PROACTIVE APPROACH TO MANUFACTURING PLANNING

DOI: 10.12776/QIP.V18I1.208

PETER BUBENÍK, FILIP HORÁK

Received 15 October 2013, Revised 11 December 2013, Accepted 1 June 2014

1 INTRODUCTION

Series of business processes after receiving an order up to its realization are interdependent. They communicate important information with each other and are processing it with appropriate algorithms. Information flow is defined by structure of these processes and by sequence of their execution. Starting of individual processes is managed by predefined rules.

Depending on characteristic of *proactive approach*, some changes of processes may start before the system begins to respond to individual occurring events. In a real world, correctness of using of selected planning actions, methods and techniques of planning depends on reality, by reviewing if changes in processes were started correctly and if required goal was reached at the end.

Proactive approach controls given situation by active influence on given process before unwanted situation occurs. Opposite approach is characteristic by reacting on situation after it happens.

„Active“ – willing to make a change. „Director“, who has an active interest in improving company processes.

„Proactive“ – acting in anticipation of future problems, needs or changes. Approach is focused on beginning of change of process before the system starts to respond to individual events or monitored process characteristics.

Based on aforementioned characteristics we can conclude that proactive approach to manufacturing planning assumes that manufacturing planning system will play an active role in fulfilling objectives based on requirements defined by company management. For example sales manager is interested in the volume of sales of products, purchasing manager tries to minimize the costs associated with buying and holding stocks of materials in warehouses. For example manager of production, trade, technical or economic manager tries to keep processes falling under his competence within the pre-defined values for the selected indicators. Management tasks are built for the purpose of achieving the planned values of indicators that reflect the goals of the company and are often tied to the motivational system. The production manager is obliged to observe the values of indicators reflecting the highest efficiency and lowest operating cost of production. Values of these indicators are monitored and adapted to the current required goals of the company.

Choice of an appropriate indicator and adjustment of its scale is an important act in control of monitored process. This also applies to the planning process, where there is a very important interconnection between all relevant indicators at different levels of the plan creation. Individual assessment of processes can cause that the effort to increase the level of one indicator on the one hand, may have a negative impact on the overall level of efficiency on the other.

The proposed proactive planning approach needs to take into account current and expected development of the business environment and its surroundings. The result of this analysis and the subsequent transformation of indicators would then decide on the manufacturing company's ability to deliver the product in required quality, cost and time based on proactively created plan. Based on the status of development of indicators monitored at given time, the company could then assess its ability to produce and deliver the product within the required time frame.

2 PROACTIVE PLANNING CONCEPT DESIGN

The suggested concept of proactive planning consists of planning modules of standard company information system, a system for transformation and analysis of selected indicators, the expert system for the design of a proactive manufacturing plan, and simulation module for modelling previously unknown situations.

Design of final proactive plan is possible to be set by expert system, whose knowledge base acquires knowledge gained by *data mining* (DM) from the *data warehouse* (DW), to which access is controlled via interference mechanism (IM).

The simulation module enables to simulate the resulting variants for newly created problems. As this concept was being developed for discrete manufacturing environment, the simulation module uses a discrete simulation engine. It is planned to integrate Simulink's SimEvents library for discrete simulation in order to run different scenarios based on configurations gathered from expert system. This module serves also as a way to validate knowledge gathered by the expert system.

The proposed concept allows historical information obtained from the realized production orders, from their proposed plans and the actual behaviour to be utilized for repeated use in the design of the production plan. This production plan can be called "proactive" because it will be constructed with knowledge of expected known and unknown events. This interconnection of information technologies enables to detect problems early and to avoid them (Božek, et al. 2009). The proposed concept is based on planning modules, and the concept also allows acquiring these data from the existing ERP systems.

