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ENERGY CONSERVATION BY REDUCING PROCESS VARIABILITY[1]

Ulrika Wising[2]
Philippe Mack[3]
Sebastien Lafourcade[4]

Abstract

Energy conservation is becoming an increasingly important instrument to stay competitive in today's increasingly global market. Important investments have been made in infrastructure and personnel in order to improve the management of energy such as increased metering, energy dashboards, energy managers, etc. Despite these investments, the results have not materialized and there is still a significant potential to further reduce energy consumption. In this paper a new methodology will be presented that helps industry better operate existing assets in order to reduce energy consumption, without having to make capital investments. The methodology uses a combination of advanced data analysis tools and a specific implementation scheme that has lead to significant savings in industry. The advanced data analysis tools are used to analyze the variability of the process in order to assess when the plant has been operated well or not so well in the past. By finding the root causes of these variations and the key variables that can explain them, improved operating guidelines and models can be developed and implemented. The specific implementation scheme is an important part of the methodology as it involves the people operating the plant. Several user cases will be presented showing an energy conservation of between 10%-20% without capital investments necessary.

Keywords: Energy conservation; Advanced data analysis; Root cause analysis; Variability.

CONSERVAÇÃO ENERGÉTICA ATRAVÉS DA REDUÇÃO DE VARIABILIDADE DO PROCESSO

Resumo

A conservação energética cresce em importância como instrumento para manter a competitividade no mercado siderúrgico global. Igualmente significativa é a pressão pela adequação às crescentes restrições ambientais, como a redução de gases-estufa. No intuito de otimizar o gerenciamento de energia, investimentos importantes tem sido realizados, como a instalação de medidores, painéis de controle, contratação de gerentes focados em energia, etc. Apesar disto, os resultados não se materializaram e ainda há um significativo potencial de redução do consumo de energia. A principal razão reside na inexistente ligação entre os gestores de energia e os dados de processo disponíveis; os dados não são apresentados / fornecidos de uma maneira compreensível para a tomada de decisões. Neste artigo, uma nova metodologia é apresentada, a qual auxilia as indústrias a melhor operar os ativos existentes reduzindo o consumo energético e os custos com energia, prescindindo de investimentos de capital. A metodologia utiliza uma combinação de ferramentas de análise de dados avançada e uma estratégia de implantação comprovadamente responsável por economias substanciais no setor industrial. Ferramentas de análise avançada são utilizadas na análise da variabilidade do processo de fabricação de aço, determinando as causas-raízes da mesma e as variáveis-chave que podem explicá-las. Diversos casos de uso serão apresentados com índices de conservação de energia entre 10% e 20% sem investimento de capital.

Palavras-chave: Conservação de energia; Análise de dados; Causas-raiz; Variabilidade

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[2] *PhD. Pepite s.a., Rue Paul Devaux 3/001, 4000 Liege, Belgium*
[3] *PhD. Pepite technologies Inc. 111 Duke street, Montréal, H3C 2M1, Canada*
[4] *MSc. Pepite s.a., Rue Paul Devaux 3/001, 4000 Liege, Belgium*

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1 INTRODUCTION

Energy conversation is gaining more and more attention in industry. Cost of fuel and power is not expected to decrease in the coming years, quite the opposite. Governmental and regulation authorities put increasing pressure on industry to improve their energy and environmental performances. Companies having a sustainable energy policy attract more easily investors and satisfy shareholders.

In steel industry, as in many other manufacturing industries, energy efficiency has not always been an important topic of interest. The focus has traditionally been on increasing production capacity and yield and not energy efficiency. The recent global crisis has impacted this situation and market conditions are forcing steel makers to decrease their operating costs to increase or at least maintain their margin.

Energy represents close to 20% of the total steelmaking cost. Recent studies indicate that for iron-making 20% to 25% of this cost can be reduced through improved energy efficiency.[(1-3)] For an average production cost of 400$/ton of steel, these savings represents approximately 16$ to 20$/ton.

Improving energy efficiency can be achieved by three means:

1. capital investments in plant infrastructure (energy integrating plants, install more energy efficient technologies);
2. improvement of the energy supply chain and procurement; and
3. implementation of good practices for energy efficient operations.

