Prognostics and Energy Efficiency: Survey and Investigations

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ABSTRACT

The paper presents firstly an overview of various definitions/concepts of energy efficiency and their related applications in different contexts, especially in industrial sectors. Each definition/concept is analyzed and recommended for different decision-making levels. Then a multi-level approach is described in detail for evaluating energy efficiency index of an industrial process. In addition, the paper discusses potential prognostic approaches in order to forecast energy efficiency index by underlining difficulties and opportunities to implement such approaches. Finally, a specific example based on an air-fan system is introduced to illustrate energy efficiency concepts and the added value of the prognostics to predict energy efficiency evolution.

1. INTRODUCTION

Today, energy is the most concerned issue in economic growth (Jollands et al., 2010; Steuwer, 2013; Andrea Trianni, Cagno, Thollander, & Backlund, 2013). Energy resources are nonetheless limited and become more and more costly while manufacturing activities or operation of complex products (Lambert, Hall, Balogh, Gupta, & Arnold, 2014; Urban & Ščasný, 2012) may involve significant energy consumption. Energy optimization of plants/centers and mobile systems (for example, industrial processes, manufacturing, computer data centers, transport, weapons systems and vehicles) is therefore an important issue to be solved in order to keep economic competitiveness and to reduce environmental impacts (Al-mofleh, 2009). This should be primarily reflected on by improving energy efficiency (EE), i.e. reducing the amount of energy required to provide products and services. Indeed, energy efficiency is considered as a key to sustainability (Oikonomou, Becchis, Steg, & Russolillo, 2009), industrial ecology (Boardman, 2004), and circular economy (Dixon, McGowan, Onysko, & Scheer, 2010; Wiel, Egan, & delta Cava, 2006).

To support these sustainability issues, Europe has set ambitious goals to promote the development of new methodologies, new technologies or disruptive technologies that can improve the energy efficiency and reduce energy costs by up to 20% in the most energy-intensive industrial sectors (European Commission, 2013).

To face with this challenge, one of powerful solutions is to implement the energy efficiency as an important indicator for various decision-makings related to monitoring, operation management, modernization and maintenance plans, etc. It is important to note that the decision-makings are essentially based on age or/and reliability/remaining useful life of components/system (Do Van, Voisin, Levrat, & Iung, 2013; Nicolai & Dekker, 1997; Wang, 2002). To be able to implement energy efficiency in decision-makings, the evaluation of energy efficiency is essential. This is the first objective of the present paper.

Moreover, it is shown that Energy Efficiency Performance (EEP) is an upheaval during process-lifetime (Hasan & Arif, 2014; Zhou & Ang, 2008). Predicting the degradation behavior of energy efficiency of components/systems is therefore crucial. It is however not very well founded. In fact, prognostics approaches have been basically used for predicting the remaining useful life (RUL) of components/systems (Byington, Roemer, Kacprzynski & Drive, 2002; Saha, Goebel, Poll, & Christophersen, 2007; Sankararaman, Daigle, Saxena, & Goebel, 2013; Saxena, Celaya, Saha, Saha, & Goebel, 2010). Enlarging this scope of prediction, several variants have been proposed to predict some other kinds of system features such as health or performance of components/systems (Cocheteux, Voisin, Levrat, & Iung, 2010). In that way, the second objective of the paper is to propose a new concept for the EE prediction.

Thus, with regards to this global EE optimization and forecasting context, an overview of energy efficiency is presented in Section 2. The assessment of EE indicators in the case of industrial applications is also investigated. Then Section 3 focuses on describing potential prognostic approaches for EE prediction. An air-fan system is introduced in Section 4 as an example to illustrate not only the proposed EE concepts but also the added value of prognostics implementation. Finally, Section 5 concludes the paper and prospects to prognostic-based energy efficiency in future works.

2. CONCEPTS OF ENERGY EFFICIENCY

2.1. General concepts

Over the past decades, many governments and industrialists have focused on energy efficiency (EE) assessment which can be used for decision-making on strategy and priority actions in order to reduce energy consumption, energy demand and environmental problems.

For this assessment, EE is expressed as using less energy to produce the same amount of services or useful outputs. In that way, EE equation is formulated as: $\frac{\text{Useful work of a process}}{\text{Energy input into a process}}$ (Patterson, 1996). It means that a smaller amount of energy input is needed for the same useful produced output, or that a higher output is provided with the same energy input. In this way, energy efficiency can be used in a very wide range of applications and for different levels of features (Hilke & Lisa, 2012) in terms of energy demand sectors (buildings, appliances, transports, industries, services, etc.), sizes (on a local, national, international or global scopes), stake-holders (decision-makers, energy providers, end-users, energy services companies, energy audit services companies, or particular equipment). For example, EE has already been investigated in several sectors such as industries (Boyd, 2014; Fleiter, Fehrenbach, Worrell, & Eichhammer, 2012), transport (Parry, Evans, & Oates, 2013; Zou, Elke, Hansen, & Kafle, 2014), and buildings (Centre, Cddex, & April, 1992; Chirarattananon, Chaiwiwatworakul, Hien, Rakkwamsuk, & Kubaha, 2010). Nevertheless, for each sector (Darabnia & Demichela, 2013; Virtanen, Tuomaala, & Pentti, 2013), different visions of EE concept have been introduced.

