An innovative approach combining industrial process data analytics and operator participation to implement lean energy programs: A Case Study

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ABSTRACT

Energy costs for process-based industries amount to over 380 billion USD per year. In today's economic climate, and considering environmental drivers, addressing energy efficiency is critical. Given that a typical plant captures and archives several thousand measurements per second, the challenge for industry today remains how to extract value from their "Big Data" to address energy efficiency. Continuous improvement programs aligned with lean manufacturing principles can optimize current assets leading to operational efficiency gains without capital investments. Combining advanced analytics and machine learning, with a strong involvement of plant staff and operators is key to deploying an Energy Management System (EnMS) compliant with ISO50001 that will help the plant to quickly achieve significant savings. This paper outlines the critical steps to implement an EnMS for a complex process: to diagnose energy consumption variability; identify energy consumption baseline; to engage all levels of production staff in root cause analysis workshops; and, to implement predictive models for real-time monitoring, decision support and performance reporting. The chemicals plant case study presented in this paper demonstrates how this approach can be applied to optimize steam production and distribution through improved operational management. This case realized operational savings of over 640 000 USD or 7000 tonnes of CO_2 per year in gas consumption, representing a 15% reduction. Experience from this case emphasizes the importance of using plant monitoring to its full potential together with involvement of plant operators in order to understand key operational practices and to help promote an energy efficiency culture.

Introduction

Considering that industry accounted for approximately 21% of CO_2 emissions worldwide in 2011 *(IEA 2013)*, along with increasingly strict environmental requirements, such as the European Union 2012/27 Energy Audit requiring annual audits for plants without an EnMS, industrial manufacturers have more reasons than ever to address their energy efficiency. According to McKinsey & Company, there is potential to reduce energy consumption in industry up to 15% by simple operational changes designed to maximize efficiency *(Gonce and Somers 2010)*. The question remains as to how to tap into this energy savings potential.

One possibility is to harness growing availability of industrial data; manufacturing generates about a third of all data today and will contribute to advance manufacturing in the 21st century *(PAW 2014)*.

Already active in the field of advanced analytics for industry and motivated to help industrial sites achieve sustainable manufacturing, Pepite developed ENERGYmaestro, a methodology designed to implement an operational EnMS. This methodology has been outlined in this article, along with a phosphoric acid plant case study.

Strategy for a successful ENERGYmaestro Project

The ENERGYmaestro methodology is a multi-disciplinary approach combining advanced analytics and machine learning, with operator and plant staff participation. The overall objective of this approach is to identify the causes of energy performance variability in order to reduce this performance variability through improved operational management. ENERGYmaestro requires no capital expenditure instead aiming to implement an Energy Management System (EnMS), compliant with ISO5001, based on continuous improvement programs.

During an ENERGYmaestro project, it is important to form a multi-disciplinary client team including a project sponsor, key production personnel, as well as technical resources from IT, engineering and maintenance.

The following sections outline Pepite's ENERGYmaestro methodology to successfully implement an EnMS for complex industrial processes.

Energy Performance Gap Analysis

The initial step of any ENERGYmaestro project is to identify the energy consumption baseline, savings potential, and therefore, to define the project scope. This potential is identified during a preliminary analysis of historical production data. At this stage, often three performance indicators are defined: production rate, energy consumption and specific energy consumption (energy consumption per unit of product). These indicators can target individual pieces of equipment, individual production lines or entire processes, depending on data availability and process configuration. Based on historical specific energy consumption, a realistic statistical target is selected which forms the baseline for a gap analysis. Historical performance above this baseline is cumulated over a 6-month or 1 year period to quantify savings potential.

Brainstorming Workshops with Operators

Having identified a significant energy savings potential, the following step is to hold brainstorming workshops with operators. A series of sessions are designed to pinpoint root causes underlying a particular energy problem, by following the *Kaizen Five Why Principal*. These workshops also provide an opportunity to engage all levels of production staff in the project and understand their operating challenges. It is often essential at the workshops to provide the opportunity for different departments to interact, including maintenance. All ideas discussed in these workshops are then synthesized in a type of Cause Tree, refer to Figure 7 for a simplified example from the phosphoric acid plant case study.

Advanced Analytics

All analytics are performed using Pepite's cloud based analytics tool, DATAmaestro. DATAmaestro's comprehensive set of analytics tools help Pepite's consultants, in close collaboration with plant staff, explore variability of past operations, detect abnormal patterns, diagnose root causes of drifts, predict and optimize performance.

