Manufacturing nonconformities management through conditional probabilities

Filippo De Carlo #1

Department of Industrial Engineering – University of Florence
Viale Giovan Battista Morgagni, 40 – 50134 Firenze - Italy

1 filippo.decarlo@unifi.it

***Abstract*— This paper enlightens Bayesian Networks (BNs) potentialities as a support tool, thanks to their capability of providing a graphic and intuitive representation of any process. As an engineering tool, BNs are sometimes used for reliability evaluation and in maintenance management of complex systems, but, as a matter of fact, they could be applied nearly to any field. This paper aims at illustrating how BNs can be applied to nonconformities (NCs) management. By means of a case study, we built an expert system that showed improvements both from the operations and from the strategic side. BNs were operated as an intelligent system: starting from a set of data, they were used not just as an inferential tool but the model created encoded also some human knowledge and experience, showing the added value of BN modelling. In addition to the ability of being used as an expert system, the BN was continuously improved and refined, making the model closer and closer to reality, without any amazing effort, thanks to their flexibility. As a result, we could verify the advantages of the BNs, with the addition of some information not found in the database and with the ability to quickly formalize new logical relationships of cause -effect.**

Keyword- Bayesian Network, nonconformities management, system modelling.

I. INTRODUCTION

The major increase in competitiveness, in almost all sectors of the market, has led public and private companies to seek out approaches, methods and tools faster and faster, concrete and effective to improve the financial results and quality levels of their business. For more than fifty years, many businesses consider Quality an area where act to prevent and reduce the costs and increase their wealth. The identification, then, of Quality as "the satisfaction of customer needs" [1] [2], was the starting point for a radical change: to observe the company and its processes no longer from within, but from the perspective of the customer, ie from the outside inwards. It is in this way that you can identify the areas which would be given greater importance and therefore need to be improved. In this direction, in 1987, Motorola has created a program for the long-term quality, called "Six Sigma Quality Program," whose purpose was, and still is, the improvement of customer satisfaction achieved by the reduction, or rather the elimination of defects and changes in existing products and processes [3]. The name was chosen to emphasize the key point of its program: reduction of defects and variations. After Motorola, the "Program for Six sigma quality" has been a huge success, and was then adopted by many other companies including General Electric, Ford, Caterpillar, Whirlpool, to name a few. The starting point that led Motorola to implement the program, was certainly the awareness that listening to customers is an essential condition for the success of a company. In fact, the Six Sigma project is born precisely as a result of complaints that Motorola had received from many customers, who wanted to be able to count on a better service in terms of delivery, order completeness and accuracy of recording transactions.

So, if you want to achieve cost reductions, increase in quality and reduced cycle times, we must fight the variability of the company's key processes and this requires knowledge of specific tools and methodologies, statistical and organizational. The six sigma projects for the management of non-compliance could be improved by developing an activity, parallel to the required system *data feeding*, entering into the matters of the content and quality of the data.

To be more specific, we must keep in mind that the information flow starts with the identification of a specific non-compliance and the inclusion in the computer systems of all data relating to it. It is always assumed that the inspector, which identifies the error, knows exactly the cause of the defect, the business function responsible, and could determine, possibly, also the time of management of non-compliance and the consequent costs.

Obviously, six sigma is not the only possible approach, since many other tools and methods are currently available and developed [4]. Nevertheless, they all require information. Let's go for a while into detail of how the operator can gather the required information that will start the flow of information that will accompany and feed the whole process of non-compliance management. Certainly, experience is one of the main factors that can allow people to identify and define an abnormality immediately in all its aspects, however, not being formalized, it can hardly be transmitted in a systematic way from one operator to another, so it can be very useful to provide a support tool in the identification phase and, possibly, also a forward looking tool. Decision making [5] is, therefore a critical issue that was faced in this project through a Bayesian network [6] [7] [8], a tool that can meet these needs and help in nonconformities management.