In fact, there are many ways to quantify energy efficiency level of a typical machine, factory or country. The well-known concept of "energy efficiency indicators" or "energy efficiency index" (EEI) is often used basically with the evaluation of energy efficiency. Indicators of energy efficiency may provide the connection between the energy consumption and certain relevant economic and physical outputs (Salonitis & Ball, 2013). Four following categories of EEI: thermodynamic, physical-thermodynamic, economic-thermodynamic, and economic indicators have been mentioned by many authors:

Thermodynamic indicators: They are measured as the energy dissipated or consumed by the system compared to the amount of energy in the resource processed. Both input and output are measured in thermodynamic units (e.g., GJ of delivered energy consumed in the production coke for coking coal). The importance of efficiency comes from the thermodynamic laws, namely the conservation of energy and the irreversible energy conversion to uselessness. By decreasing the energy loss in the processing, the useful energy transformed from energy input is increased. Thus, the thermodynamic definition of energy efficiency can be expressed as follows: $\frac{\text{Useful work or energy output}}{\text{Energy input}}$ (Jørgensen, 2010; Udphzrun, 2001). For example, the energy efficiency of a steam boiler is calculated as the ratio of the energy amount of steam output to the input heat needed to boil the water inside. In the case of motors, it should be the mechanical energy output divided by the input electricity. This type of EE indicators should not be applied to unknown thermodynamic characteristics or to the case in which there is no or poorly-monitored process because of missing information about energy loss. Relatively, thermodynamic indicators are not the best choice at the top level of national and international energy. According to (Tanaka, 2008), thermodynamic energy efficiency can be used only at the device level, end-use technology or energy conversion technology.

Physical-thermodynamic indicators: This kind of indicators has been introduced to avoid the limit of thermodynamic indicators in systems with output units that are uncountable or specific energy format like systems in transport or agriculture. In fact, the output is evaluated in physical units while the input is in energy. In this way, the energy efficiency can be evaluated as follows: $\frac{\text{Useful physical work output}}{\text{Energy input}}$ (Ang, 2006; Bor, 2008; Giacone & Manco, 2012). It is important to note that the units of physical output have to be expressed in the designed units of the system capacity (tonnes of cement, passengers, kilometers, vehicles, the number of rooms, etc.). Calculated in either aggregated or disaggregated methods, these indicators directly stick to the technical power flow. As a consequence of various physical outputs, multiple forms are used for physical-based indicators such as energy intensities, specific energy consumption, etc. In spite of difficulties in quantifying the higher level of aggregated process, the physical-thermodynamic indicators can be applied to a variety of levels ranging from a very simple component level to a sector level (Farla & Blok, 2000).

Economic-thermodynamic indicators: These indicators are hybrid indicators, in which the energy input is measured in thermodynamic units and the output is measured in market prices ($). The market prices are measured by the gross domestic product (GDP) or the market value of all final goods and services produced within a country or a sector (Gavankar & Geyer, 2010; Rosenquist, McNeil, Iyer, Meyers, & McMahon, 2006; Scofield, 2009; Tsvetanov & Segerson, 2013). In this case, any difference in the output or input number can be affiliated to economic, social behaviors or calculation methods. The information of technical process is unnecessary and the energy output number is conveyed through energy price factors. The "Energy:GDP" increments may be misunderstood as the positive result of energy efficiency investment. But economic-thermodynamic indicators can be calculated by multiplying thermodynamic indicators with the economic value of output units. Thus, these indicators can be applied to high levels of economic structures such as the corporate, sub-sector, sector and national levels.

Economic indicators or monetary indicators: These indicators are used to measure changes in energy efficiency purely in terms of market values. They are named as the energy to GDP ratio, energy coefficient or energy elasticity. Economic indicators are given as the ratio of energy consumption in an energy unit to an economic activity in a monetary unit $\frac{\textit{dollarized of output}}{\textit{dollarized Energy input}}$ (Ang & Xu, 2013; Gvozdenac-Urosevic, 2010; Worrell, Price, Martin, Farla, & Schaeffer, 1997; Wu, Chen, Bor, & Wu, 2007). Sometime, these indicators would be convertible from their physical-thermodynamic indicator counterparts by simply multiplying the energy input with appropriated added energy prices. But, in another way, these economic indicators are just seen as a purely economic efficiency indicator rather than as an EEI because they are fully measured in economic values. This type of indicators should not be used in monitoring EEP systems. The economic indicators are often used when energy efficiency is measured at a high level of aggregation (international, national and sector levels), where it is impossible to characterize the output by a single physical unit.

The EEI concepts previously detailed have been used in a number of studies as the root definition and referred to by various names like thermal energy efficiency (IEA, 2008), economic ratios, techno-economic ratios (Gavankar & Geyer, 2010), energy intensity or energy efficiency intensity (Hsu, 2014), Energy Efficiency Design Index (Lloyd's Register, 2012), or benchmarks for energy efficiency (D. Phylipsen, Blok, Worrell, & Beer, 2002).

From these definitions, it is possible to characterize also EEIs with regards to the abstraction level of decision-makers mainly in terms of energy consumers and usage functions. In that way, we propose a classification of EEIs based on their potential applications (Figure 1).

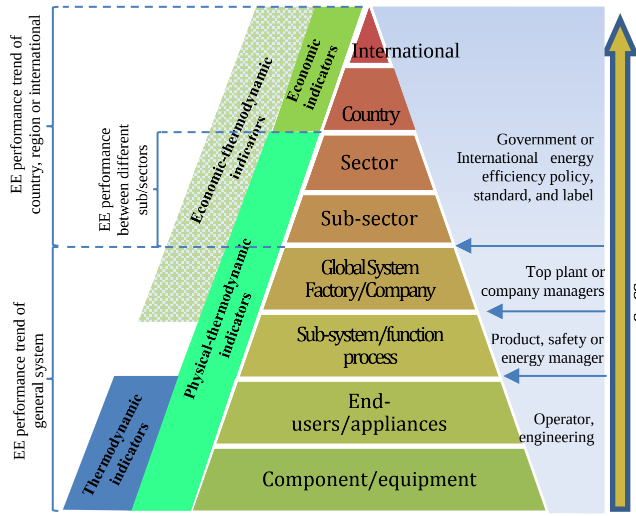

Figure 1. Potential applications of energy efficiency indicators depending on levels of decision-makers and aggregation

In Figure 1, it is illustrating that the more the energy consumers, the more chance and benefits energy efficiency investment brings about. Therefore, opportunities and challenges of energy efficiency applications at industrial sectors have to be addressed.

2.2. Concepts of EEIs for industrial sectors

As multiple factors are affecting energy efficiency performance of industrial sectors (process complexity, internal energy transformations various products and production rates, etc.), quantifying movement of energy efficiency needs explicit definitions and energy efficiency measurement.