Data input for the advanced analytics stage generally requires hourly averages from one year of historical production and quality or laboratory data.

There are four main analytics stages, as follows:

1. Root Cause Tree Quantification
2. Exploratory Analysis
3. Root Cause Analysis
4. Predictive Model Development and Testing

Root Cause Tree Quantification. The brainstorming workshops provide a series of root causes. Based on data availability, the first stage of analysis requires that these causes be quantified. **Figure 1** shows an example of cause quantification; in this instance the total high pressure steam lost over a two-month period represents almost 1200 tonnes. This initial stage of analysis can already provide interesting improvement opportunities, which can often be addressed by improved operations management.

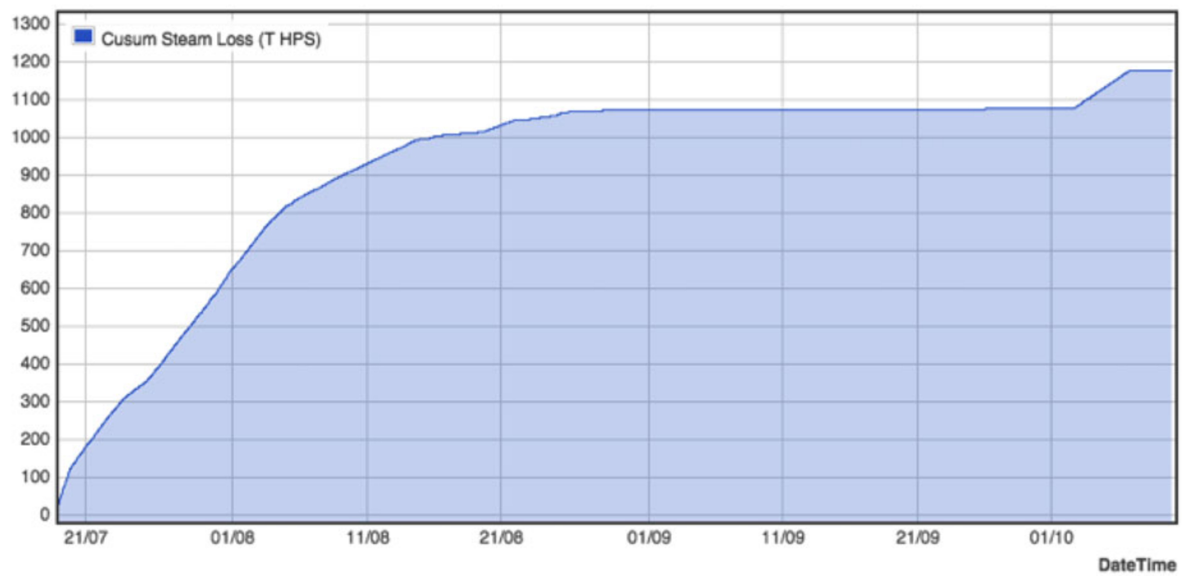

Figure 1. Cumulative sum of High Pressure Steam (HPS) lost over a two-month period. *Source*: *DATAmaestro© Pepite 2015. Prayon 2015*

Exploratory Analysis. This stage of analysis seeks a greater understanding of operating conditions and will progressively lead to data cleaning to concentrate analysis on stable production regimes while removing outliers, abnormal or one-off events, and problematic variables. A series of advanced analytics techniques can be used for the exploratory analysis, including temporal curves, histograms, clustering[1] or dendrograms, such as the example provided in **Figure 2**. Dendrograms in DATAmaestro are a form of unsupervised learning, which seeks linear dependencies between variables. In the example provided below, there is the highest dependency between Steam Inlet Enthalpy and Steam Inlet Temperature at 0.95, where one would represent a perfect linear correlation.

[1] A clustering model is an unsupervised learning algorithm that groups similar objects or similar attributes.

