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Context-based decision support for sustainable optimization of energy consumption

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Abstract This paper describes the algorithm for context-based decision support in industry to achieve optimization of energy consumption. The proposed approach is based on Case-based Reasoning and probabilistic analysis and implements the support for immediate reaction, which is based on the paradigm of intelligent decision support systems. The proposed algorithm envisages the elimination of deviations on normal (desired) energy consumption and was tested in energy intensive industry scenario using real data. The research work here presented was developed in the context of LifeSaver project and results obtained are adequate for project's objectives in the field of decision support for immediate reaction and answer to industrial requirements.

1. Introduction

The overall objective of the LifeSaver project is to develop a methodology and platform to support companies in optimizing their operations and enabling them to increase energy savings and decrease CO_2 emissions [1]. This support is in the form of a set of Information and Communications Technologies (ICT) building blocks that combine context awareness, ambient intelligence monitoring and standard energy consumption data measurement.
LifeSaver complements currently measured energy consumption data with diverse information from ambient intelligent systems (e.g. interactions between human operators and machines or processes) and process-related measurements (e.g. temperature or oil level of a specific machine). The main objective is to enrich energy consumption data with information about the context in which the use actually occurred. This enables LifeSaver to access and process more complete information to target energy efficiency optimization and CO_2 emission reduction. The monitored energy consumption enriched with context from ambient intelligence data, is the basis for the identification of energy profiles and energy consumption and emissions patterns. These profiles and patterns are then used to support

decision-making in different situations. One of the main building blocks being and pillars of the LifeSaver platform is a set of services to support decision-making. The strategy used for developing this building block was to start by identifying the type of situation requiring support to decision in order to establish a time frame for the decision. Thus, LifeSaver decision support approach congregates:

- Support for immediate reaction - involving the definition of a strategy to respond to an abnormal situation that must be normalised. This approach implies the application of a corrective measure based on real-time performance monitoring and measurements;
- Support for reconfiguration and ETS (Emission Trading System) – involving the elaboration of scenarios to be evaluated in order to reach a decision about the best alternative. The approach is to be applied during operational phase but without interacting with production process in real time.

This paper describes the algorithm for context-based decision support in industry through the system of metering, monitoring and evaluation of business, energy and environmental performance. Authors start by introducing the topic describing the background, the objectives and the concept. Then the section on the *LifeSaver decision support for immediate reaction* briefly describes the developed algorithm which is then tested in the scenario presented in section *Case test: Energy Intensive Industry*. The results obtained with the testing of the algorithm are presented and discussed in the appropriate section. Finally, conclusion section provides a summary of the key elements presented within the paper.

2. Background

Many organizations view energy as an escalating, uncontrollable cost when, in reality, energy consumption can be controlled by acquiring new, more efficient technology and through behavioral modifications ([2][3]). The need to reduce the energy intensity of production and corresponding greenhouse gas emissions is acknowledged, but there are significant technical and non-technical barriers to achieving this [4]. The greatest perceived barriers are the perception of the lack of resources to be devoted to improving energy efficiency, and the existence of other priorities such as the importance of guaranteeing business continuity [5].
Pons *et al* [6] concluded that the use of energy and material saving technologies does not have a clear and significant relationship with economic performance although a significant positive relationship is found between energy and material saving technologies and environmental performance.
Yet, rising energy prices, and customers' increasing ecological awareness have pushed energy efficiency to the top of the agenda [7]. Moreover, and even under very demanding values of payback period the margin of improvement of the CO2 emissions is around 20% [8].

The implementation of measures to increase energy efficiency in industrial companies are becoming a key aspect of their future development and the importance of having a comprehensive view of the systems when making such changes in industry is widely recognized ([9][10][11]). This aspect is crucial, as industrial systems form complex relations both within the industrial equipment at plant level and in the interaction with their surroundings. Complexity of industrial operations together with multiple products and fuels in combination with the influence of the production rate on energy efficiency, contribute for need of adopting a structured framework to define and measure energy efficiency more precisely [12]. Thus, the development of computer-based decision support increases the possibility to make as adequate analyses as required of different complex systems [13].

