parameter is the coefficient of performance (COP) which allows to link directly the distributed energy Q_{evap} with the consumed electricity W_{in} as shown in equation 11:

$$COP = \frac{Q_{evap}}{W_{in}} \tag{11}$$

This parameter is highly influenced by the efficiency of the compressors which has also been identified. These parameters are presented in table 6 together with the condensing and evaporating temperature. Since the condensing and evaporating pressure are maintained constant all over the year, the COP can be considered as constant in first approximation.

Table 6
Characteristics of the NH₃ refrigeration cycle as identified by data reconciliation

Condensing temperature	30.4°C
Evaporating temperature	-3.3°C
Isentropic efficiency of compressor	75.2 %
COP	5.1

Once the parameters of the model are known, it is possible to simulate the monthly electrical consumption of the chiller from the data history of the distributed energy. From these simulations, it appears that this unit consumes 8.3% of the factory electricity. The monthly consumptions can then be used together with the independent variables (monthly production data, CDD) in a regression analysis to model the electricity consumption of the chiller.

This analysis has been performed on the small data history that was available (12 months). The results (see table 7) show that the relevant variables are the products 2 and 3 as well as the CDD. The share of the different variables in the electricity consumption of the refrigeration cycle are respectively 55.6%, 35.5% and 8.9%. We can observe here that this unit do not contribute significantly to the high base load that appears on figure 4. in the other hand, the CDD seem to be relevant to model the electricity consumption of the chiller although they are not at the factory level (see table 5). However, their share is low in the consumption of the chiller (8.3%). As a consequence, they become negligible at the factory level. Indeed, their contributions to the factory consumption is $8.9\% \times 8.3\% = 0.7\%$.

5 Top-down approach: discussion

In the proposed methodology, the top-down approach is used to focus the next step of the method (the bottom-up approach) on the major energy drivers in

Table 7
Results of the regression for the refrigeration cycle

	k	a_1	a_2	a_3	h	R^2	Computed F-value
Unit	$\frac{GJ}{day}$	$\frac{GJ}{t}$	$\frac{GJ}{t}$	$\frac{GJ}{t}$	$\frac{GJ}{HDD}$		
β coefficients	-	-	0.56	0.36	1.39	0.989	236.5
Computed t-value		-	6.67	3.95	4.49		
Table t-value	2.31				Table	F-value	4.46

the process by defining the their contribution to the energy bill. Compared to similar analysis (1), the top-down approach appears here to be more appropriate than in other processes like chemical batch plants. This can be explained by the fact that the product mix does not vary as much as in multi-products and multipurpose chemical batch plants. Moreover, the models developed in the top-down approach have also been used for consumption forecasting for budgeting purpose. They have allowed for detecting errors in the production volume records. As mentioned in table 1, they can also be used easily for targeting-monitoring in order to detect shifts in the process. It has to be noticed that the availability of reliable data record is essential in the top-down approach. The data should also be available for the same periods for dependent and independent variables. For example, in this study, the electricity consumptions used in the models are not the one available through the monthly bills (which cover the period from the first day to the last day of a month) but from measurements taken daily in the factory. Indeed production volumes are available by weeks and can not be determined for a given months. Some month presented in figure 2 and 4 are composed of four weeks while some others of five weeks. It is the reason while the base loads plotted in this 2 figures is not constant.

The same approach can be used on a weekly basis if all the needed data (energy consumption, production volumes, temperatures) are available with this frequency. This has be done in the factory under study for the same period as for monthly data (January 2000 to December 2002) representing 159 weeks. The results showed that the models for the electricity and the fuel were the same as for the monthly models, i. e. the same independent variables are rejected after the tests of the parameters. However, the coefficient of determination obtained are lower than for the monthly approach. It was 0.84 for the fuel model and 0.65 for the electricity model. This can be explained by the fact that the data are less accurate and are not always available for the same period as discussed above.

6 Bottom-up approach

Though the top-down approach has allowed a quick identification of the main energy drivers in the studied facilities, this analysis does not usually lead to direct energy savings opportunities. Another approach, called bottom-up, is used for that purpose. As an example, the significant base load in the two major utilities (electricity and fuel) made them natural priorities in the bottom-up approach. The methodology used has been to compute the thermodynamic requirements of different process units contributing to base load consumptions and to compare them with their technological implementation. This dual representation of the requirement (14) is important to identify situations where the process requirements are satisfied with the wrong utility or the wrong technology. It will also highlight opportunities for energy savings by process integration when the process energy supply is changed. To illustrate this concept, let us consider some examples.