The first means requires access to capital, which can be challenging when energy project are in competition with capacity increase projects. The second means often involve complex renegotiation of long-term contracts and highly depends on local energy regulations. The third means requires no or little capital and bring immediate savings. Hence a plant can make cash flow available for capital projects, secure the return of these projects and place the plant in a better position to renegotiate energy contracts.

In this paper, the third means will be the focus. A new way to discover and deploy good practice for energy efficient operations will be presented. How historical data can be leveraged to closely monitor energy consumption will, how to link operations with energy efficiency and how to discover good (or bad) practices will all be shown. These measures can quickly reduce energy costs significantly.

2 MATERIAL

We will show results we have obtained on two main energy account center in the steel making process, an electrical arc furnace and a boiler providing steam and electricity for an integrated steel plant.

The boiler was burning gases from a coke oven and a blast furnace. To increase the lower heating value of the mix, natural gas was added. The steam produced was re-dispatched in the utility network and/or used to produce electricity. The operators tried to maximize the use of gas byproducts and minimize the use of natural gas.

The second example is an electrical arc furnace (EAF). About 40% of the transformation cost is due to the energy consumption of the EAF.

For both the boiler and EAF, many parameters were measured automatically and archived in a plant information system. One year of this historical data was available and used in these projects.

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2.1 Data Mining

Data mining has been used to extract relevant knowledge from historical data related to the energy performance. The multivariate nature of the energy performance is particularly well suited for advanced machine learning tools.
Data mining is a very broad area covering different fields of data analysis (statistics, visualization, machine learning, optimization, etc.). The purpose of data mining is to use algorithms in order to automatically extract new and interesting knowledge from archived data.(4) Although data mining has become a must-have in many areas like marketing, finance, etc. the use of this technology is still very limited in the process industry. Many examples have shown that data mining can be effectively used to troubleshoot product quality, reduce energy costs, improve products quality, increase equipment lifespan, etc.(5) Modern data-mining tools are very easy to use even for non-experts in the field of statistics and machine learning. The tools can also interface easily with available data stored in plant information systems (PIMS).
Data was analyzed with PEPITo data mining and predictive analytics tool.(6,7)

3 METHODS

The process used is a proven methodology that has been used in several industrial projects. It is divided into several phases:

- Gap analysis;
- KPI hierarchy definition;
- Data collection;
- Energy efficiency variability analysis;
- Targeting and modeling;
- Smart monitoring and real-time diagnostics;
- Implementation.

3.1 Gap Analysis and Implementation Plan

Many studies today state that it is possible to reduce energy consumption in industry. This is generic data and the opportunity is different for each individual plant due to its technical and business environment. In order to more accurately evaluate the opportunity of improvement a gap analysis was performed where the current situation was assessed, actual performances calculated, best opportunities were detected and ranked. This way more realistic improvement objectives can be defined.
The gap analysis is a tool that combines technical, financial, management and market data to provide various reports on the actual energy performance of the plant. In Figure 1, we show a typical data set that has to be entered in this tool by the plant personnel. KPI are computed in standard forms so that it is possible to benchmark own performance with state-of-the-art technologies, with other sister plants or with plant past and future situations.
Once performance gaps have been identified and quantified, an implementation plan can be put in place. This plan ensures progressive and cost effective implementation of the energy efficiency projects consistent with plant current situation, highest opportunities and plant strategic plan. A first project is then defined. Following sections describe the different project steps.

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3.2 Hierarchy of KPIs

Most of the time energy performance analysis is done at a business level based on aggregated process data (e.g. total amount of kWh used in the month) and on numbers available at the accounting department (e.g. power bill for the month). This performance is the results a multitude of decisions, actions and design constraints at operational level and is reflected by technical information (e.g. exhaust fan set point). The key to energy efficiency is to link high-level business information with floor level technical information. Business information is often too aggregated and technical information is too detailed to be linked effectively.
In the approach described here the first objective is to develop a structure of Key Performance Indicators (KPI) that covers every level (corporate, plant level and operation) of the organization. This is a hierarchy of KPI where KPI are organized into a cascade structure based on decisions that need to be made and process interactions. By focusing on decision centers (as opposed to just accounting centers), it is easier to link operational actions with high-level energy KPI in a cause and effect relationship.