In industrial sectors, for measurement and management purposes, Specific Energy Consumption(SEC) is the most common EEI ("ODYSSEE database," 2010; G. J. M. Phylipsen, Blok, & Worrell, 1997; Sudhakara Reddy & Kumar Ray, 2011). SEC is the ratio of the energy consumption to the useful physical output of a process or activity. By multiplying the physical unit by its economic value, the monetary unit can be created and the effect of economic factors could be concerned. When the output is measured in common physical units, an estimate of physical energy intensity is obtained (e.g. TJ/tonne). The total energy consumption in an industrial process is the summation of all types of energy such as electricity, gas, coal, and oil. The SEC for industrial processes is expressed as follows:

$$SEC = \frac{E_{Consumed}}{P_{out}} \tag{1}$$

Where: $E_{Consumed}$ is the used total energy input, P_{out} is the process output in physical units.

When the output of industrial processes is uncountable or invisible (for example, electrical power distribution system or production process are pending but auxiliary system still running and consuming energy), then SEC is the ratio of energy inputs to energy outputs. It will be the inverse formula of thermodynamic energy efficiency. In this case, the difference between the input and the output is the total energy losses during equipment operation or an individual task of processes.

$$SEC = \frac{E_{Consumed}}{P_{Out}} = \frac{E_{In}}{E_{Out}} \tag{2}$$

Where: E_{In} is the necessary energy input used by industrial processes, E_{Out} is the useful energy output delivered for industrial processes.

In a typical industrial process, there are at least several factors affecting the EEI during its life. These factors could be classified into: the structure or function of the process and facility; management, operation methods and maintenance plans; energy categories; raw materials; ages of equipment; and production plans or load profiles. These factors change over time and depend on other parameters. Thus, it is important to discuss methods of EEI evaluation or EEP during its life-time for industrial processes.

2.3. Assessment of EEIs in industrial applications

For focusing on the assessment step, it is necessary to divide the study of energy efficiency into several different abstraction levels. Thus potential applications of EEIs regarding to aggregation/abstraction levels, are the most important factors that affect energy efficiency at each level and the inter-level interactions. They need to be detailed and discussed.

2.3.1. At the component level

According to the evaluation of changes in the efficiency of production equipment or a particular production process, the lower the disaggregation level can be analyzed, the more accurate the measurements of achieved technical energy efficiency improvements can be improved. Applying the component, process unit or sub-system concept offers a way to divide the energy use in an industrial system into smaller parts. A process unit can be considered as the smallest component of an industrial energy system (Schenk & Moll, 2007). A single process/component unit is based on the function of the industrial process, for example, cooling, heating, and packing or air compressors. Input variables of operation conditions are classified into physical indicator (PI) and nonphysical indicator (NPI) categories. Total energy input E_i^t, and total output P_i^t of one component *i* at time *t* (the time unit could be one hour, one day, one month, etc) can be expressed as:

$$E_i^t = f_i^t(PI_i^E, NPI_i^E) \tag{3}$$

$$P_i^t = g_i^t(PI_i^P, NPI_i^P) \tag{4}$$

$$SEC_i^t = \frac{f_i^t(PI_i^E, NPI_i^E)}{g_i^t(PI_i^P, NPI_i^P)} \tag{5}$$

Where:

- PI_i^E is a set of physical indicators affecting energy consumption of component *i* such as energy transformation, working duty cycles, available capacity, deterioration levels of elements, quality of raw materials, etc;
- NPI_i^E is a set of nonphysical indicators affecting energy consumption of component *i* such as ages, production planning, product programs (load profiles or process productivity), human skills, etc;
- PI_i^P is a set of physical indicators affecting output of component *i* such as supplier availability, waste products, product types, etc;
- NPI_i^P is a set of nonphysical indicators affecting output of component *i* such as storage, transport stations, etc.

It should be noted that f_i^t and g_i^t are the functions of PIs and NPIs. These functions can be built up based on the data collected from the system or the understanding of the dynamics of the system. Both PIs and NPIs should be specified before applying the aggregation method to calculate energy inputs and useful outputs for each individual component. The PIs and NPIs should be collected. After determining and filtering processes to identify clear trends indicators, the EE threshold can be set from the requirement or field data. In that way, EEP for separated components can be foreseen.

2.3.2. At the function/system level

Together with using EEIs for separated components, the EEP of the global system should be taken into account. It has been shown that each component has its own energy profile depending on its operation modes (stop, on-load, off-load, standby, etc.) and operation modes may be modified by system functions. During the operation process, the EEP at the function/system level may not be equal to the total value of all components. Many studies have shown that energy consumption varies with product capacity. Moreover, the system function has a strong impact on EEP and operation sustainability. The biggest challenge is to compute the volume of outputs of largely diverse products produced by industrial processes. For example, it is widely accepted that 'tons of steel' is a well-known measure of capacity and real output in the steel industry. But the output evaluation of a beverage factory by summing liters of beer, alcohol, mineral water, and nutria drink, is inaccurate. The aggregation method to add multiple forms of outputs should be considered. Converting various physical output units into a common unit is commonly applied. In this case, it is needed to consider the weighting factor of separate subsystems or unit processes to produce one output type as Eq. (6).

$$P_{\Sigma}^{t} = \sum \lambda_{i}^{t}.P_{i}^{t} \quad (6)$$

Where: P_{Σ}^{t} is the total system output at time point *t*. λ_{i}^{t} is the output weighting physical factor of the separated disaggregated component *i* at time point *t*.

In comparison with Eq. (4), the value of λ_{i}^{t} is a function of total PI_P and NPI_P, which affect the role/duty or position of components in production sequences.

At the component or separated process/sub-system level, the individual activities and processes in the complex process have to be disaggregated. The energy inputs can be simply summed to generate an aggregate energy indicator. But, in a general system, load profile and operation/process functions decide the available productivity, operation mode of production equipment and influence the energy consumption. In this case, in computing energy input, integration of load profile into function factors is highly recommended. The total energy consumption is defined by aggregating the individual energy consumption multiplied by the corresponding weighting energy factor as Eq. (7).

$$E_{\Sigma}^{t} = \sum \omega_{i}^{t}.E_{i}^{t} \quad (7)$$

Where ω_{i}^{t} is the energy weighting energy factor of the separated component *i* at time point *t*.