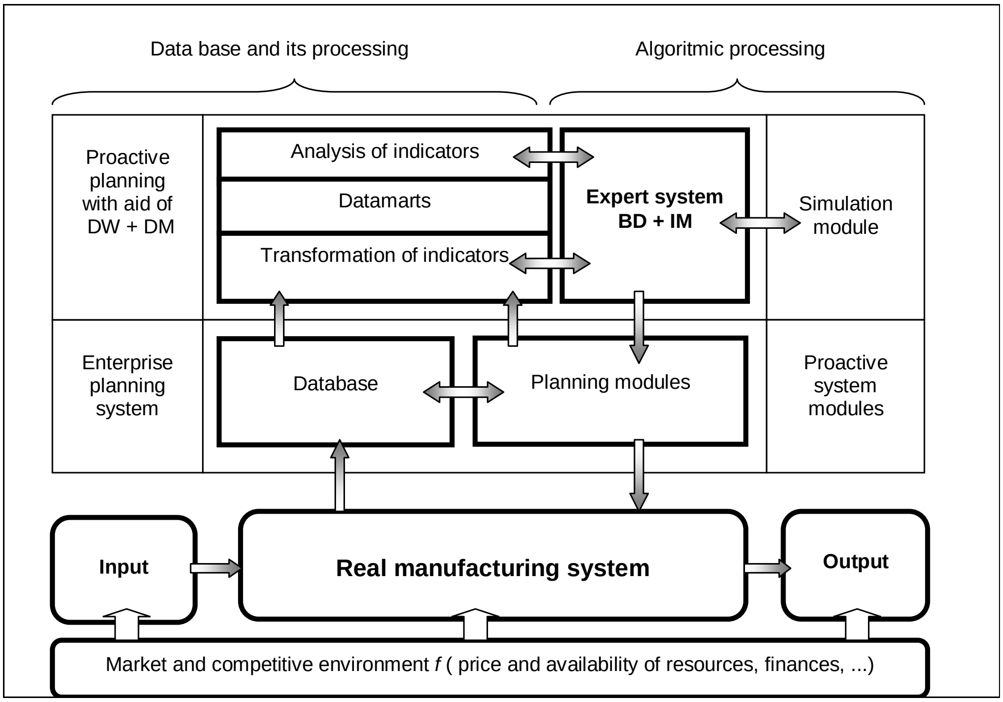

Figure 1 – Proactive manufacturing planning concept design – modules

The resulting data of realized business cases, purchases and realized production, but also the resulting economic evaluation of the performance of manufacturing company are transformed into indicators at the end of the business case. The concept captures the change of indicators and their development also after changes in the input parameters. The dynamics of the system are captured and indicators can assist in the design of a new production plan.

Algorithm of the concept describes the transformation of the data to indicators that reflect the state of the manufacturing system at a given time in Figure 2. The result of individual steps is evaluation of implementation of the proposed plan using the required economic indicators as well as customer requirements, which clearly determine the suitability or unsuitability of the decision made. In the case of using modelling tools, concept enables to define the upper and lower boundaries of individual indicators, or the definition of "warning" about potential failure caused by the decision.

Hierarchy of indicators is designed in the way that it could describe as accurately as possible what is happening in the company and what is the development of customer requirements, in order to satisfy him in terms of time, volume and quality.