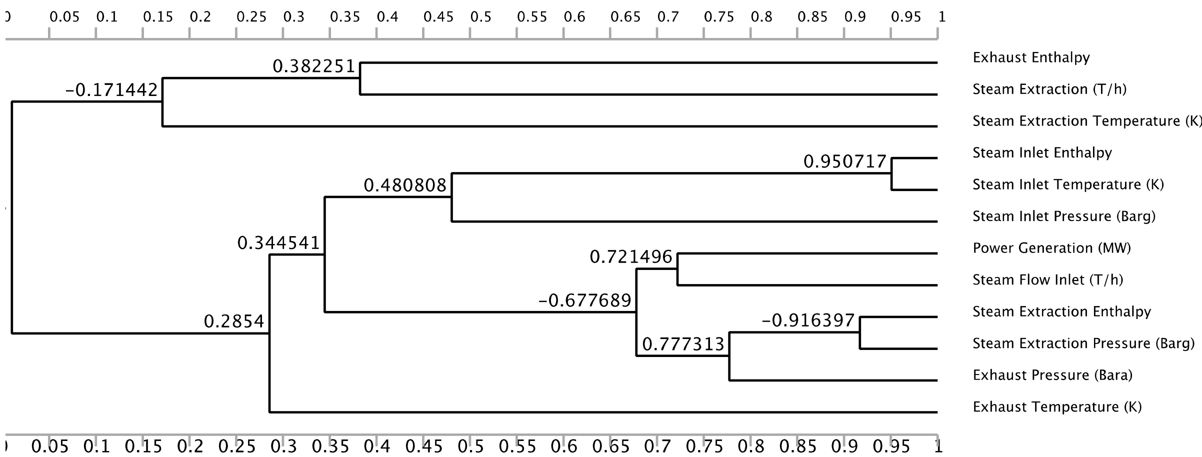

Figure 2. Dendrogram of linear dependencies for a steam turbine between steam inlet, extraction, exhaust and power generation. *Source: DATAmaestro© Pepite 2015, Prayon 2015*

Root Cause Analysis. Unlike exploratory analysis, which largely focuses on ideas from the brainstorming workshops, Root Cause Analysis utilizes data mining techniques to gain a deeper understanding of process dependencies. A common algorithm employed to identify top explanatory variables, is an Ensemble Tree. This tool seeks to determine non-linear dependencies between a series of process parameters and their respective impact on a given output. The results of an Ensemble Tree are displayed on a Pareto, such as in the following example, **Figure 3**. This example provides the top variables influencing power generation of a steam turbine based on steam flow rates, temperatures and pressures. In this case, Steam Extraction (T/h) intervenes for 70% of power generation variability.

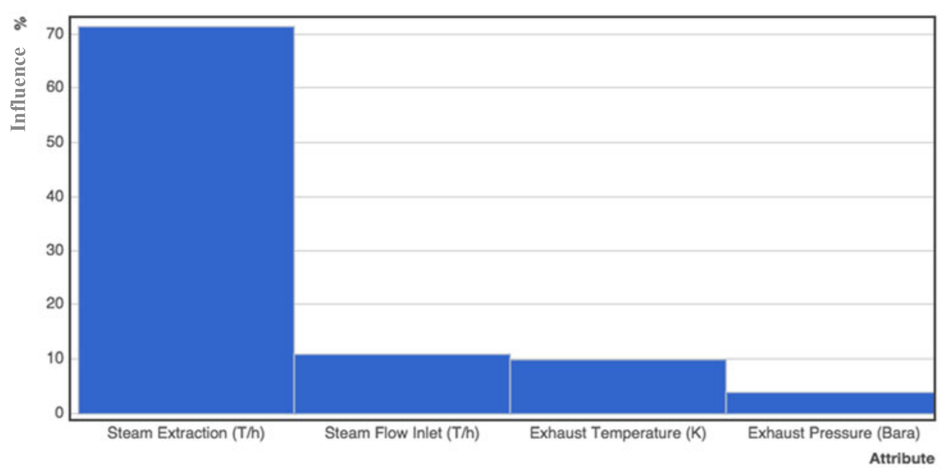

Figure 3. Ensemble Tree Pareto of non-linear dependencies for power generation of a steam turbine based on steam inlet, extraction and exhaust. *Source: DATAmaestro© Pepite 2015, Prayon 2015*

It is essential during the root cause analysis to combine multiple analytics methods, along side collaboration with plant staff, in order to validate which process variables are deteriorating energy performance. These variables are then required as inputs for the final analysis stage, predictive modeling.

Predictive Model Development. Based on the key process variables previously validated with plant staff, this stage aims to develop a model that predicts an energy performance target. This target can then be compared to actual performance and in the case of a drift, to provide decision support tools to correct the drift. **Figure 4** shows a simplified Decision Tree. This model is designed to predict if electricity production of a steam turbine is "Good" (Green) or "Bad" (Orange) based on two input variables: Steam Extraction and Steam Flow Inlet.

