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Diego GALAR
Luis BERGES
Peter SANDBORN
Uday KUMAR

THE NEED FOR AGGREGATED INDICATORS IN PERFORMANCE ASSET MANAGEMENT

POTRZEBA ZAGREGOWANYCH WSKAŹNIKÓWWYDAJNOŚCI W ZARZĄDZANIUAKTYWAMI

Composite indicators formed when individual Indicators are compiled into a single index. A composite indicator should ideally measure multidimensional concepts that cannot be captured by a single index. Since asset management is multidisciplinary, composite indicators would be helpful. This paper describes a method of monitoring a complex entity in a processing plant. In this scenario, a composite use index from a combination of lower level use indices and weighting values. Each use index contains status information on one aspect of the lower level entities, and each weighting value corresponds to one lower level entity. The resulting composite indicator can be a decision-making tool for asset managers.

Keywords: *Indicator, aggregation, KPI (key performance indicator), performance, hierarchy, DSS (Decision Support Systems).*

Wskaźniki złożone tworzy się poprzez zebranie pojedynczych wskaźników w jeden indeks. Idealnie, wskaźnik złożony powinien mierzyć pojęcia wielowymiarowe, których nie da się uchwycić przy pomocy pojedynczego indeksu. Ponieważzarządzanie aktywami jest dziedziną wielodyscyplinarną, przydatne byłoby wykorzystanie w niejwskaźników złożonych. W przedstawionej pracyopisano metodęmonitorowania złożonej jednostki w zakładzie przetwórczym. W podanym scenariuszu, złożony wskaźnik wykorzystania powstał z połączenia wskaźników wykorzystania niższego rzędu z wartościami ważonymi. Każdy wskaźnik wykorzystania zawiera informacje na temat statusu jednego aspektu jednostek niższego rzędu, a każda wartość ważona odpowiada jednej jednostce niższego rzędu.

Słowa kluczowe:*Wskaźnik, agregacja, KPI(kluczowy wskaźnik wydajności), wydajność, hierarchia, DSS (systemy wspomagania decyzji).*

1. Introduction

Companies aim to get maximum return on their investments, i.e. assets. Therefore, a proper asset management policy is essential. A good asset management policy requires that asset managers receive accurate information. Indicators have become a popular decision-making support tool for engineering asset management, especially in the maintenance field [13].

However, the recent flurry of indicator related activity has led some to argue that there is a danger of information overload. In this case, one way to assist asset managers is to develop composite indices that summarise the information contained in the many maintenance indicators. To date, little work has been done on developing composite maintenance indicators that take into consideration more than two information sources. Only the OEE (overall equipment effectiveness) uses maintenance indicators. Many authors suggest further research into indicators focusing on the development of highly aggregated indicators is required.

Others are not so sanguine about the appropriateness of composite indicators [3]. The purpose of this paper is to address the debate surrounding composite maintenance indices. The paper first highlights the strengths and weaknesses of composite indices. It then presents a framework to guide the development of composite asset indices. This framework provides insight into several methodological issues that must be addressed when calculating composite indices for a complex function like maintenance.

2. Why Composite indices?

It is often argued that those making decisions about maintenance have specific requirements of indicators. References [13] and [2] summarise the decision-makers' demands as follows:

- Only a limited number of indicators should be used to convey the performance of assets. Too many indicators can compromise the legibility of the information.
- Information should be presented in a format tailored to decision-making. This requires the construction of indicators that reduce the number of parameters needed to only those necessary to give a precise account of a situation.
- In the context of global business competition, decision-makers are interested in the relationship between asset management and company profitability. Indicators should, therefore, concentrate on the interaction, rather than on just the asset management itself.

In the production of accurate performance indicators, maintenance managers face a problem of data quality. Information is not easily accessible and sometimes even not collected, so decision-makers cannot rely on scientific data as it stands. The challenge is to transform existing data into condensed, or aggregate, information for decision-makers [9]. An alternative to a matrix of indicators is a aggregate index or indices. A single index may be easier for decision-makers to use because it summarises important information in one or a few numbers.

Preferences for scalars (composite indices like OEE) or matrices (indicator 'profiles' configured as scorecards, for instance) triggers a controversial and long-standing methodological debate. Essentially the debate centres on the amount of information that is lost in the simplification made possible by the index proposed by defenders of balance Scorecard and other groupings of indicators.

In an indicators' matrix, the observer's eye scans the individual indicators; he/she is implicitly asked to aggregate the indicators to form an overall impression of the issue of interest. Because the mathematical aggregation of different variables to form a single number does not occur, proponents of profiles argue that they have 'less chance for misinterpretation or misunderstanding than composite indices' [15].

On the one hand, people who are familiar with the complexities of monitoring interactions generally prefer profiles and view the potential distortion occurring in an index as unacceptable.

Also, people who are removed from the measurement process have a greater willingness to accept the simplification, and potential distortion of information for the sake of obtaining an easy-to-understand, albeit crude, picture of the environment.