Since BN are graphic representations of reality, they can be applied to many different fields [9]. In this paper an innovative application is presented: BN as a support and prevision tool for nonconformities (NCs) identification and management. The work is innovative, since no applications of BNs applied to NC management have been found in the scientific literature.

The remainder of this paper is organized as follows: section 2 shows the BN theory fundamentals, and in section 3 the case study is presented. Section 4 describes the experimental results and the fifth one presents a discussion of the results. Finally the main conclusions and future developments are presented.

II. Methods

Reliability [10] [11] [12], safety [13] and maintenance management [14] [15] [16] issues are some of the most interesting issues of international scientific research and have been deeply analyzed by the authors[17]. Bayesian networks can be a valuable support tool the management problems of complex systems. Hence, they may be employed in different ways in the management of maintenance, reliability and safety.

Bayesian networks (BN) are a probabilistic graphical representation consisting of two elements: a qualitative one which is a network and a quantitative one made by some parameters [18] [19]. The net structure is a directed acyclic graph (DAG) formed by a collection of nodes and directed arcs. The nodes represent the model variables and the directed arcs represent the causal relations among nodes [20], [21]. These arrows mean potential cause–effect correlations. The quantitative part, instead, consists of the conditional probability tables, which describe the strength of relationship between variables. The network parameters are, therefore, the conditional probability values that quantify these connections. All the network elements can be inferred and estimated basing on the combination of both empirical data and expert knowledge. Thanks to its probabilistic and graphical nature, such a modelling technique can deal with complexity and uncertainty.

As the name suggests, the basis of Bayesian networks is the Bayes' rule (see Eq. 1) [22], derived from the product rule applied alternately to two random variables H and E, where H denotes a hypothesis and E indicates an evidence

$$\mathrm{P(H|E)} = \frac{\mathrm{P(E|H) \cdot P(H)}}{\mathrm{P(E)}} \tag{1}$$

If we set *H* equal to any random variable indicating the cause of an event, and *E* equal to the consequent effect, we can write Bayes' rule as follows:

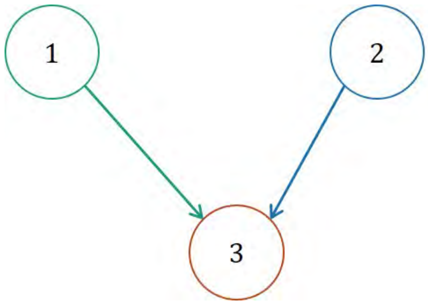
$$\mathrm{P(cause|effect)} = \frac{\mathrm{P(cause|effect) \cdot P(cause)}}{\mathrm{P(effect)}} \tag{2}$$

From these simple steps then we can note that, if there is a value of the random variable E, then one of the possible causes must have acted, and with Bayes' theorem we can investigate, in a probabilistic manner, which of them has verified. The essence of the Bayesian approach is therefore to provide a mathematical rule explaining how to change and update the status of trust (belief) concerning the occurrence of an event in the light of new evidence. In other words, it allows you to combine new data with previously acquired knowledge.

The importance and innovation of Bayesian networks, derives from the possibility to take the variables on which you want to focus the study, represent graphically the relationships, and express - in a concise way - the joint probability distribution by means of conditional dependency relationships [23]. An example of a simple Bayesian network with the appropriate conditional probabilities table, is visible in Figure 1.

In the formulas of the joint probability, $\mathrm{P}(X_1; X_2; \dots; X_n)$, the ability to simplify the terms has a significant influence in order to obtain a concise representation, since a factorized expression requires a number of parameters exponentially less than the complete form.

In general, if we have *n* binary nodes, the space needed to represent the joint probability in full form would be $O(2^n)$, while in the factorized form would be $O(n2^k)$, where *k* is the maximum fan-in, i.e. the maximum number of parents of a node. In turn, this leads to two important consequences: First you get a lower complexity sampling and therefore the need of a smaller number of data for the learning of the network. Secondly you get a shorter time for the inference.