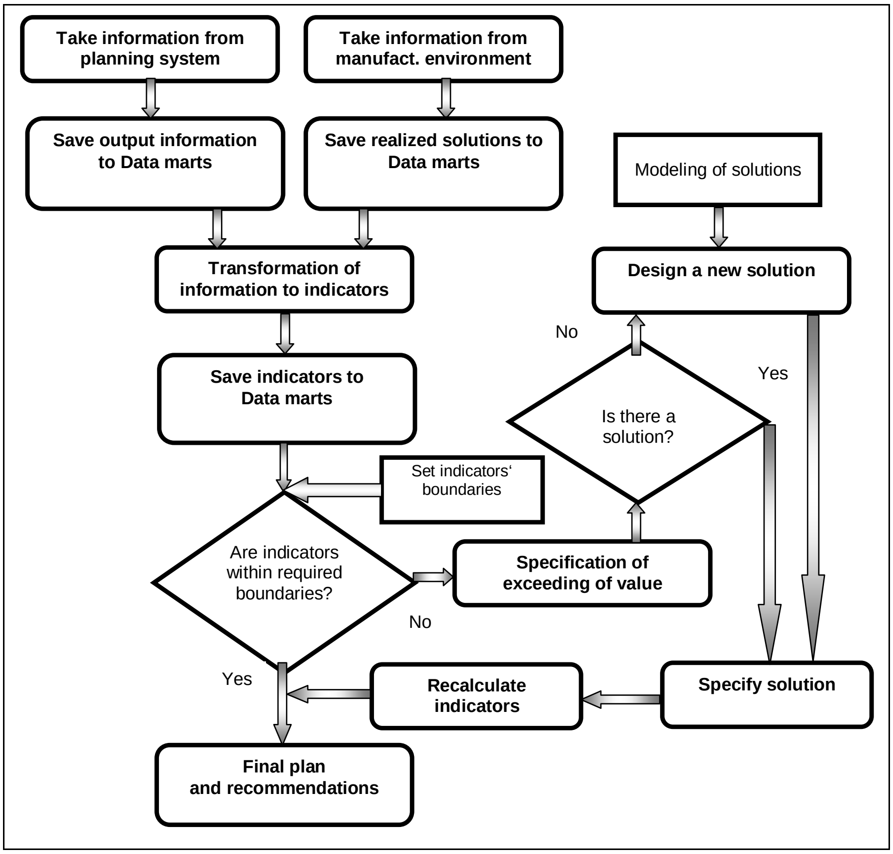

Figure 2 – Basic algorithm of proactive planning concept

Finding a suitable setting of indicators and searching for known and less known causes and relations to successfully plan production in this concept ensures the top module, which will search and recommend best plan variants based on historic and present values of indicators.

The best variant is characterized by required values of selected parameters, which will be adjusted by production planner, market analyst and chief economist.

On exceeding of the boundary set for selected indicators, the system would respond by querying the data warehouse using data mining techniques to help find a solution based on our knowledge of the processes we have so far. After implementation of the selected solution, the system as an expert would make a conclusion making an entry into the system. The content of the entry would be a result that brought the decision.

The concept of proactive production planning with support of data technologies requires a high-quality database platform with an integration of techniques for data mining. Nowadays, with support of fast data technologies, processing of these data should no longer be a problem. Great emphasis should be put on the design and type of information, their location and how to work with them to make gradual information processing leading to usable knowledge that would be used by expert system for further work in order to design a more suitable plan.

This structure of concept ensures that comprehensive information on the status and development of indicators for a selected business case are available at given time and that it is possible to determine which parameters and their development and indicators caused the adverse conditions. Or in other case, which warnings were issued with enclosed record of action taken or not taken by responsible manager.

3 KEY PERFORMANCE INDICATORS

Companies create a number of indicators for monitoring the performance of individual processes. The existing system of indicators and their influencing parameters is necessary to be arranged to a suitable structure for the purpose of further use. The present concept is considering a group of selected indicators, which will be constantly updated through data warehouse. Exact number of selected indicators depends on company and should be discussed with management (Guide to Key Performance indicators, 2007). In creating process optimization, stochastic algorithms should be applied (Zelenka, 2010). Emerging situations will therefore be analysed by data mining methods such as Spearman's correlation method in Figure 3, and decision tree learning. The resulting knowledge of the behaviour of the indicators in a given situation will be entered into a knowledge based system for further use. Data mining techniques can discover seemingly hidden relations, which might have a high impact on the final decision. At the same time they can recommend which exact values should be set as warning limits, i.e. when the values of indicators being monitored are already insufficient for fulfilment of assigned task.

$$r = \frac{\sum_{i=1}^{n}(x_i y_i) - \frac{\left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i\right)}{n}}{\sqrt{\sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}}\sqrt{\sum_{i=1}^{n} y_i^2 - \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n}}} \tag{1}$$

Where r is Spearman's correlation coefficient, x is ranking variable and y is second ranking variable. In this concept, Spearman's ranking correlation coefficient defined in (1) is used because it can easily find dependence between two monotonously developing indicators and thus is better than commonly used

Pearson's correlation coefficient, which may misclassify some forms of non-linear relationship. It may be acquired by subjecting ranks, instead of real measurements to calculations used in computation of Pearson's correlation coefficient (Zar, 2010). What it does, is that it "straightens" these non-linarites by replacing actual values of indicator with its rank.