This paper uses the terms 'composite/grand index' and 'composite/grand indices' to refer to composite indicators. When calculating an index, the aggregation process is carried out using a mathematical equation; it is not necessarily done by the observer. This method necessarily simplifies the information in the matrix of indicators.

Asset managers have shown considerable interest in developing composite indices, including financial ones. The quantity of data describing maintenance that has to be handled by the top management must be reduced, i.e., no large sets, but the data should contribute excellent information to facilitate good decision-making. The maintenance budget that concerns the replacement value of the assets is an indispensable element in decisions associated with renovation of equipment and plant delocalisation. Equally, the relationship of maintenance to the manufactured product(s) or to the cost of that manufacture, they will present/display all the scenarios in which present maintenance occurs.
The following indicators measure the costs of maintenance incurred in the process of manufacturing the end item, relative to the secured availability or the value of the machinery. These corporate numbers are used at the highest levels of management to guide overall changes in manufacturing policies and, by extension, in maintenance policies. These figures are the most rudimentary composite indicators widely used in asset management:

$$E1 = \frac{\text{Total Maintenance Cost}}{\text{Assets Replacement Value}} \quad (1)$$

$$E4 = \frac{\text{Total Maintenance Cost}}{\text{Production transformation Cost}} \quad (2)$$

$$E3 = \frac{\text{Total Maintenance Cost}}{\text{Quantity of Output}} \quad (3)$$

For the directors of factories or operations departments, excellent composite indices refer to availability with respect to production.

$$E5 = \frac{\text{Total Maintenance Cost} + \text{unavailability costs related to maintenance}}{\text{Quantify of output}} \quad (4)$$

$$E6 = \frac{\text{Availability related to maintenance}}{\text{Total Maintenance Cost}} \quad (5)$$

The indicators mentioned above and proposed by UNITE 15341 [8], are examples of costs aggregated with other parameters. This aggregation is produced by forming a ratio of two magnitudes. Three or more maintenance indicators are seldom involved in the production of composites. In maintenance, and beyond, there is an ongoing debate on the appropriateness of aggregating indicators.

3. Issues and challenges of aggregation.

A. Strengths of composite indices

Proponents of indices argue that there are several reasons for aggregation. One obvious benefit of a composite index is its production of a single or a few numbers, making the use of indices for decision-making relatively straightforward. Composite indices assist decision-makers by reducing the clutter of too much information, thereby helping to communicate information succinctly and efficiently [1, 4, 17].

As [14] states, 'aggregation is necessary to keep from overwhelming the system at the higher levels of the hierarchy.' Heycox [12] adds that 'a complex, information-rich world requires frameworks that organise data to reveal succinct views and interrelationships.'

An aggregation function formalises what is often done implicitly. Ultimately, when making a decision, the decision-maker must go through a process of condensing information to make simple comparisons. Proponents of composite indices argue that it is better to make this process explicit through an aggregation function.

B. Weaknesses of composite indices

Critics of composite indices proffer equally persuasive arguments. They argue that composite indices can lead to incorrect conclusions about policy performance. Development of the aggregation equation almost always requires more assumptions and arbitrary decisions than the design of a profile warrants. Thus, composite indices are frequently criticised by scientists familiar with the data; they feel that assumptions can lead to a loss of information and introduce serious distortions [14]. Critics caution that the distortions can lead the observer to misinterpret the data. As [14] states, 'if too many things are lumped together, their combined message may be indecipherable.' However, it is important to note that 'it is not that more detailed information is lost – usually it is possible to look at the details of how any composite indicator has been constructed – but rather that decision-makers are too busy to deal with these details' [5].

If users are not careful and informed, they can be ignorant of the source of the numbers, how the numbers were aggregated, and the uncertainties, weights, and assumptions involved, etc. This can also lead to spurious conclusions. A major limitation of composite indices is the manner in which the constituent variables to be included in the index are determined. Generally, the parameters are chosen on the basis of expert opinion. Critics argue that there is no single satisfactory method of selecting parameters. Therefore, an index is always in danger of missing important parameters. However, it is generally not feasible or practical to monitor the hundreds of potential variables.

Another problem with composite indices is that it is difficult to capture the interrelationships between individual variables. Gustafsson [10] warns against the reductionist views encouraged by composite indices. Physical processes that occur in the assets producing degradation are complex and interdependent. And a stress on one part of the system affects other system elements as well. It is unrealistic to expect composite indices or a single index to capture this complexity.

In reality, the two views of composite indices are not so black and white. In fact, they are necessarily complementary. A high level of indicator aggregation is necessary to increase the awareness of economy-environment interaction problems. But even given the advantages of composite indices, no single index can possibly answer all questions. Multiple indicators will always be needed, as will intelligent and informed use of the ones we have [5]. Nevertheless, it can be argued that composite indices have a role in assisting policy development and evaluation.

4. Methodological considerations for aggregating asset management indicators

Given that composite indices have a role in informing policy makers, the question remains, what can be done to ensure that high quality composite indices are produced?