Random Variable 1	Random Variable 2	Random Variable 3 = True	Random Variable 3 = False
True	True	$P(3 = T \mid 1 = T; 2 = T)$	$P(3 = F \mid 1 = T; 2 = T)$
True	False	$P(3 = T \mid 1 = T; 2 = F)$	$P(3 = F \mid 1 = T; 2 = F)$
False	True	$P(3 = T \mid 1 = F; 2 = T)$	$P(3 = F \mid 1 = F; 2 = T)$
False	False	$P(3 = T \mid 1 = F; 2 = F)$	$P(3 = F \mid 1 = F; 2 = F)$

Fig. 1. Simple example of a Bayesian network. In the figure is shown an easy network consisting of three events represented by the same number of random variables (1, 2 and 3). On the right you can see the conditional probabilities table of Variable 3, conditioned from the first two.

Briefly, the *learning* is the learning phase of construction and the structure of the network, while the *inference* consists of a continuous update of the probabilities associated with the possible states of each node, starting from the knowledge acquired on the value of one or more nodes.

When we talk about *learning* of the Bayesian network (or model selection), we refer to the definition of the topology of the graph, i.e. the identification of all connections between the nodes of the network to build the directed acyclic graph (DAG) which explains as better as possible the data.

The network structure can be defined "manually" on the basis of the knowledge of the problem, or you can take advantage of tools that build the structure automatically from the data.

It is possible to distinguish four cases, as visible in Table I:

TABLE I
Types of Bayesian networks and of learning methods

	Structure	**Observability**	**Method**
a	Known	Full	*Maximum Likelihood Estimation*
b	Known	Partial	*Expectation Maximization, (EM)*
c	Unknown	Full	*model selection*
d	Unknown	Partial	EM + *model selection*

a) The first case is of course the most simple. In this case, the objective is to find the maximum likelihood estimates of the parameters of each table of the *Conditional Probability Table*, CPT (Figure 1).

b) When the structure is known but the observability is partial you must use the *Expectation-Maximization algorithm* (EM) to find (locally) the optimal estimation of maximum likelihood parameters.

c) In the case of a unknown structure and of full observability, an important tool for the proper model selection is the so-called *scoring function*, which allows you to rate the possible structures examined.

d) The case certainly more difficult is that in which we do not know neither the structure nor the variables for hidden or missing data. Generally, we examine systems where the lack of information is not so high, we try - in other words - to have as much as possible data that make it possible to fall in one of the situations seen above.

The interest in Bayesian networks stems not only from the ability to represent human knowledge in a direct and "modular" way, but also by the fact that, even assuming quite complex means, they're easy to understand, thanks to the graphic structure that enhances the intuitive aspect and thanks to technologies developed by the software tools available nowadays to the operators.

Bayesian networks, are mainly used in the following cases:

- Diagnosis: search for the most likely explanation, i.e. the scenario, the causes that best explain the effects that occurred.
- Forecast: search the posterior probability, i.e. the probability that, given a cause, an effect occurs.
- Support in the process of decision making.

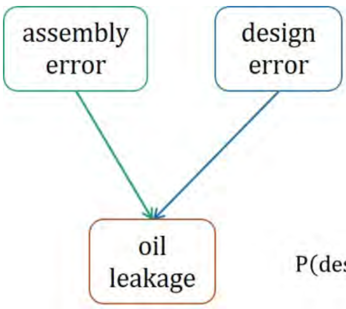
All these calculations are in turn a concrete application in many different fields, including medical diagnosis, genetic analysis, the recognition of speech, and many others.

The most common case in the medical industry is certainly one in which the hidden nodes represent diseases, while those observed represent the symptoms. The goal is to infer the posterior probability of a specific disease, given a set of symptoms. Certainly, this is also the example that mostly binds to the application of the BN in the field of reliability diagnostic, in which, given the data detected by sensors, (symptoms) you want to infer about the state of health of an elementary component, of a machine or of an entire system, to estimate the reliability and to be able to take more safely and automatically the best possible decisions regarding the maintenance policy.