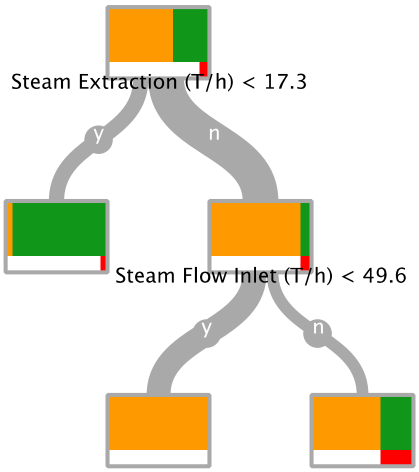

Figure 4. Simplified Decision Tree to predict power generation of a steam turbine based on steam inlet and extraction. *Source: DATAmaestro© Pepite 2015, Prayon 2015*

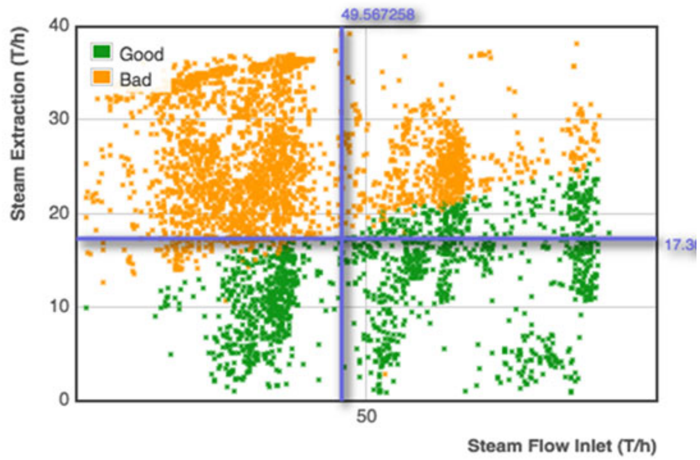

Figure 5. Scatter plot representing rules defined by simplified Decision Tree to predict power generation of a steam turbine. *Source: DATAmaestro© Pepite 2015, Prayon 2015*

The following rules represent the possible paths leading to three possible conclusions or nodes on the Decision Tree example in Figure 4:

5. Rule 1: If (Steam Extraction < 17.3 T/h) then Power Generation is Good (green with small residual error).
6. Rule 2: If (Steam Extraction > 17.3 T/h) and if (Steam Inlet < 49.6 T/h) then Power Generation is Bad (orange).
7. Rule 3: If (Steam Extraction > 17.3 T/h) and if (Steam Inlet > 49.6 T/h) then Power Generation is Good (green with residual error).

Figure 5 demonstrates those rules selected by the Decision Tree to predict the Power Generation. For Steam Extraction less than 17.6 T/h there is predominately good Power Generation (green). However, for Steam Extraction greater than 17.6 T/h and Steam Flow Inlet less than 49.6 T/h, there is entirely poor Power Generation (orange).

This model has been limited to three nodes, and therefore, as can be seen in Figure 5, there is residual error; even when respecting the above three rules, the model can falsely predict electricity production. When implementing a predictive model for energy performance monitoring, there needs to be balance between model accuracy and robustness or simplicity.

Before implementing a predictive model, model testing on an independent data set is essential to ensure the model robustness against the most recent operating conditions.

Other examples of model types that could be used to predict energy performance include Multi-Linear Regressions or for more complex cases Artificial Neural Networks[2].

Implementation and Training

Based on results from data analysis, Key Performance Indicators are developed with the plant team. In order to communicate these indicators, operator control screens and energy reports are implemented in the existing plant information system. When deploying these control screens and reports, training of plant staff and operators is essential.

Review Period and Continuous improvement

Following implementation, a systematic review period ensures that models are performing as expected. In some instances, it is necessary to adapt models to changes in operating conditions or production practices. However, by implementing an energy reporting structure, plant staff are able to continuously assess their energy performance and make informed decisions based on fact rather than feeling. Figure 6 below shows Pepite's Continuous Improvement Methodology.