A. The aggregation process

A significant gap in theory relating to composite indices is the lack of a framework to guide aggregation. A generic framework is shown below (see Figure 1). This framework can be applied to the estimation of composite asset management indices. Several of the steps are described in more detail below.

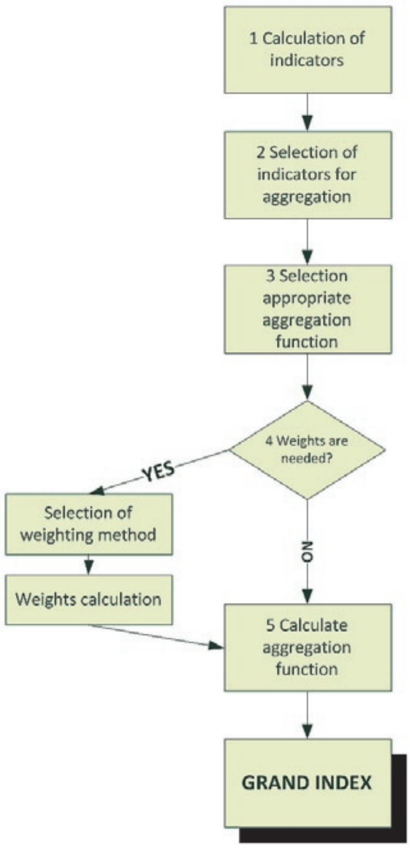

Fig. 1. A generic process for calculating composite indices

B. Selection subindices for inclusion in aggregation

After the indicators are calculated, the second step is to select variables for inclusion in the aggregation function. The selection of the variables is a contentious issue and must be approached with caution. First, the range of the indicators should provide an overarching representation of the principal factors of interest. In the context of asset indicators, this suggests a need for a representative coverage of functions or services for which data are available [18].

Second, the problem of 'multicolinearity' should be addressed by eliminating any correlated variables [18]. A standard test is the correlation coefficient. For example, variables that are highly correlated can be considered substitutes. By including only one indicator from a highly correlated set and excluding the others, we not only account for the trend in the variables, but also achieve parsimony in the data matrix.

Finally, and perhaps most importantly, there is a need to weigh data parsimony against the purpose. For example, often there is policy interest in both maintenance efficiency and effectiveness. Obviously, these are correlated. However, if decision-makers require an aggregate that reports both, the analyst (often implicitly) considers the balance between policy relevance and statistical integrity.

C. Selection of appropriate aggregation function

There is considerable debate over the most appropriate method for aggregating subindices. Aggregation functions usually comprise one of the following:

- Summation operation, in which individual indicators are added together;
- Multiplication operation, in which a product is formed of some or all of the indicators;
- Maximum or minimum operation, in which just the maximum indicator or minimum indicator is reported, algebraically shown as I = max{ε1, ε2, … εi,… εn} or I = min{ε1, ε2, … εi,… εn} respectively.

Several aspects must be considered when choosing the most appropriate aggregation function. First, the functional form of the indicator is important. Indicators can take the form of an increasing or a decreasing scale. In increasing-scale indicators, higher values are regarded as a 'worse' state than lower values. In decreasing-scale indicators, the reverse is true: higher values are associated with 'better' states than lower values.

The second consideration is the strengths and weaknesses of the aggregation function itself. Ott [15] identifies two potential problems with aggregation functions:

- An overestimation problem, where the composite index exceeds a critical level without any subindex exceeding that critical level.
- An underestimation problem, where an index does not exceed a critical level, despite one or more of its indicators exceeding that critical level.

The above are particularly problematic with dichotomous indicators (where they take on just two values, such as acceptable or unacceptable). An appropriate aggregation function will minimise the risk of both of the overestimation and underestimation problems.

A third aspect to consider when selecting the most appropriate aggregation function is the parsimony principle. That is, when competing aggregation functions produce similar results with respect to overestimation and underestimation, the most appropriate function will be the 'simplest' mathematically. In other words, simple mathematical functions are preferred over complex functions.

Finally, an aggregation approach will succeed if all assumptions and sources of data are clearly identified, the methodology is transparent and publicly reported, the index can readily be disaggregated to the separate components and no information is lost.

D. The challenge of setting the weights

The most popular aggregation function is the weighted summation given as:

$$ai = \frac{\sum_{i=1}^{n} w_i \cdot p_i}{\sum_{i=1}^{n} w_i} \tag{6}$$

where w_i is the weight, p_i denotes the selected performance indicators to be aggregated (individual assets or asset groups), n is the number of asset considered for study and ai is the grand index.

As can be seen in the above equation, the composite index for a group can be created as a normalized expression in which the range of the composite index is within the range of the indices used to create it. This allows the equation to be used with various index ranges and allows the composite index to be used for various asset groups with assets of differing importance. In particular, the index value for each asset in the group is within a common range of index values and the weighting value for each asset in the group is within a common range of weighting values. As a result, the composite index for the group will be within the same range and the range used for the indices of the assets within the group.