3.3 Data Collection

A set of energy KPI has to be selected based on the KPI structure and available data. It must be possible it to compute the KPI at an appropriate frequency (every hour for example).
Fault tree analysis is used to determine, together with operators and engineers, the entire set of possible sources of energy KPI variability. This activity has three goals. First it allows capturing the knowledge and valuable experience the plant personnel have. Second, this engages project stakeholders as part of the solution. Third, it guides data collection. These potential sources of variability are used to identify the measurements to be collected in the plant information systems. Typically this can lead to several hundred measurements related to process operations and product characteristics. Having enough measurements archived in a database (typically a data historian) is absolutely necessary deploy this solution.

3.4 Understanding Performance Variability

The goal is to link each identified KPI with parameters at operational level. The amount of data collected is usually too large and the problem too complex to be processed with standard spreadsheets software. The variability of energy consumption is the results of complex interactions and the identification of the parameters of operations that have the most impact is not a trivial task.
Advanced data mining and machine learning tools are used to extract from the collection of historical data the combination of parameters that explain the energy performance variability. During this process, the parameters identified by the algorithms are discussed with the plant personnel in order to validate the findings.

3.5 Targeting and Modeling

The variability of the KPI exhibits past operations with higher energy consumption and others with lower energy consumptions.

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Based on the data, the knowledge of plant personnel and on industry benchmarks, plant personnel can define an improvement objective for each KPI. Data Mining is then used to identify conditions explaining why past operations are below or above this objective. This rule-based model is available to the operators so they know if operation is energy efficient. If not, the model suggest possible actions to bring operations back to an energy efficient regime.
Predictive models are built from historical data to forecast, in real-time, the consumption represented by each KPI. This predictive model is used to detect drifts compared to the actual real-time energy consumption.

3.6 Monitoring and Continuous Improvements

As consumption models and rules to explain the variability of consumption are available, operations can monitor in a more intelligent way their energy consumption. When the actual consumption is close to the forecasted consumption, the system will inform operators why performance is good or bad.
However as soon as a significant drift between the actual consumption and the forecasted consumption is detected, the system can't explain why operation is at higher or lower energy efficient than expected. The error of the forecast is due to the fact that the model detects a new situation that never occurred in the past.
This "drifting" period has been triggered by a change in the operation or a change in design that affected the energy balance. Data mining is then used to detect the change of conditions that have initiated this drift. If this change is causing poorer energy efficiency than expected, then corrective maintenance actions should bring the operation back to normal conditions. If this change is causing improved energy performance than expected, then data mining helps to extract new good practices. In both cases the rule and forecast models will be updated so that if similar conditions appear in the future the operator will know what to do.

3.7 Implementation

This is the most challenging part of the project, as the result has to be used by various levels in the organization. Many companies are providing Energy Management Systems that are separated from existing plant information managements systems (PIMS). In this traditional approach energy is managed not as an integrated part of the operations but as a side activity. This management in "silo" misses an essential point: energy must be managed together with production in day-to-day operation.
In our view energy monitoring should be integrated in the decision-makers current ecosystem. Models can be integrated in various existing information systems that fit the end-users: DCS, PIMS, historian interface, intranet...
When implementing the Energy Management System within an existing infrastructure, it is much more easier to deploy, more cost effective as you are already paying for an information systems, more successful in getting people buy-in and it is easier to update energy consumption models in the entire plant.

4 RESULTS

Here the results for the different steps are shown for different sources of energy consumption/recovery in steel making.

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How to compute an energy KPI for a blast furnace will be briefly described. Then how to define a KPI for an EAF will be shown as well as how to explain the variability of this KPI.

A rule model, explaining the level of energy efficiency of a boiler and how to implement these results in the plant information system, will be shown.

Figure 1 shows a typical form that has been developed to be filled in by the plant personnel. The plants own values are entered in the green cells and energy indicators are computed with first principal models. This value can then be benchmarked with other blast furnaces so that the plant can select the best improvement opportunities. From there a first layout of KPI hierarchy can be set up.