6.1 Compressed air

From the top-down approach, it appears that 7.5% of the electricity consumption base load comes from the compressed air production. In this consumption, the process unit sealing amounts to 70%. The thermodynamic requirements of this operation shows that each unit requires 16.1 Nm³/h of 0.5 barg air. Assuming an isentropic compression of atmospheric air, the power needed is 0.2 [kW]. This is to be compared with its technical implementation, which consists of using the 7.5 bars compressed air network. In this system, compressed air is produced by screw compressors with an isentropic efficiency of 76% identified from data reconciliation of measurements. Consequently, the required power to produce the necessary amount of air is 1.9 [kW], giving a maximum saving potential of 1.7 kW or 89% of the present load. The related energy saving option deduced from this analysis is to supply sealing air by a dedicated blower whose consumption will be 0.6 [kW] resulting from the lower isentropic efficiency of the blowers (35%). Nevertheless, considering 8000 hours of operations per year, the annual energy saving has been estimated to 68% of the process units sealing consumption.

6.2 Vacuum production

Another example is the production of vacuum of 25 mbars that is needed in a dryer. Presently, it is performed with a liquid ring vacuum pump coupled with a high pressure steam ejector. Both device are used simultaneously to create and maintain the required conditions. From a thermodynamic model of

the vacuum production sub-system and through tests on site, it appeared that the steam ejector was needed only for the creation of the vacuum at starting of the process and that low pressure steam could be used. Once the vacuum is established, the steam ejector can be shut down since the liquid ring pump is sufficient to maintain the desired vacuum. The saving associated with this initiative are of approximately 15,000 liters of fuel per year.

6.3 Summary of energy savings

If part of the energy savings are identified using the bottom-up approach, the implementation of best practices and good housekeeping measures also lead to energy savings without great efforts. Typically, it concerns the compressed air leakage and the insulation of high temperature pipes that contribute to the high base load observed in both fuel and electrical consumption. These measures have been classified in three categories: measures that requires only changes in process practice, modifications that require process operation optimisation and modifications that require equipment investment. Table 8 presents the main yearly energy savings obtained in this study. The analysis of this table confirmed the results of similar studies (15; 13), which showed that a significant part of the savings can be considered as good housekeeping and require no or few investments.

Table 8 Summary of some energy savings identified

	Annual	Estimated	
Measure	energy saving	payback	
Compressed air with blower instead of compressor*	166 MWh	2	
Regulation of HVAC*	80 MWh	negl.	
Removing stand-by of air compressors with a VSD unit*	69 MWh	2.3	
Fixing compressed air leakage*	50 MWh	negl.	
Insulating pipes of high temperature condensate return**	33,800 liters	1.5	
Vacuum production in dryer**	15,000 liters	1	
Regulation of steam user**	5,000 liters	negl.	

Notes: * and ** denote electricity and fuel savings respectively.

7 Conclusion

This paper has introduced an energy management method combining topdown and bottom-up approach. As shown by the application presented in a food industry process, this method is especially appropriate for non-intensive energy industry where the resources for energy management are often limited. However, it could also be applied to other industries. The top-down approach has permitted to model the energy consumption with multi-linear regression models. Statistical tests were used to include in the models only the variables that have significant impact on energy consumption and to test the validity of the models. The regressions have showed high coefficient of determination (0.954 in the case of fuel consumption and 0.872 for the electricity consumption), which are good indicators of their quality. These models have been used to set priorities for more detailed studies performed through bottom-up approach and application of best practices. They could also be used as reliable tools for forecasting and budgeting energy consumptions and for follow-up. The bottom-up approach aim at modelling the thermodynamic requirements of the prioritized process operations. The results have demonstrated that there is in some process units a gap between the thermodynamic requirements of a unit and its technological implementation allowing for energy savings. The study has also confirmed that a significant part of the energy savings identified is linked with good housekeeping and require no or few investments.

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A Nomenclature

COP Coefficient of performance CDD Cooling degree day HDD Heating degree day

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