A significant challenge is the selection of appropriate weights. Methods like public polls or expert assessment are based on the knowledge and criteria of the people working with the assets, as their opinions on performance are relevant. However, this is a subjective (i.e., qualitative) approach, strongly dependant on humans, and quantitative methods, mostly statistical, are becoming more popular in assessments of performance. Statistical methods offer an alternative to 'subjective' systems of setting weights. Statistics provides a multivariate technique, namely, principal component analysis (PCA), that is useful for setting weights in the context of multi-dimensional data.

There is still considerable debate among experts about which weighting system to use. While each approach has merits, one advantage of PCA is its relative 'objectivity'. Unfortunately, PCA has received little attention in indicator aggregation literature in general and asset management literature specifically. Possible reasons include a lack of statistical skills among researchers and/or little linking of PCA with the need for composite indices. For a detailed discussion of these techniques, refer to [16].

5. Index aggregation in asset management

A. Asset information sources in plants

Process control systems, like those used in chemical, paper mills, etc., typically include one or more centralized or decentralized process controllers communicatively coupled to at least one host or operator workstation and to one or more process control and instrumentation devices which perform functions within the process such as opening or closing valves and measuring process parameters.

Process controllers receive thousands of signals indicative of process measurements or process variables made by or associated with the field devices and/or other information pertaining to the field devices; they use this information to implement a control routine and then generate control signals which are sent over one or more of the buses to the field devices to control the process. This information from the field devices and the controller is typically made available to one or more applications executed by an operator workstation; this enables an operator to perform functions related to the process, such as viewing its current state, modifying its operation, etc. All of this data contains performance information that is rarely extracted and sent to the proper decision-makers.

A typical processing plant has many hierarchical levels because of the interconnected assets, and a business enterprise may include interconnected processing plants. Assets related to a processing plant or processing plants themselves may be grouped together to form assets at higher levels; the complexity increases when decision-makers and information are found on different hierarchical levels and in different functional units.

In a typical plant, people have a number of different functions. For example, process control activities, device and equipment maintenance and monitoring activities, and business activities such as process performance monitoring all play a unique role. Process control operators generally oversee the day-to-day operation and are primarily responsible for assuring the quality and continuity of the operation; they typically set and change certain points within the process, scheduling processes like batch operations, etc. As a result, process control operators may be most interested in the status of process loops, subunit, units and areas. Of course, this is not always the case, and process control operators may also be interested in the status of devices that may have an effect on the loops, sub-units, unit, areas, etc.

B. Maintenance related information in processing plants

Maintenance personnel are also responsible for assuring that equipment is operating efficiently, repairing and replacing malfunctioning equipment and using tools such as maintenance interfaces and other diagnostic tools which provide information on the operating states of the various devices, Figure 2. As such, maintenance personnel will be interested in the status of devices and control loops, though they may also be interested in the status of sub-units, units, etc. [7].

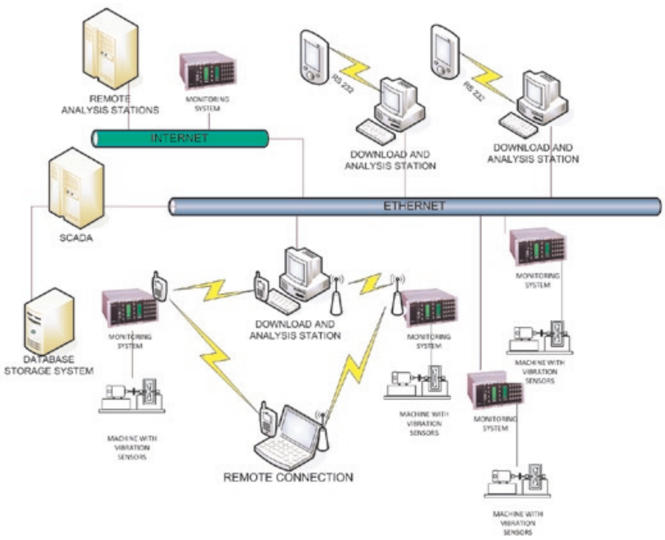

Fig. 2. Typical maintenance data architecture within a plant

Others may be responsible for business applications, such as ordering parts, supplies, raw materials, etc., making strategic business decisions such as choosing which products to manufacture, what variables to optimize within the plant, etc., based on process performance measures. Likewise, managers or other persons may want to have access to certain information within the processing plant or from other computer systems associated with the processing plant to oversee the plant operation and to make long-term strategic decisions. Such persons may be interested in status information pertaining to areas within a processing plant, the processing plant itself and/or all processing plants that make up a business enterprise.

As a result, a processing plant may have several persons (at different hierarchical levels) interested in the status of devices, loops, subunits, units, etc. To meet their often quite different needs, a variety of systems monitor and report the status of various devices, including health, performance, utilization, and variability [11]. The problem with this approach is that there are thousands of devices in a typical plant and the status of any single device generally cannot be used to determine the overall status of the loop, sub-unit, unit, area or process plant where the device is found.