Figure 6. Pepite's Continuous Improvement Methodology aligned with ISO50001. *Source: Pepite 2015*

ENERGYmaestro Success Factors

ENERGYmaestro has been designed as a robust multi-disciplinary program; nonetheless there are certain factors that are essential to ensure the success of an ENERGYmaestro project. As this approach relies on advanced analytics, adequate historical data is required. One year of production data is ideal, in order to understand external factors such as seasonal variability, however, an initial analysis can be performed with as little as two months data. It is important to note that absolute data accuracy is not necessary for this approach, as this method does not seek to create a model based on first principles but rather to analyze data variability.

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[2] Artificial Neural Networks are a form of regression models, which is a supervised learning algorithm that uses numerical input attributes to predict or explain a numerical output.

The second success factor for an ENERGYmaestro project is to ensure that plant staff, especially those making up the project team, have a sufficient understanding of the project methodology. For example, those unfamiliar with advanced analytics will attribute variability to discrete events such as shutdowns; however, the data cleaning stage ensures that this type of event does not influence the analysis.

Along with understanding the methodology, it is essential that the plant staff commit to ongoing energy performance reviews. ENERGYmaestro provides energy control screens and reports, however, it is the plant staff and operators that will ensure that this system is successfully adopted on an ongoing basis. This also requires that the plant staff are prepared for a continuous improvement methodology.

ENERGYmaestro Advantages

There are many advantages to an ENERGYmaestro style EnMS:

- ENERGYmaestro is relatively fast to implement (less than 6 months).
- No capital investment required, changes focus on improved operations management.
- Multi-disciplinary approach, combines a people participation with advanced analytics to ensure best results and potentially provide greater process understanding.
- Multi-level approach, by including operators in the project, real operational changes can be achieved.

Optimization of steam production and distribution in a phosphoric acid plant through a people minded project

Project Description

The Prayon plant located in Engis, Belgium produces a wide range of phosphate-based products. Its steam network includes six boilers that produce steam for eight independent departments across the site. The plant operates a turbine to produce electricity. Part of the steam extracted from the turbine is either condensed, or sent to the plant's steam network. The network was not operated optimally, causing extra consumption of natural gas and lower electricity production.

Prayon mandated Pepite to optimize steam extraction to minimize the global energy spending (natural gas and electricity). Through this project, the plant also aimed to initiate a site-wide energy management process and to improve communication between departments. The project included 3 months of work; total project span was 6 months, because of workshop scheduling, plant staff availability, and model testing, offline and online.

ENERGYmaestro solution for optimized steam production and distribution

To address Prayon’s excess natural gas consumption and to improve electricity production, Pepite’s consultants followed the ENERGYmaestro strategy outlined earlier in this article. This section describes the particular solutions developed for Prayon’s cogeneration.

Cause Tree. A series of problem solving workshops, including more than sixty operators implicating five departments, generated approximately two hundred improvement ideas. **Figure 7** highlights the simplified Cause Tree aimed to target reasons for reduced steam extraction. As can be seen, there are three main branches to this problem. These branches include problems related to steam extraction capacity, low pressure steam network capacity and overall management.

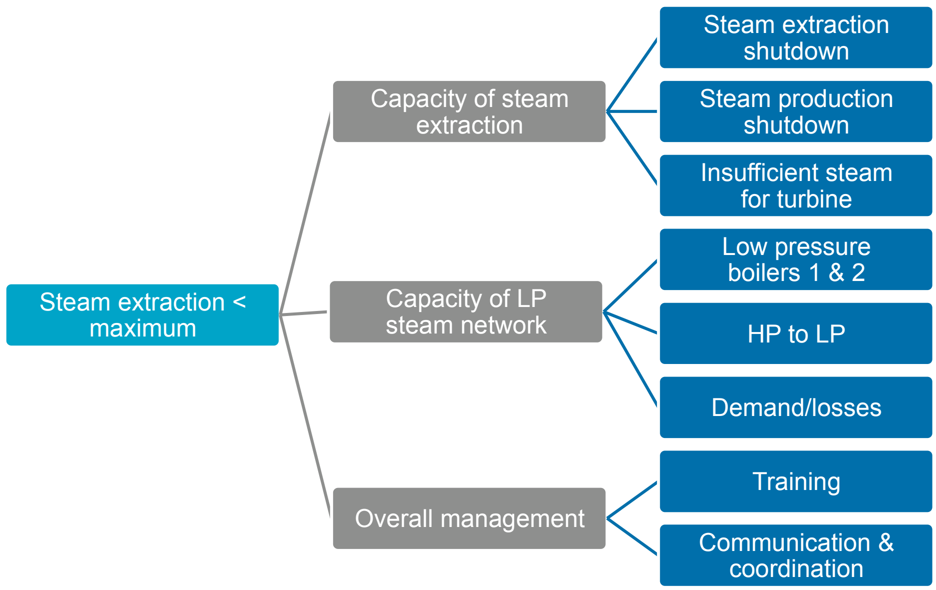

Figure 7. Simplified Cause Tree developed from brainstorming workshops with operators to target reasons for reduced steam extraction. *Source: Pepite SA, 2015, Prayon SA. 2015*