The energy weighting energy factor ω_{i}^{t} is based on the energy used within one complete component. At the function/system level, ω_{i}^{t} is deeply depended on PI_E and NPI_E of the structure of function/system production sequence. Together with weighting factors of outputs, the impact of weighting factors of each component can be shown clearly in comparison with other components. The higher the values of ω_{i}^{t} and λ_{i}^{t}, the higher the contribution of component *i*. With the Eq. (6) and (7), formula (1) can be changed to:

$$SEC_{\Sigma}^{t} = \frac{E_{\Sigma}^{t}}{P_{\Sigma}^{t}} = \frac{\sum \omega_{i}^{t}.E_{i}^{t}}{\sum \lambda_{i}^{t}.P_{i}^{t}} \quad (8)$$

By conducting energy measurement, the total energy input and total system output at the global system level can be evaluated. The dependence of each component on the others ones and function/system process can be shown in Figure 2.

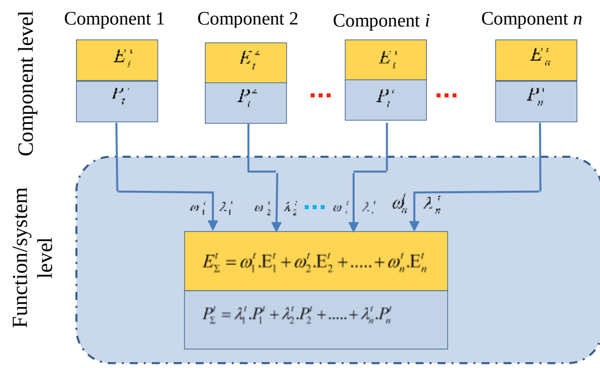

Figure 2. Aggregation approach to calculate EE parameters for the upstream level from separated component levels

Nevertheless, these two types of weighting factors are defined by the share of each component in the total of contribution of the function/system at the upper level of aggregation. They are used to get the weighted aggregate. The function/system factors with characteristics like flexible organizations of process sequence, multi-functional production should be taken into account. The movement of weight factors during time-line depends on the contribution of components to the global system. Thus, weight factors of components will not only influence EEIs and EEP at function/system levels, but also point out the critical components in the archived EEI target.

Based on historical data and measured parameters via conducting energy audit or power management system, EEIs at current time and EEP can be reviewed. Industrial system performances with a variety of system functions, flexible processes and complex equipment are one main target to apply prognostics. Thus predicting the movement of EEIs or EEP is an issue to be supported by prognostics approaches.

3. PROGNOSTIC APPROACHES FOR ENERGY EFFICIENCY

3.1. Prognostics conventional approaches: an overview

With the demand to anticipate the failure of a component/system, prognostics concepts have been introduced and successfully applied for different application fields (Muller, Suhner, & Iung, 2008; Si, Wang, Hu, & Zhou, 2011). The most obvious and widely used prognostic consists in predicting how much time is left before a failure occurs given the current condition, past and future operation profiles. The time left before an occurring failure is usually called remaining useful life (RUL). To support this prediction, various approaches have been developed from experience-based prognostics to model-based prognostics. The required information (depending on the type of prognostics approach) include: engineering model and data, failure history, past operating conditions, current conditions, identified fault patterns, transitional failure trajectories, maintenance history, system degradation and failure modes.

The main prognostics approaches that have successfully been applied on different types of problems are:

- Experience-Based Prognostics. Use statistical reliability to predict probability of failure at any time (Dragomir, Gouriveau, Dragomir, Minca, & Zerhouni, 2009; Muller et al., 2008);
- Evolutionary/Statistical Trending Prognostics. Multivariable analysis of system response and error patterns compared to known fault patterns (Muller et al., 2008; Si et al., 2011; Yang, Yu, & Cheng, 2007);
- Data-driven prognostics. These approaches are used to determine the remaining useful life by trending the trajectory of a developing fault and predicting the amount of time before it reaches a predetermined threshold level (Goebel, Saha, & Saxena, 2008; Sankararaman & Goebel, 2014). The strong points of data-driven techniques are their ability to link with recognized system behavior by experience methods and simple in installation and implementation.
- Model-Based (Physics of Failure Based Prognostics). These approaches need fully understanding of system to be expressed by mathematic functions or existing accurate mathematical models (Dai, Das, Ohadi, & Pecht, 2013; Fan, Yung, & Pecht, 2014; Medjaher, Skima, & Zerhouni, 2014). The accuracy of model and also the provided parameters of variables decide the precision of technical approaches. The main advantage of model-based approaches is reusing of model and flexible in configuring input data.

3.2. Prognostic formulation method for energy efficiency: a generic approach

As mentioned above, the existing prognostics concepts concern basically with the prediction of RUL or the failure date. Thus, they seem difficult even no longer to be applied for energy efficiency prediction since the energy efficiency behavior of a machine may be independent with its failure behavior. In this context, prognostic approaches should be used to predict the potential evolution of EEI of a machine, which is directly linked to its energy efficiency behavior, given the current condition, past and future operation profiles. Based on the evolution of EEI of a machine, it is possible to determine the time when EEI reaches its critical value related to the energy efficiency property of the machine. In this way, we propose an extension of RUL, namely REEL, in the framework of prognosis-based EE as follows:

Remaining energy-efficient lifetime (REEL) is defined by the time left before a machine loses its energy efficiency property, which is technically and/or economically fixed in advance, given the current condition, past and future operation profiles. Mathematically, REEL can be expressed as:

$$REEL(t) = \{E[T] : SEC^{t+T} = SEC_{Threshold} \mid SEC^{t} < SEC_{Threshold}\} \quad (9)$$

Where: T is a random variable; E[T] is mathematic expectation of T and $SEC_{Threshold}$ is an energy efficiency threshold as Figure 3.