Some solutions already exist for determining the status of devices, sub-units, units, areas and/or plants. Several Computer Maintenance Management System (CMMS) applications provide asset utilization indexes that include index generation routines related to the health, performance, utilization and variability of various assets at different levels of the plant's hierarchy.

C. The need for aggregation in process plants

An index can be generated by interconnecting various models representing, sub-units, units, areas, etc., within the plant to produce information on the operation of each loop, sub-unit, unit, area, etc., [6]. Alternatively, an indicator can be defined for each device to create a composite index at each level in the system hierarchy.

The composite index could be a weighted average or a weighted combination of the indices of the assets that make up the larger asset.

However, within a typical processing plant, some assets are considered more important than others within a group of assets. Some devices are considered more critical to the larger loop, or to the sub-unit, unit, area, etc., of which they are a part. If such a device were to fail, it would have a greater impact on the loop, sub-unit, unit, area, etc., than if others were to fail and should therefore be prioritised. Likewise, some loops are more important than others among a group of loops interconnected to form a sub-unit, unit, area, etc. In short, the importance of an asset among a group of assets may greatly affect the overall status of the group. However, in the past, varying degrees of importance were not necessarily considered.

In this paper, we propose a way to monitor an entity with a plurality of lower level entities and accounting for varying degrees of importance among the lower level entities. We acquire use indices pertaining to status information of the lower level entities, as well as weighting values. Generally, the weighting value indicates the importance of a lower level entity among a plurality of lower level entities. The weighting values may be based on the impact and frequency of failure. The impact and/or frequency of failure may, in turn, be based on maintenance information, process data, diagnostic data, on-line monitoring data and/or heuristic data. A composite use index representing status information on the entity can be created from a combination of the lower level use indices and weighting values. It may be a composite health index, a composite performance index, an aggregate variability index (indicating the deviation of a parameter of the entity) or a composite utilization index (indicating a degree of exploitation of the entity). The combination of the lower level use indices and weighting values may be a normalized expression, such that the range of values for the use indices is the same among the lower level entities. The combination may involve creating a weighted average of the use indices of the lower level entities.

D. The aggregation process

A processing plant can include a number of business and computer systems interconnected with a number of control and maintenance systems by one or more communication networks as shown in Figure 2. The plant can also include one or more process control systems. Maintenance systems, such as computers or any other device monitoring and communication applications may be connected to the process control systems or to the individual devices therein to perform maintenance and monitoring activities. Similarly, maintenance applications may be installed in and executed by one or more of the user interfaces associated with the distributed process control system to perform maintenance and monitoring functions, including data collection related to the operating status of the devices.

As mentioned above, the index aggregation methodology will receive information from various data sources, such as data collectors, data generators or data tools including index generation routines, model generation routines, control routines, maintenance system applications, data historians, diagnostic routines, etc. This application may receive information from performance systems embedded in CMMS, SCADA (Supervisory Control and Data Acquisition) etc. This information may include indices related to the health, performance, utilization and variability of a particular device, loop, unit, area, etc. This data can take any desired form based on how the data are generated or used by other functional systems. Finally, these data may be sent to the index aggregation using any desired or appropriate data communication protocol.

Information received from the index generation, control routines, maintenance system applications, data historians, diagnostic routines, etc., may be used to create and assign a weighting value to each of the devices within a logical and/or physical group of devices. Further, weighting values may be created and assigned to logical and/or physical groups including a logical process, a subunit, an area or a plant.

The weighting value generally indicates the importance or priority of a device, loop, sub-unit, etc., among the corresponding devices, loops, sub-units, etc. within the same physical and/or logical grouping. In other words, each asset within a group is ranked according to system criticality, operational criticality, asset criticality, etc. based on an assessment of each asset within the group, and a weighting value is assigned based upon its importance. For example, within a sub-unit that includes a plurality of devices and/or loops, a particular piece of rotating equipment may be considered more critical to the operation of the overall sub-unit than a field device. If both the rotating equipment and the field device require maintenance, the rotating equipment may receive priority over the field device in terms of resources allocated to maintenance. As a result, the rotating equipment is assigned a greater weighting value greater than the field device.

Similarly, among the subunits and/or units within an area, a particular sub-unit may be considered more important than another subunit, and is weighted accordingly. Areas within a plant may be weighted according to importance, and plants within a business enterprise may likewise be weighted. It should further be recognized that assets within a grouping need not be limited to an immediately preceding level. For example, weighting values may be assigned to each device, loop, sub-unit and/or unit within an area, rather than just each unit within an area. Likewise, weighting values may be assigned to each device, loop, sub-unit, unit and/or area in a plant. A user may define the groupings in a manner most helpful him/her, and weighting values may be assigned accordingly. As a result, each device, loop, sub-unit, unit, area, plant, etc. may be weighted according to its importance within a particular grouping. Generally, the importance of a device, loop, sub-unit, unit, area, etc., and its corresponding weighting value is based on two contributing factors: the impact on the group when the asset fails and the frequency of failure.