From the theoretical point of view, we can say that Bayesian networks are a special case of Markov networks, in which the arcs have an orientation. As a consequence, they come under the global and local Markov property.

III. Case study

The idea of applying Bayesian networks to the management of scrap & reworks was born with one main purpose: to create a tool to help the operator in identifying the causes of non-compliance and for the prediction of the most affected products and components, the costs of scrap and rework, the duration of the anomaly management, and so on. Figure 1 shows how the application of Bayesian networks to NCs management is intuitive and how the inference action is very befitting to this type of problems



Assembly error	Design error	Oil leakage = YES	Oil leakage = NO
Yes	Yes	84%	16%
Yes	No	62%	38%
No	Yes	42%	58%
No	No	2%	98%

$$P(\text{design error } | \text{oil leakage }) = \frac{P(\text{oil leakage } | \text{design error }) \cdot P(\text{design error })}{P(\text{oil leakage })}$$

Fig. 2. Application of Bayesian networks to the management of NCs. In the figure is shown a simple example of a Bayesian network in which the effect (oil leakage) may have two causes (assembly error or design error). Bayes' theorem allows to calculate the probability of each of the two cases, once the existence of the effect is known. The conditional probabilities are shown in the CPT.

In the industrial environment chosen for the case study, a big manufacturing company, are in force regulations concerning the NC management process: every time a nonconformity is detected, a dedicated report must be filled by the operator. This is made in order to track data, such as defect description and cause, department responsible for NC and additional details. Obviously, a correct and complete NC identification is fundamental to drive a further analysis and to forecast its consequences such as repair costs or days necessary to solve it. Frequently, the investigation for cause of the problem is performed by the root cause analysis process.

On the one hand, this approach allows a relatively easy and quick application, thanks to its structure of repeated applications. On the other hand, if the root-cause analysis is based on data that do not adequately explain the non-compliance, it is verified that they can lead to erroneous conclusions about the weaknesses of the process, and to waste efforts dealing with not effectively improving actions.

Given the large amount of data to handle, is often used in information systems which are able to automatically collect and analyse information of non-compliance. This approach makes the analysis much less burdensome for the company, but it hides a dangerous pitfall. In fact, though this first phase is so crucial for the whole NC management process, the sole automation can't be an exhausting solution, because NC identification and description comes directly from the operator experience and knowledge. This cannot be easily coded or formally defined in any system, since every NC is different from another, nor can it be inferred automatically by an information system.

For this reason, a Bayesian network was created as a support tool whose answers are determined both by historical data on NCs and practical experience coming out of every-day working experience.

IV. Results

The first step, when building a BN, is the *learning* of the structure which consists in creating all causal relations between the nodes. Then, the inferential computations allow to update all the probabilities associated to each of the node values.

A. Database loading

The first step, when building the non-conformities BN, was importing the company's database containing all the data of interest (see Figure 3). As previously said, loading a database into a Bayesian software allows to immediately transform each data field into a random variable represented by a node and to associate an *a-priori* probability of occurrence. Starting from them, all the conditional probability tables are calculated for each node of the network.

The data, based on which we carried out the analysis, were taken from Scrap & Rework Cost of quality reports, published periodically, in which most of the information needed for the analysis is present. These reports are made up of as many records as the non-conformities recorded in the system, and are structured in a tabular form: each record corresponds to an identification number of non-compliance, and information about each record are structured and arranged in multiple columns. This structure is suitable for modelling a Bayesian network: the information present in each column has formed the nodes of the network, namely the variables of the model, and all the possible values within each column have become the values of variables (nodes).

To complete the database, were added and crossed also data extracted from the information system dedicated to the NC management.