From previously stated facts it is clear that the main interest of this concept are not the actual values of indicators, but rather their tendency to rise or fall over time. As values of these indicators evolve in real time, it's also necessary to create a technique to capture recent changes. It is also important to localize the use of correlation analysis, because applying it to whole historic data set in most of the cases wouldn't produce any usable relationship due to their tendency to fluctuate over time (Papadimitriou, Sun & Yu 2010). In order to localize correlation analysis, this concept uses modified version of Spearman's correlation coefficient as in (2).

$$r_t = \frac{\sum_{i=t-w/2}^{t+w/2}(x_i y_i) - \frac{\left(\sum_{i=t-w/2}^{t+w/2} x_i\right)\left(\sum_{i=t-w/2}^{t+w/2} y_i\right)}{n}}{\sqrt{\sum_{i=t-w/2}^{t+w/2} x_i^2 - \frac{\left(\sum_{i=t-w/2}^{t+w/2} x_i\right)^2}{n}}\sqrt{\sum_{i=t-w/2}^{t+w/2} y_i^2 - \frac{\left(\sum_{i=t-w/2}^{t+w/2} y_i\right)^2}{n}}} \tag{2}$$

Where *t* is current time of observance and *w* is a time window to analyse by Spearman's correlation.

Computation of correlation coefficient would be carried out the way it's shown in Figure 3. This correlation represents evaluation of selected indicator and its transformation into <-1,1> interval. This way it is easier to find exact knowledge, which is represented by combination of discrete values, because it reduces the amount of data needed as an input to data mining algorithms, and simplifies the explanation of logical steps needed in order to compose a better plan. Indicator that is shown in Figure 3 can be any of selected and measured key performance indicators, like for example production performance of selected machine. After transformation into the interval mentioned above, it can be automatically compared with transformed performance indicators of another machines in a workplace, in order to find a knowledge about what machines influence the overall workplace performance indicator the most. As you can also see in Figure 3, there are significant intervals where the Spearman's correlation coefficient converges to 1, 0 and -1. These intervals could be subjected to further analysis.

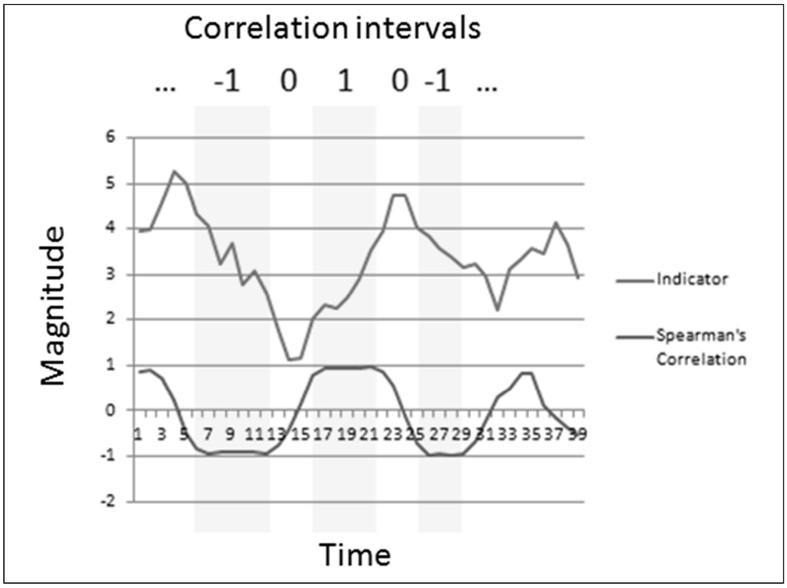

Figure 3 – Spearman's ranking correlation locally computed on sample indicator with sliding-window of 10 values

By specifying these intervals we can assign them discrete values and use them as input nominal values for creation of decision tree. This way we can search for interesting relationships between many indicators at the same time and establish the required settings for independent variables (various indicators) in order to anticipate desirable local trend for dependent variable (target indicator) (Tanuska et al. 2012).