Blast Furnace

FURNACE #1		Units		
Productivity (Hot metal)	105	ton/h		
Hot Blast Temperature	1650	°C		
Pressure at Furnace Top		psig		
Raw Material Consumption				
Iron Ore		ton/h		
Limestone		kg/h	KEY PERFORMANCE INDICATORS:	
Refractory Bricks		kg/h		
Energy in			**Spec Energies**	**MJ/ton (hot metal)**
Coke	45	ton/h	29500 MJ/ton	12642,9 MJ/ton(hm)
O2 injection rate	1000	Nm3/h	18,72 MJ/Nm3	178,286 MJ/ton(hm)
LP Steam pressure	3	bar		
LP Steam Flow	10	ton/h	2718,3 MJ/ton(st)	258,886 MJ/ton(hm)
HP Steam Pressure	10	bar		
HP Steam Flow	5	ton/h	2765,5 MJ/ton(st)	131,69 MJ/ton(hm)
Oil (n°6) Consumption	55	L/h	41200 MJ/ton(oil)	20,2429 MJ/ton(hm)
Blast Furnace Gas (BFG) Recov Rate	43%	%	3,573511 MJ/Nm3	21,9516 MJ/ton(hm)
Electricity	350	KWh	3600 MJ/MWh	12 MJ/ton(hm)
Fuel Offgas Consumption				
Coke Oven Gas (COG)	1000	Nm3/h	16,6759 MJ/Nm3	158,818 MJ/ton(hm)
Basic O2 Furnace (BOFG)	2500	Nm3/h	8,3736 MJ/Nm3	199,371 MJ/ton(hm)
Energy out				
Slag Rate		ton(slag)/ton(hm)		
BFG flow out of furnace	1500	Nm3/h	3,573511 MJ/Nm3	29,099 MJ/ton(hm)

Figure 1. KPI for blast furnace.

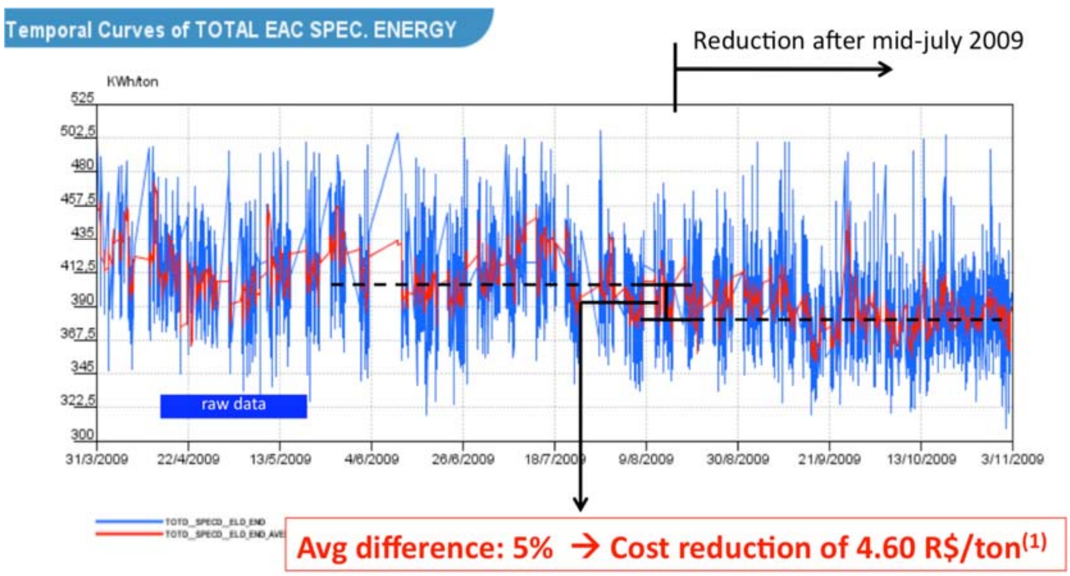

Figure 2. EAF energy monitoring.

Figure 2 shows the trends of the energy consumption during nine months for an EAF in a plant of a Brazilian crude steel producer. The blue curve shows the actual value measured and the red one is a moving average. It is clear by looking at the moving

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average that the later months were more energy efficient that the first months. There is a difference of about 6.35% between the periods.
Using machine learning on process measurements from the EAF, it was possible to automatically rank the parameters having the highest impact on the EAF energy efficiency variability. The variable importance ranking shows that yield and the type of scraps are the main root causes of this energy efficiency variability. In fact yield explains the high short-term variability, while the type of scrap explains the reduction of energy consumption mid-July 2009.