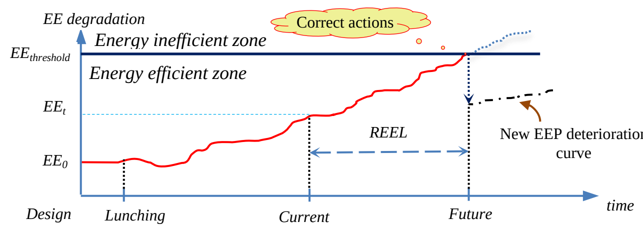

Figure 3. EE deterioration behavior and REEL prediction effect on decision-making

It cannot be denied that there are many difficulties to control global EEP because the system environment is changing. EE and system functioning mode are dependent on product flow and component ageing continuously modifies the system characteristics. There is a lack of decision support when it comes to questions of procuring, distributing and accounting for energy in production systems. Decisions in planning and operating production systems are mainly based on traditional metrics such as cost, quality and flexibility and rarely consider energy efficiency (Apostolos, Alexios, Georgios, Panagiotis, & George, 2013; Seow & Rahimifard, 2011; Thiede, Bogdanski, & Herrmann, 2012; Weinert, Chiotellis, & Seliger, 2011). New forecast REEL situations can be seen in the vision deployment of combination the current degradation and EEP deterioration trends.

With prognostic approach for EE, the EEP will be illustrated clearly and REEL can be predicted for various scenarios of actions plan. The predicted development of REEL scenarios will be used as aided-decision-making factor to select most efficient plans. If predicted EE value is not acceptable, various corrective actions such as replacement, update, and maintenance must be conducted at any identified critical level of system. In the other case, the value of EEI value of system is considered as under EE threshold and the remaining efficient life is long enough for securing functions of system, correction action is not necessary taken. The process will be repeated when new monitored data is updated. The outcomes of prognostic analysis combined with a database of traditional commercial operation principal will provide the different references of deciders.

From this definition, it is now needed to discuss on how prognostic approaches can be applied for predicting REEL at component level and function/system one.

3.2.1. REEL at component level

A small number of studies already mentioned about energy aspect with the common issue-energy consumption (Balaban et al., 2013; Chiach, Chiach, Saxena, Rus, & Goebel, 2013) and highlight prognostics as potential tool for prediction of energy demand. But for evaluating the REEL of a component, both the energy consumption and the output for future operation profiles must be estimated. However they depend on several physical and nonphysical indicators, see again Eq. (3) and (4). This means that these physical and nonphysical indicators must be firstly identified and evaluated. Model or experience based techniques (Fleiter et al., 2012; Salta, Polatidis, & Haralambopoulos, 2009) may be secondly used to evaluate the energy consumption at and output from the determined physical and nonphysical indicators.

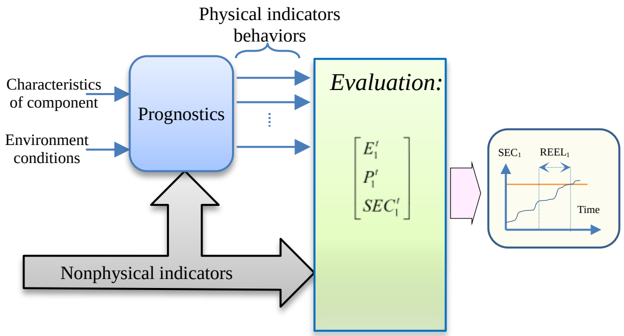

Figure 4. REEL Prediction process at component level

In general, nonphysical indicators are usually known in advance and physical indicators, which may depend on component characteristics, related environment conditions and nonphysical ones, are often unknown. The deterioration evolution of these physical indicators may be predicted by prognostic approaches mentioned in the previous section (B. lung, M. Veron, M.C. Suhner, 2005; Muller et al., 2008). The proposed generic approach is shown in Figure 4. Only at this level, the EEP of component without the impact of other component or function of system can be evaluated directly. Any correction action at this level can help the component restore the EEI of individual component. Its EEI will be reduced under the $EE_{Threshold}$ or as equal the value of launching time.

3.2.2. REEL at function/system level

As mentioned in Section 2.3, to evaluate the REEL of a function/system, we need not only the information (energy consumption, output, REEL) related to all components but also the information related to function/system such as system structure, dependencies between components, production schedule, support system, operation condition and management, The link between the global energy consumption, the global output and this information are crucial. In fact, as proposed in Section 2.3 these relationships are represented by the weighting energy factors and the weighting physical factors. In this way, based on the results at component level, to predict the REEL at function/system level, the weighting energy factors and the weighting physical ones must be estimated. Figure 5 illustrates the REEL prediction process for a function/system.

The implementation of the REEL methodology both at the component and function levels need now to be illustrated in order to show its feasibility and added value. At this level, the optimization of operation or function system has strong impact in the energy consumption of each component. An efficient equipment could have a strong weighting factor and have a high opportunities in EE improvement at system level, caused of optimized working chain process, lack of skills of operator or low awareness of manager (A. Trianni & Cagno, 2012).

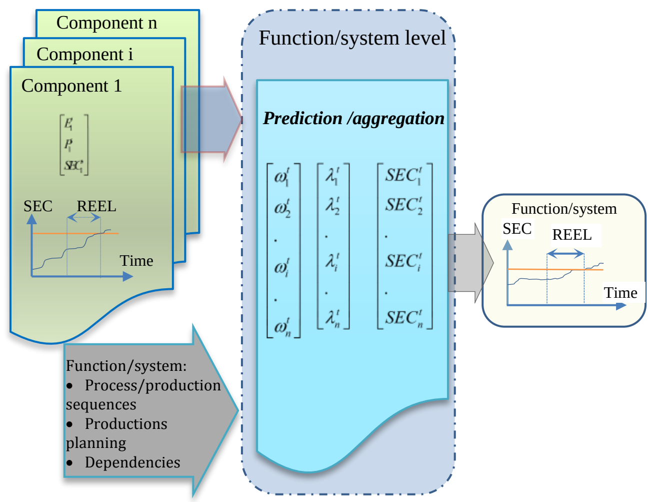

Figure 5. REEL Prediction process at function/system level

4. REEL EXPERIMENTATION TO A SPECIFIC EXAMPLE

For illustrating the proposed concepts for energy efficiency and related evaluation/prediction approaches, it is chosen an industrial sub-system which is composed of a motor associated to a fan (Figure 6). The electrical motor-drive converts electrical power into mechanical power (via a rotating shaft connect to mechanical load). The electrical motor-drive has a big amount percentage of total power consumption in industrial applications.