The recommended business practice [11] for industrial companies is to actively participate in energy efficiency programs, monitor energy consumption, emissions and raw material usage using an auditable system, manage the CO_2 emissions and position using a simple trading system and finally integrate previously mentioned activities in one decision support system to eliminate operational risk, investment and trading exposure.

Nonetheless, even enterprises with advanced management systems rarely monitor efficiency of energy usage and materials flows within their processes, thus having difficulty to effectively manage their resource efficiency [14]. To achieve the desired efficiency improvements, energy use should be measured in more detail and in real-time, to derive an awareness of the energy use patterns of every part of the manufacturing system [15].

In recent years, the development of decision support methods for energy savings has been strongly oriented for the application in building energy efficiency. For this the European energy policy has contributed with its clear orientation towards the preservation of energy and the improvement of indoor environmental quality in buildings through the adoption and recast of the European Commission's (EC) Energy Performance of Buildings Directive [16]. To this end, in the past decades, there have been significant efforts towards designing, operating and maintaining energy efficient and environmentally conscious buildings [17]. Examples of this research can be found in [18][19][20][21]. Additionally, some research has been conducted in the development of decision support systems for environmental management[22][23]).

Some of the concepts used for energy efficiency in buildings can be applied in the industrial sector but truth is that, specificities of the problems are not the same. Thus, methods specifically developed for the industrial problem are quite few and are mainly based in modeling and simulation of the industrial facility and do not consider important aspects such as keeping the values of the decision-making criterion close to normal business conditions [8].

3. LifeSaver Decision Support for Immediate Reaction

One of the main research lines on decision support systems has evolved towards including intelligent abilities on them. These, new and improved, systems are based on artificial intelligence or intelligent agent technologies and are commonly called Intelligent Decision Support Systems (IDSS) [24]. Their main objective of the IDDS is to realize decision making functions by gathering and analysing evidence, identifying and diagnosing problems, proposing possible courses of action and evaluating the proposed actions representing some human brain competences. A solution that demonstrated to be quite successful is CBR (Case-based Reasoning) [25]. CBR systems are based on a starting set of cases that are structured in an appropriate format in order to constitute training examples. It is a problem solving approach that works by identifying commonalities between the target problem and retrieved cases.

3.1 Decision Model

The approach proposed in LifeSaver is to combine CBR with probabilistic analysis in order to provide the user with a brief idea of which might be the result of following a specific course of action [26]. This is made through the collection of information and data about the industrial plant along its operational phase. The idea is to collect information coming not only from the machines but also from experts that have deep knowledge on the specific production processes.

The following aspects must be covered:

- List of variables important to assess the overall energy consumption of the plant/machines;
- List of rules associated to the normal behaviour of the variables according with the current context;
- List of common causes for rule violation (i.e. abnormal energy consumption);
- List of possible alternatives (actions) to deal with the causes (i.e. restore normal energy consumption).

The initial modelling work must also include the definition of energy cost centres (ECC), which stand as the core elements of entire energy model of the industrial plant [11]. Unfortunately, a comprehensive literature review did not provide any fixed rules on how to setup a model of ECCs for each particular industrial branch. An ECC can be any department, section or machine that uses a significant amount of energy or creates significant environmental impacts. However, the guiding principle for modelling setup is to follow the production process stages as given by the process flow chart for each industrial branch, and try to define the ECCs so that they coincide with the existing production quantity control boundaries.

3.2 Decision Algorithm

To avoid undesired or critical energy consumption values it is considered the observation of energy consumption thresholds. When the thresholds are violated, a decision point is achieved and a set of different alternatives must be considered: $A = \{A_1, \dots, A_n\}$. The success of the applied alternative is evaluated by the user who, in the absence of new threshold violations, may conclude that the alternative was succeeded.