Key Performance Indicators (KPI). The first challenge was to develop a Key Performance Indicator Structure which would address the key issues that had been identified in the brainstorming workshops, at all levels of Prayon's operations. Only by ensuring that operators receive the right information in real time, to help their ongoing operations, can high-level indicators begin to improve. This also requires that each indicator and the chain of command are clearly defined.

For the example structure provided in Figure 8, operators are provided in real time the steam extraction ratio, steam extraction versus a predefined target and key control variable set points. These indicators are designed to feed into a daily discussion focused around steam extraction ratio and steam extraction versus a predefined target. Following the recommended set points and addressing challenges on a daily basis helps improve monthly indicators, these being reduced costs, improved average steam extraction and extraction ratio.

New control strategies, and therefore targets and key process variable set points, are determined by analyzing historical performance. For Prayon, Exploratory Analysis of network variations and different operating regimes identified sub-optimal operating conditions. Furthermore, Root Cause Analysis pinpointed pressure set points in the steam network to maximize extraction and minimize venting.

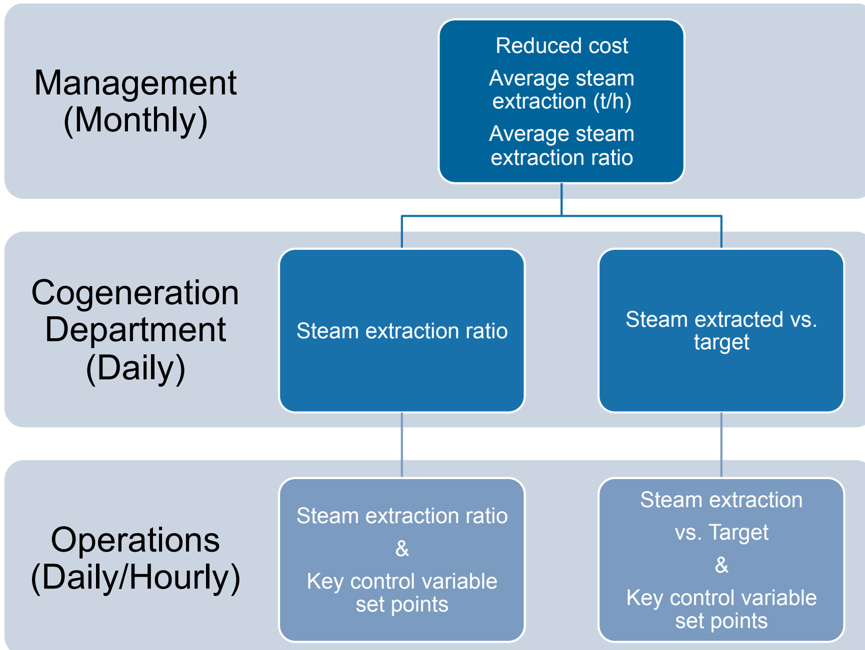

Figure 8. Key Performance Indicator structure for steam extraction optimization from operator to management level. *Source: Pepite SA 2015*

Having determined all key performance indicators and new operating conditions, there are two main means of communication: operator control screens or energy reporting. Understanding of plant personnel of the indicator and reporting structure at this stage is essential to ensure successful implementation and acceptance of the new operating procedures.

Operator Control Screens. In **Figure 9**, there is an example of a control screen programmed into Prayon's existing plant information structure. This Distributed Control System (DCS) dashboard is designed to simplify steam extraction management. On the left-hand graph, there is current extraction (green) versus target extraction (yellow), and on the right-hand graph, there is the required and excess boiler steam production. The objective is simple: to reduce excess steam production at the gas powered boilers by increasing current steam extraction from the turbine to the target level.