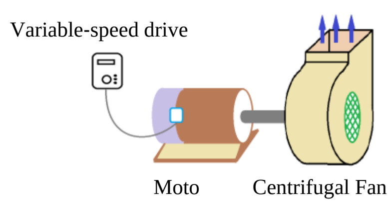

Figure 6. Basic components of fan system

The proposed evaluation/prediction is applied at both component and function/system level.

4.1. SEC at component level

For reviewed air-fan system, we are considering the EE effect of three main components which are the control system, the electrical motor and the centrifugal fan. The power and air flows of the system are shown in Figure 7.

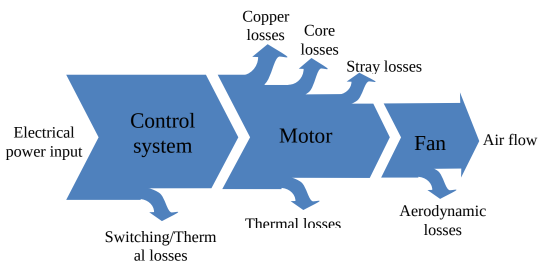

Figure 7. Energy flow and Air flow output of fan system

According to the disaggregation method, the detailed mathematic function of EEI at component level have to include both physical and thermal laws in time point *t* as below:

1. *Centrifugal fan*: Centrifugal fan is used for applications requesting low noise and vibration. It can produce high air pressure, lower noise than axial fan. Fan consumes transformed input energy and converts it to the air-flow power. Fan efficiency is the ratio between the power transferred to the air stream and the mechanical power delivered by the motor. In that way, SEC of centrifugal fan SEC_M^t is the ratio of electrical input power to air-flow power output:

$$SEC_F^t = \frac{E_{F-in}^t}{E_{F-out}^t} \tag{10}$$

Where: E_{F-in}^t is mechanical input of fan and E_{F-out}^t is air-flow power of drive system.

With the direct connection, an adjustment of fan speed can cause different airflows and pressures or performance levels. According to fan law, power input varies with the cube power while air flow rates vary in direct proportion to the rotational speed of the fan (International Energy agency, 2011). The energy efficiency of the centrifugal fan is shown in Figure 8a.

2. *Electrical motor*: An electric motor converts electricity into mechanical power, usually in the form of a shaft delivering torque at a defined rotational speed to an application machine. SEC of motor SEC_M^t is the ratio of electrical input power to mechanical output power.

$$SEC_M^t = \frac{E_{M-in}^t}{E_{M-out}^t} \tag{11}$$

Where: E_{M-in}^t is electrical input and depends on different physical and nonphysical indicators. However, in this work, it is assumed that E_{M-in}^t depends only on the speed of motor. More precisely, by connected in serial with centrifugal fans, that power input E_{M-in}^t and power output E_{M-out}^t are proportional with the cube power of the operating speed of motor (U.S. Department of Energy Energy Efficiency and Renewable Energy, 1989). This means that SEC of the motor depends on its operating speed. The energy efficiency of the motor in function of its speed is shown in Figure 8b.

It is important to note that the operating speed of the motor may depend on different physical and/or nonphysical factors such as deterioration of the bearing, temperature, control strategy, etc. In this work, only the deterioration of the bearing is considered. Based on the condition/deterioration level, motor speed is set, for example, when the deterioration of bear increases, the speed of motor should be reduced due to a limited noise level constraint. It is assumed also that the motor is considered as failed if the deterioration level of the bearing reaches a limit level, usually called the failure threshold. In this study, this threshold is equal to 200. To predict the deterioration behavior of the bearing, a model-based prognostic is implemented with noise and vibration level as the main indicators of bearing health (Fernández-Francos, Martínez-Rego, Fontenla-Romero, & Alonso-Betanzos, 2013; Satish, Member, Sarma, & Member, 2005). More precisely, stochastic Gamma process is used to model the deterioration behavior of the bearing. The illustration of the bearing deterioration according to physical vibration signal and its corresponding speed are shown in Figure 9.

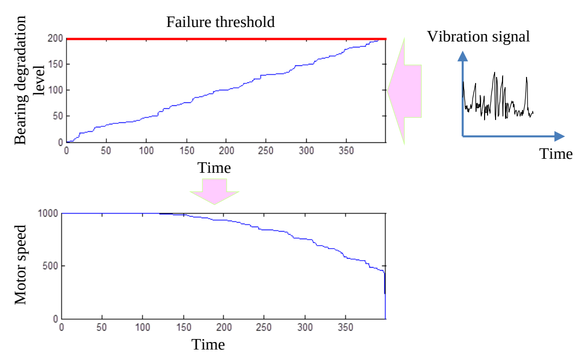

Figure 9. Illustration of the motor deterioration and its corresponding speed

3. *Control system* is adjusting working-point of fan according to demand of fan or control strategies (noise, positive pressure or negative pressure…). We are considering controller with variable-speed drive (VSD) and limitation of vibrations noise. So that, speed of motor will be reduced when the bearing deterioration level is

increasing. We estimate the SEC of control system SEC_C^t as:

$$SEC_C^t = \frac{E_{C-in}^t}{E_{C-out}^t} = \frac{E_{Electrical-in}^t}{E_{C-out}^t} \qquad (12)$$

Where: E_{C-in}^t is electrical input and E_{C-out}^t is electrical power output of control system. $E_{Electrical-in}^t$ is the electrical input for the air-fan system during at time *t*.

It is show that the energy efficiency of VSD depends principally on the operating speed of the motor (Rooks & Wallace, 2004). The energy efficiency of VSD in function of the speed of the motor is shown in Figure 8c.