In the proposed approach energy consumption is monitored and, in case there is an abnormal consumption, an event is generated. This event represents the need for an action to restore the normal energy consumption level. The event triggers a search for similar cases, which will result in a set of cases, and some of them could even be caused by different causes. The selection and elimination of the cause is made by providing the user with information on the alternatives that were used to solve similar past cases. To suggest an alternative there is the need to compute cause probability, alternative probability and case similarity have been found. This is made by:

- Search for Decision Processes (cases) with status "CLOSED" (this indicates that the user confirmed the effectiveness of the alternative in solving the case)
- Select the set of cases to be considered by computing similarity between the detected Event and the different Events associated to stored cases
- Group the Cases associated to the same Cause in different sub-sets
- In the selected set of similar cases, compute the Cause probability by counting how many times a specific Cause was established as the Cause of a specific case, $p(C|E)$
- Group the Cases associated to the same Alternative in different sub-sets
- For each sub-set, compute the Alternative probability by counting how many times a specific Alternative was used to deal with a case, $p(A|(C|E))$
- Compute the mean similarity of the cases that are part of the sub-set:

$$\overline{Sim} = \frac{\sum_{i=1}^{n} Sim}{n} \tag{1}$$

- Compute the final Score:

$$Score = p(C|E) \times p(A|(C|E)) \times \overline{Sim} \tag{2}$$

The model was built following the logic of the problem, ensuring that, at each probabilistic node, probabilities along any outgoing branch sum one. The model complexity depends on the number of causes as well as on the number of possible alternatives.

4. Test Case: Energy Intensive Industry

4.1. Cement Industry

Cement production is one of the most energy intensive processes in industry, causing large amounts of CO_2, dust and other emissions, noise (quarry). According to [28], global cement industry accounts for about 70 to 80% of the energy use in the non-metallic minerals sub-sector, consuming 8.2 exajoules (EJ) of energy a year (7% of total industrial fuel use – year 2005) and accounts for almost 25% of total direct CO_2 emissions in industry.

LifeSaver platform is being tested via a prototype information system in the largest cement-producer in Slovenia, Salonit Anhovo (Salonit). Salonit has provided a real testing environment for the validation of the proposed concept. Company has a rich industrial tradition and it has been producing cement since 1921. Constant need for competitiveness on the market is forcing Salonit to systematically and continuously analyze all possibilities for the optimization of production activities and related costs reduction. Also, Salonit is one of Slovenia's largest CO_2 emitters and it is included into emissions trading scheme. As energy costs were increasing and CO_2 emissions were subject to emission trading, Salonit utilizes alternative fuels for combustion (such as used tyres). In 2010 and 2011, around 50% of heat energy was produced from alternative fuels and the trend is to increase it even further. Total heat consumption in year 2011 was around 1.7 petajoule (PJ) (fuel mix is given in Figure 1).

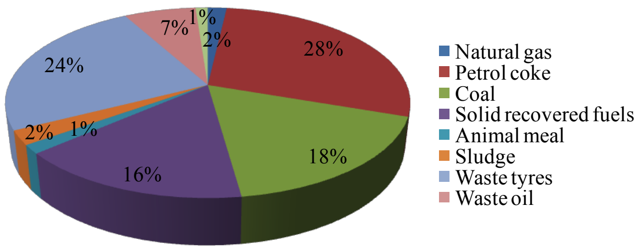

Figure 1. Fuel mix for heat production in Salonit in year 2011.

Main production processes in Salonit are: grinding, clinker burning and cement production, and in all processes improvements are expected through better control, regulation and fuel substitution. Grinding process includes grinding of raw materials from local quarry, where one third of electricity is used. By setting the parameters and using electricity in off peak times, additional savings can be expected. Savings are also expected through optimization of grinded material stock. Clinker burning is the most energy intensive process where, due to high influence of energy costs, alternative fuels are used to a large extent (around 50%). Fodor and Klemeš [27] have documented the recent developments in design and technologies of waste treatment for producing heat and power. Also, methodologies that are considered in (Fodor and Klemeš, 2012) include criteria for technology selection, together with procedures that comply with the environmental EC regulations Best Available and Best Applicable Techniques (BREFs).

Within LifeSaver Salonit's main objective is overall performance improvement. The proposed approach combined with the new hardware and software and introduction of postulates of energy and environmental management into Salonit's daily activities represents introduction of change in people's attitude about energy use in daily operational practices and routines. Also, continuous and systematic evaluation of energy and environmental issues should ensure smoother implementation of many future energy efficiency measures.

To guarantee that the proposed ICT solutions correspond to the real industrial requirements and to achieve a full transparency of the implementation process, an intensive involvement of the Salonit's personnel was necessary, especially during the definition of benchmark values, and recognition of desired and undesired process situation (context recognitions). Furthermore, several development loops covering all development phases are carried out, to achieve an on-going user driven optimization of the early prototype implementation. By this user centric and iterative software development approach, orientated at the users' way of thinking, it is guaranteed that the resulting software solution corresponds to the users' needs.