Decision tree is generated by recursively partitioning the training data using a splitting attribute till all the records in the partition belong to the same class (Chandra & Varghese 2008). In this case, it will create a working model of system behaviour based on historic values of indicators. This model will then be used for classification of current situation based on used attributes. If the current situation is unwanted (i.e. the boundaries of target indicator have been reached), the task of the system would be to offer a change of independent variables in such a way that the current value would fall into more beneficial leaf of decision tree, thus proactively averting possible occurrence of further worsening of target indicator. Figure 4. demonstrates this process.

As different conditions occur, there is a need to reprocess decision tree model over time in order to maintain its accuracy. Trigger event for reprocessing of mining model can either arise from computation of actual value in case of exceeding set limits, or can be set periodically. In Figure 4, there is also possibility to feed target indicator values to Spearman's coefficient computation module as well before inputting this data to decision tree learner as prediction data column.

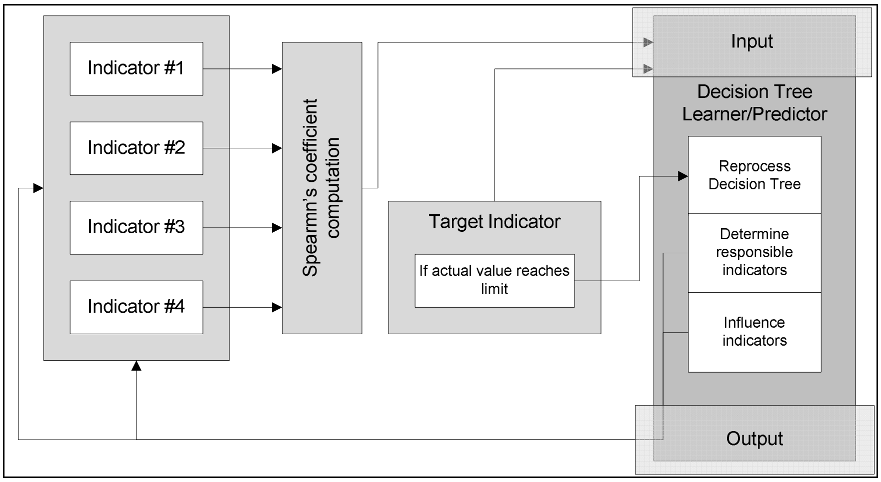

Figure 4 – Data mining techniques applied to indicators

4 CONCLUSION

This proactive concept demonstrates relatively easy way to acquire knowledge from existing monitored company indicators and applies data mining techniques to their transformed version. Absence of need to model complex indicator functions over time makes it a very flexible solution for further data mining. Using decision tree classifier is just one of the options. Correlation information could also be fed into other more complex types of data mining algorithms such as artificial neural networks. In this case, another advantage of this concept would appear which is that there would be no need to additionally normalize transformed correlation data. We see a practical use of proposed concept in combination of information system and data mining technology in order to proactively plan the production with a goal to reach an effective plan based on available knowledge. Proposed concept forms a basis of authors' current research.

ACKNOWLEGEMENT

This work was supported by the Cultural and Educational Grant Agency of Ministry of Education, Science, Research and Sport of the Slovak Republic KEGA no. 043ŽU-4/2014.

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ABOUT THE AUTHORS

Peter Bubeník, PhD., lecturer at University of Žilina, Faculty of Mechanical engineering, Department of Industrial engineering,
e-mail: peter.bubenik@fstroj.uniza.sk, Univerzitná 1, 010 26 Žilina, Slovak Republic, Tel.: + 421 41 513 2719

Filip Horák, PhD. student at University of Žilina, Faculty of Mechanical engineering, Department of Industrial engineering,
e-mail: filip.horak@fstroj.uniza.sk, Univerzitná 1, 010 26 Žilina, Slovak Republic, Tel.: + 421 41 513 2733