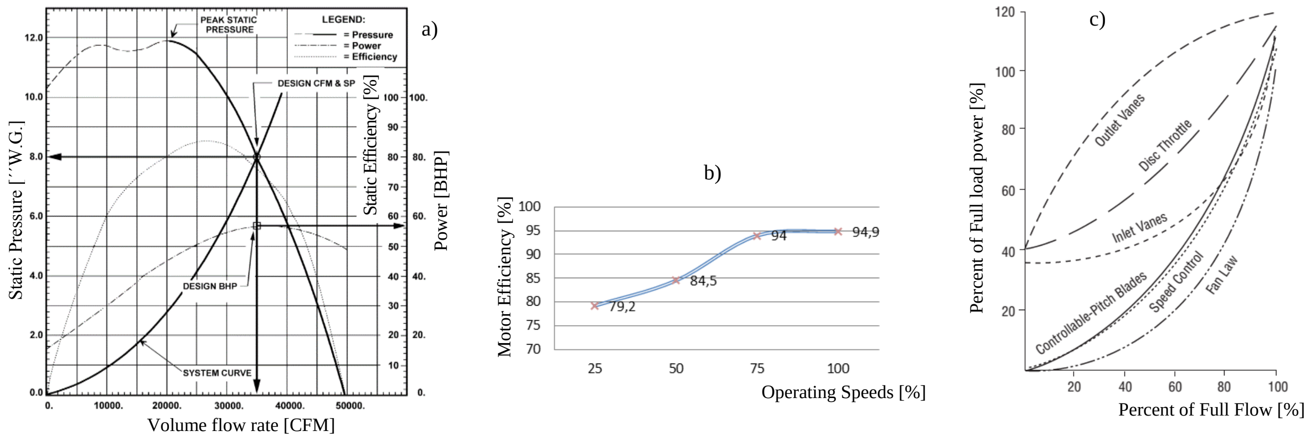

Figure 8. Energy efficiency indicator of (a)- fan head, (b)- motor and (c)- flow control with operation conditions (CML Northern Blower Incorporated, 1991; Rooks & Wallace, 2004; U.S. Department of Energy Energy Efficiency and Renewable Energy, 1989)

4.2. SEC and REEL evaluation at function/system level

As discussed above, the energy efficiency performance at function/system level is the most important issue. In fact, it is possible to show the reusability of SEC concept for function/system. For the air-fan system, two cases are considered:

- If we consider that useful output is the air-flow power. EE of fan system is defined by the ratio of power transferred to the airstream to the power input to the fan. the SEC of the air-fan system has to be calculated as:

$$SEC_{System}^1 = \frac{E_{System-in}^t}{E_{System-out}^t} = \frac{E_{Electrical-in}^t}{E_{F-out}^t} = \frac{E_{Electrical-in}^t}{\int_o^h V^t.\Delta_p^t.\mathrm{dt}} \qquad (13)$$

Where: *h* is operating hours; V^t is air flow (m3/hour) and $\Delta^t p$ is pressure difference from the fan inlet to the outlet (Pa)

- If we calculate the useful output as air-flow, in this case, SEC or usually called as “Specific air-fan power (SFP)” is used to estimate the specific power consumption per volume of air delivered and the energy consumption required for transporting air:

$$SEC_{System}^2 = \frac{E_{System-in}^t}{P_{System-out}^t} = \frac{E_{Electrical-in}^t}{\int_o^h V^t \,\mathrm{dt}} \qquad (14)$$

The Eq. (13) and (14) clearly show that with different types of useful outputs, the final SECs of system may be dramatically different. With complex air-fan systems, in which demanded air-pressure is varied according to the technical process or many types of air distribution existing, the impact of pressure has to be taken into account for EEP. The SFP is a good energy-performance indicator for the whole system, but it does not necessarily indicate the efficiency of the fan. The SFP will be calculated by the real operating conditions, and maximum SFP will be specific by energy standard. So the first one will be used more common in industrial application where air-fan is seen as one component of complex system but the second one will prefer for designing and standalone air-fan system. Thus to be able to evaluate SEC for a function/system, the outputs of the function/system have to be standardized by a unique one.

According to energy flow and air flow shown in Figure 7, the global energy consumption and useful physical output can be calculated as follows:

$$P_\Sigma^t = 0 + 0 + P_F^t \qquad (15)$$

$$P_\Sigma^t = 0.P_C^t + 0.P_M^t + 1.P_F^t \qquad (16)$$

$$E_{System}^t = \mathrm{E}_{C-Consumed}^t + \mathrm{E}_{M-Consumed}^t + \mathrm{E}_{F-Consumed}^t \qquad (17)$$

$$E^t_{System} = (1-\frac{1}{SEC^t_C})E^t_{C-in} + (1-\frac{1}{SEC^t_M})E^t_{M-In} + 1.E^t_{F-In} \qquad (18)$$

Where:

P^t_C , P^t_M and P^t_F are useful output produced by control system, motor and centrifugal fan at time *t*.

$E^t_{C-Consumed}$, $E^t_{M-Consumed}$ and $E^t_{F-Consumed}$ are the energy consumed by at controller, motor and fans, which are considered equal to the total energy losses during component operations at time *t*.

From Eq. (6) and (16) we have the weighting factor for air output of each component as:

$$\boldsymbol{\lambda}^t = \left[\lambda^t_C, \lambda^t_{M,}\lambda^t_F\right] = \left[0,0,1\right] \qquad (19)$$

From Eq. (7) and (18) we have the weighting factor for energy consumption of each component as:

$$\boldsymbol{\omega}^t = \left[\omega^t_C, \omega^t_{M,}\omega^t_F\right] = \left[(1-1/SEC^t_C),(1-1/SEC^t_M),1\right] \qquad (20)$$

At system level, these vectors $\boldsymbol{\omega}^t$ and $\boldsymbol{\lambda}^t$ are closely related to energy consumption, useful output of control system, motor and centrifugal fan at time *t*. By applying an aggregation method, we can assess the EEP deterioration of the air-fan system in the future. The illustration is shown in Figure 10b.