4.2. Test scenario

For testing purposes Salonit provided data related to rotary clinker furnace. Figure 2 shows the Salonits' production process through ECCs with inputs, outputs and interactions with the environment. Within the energy model of the Salonit factory the rotary furnace has been defined as a single ECC as presented in Figure 2. Also, such concept provides a framework for performance monitoring and improvements at each designated responsibility centre and directly connects people with tasks in each ECC.

The modeling work covered the aspects presented in section *3.1 Decision Model* and resulted in:

- List of variables: production stage, control room team, fuel mix (resulting from different usages of fossil fuels, alternative fuels and auxiliary systems)
- List of rules: defining normal consumptions for each production stage, each control room team and each fuel mix.
- List of common causes for rule violation and associated list of possible alternatives:
    - Unbalanced fuel dosing:
        - Reduce dose rate of X1, confirm dosing of X2 and check the status of the auxiliary systems;
        - Reduce dose rate of X1, confirm dosing of X2 and X3 and check the status of the auxiliary systems;

- Confirm dosing of X4, X5, X6 and check the status of the auxiliary systems;
- Confirm dosing of X1 and X3, confirm dosing of X4 and X6 and check the status of the auxiliary systems

- Problems with fuel sensor: Reset or Replace sensor
- Quality of the fuel: Need to retrain the prediction engine
- Malfunctioning of dosing equipment: Reset or replace dosing equipment

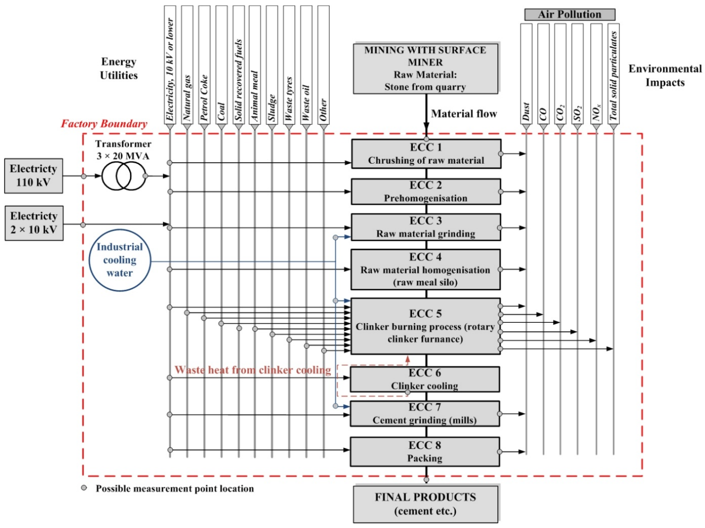

Figure 2. Process and energy flow chart of the Salonit's cement production process using ECCs

For the initial testing the data samples were collected on a one minute interval for the period of seven days, which resulted in 10080 samples of each input signal. Testing days were carefully selected assuring that all used fuels were covered, meaning that each individual fuel has been used at least once. Data was collected using the format presented in Table 1, where (PS) represents the production stage, (T) represents the control room team, (X1, X2, X3, X4, X5, X6, X7, X8) represent the energy carriers flow from which fuel mix is derived, and (AS1, AS2) represent auxiliary systems.

Table 1. Data collection format

PS	T	X1	X2	X3	X4	X5	X6	X7	X8	AS1	AS2
ps_a	t_a	x_{1aa}	x_{2aa}	x_{3aa}	x_{4aa}	x_{5aa}	x_{6aa}	x_{7aa}	x_{8aa}	as_{1aa}	as_{2aa}
	t_b	x_{1ab}	x_{2ab}	x_{3ab}	x_{4ab}	x_{5ab}	x_{6ab}	x_{7ab}	x_{8ab}	as_{1ab}	as_{2ab}
	t_c	x_{1ac}	x_{2ac}	x_{3ac}	x_{4ac}	x_{5ac}	x_{6ac}	x_{7ac}	x_{8ac}	as_{1ac}	as_{2ac}
Factory benchmark		x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	as_1	as_2

LifeSaver compares the actual energy consumption data with the predicted values and benchmark values for the team and factory. Also, the system compares the predicted energy consumption data with the benchmark values for the team and factory. In case a deviation is detected (i.e. value higher than the benchmark value for the team and factory) the system generates Event 1 "Deviations on Fuel Mix" and a Decision Process with status "CREATED" is stored at the database.