In fact, a device that has little impact on an area when it fails may be weighted lower than a device that has a high impact on an area during failure. Likewise, a device with a low frequency of failure may be weighted lower than a device with a high frequency of failure. The impact and the frequency of failure may be quantified, with the product of the impact and frequency of failure resulting in the weighting value. The evaluation of impact and frequency of failure may be based on a variety of factors, including, but not limited to, process information, on-line monitoring information, historical information, maintenance information, diagnostic intonation, and heuristic information based on the experience of plant personnel.

The index aggregation process may acquire weighting values related to each device, loop, sub-unit, unit, area, plant, etc., within a group by receiving each weighting value from another source or by creating each weighting value based on information from a variety of sources. For example, it may receive data relating to the impact and frequency of failure of each device, loop, sub-unit, unit, area, plant, etc. within a group and create each weighting value based on the impact and frequency of failure, (e.g., the product of the impact and frequency of failure).

The aggregation process may also receive information relating to each device, loop, sub-unit, unit, area, plant, etc., within a group to evaluate the impact and frequency of failure of each asset within the group, and to create a weighting value for each asset within the group. The information may include process information, on-line monitoring information, historical information, maintenance information, diagnostic information, and heuristic information as described above.

Accordingly, this process should be communicatively coupled with control routines, maintenance system applications, data historians, diagnostic routines, or other data. Each of the various types of information may be used to evaluate the impact and/or frequency of failure of an asset within a group of assets. For example, historical information, diagnostic information and maintenance information may provide information on previous failures of a device, while historical information, process information, on-line monitoring information and heuristic information may provide information on the impact of past failures on the group or the predicted impact of a failure on the group.

Of course, it should be recognized that the weighting values may be created in a similar manner using other routines or systems within the processing plant or created outside it. In addition to acquiring weighting values pertaining to each device, loop, sub-unit, unit, area, plant, etc., within a group, the index aggregation application acquires indices pertaining to their status within the group. The indices may be acquired from the application and each aggregated index may include a health index, a utilization index, a performance index or a variability index as described above.

Accordingly, weighting values may be acquired by receiving impact and frequency of failure information or by receiving information from the model generators, control routines, maintenance system applications, data historians, diagnostic routines, etc., to create a weighting value for each of the devices, loops, sub-unit, units, areas and/or plants, etc. within a logical and/or physical group. Further, indices pertaining to each devices loop, sub-unit, unit, area and/or plant, etc., within the logical and/or physical group may be acquired by the aggregation process. Using the weighting values and indices, the aggregation process may create an index pertaining to the overall status of the group, such as an aggregate health index, an aggregate utilization index, an aggregate performance index or an aggregate variability index.

6. Case study: aggregation of qualitative and quantitative maintenance data

Traditional models advocate audit to measure maintenance performance through surveys of various aspects of the maintenance function. The model considers the information from those involved in maintenance function as very important if it is duly validated by objective numerical indicators. Validation by objective indicators reduces part of the human factor inherent to surveys and interviews.

The case study combines the results of maintenance KPIs (Key Performance Indicators) wit questionnaires, both strongly correlated in terms of content and information to be achieved. The resulting model is shown in the figure below:

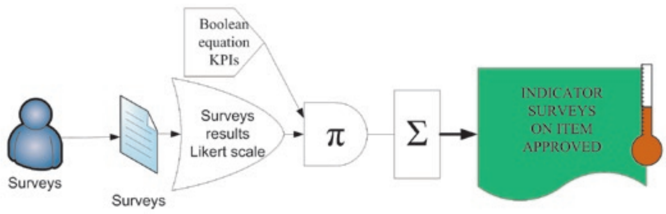

Fig. 3. Model validation surveys through equations based on efficiency KPIs

$$Validated\_surveys\_results = \\ = \sum_{i=1}^{n} Raw\_survey\_results \bullet KPI\_efficiency\_equation \tag{7}$$

Where n is the total number of questions performed in the survey and the KPI equation is as follows:

$$KPI\_efficiency\_equation = \prod_{i=1}^{n} KPI_1 \cdots KPI_n \tag{8}$$

Where n is the total number of normalized KPIs selected because of their strong correlation with the audited item in the figure.

It can be observed how the results obtained from questionaries are multiplied (block π) by the results of the efficiency equation proposed as a combination of one or more KPIs. Two aggregation functions have been explored. In one case, normalised KPIs (between 0 and 1) are multiplied to get a combined grand index related to some specific topic where the lowering effect of the product will be visible and will produce a final value that is less than one (the goal of efficiency or effectiveness in such aggregation function).

Afterwards, this grand index is multiplied by the indicators resulted from questionaries. This last stage aggregation reduces the numerical value in function of the value of the KPI grand index. In this case study, survey results from two paper mills are presented to compare traditional and the proposed methods of aggregating maintenance data.