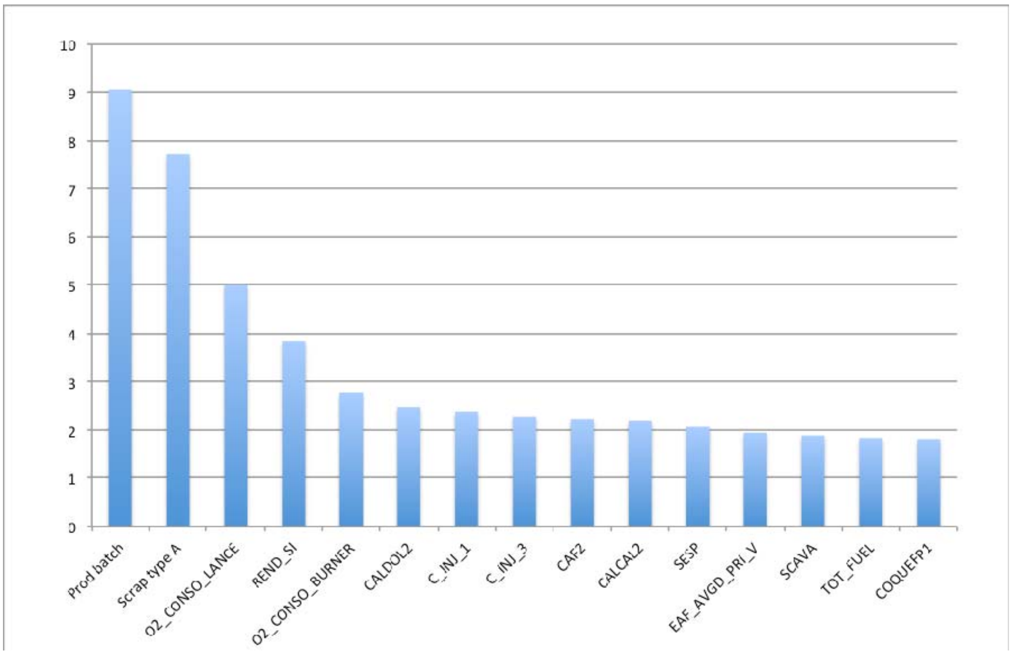

Figure 3. Importance of process parameters on energy efficiency variability.

Figure 4 shows the variability of energy efficiency of a boiler burning byproduct gases at an integrated steel plant in Europe. We have defined several performance targets showed by the colors in the histograms. In order to understand the conditions of operation leading to a particular performance target, a decision tree machine learning algorithms was used.

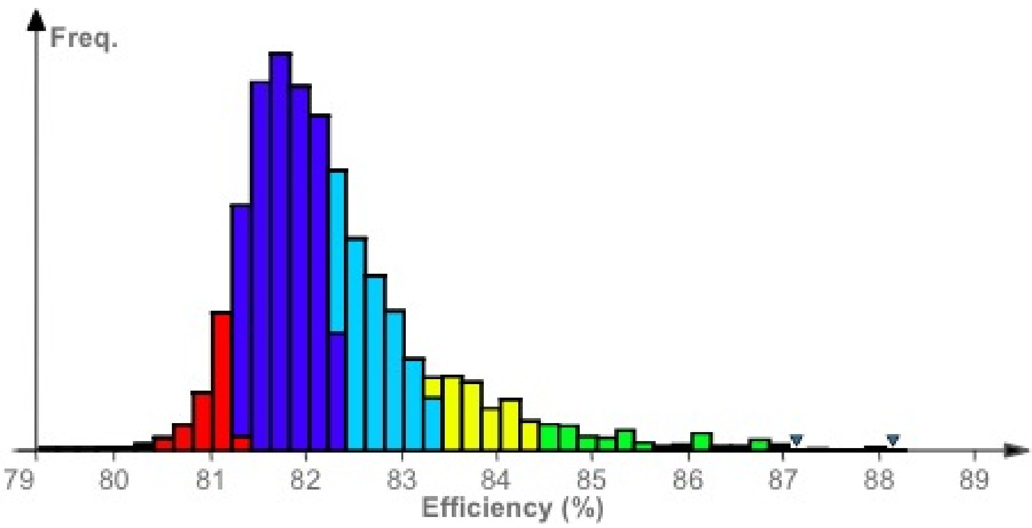

Figure 4. Distribution and discretization of energy efficiency.