The Decision Support Services BB initiates the support for immediate reaction(s) and finds 50 Decision Processes stored at the database with status "CLOSED". All these Decision Processes are related with situations of abnormal energy consumption. The degree of similarity between cases is established through the Event detected (which congregates the information presented in Table 1) and is computed as follows:

$$Sim(E_1, E_2) = \sum_{i=1}^{n} w_i \, e^{-(\gamma|\alpha_{1i} - \alpha_{2i}|)} \tag{3}$$

where α_{1i} and α_{2i} are the parameters of each Event, w_i is the weight of each parameter and γ is a scaling factor. The computation of similarity, and the subsequent selection of cases, is performed using a similarity threshold of 90% (all the cases with similarity level below 90% are discarded). The set of similar cases includes 23 Decision Processes. From these, six are associated to Cause 1 "Problems with fuel sensor" and 17 are associated to Cause 2 "Unbalanced fuel dosing", thus: $p(C_1|E_1) = 0.26$ and $p(C_2|E_1) = 0.74$.

All the cases associated to Cause 1 were solved using Alternative 1 "Reset or Replace sensor", whereas half cases associated to Cause 2 were solved using Alternative 2 "Reduce dose rate of X1, confirm dosing of X2 and check the status of the auxiliary systems" and the other half using Alternative 3 "Confirm dosing of X4, X5, X6 and check the status of the auxiliary systems", thus: $p\big(A_1\big|(C_1|E_1)\big) = 1$, $p\big(A_2\big|(C_2|E_1)\big) = 0.5$ and $p\big(A_3\big|(C_2|E_1)\big) = 0.5$.

The cases were grouped considering the Cause and the Alternative and the mean similarity was computed for each sub-set of cases, resulting in: $\overline{Sim_1} = 0.9308$, $\overline{Sim_2} = 0.9180$ and $\overline{Sim_3} = 0.9702$.

The final score for each is then computed using (1): $Score_1 = 0.2428$, $Score_2 = 0.3392$ and $Score_3 = 0.3585$.

After this process the alternative recommended to the user is Alternative 3 (due to the higher score obtained). Nonetheless, all the alternatives considered are presented to the user. The user selects and implements one of the possible alternatives and closely monitors the clinker burning process. The system stores the user selection and changes the status of the Decision Process from "CREATED" to "SELECTED". In case no new deviations are detected in a specific time frame the user informs the system that Alternative 3 was successful and the status of the Decision Process is changed to “CLOSED”. From now on, this Decision Process will be usable in future situations.

5. Results and Discussion

The results of the decision model have confirmed the possibility of using such a model for a reacting to energy consumption deviations that required an immediate reaction to restore normal situation. Due to availability of the reliable historical/past data the results obtained with the decision model were appropriate for the situations detected and considered excellent.
During the testing phase predicted values of the energy consumption (for each particular fuel and electricity) were compared with the context specific benchmark values (for each team and fuel mix) to facilitate understanding of energy use patterns and trigger early warning and reaction if needed. Initial testing results have confirmed the potential of energy savings up to 8% enabled by proper and tailor made consumption feedback through decision support services which successfully influenced on the established behavioral patterns of less efficient process operators. However, limitations of the proposed concept are related with the requirements for expert knowledge during training period and definition of the initial set of context sensitive benchmark values. Also, context extraction from the available history data requires a significant amount of time, efforts and experience, especially when there is an intention to involve variables that will contextualize complex industrial operations like clinker burning process.

6. Conclusions

The work developed and results obtained are adequate for LifeSaver objectives in the field of decision support for immediate reaction. The categorization proposed, in the form of two different decision support strategies, served as base for defining the methods to be applied. The *support for immediate reaction* is based on the paradigm of intelligent decision support implemented through the use of Case-based Reasoning together with probabilistic analysis. The proposed algorithm was tested in energy intensive industry scenario using real data. The results obtained at trials provide an excellent input for the rest of the development and refinement of the tool.

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