This case considers data collected from the information systems of the companies and questionaries filled out by three different levels: Level 3 maintenance manager, level 4 maintenance supervisors and finally level 5 technicians. The topic of the questions was the quality and performance of "Maintenance Scheduling". For this purpose, thirteen questions were formulated:

1. Are there work requests to the department from other areas such as production, quality and prevention labor risks?
2. Are there priorities between jobs?
3. Is there a workload known as outstanding work?
4. Are these tasks scheduled?
5. Are these tasks planned?
6. Is the duration of the planned and scheduled work known with any degree of accuracy?
7. Is there a checking on both the work performance and the results obtained?
8. Are 95% of maintenance works scheduled and planned at the latest 1 day before being made?
9. Are spare parts, tools, equipment needed and appropriate documentation ready for the completion of this work?
10. Do planners clearly suggest the tools to use and the components to replace?
11. Are there instructions or procedures for carrying out the work?
12. Do maintenance people know tasks previously to be performed?
13. Is the role of planner defined?

The values received from questionaries are shown in Figures 4 and 5. These questionaries were made following Likert scale, ranked from 1 to 5, as shown in Table I for paper industry 1.

Figure 5 shows the responses of the three organisational levels surveyed: maintenance manager, supervisors and technicians, for paper industry 2. Table II shows the number of questionaries collected from each level for paper industry 1 and 2.

It can be seen that the work planning indicators are generally given high values by the three hierarchical levels and at the two plants audited. In fact most of the values and averages are above 4. This fact indicates that according to questionaries, i.e., human perception, the planning work is being carried out in a successful way.

These values are the result of aggregation, i.e. average of different questions and different hierarchies. However an aggregation with a different indicator is proposed. This index can be part of a grand index if multiplied by the maintenance KPI that are strongly correlated with the goals of the questionaries. In the studied case of questionaries about work planning, the numerical indicator that resulted from filling the forms can be the result of the product with O5, as seen in Figure 7.

O5 is an indicator proposed by EN 15341 that represents the volume of the total planning:

$$O5 = \frac{\text{Planned and scheduled maintenance man hours}}{\text{Total maintenance man hours available}} \tag{9}$$

Table I. Results of questionaries on work planning. Paper industry 1

	Planned maintenance							
	Level 3 Maintenance Manager	Level 4 Supervisor			Level 5 Technician			
		1	2	Avg	1	2	3	Avg
1	4	5	5	5	4	5	4	4,333
2	3	5	4	4,5	5	5	5	5,000
3	5	5	4	4,5	5	5	3	4,333
4	4	5	4	4,5	5	5	5	5,000
5	4	4	4	4	5	5	4	4,667
6	4	4	3	3,5	4	5	3	4,000
7	3	4	4	4	5	5	4	4,667
8	4	5	4	4,5	5		4	4,667
9	3	4	4	4	4	5	4	4,333
10	4	3	2	2,5	4	4	4	4,000
11	3	4	4	4	5	5	4	4,667
12	4	3	3	3	5	5	3	4,333
13	4	5	4	4,5	5	5	5	5,000

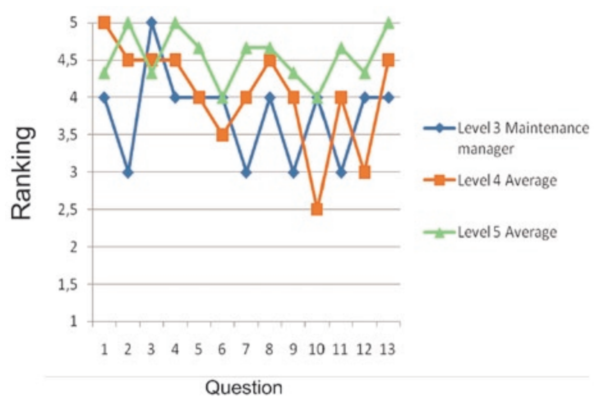

Fig. 4. Results of surveys on maintenance planning. Paper Industry 1

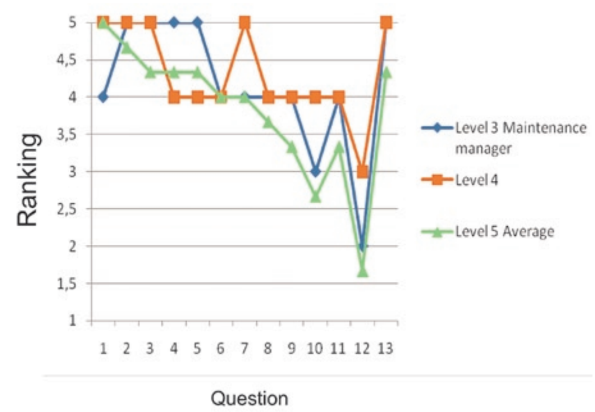

Fig. 5. Results of surveys on maintenance planning. Paper Industry 2

There are many theories and proposals on this indicator, 'World Class' perspective being adopted by the company. According to the current one the majority, around 95% of labor available hours, must be occupied in planned maintenance. Thereby, the problem of hypothetical lack of contingency workforce is solved by hiring overtime associated with outside companies.