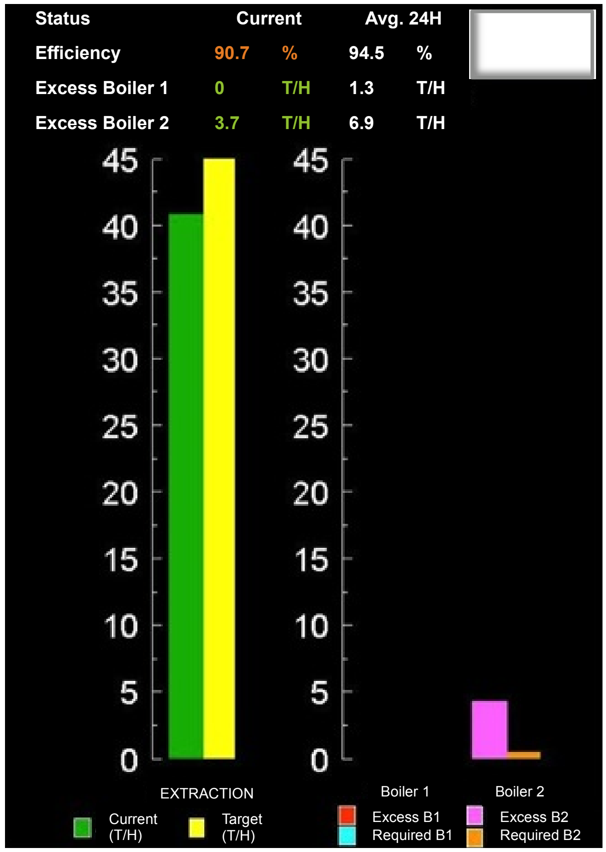

Figure 9. Operator control screen for steam extraction management. *Source: Prayon, 2015*

Reporting. Along with real-time information provided on control screens, a reporting structure was deployed. Reports can either be programmed into an existing information system, i.e. Pi or Wonderware, or alternatively, automatic Excel based reports can be developed. Reports as frequently as daily are required to ensure that energy indicators are discussed on a regular basis, and are accorded an equivalent importance to production, quality and safety. A daily energy report was developed for Prayon's cogeneration team, to be discussed at the morning production meeting, as well as a monthly report to follow on-going performance and savings, as can be seen in **Figure 10**.