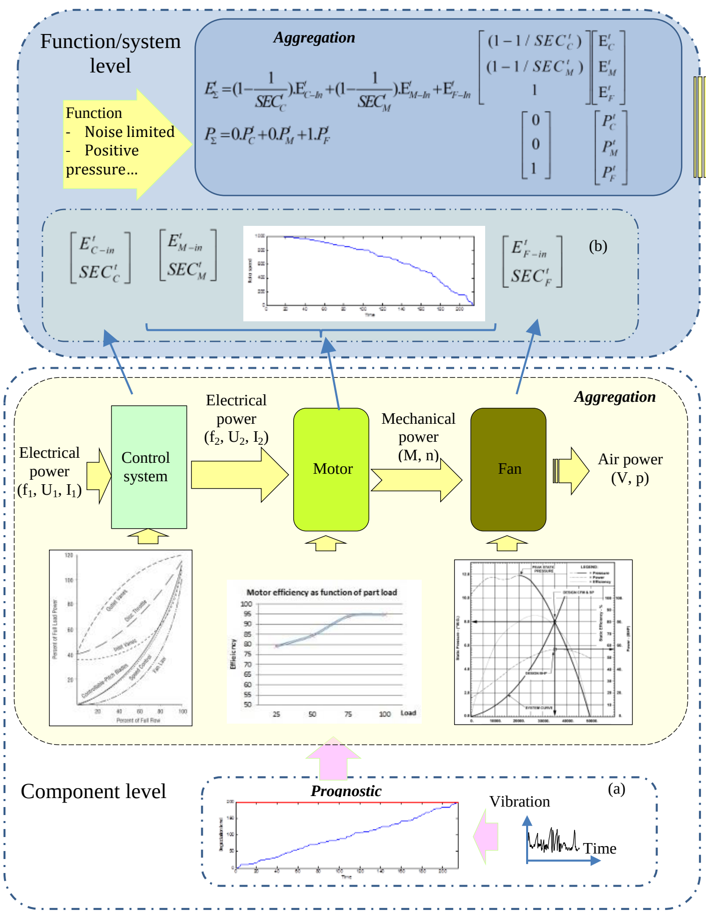

Figure 10. Integrated generic prognostic approaches for EEP deterioration of fan system

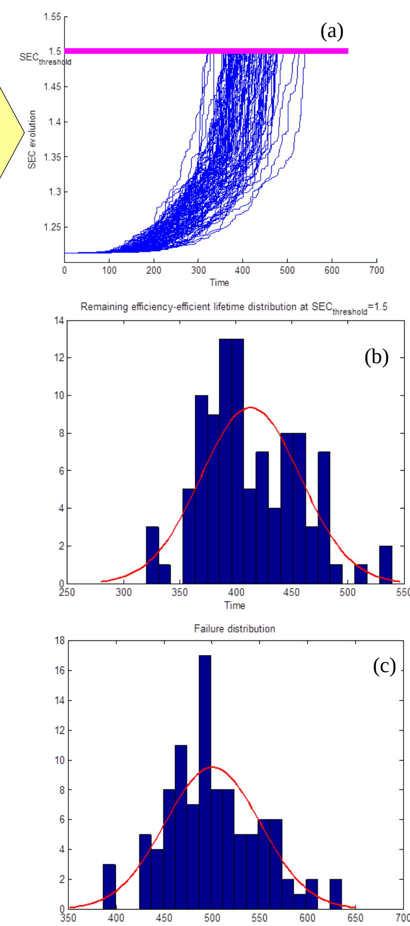

Figure 11. EEP deterioration and prognostic effect on decision-making indicator

Based on the EEI (SEC) behavior predicted, REEL is evaluated by using Eq. (8). Figure 11a describes the potential evolution of SEC. Given a SEC threshold (herein $SEC_{threshold} = 1.5$) the distribution of REEL is reached, see Figure 11b. The failure distribution of the motor is illustrated in Figure 11c. When compared with the distribution of REEL, it have a dramatically differences. Air-fan system is seen to reach the energy inefficient zone before it can touch the limit of physical life. This means that air-fan is available to deliver air, but consumed more energy than usual to distribution air and high level of noise and vibration of fan can have bad affections to the convenience of general system. The SEC of any component (motor, controller, etc.) and its EEP evaluation are used to identify the key component to maintain the general EEP of air-fan system. The benefits and complexity of conducting correct actions to maintain EEP with can be consider as a main additional factor for plan-making process. For example, the dust removing of fresh air-filter or air duct should be conducted more often to maintain the EEP than waiting for the next shutdown time of air-system for general inspection period. Thus, various decisions making based RUL may be no longer appropriate when considering the EE performance criterion.

5. SUMMARY AND CONCLUSIONS

In this paper, it is first described an overview on energy efficiency concepts. Different concepts are classified according to the related decision-making levels. Then an EE concept for industrial sector is deeply discussed and developed. It leads to focus on the assessment of the energy efficiency behavior of an industrial component/system. In that way, an energy efficiency indicator (EEI) is introduced. Furthermore, it is proposed a mathematical formulation for calculating the proposed EEI at both component and function/system level. This formulation is illustrated by the implementation of an electrical fan-blower system. In addition, a novel concept related to the remaining efficiency-efficient lifetime, named REEL, of a component/system is proposed. In relation to conventional RUL providing information about failure date, REEL provides the remaining efficient lifetime of a component/system before it loses the energy efficiency property. REEL may be an interesting tool for decision making, for example, in areas such as maintenance, production scheduling, etc. In addition, the paper proposes a prognostic formulation approach which can help to predict the REEL at component and function/system level. This formulation is also tested on the case of electrical fan-blower system. To add the human experiences about EE in modeling need extra interesting studies and also analyze the model properties (big data problems, combinatorial explosion, metrics, etc.). These both conceptual and analytical proposals for evaluating the EEI seem powerful. It should be however validated on real industrial system applications to prove its added value and benefits. The later will be our future works.

NOMENCLATURE

EE	Energy Efficiency
EEI	Energy Efficiency Indicators/Index
EEP	Energy Efficiency Performance
REEL	Remaining energy-efficient lifetime
SEC	Specific Energy Consumption
VSD	Variable-Speed Drive

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