This strategy stems from an aversion to the waste caused by idle resources and requires a comprehensive work planning and control,

Table II. Results according to hierarchical levels in industry surveys evaluated

Results Paper Industry 1	Planning work	
	Level 3	3,769
	Level 4	4,038
	Level 5	4,538
Average result		4,115
Results Paper industry 2	Planning work	
	Level 3	4,154
	Level 4	4,308
	Level 5	3,821
Average result		4,094

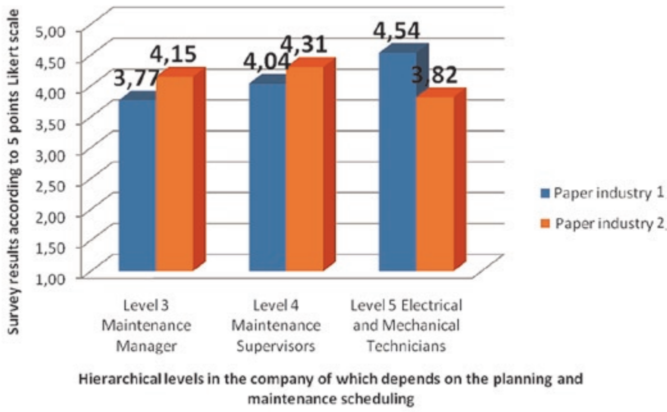

Fig. 6. Result of the survey planning work. Paper industry 1 versus Paper industry 2

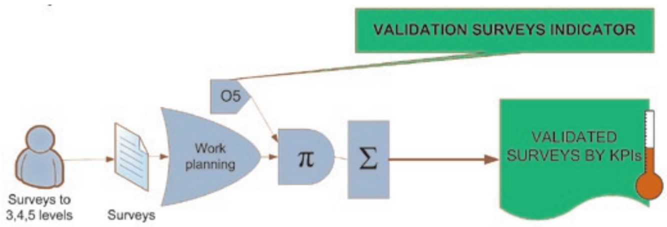

Fig. 7. Variation of classical model validated by KPIs. Calculation mode

i.e., an indicator close to unity, like the previous one, which is true. The companies in the past three years have come and gone into the range of 95% in compliance with the mark of World Class Maintenance (WCM). As for the industry 1, IO5 value is 96.96% while the second industry value is 28.32%, being these quantitative figures extracted from the CMMS.

Results of aggregation can be seen in Table III and compared with questionaries results in figure 6. Aggregating the values derived from surveys with the KPis, very high values around 4 are obtained again for industry 1, which means that the findings of the surveys are reliable and perform a work schedule maintenance work. Therefore the human per-

Table III. Validated indicator

COMPANY	Survey results	O5	Validated surveys
Paper Industry 1	4,115	96,96%	3,9899
Paper industry 2	4,094	28,32%	1,159

ception matches with the audit results. It is not like that for the second industry, since we see a significant reduction between the grand index and the one obtained from the surveys, reflecting the feeling timidly expressed in the responses regarding knowledge of the planned activity.

This aggregation process shows a failure of the traditional model based on questionaries that only take the human perception into consideration. Therefore corrective actions should be taken address the situation where the performance is low but people perceive that they are being successful.

7. Conclusions.

Composite indices are a useful communication tool for conveying performance information in a relatively simple way and to signal policy priorities. They are used widely in many sectors, but rarely in asset management. Composite performance indicators have a number of advantages, such as focusing attention on important policy issues, offering a more rounded assessment of performance and presenting the 'big picture' in a way the public can understand. It is likely, therefore, that they will be used in the future in many policy areas.

However, it is important to recognize that the construction of composite indicators is not straightforward; many methodological issues must be addressed if the results are not to be misinterpreted. Some pragmatism in the approach to composites may be appropriate.

Technical and analytical issues in the design of composite indicators clearly have important implications. This paper highlights some considerations in the construction of robust asset management composite indicators. For example, if the potential for producing misleading information is not addressed, composite measures may fail to deliver the expected improvements in performance or may even induce unwanted side-effects.

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Diego GALAR
Division of Operation and Maintenance Engineering
Luleå University of Technology
Luleå, 97187 Sweden
E-mail: diego.galar@ltu.se

Peter SANDBORN
CALCE Center for Advanced Life Cycle Engineering
University of Maryland
College Park, MD USA
E-mail: sandborn@calce.umd.edu

Luis BERGES
Department Design Engineering and Manufacturing
University of Zaragoza
Zaragoza. 50018 Spain
E-mail: bergesl@unizar.es

Uday KUMAR
Division of Operation and Maintenance Engineering
Luleå University of Technology
Luleå, 97187 Sweden
E-mail: uday.kumar@ltu.se