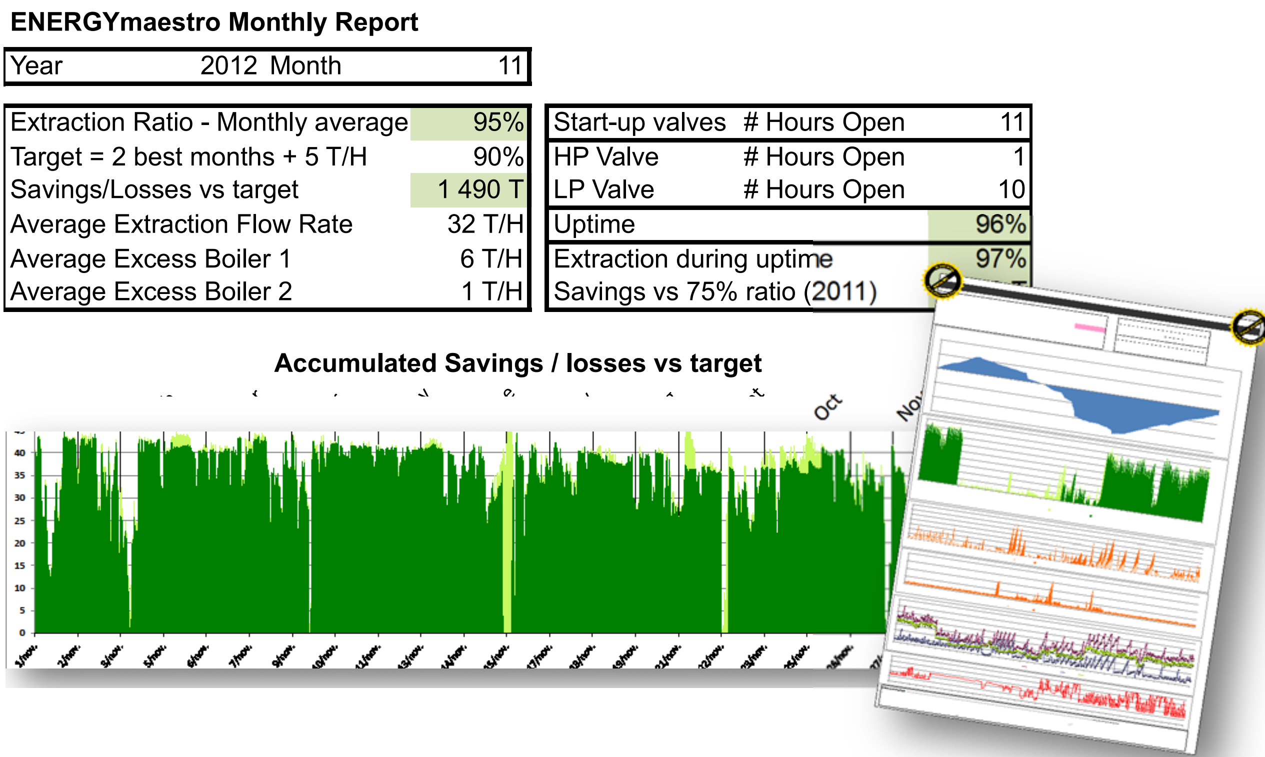

Figure 10. Example ENERGYmaestro Monthly Report for optimized steam extraction. *Source: Prayon, 2015*

Implementation and Training. At the deployment of the new control screens, operating conditions and reports, a vital stage of the project is operator and plant staff training. This includes training and coaching of management teams on the new KPI and reporting structure. Even more importantly, this requires training of operators on the new decision tools and the new set points to ensure adoption of these new conditions.

Benefits. Since the deployment of the ENERGYmaestro project at Prayon in 2012, they have benefited from the follow advantages:

1. Increased by more than 5 t/h of extracted steam, leading to a reduction of natural gas use (savings of 640 000 USD per year) equivalent to 7000 tonnes of CO_2 per year in gas consumption or a 15% reduction *(Prayon 2015)*.
2. Better management and monitoring of steam network leading to a reduction of steam venting and an increase of electricity production.
3. Communication between the main stakeholders was greatly improved as well as their understanding of site-wide energy challenges.
4. Success of the project convinced upper management of the benefits related to better energy management – the on-site energy team was reinforced in its role.
5. Adopted a similar reporting structure for other indicators related to production performance in the cogeneration department.

Conclusion

Experience from the Prayon project, amongst others, emphasizes the importance of involving all levels of a plants organization in the ENERGYmaestro approach. Operators are at the forefront of process control and are therefore in the best position to implement enhanced process practices, however, in order to mitigate change management risk, it is vital to involve them from the beginning of the project, especially in the brainstorming workshops. This approach ensures that the EnMS is adopted by all plant staff and helps promote an energy efficiency culture.

This methodology has been deployed in many industries to date, including Pulp and Paper, Fertilizers, Cement, Chemicals and Steel. Not only transferable across manufacturing industries, this approach can be adapted to optimize water consumption, quality, productivity and predictive maintenance. As was seen with the Prayon case, clients participating in this project can then adapt a similar approach to other performance indicators.

There are many indirect advantages to improved energy understanding, control and flexibility. Given the currently volatile energy market and electrical grid instability, created by renewable sources, such as wind turbines, industrial sites that have developed sufficient flexibility in their energy consumption allowing them to respond to demand side management have substantial potential to increase their revenue *(PJM 2015)*.

References

DATAmaestro, 2013, https://docs.mydatamaestro.com

Gonce, A., K. Somers, 2010, *Lean for green manufacturing,* Climate Change Special Initiative Energy Efficiency, https://www.mckinsey.com/~/media/mckinsey/dotcom/client_service/Sustainability/PDFs/lean_green_manufacturing.ashx

IEA (International Energy Agency), 2013. *CO2 Emissions From Fuel Combustion Highlights* 2013 Edition, http://www.iea.org/publications/freepublications/publication/co2emissionsfromfuelcombustionhighlights2013.pdf

PAW (Predictive Analytics World), 2014, *Predictive Analytics World for Manufacturing Conference* 2014, http://www.predictiveanalyticsworld.com/mfg/2014/

PEPITe, 2015, http://www.pepite.be/

PJM, 2015, *Fast Response Regulation Signal*, http://www.pjm.com/markets-and-operations/ancillary-services/mkt-based-regulation/fast-response-regulation-signal.aspx

Prayon, 2015, http://www.prayon.com/en/index.php