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The decision tree was built automatically from historical data. Decision tree is a multivariate model that has very convenient properties to understand the relationships between operation parameters and levels of energy efficiency.
The decision tree showed at Figure 5 is describing eight rules based on five monitored parameters. The rules are read in top-down fashion. The rules that explain the highest energy efficiency states (green area) that if the GAZ_MIX_LHVWT_V > 2927 and if GAZ_MIX_LHVWT_V > 3439 and C12FUTSOR_V > 195 then the energy efficiency is higher that 84.5% (lower threshold of the "green" area").

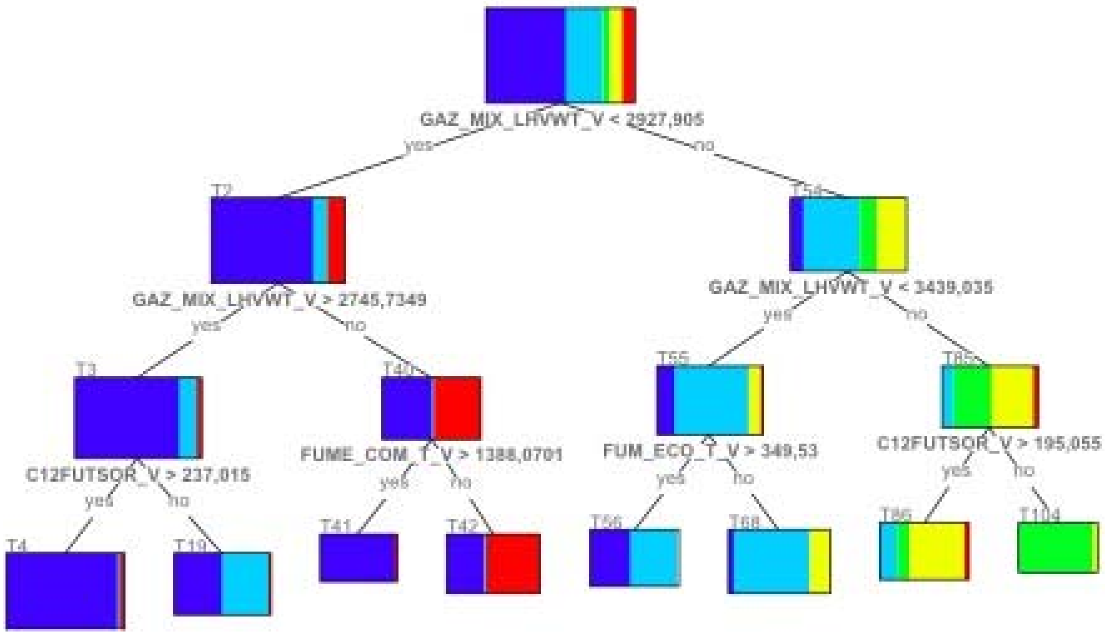

Figure 5. Decision tree explaining the level of energy efficiency.

5 DISCUSSION

In these energy efficiency projects gap analysis was a very important tool to detect opportunities and prioritize projects. It can help the manager to better understand the current situation. In most plants KPIs available at corporate level by the accounting department is too aggregated to easily understand technical drifts impacting costs of energy.
Gap analysis is the first step to explicitly connect technical description of the process behavior with energy costs.
When these projects are implemented it is also critical to have a strong commitment of the various stakeholders (plant manager, energy manager, accounting, operators, superintendents) to give relevant feedback, validate findings and deploy the results in day-to-day operations.
Data mining is a key tool that can help to quickly build compact models that connect operating conditions with energy performance. The models can be easily implemented in any information system at plant level. As they are not based on detailed physical models, they can be updated quickly to reflect changes in the production process (new equipment, new product mix).
With explicit rules, it is easy to extract quantitative knowledge to be validated and discussed with operators and energy managers. Some of these rules will typically help to avoid operating conditions with poor energy performance while others would be used to share good practices within the plant.

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6 CONCLUSIONS

Implementing a smart energy monitoring system as described in this paper has proven to quickly bring significant payback. The energy saved by implementing this methodology will typically decrease the energy costs 5-25% often representing hundreds of thousands of dollars per year.
As energy cost is getting more and more attention, these types of projects can easily identify opportunities that can be only be realized through a better integration of energy management in operations.

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