Fig. 3. Database loading. The above figure shows the process of creating a Bayesian network: starting from the database, you get the nodes representing the states, to each of which is assigned its own probability of occurrence.

B. Modeling variables

The choice of a database that contains key data fields is crucial since this phase will influence the following network construction, the observed variables and, obviously, the results. BN are sensitive neither to the number of records nor to the number of variables, but are rather influenced by number of possible states available for each variable. This was unfortunately also our case, in fact the BN developed is a borderline case in which three out of ten nodes have nearly ninety possible states.

Considering the process to be represented can provide useful suggestions for the selection of variables. In a nonconformity management process, the main elements to be tracked are certainly the defects discovered, the causes of defect, the responsible departments, all the costs and the days required for management. All these variables were included in the BN carried out.

Since the initial loading of the database, there have been some problems. The first obstacle was the size of the database, consisting of 2382 records: the software allowed you to import the database and then build, albeit very slowly, the arcs between the nodes. However, the size of the network caused memory problems. Initially it was thought simply to a problem of excessive abundance of records, but the real problem was found to be the amount of possible values of each variable.

Solutions to the problem could be twofold: eliminate all cases or less frequent use, instead of the individual fault codes and cause codes, the codes of the families of defects and families of causes. Such a road would, however, departed from the primary purpose of the network, i.e. to provide support to the operator that identifies the non-compliance and receives guidance on the precise cause of which may have resulted in the defect.

The way chosen to reach a possible solution was, therefore, to replicate the 2382 record four times, in order to get about 10000 records. So doing, the large number of records allowed to reduce the weight of the amount of the states of each node. These latter were unchanged, however, distributed over four times the number of data.

Since statistically the variance is inversely proportional to the sample size, this solution has the drawback of obtaining statistical estimates apparently much less affected by uncertainty. Must always remember that the operation of quadrupling the data has altered the data base significantly, influencing the conclusions that can be drawn. This stratagem was used to solve the problem of insufficient amount of data but, nevertheless, involved an element of artificial consolidation of records that can not be considered a systematic remedy, but a temporary measure that will no longer be used when the collection of additional data will allow to have a larger population.

C. Bayesian network construction

Once all nodes have been defined, the arcs creation allowed to set the causal relationships among variables. The final structure determines the information flow performed every time that the network is inquired.

In the present case study, two different networks were built: in the first one (see Figure 4) all the arcs were manually created according to logical criteria, whereas in the second one the learning of the structure was completely made by the software's built-in algorithm.

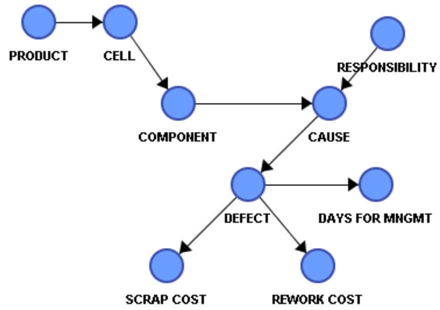


Fig. 4. First Bayesian network built. In the picture is shown a schematic example of the qualitative part of the network in which the structure was built considering the logical liaisons among the variables.

The rationale behind this first network is that that any nonconformity has an impact in terms of time and costs spent for NC management (i.e.: scrap of material, rework activities). At the same time, each non conformity depends on a particular cause which can be determined selecting the component being produced and the business function responsible for the NC. Going through the network, we notice how each component is linked to the working cell and to the final product being made.

Considering the structure of relationships among the events, there are many possible configurations of the network. In fact, logical criteria can suggest different configurations, but the simpler the network structure is, the better results follow. As for Dynamic Programming inferential algorithms, whenever a singly-connected network doesn't fit the problem, a multiple-connected network could at least allow to build a *linear* junction tree in order to assure a unique information flow through all the nodes. Therefore, particular attention has to be paid on triangular connections.

The second network (Figure 5) was automatically built by the modelling tools of the software, so it was entirely based on the bare data analysis rather than on any other external process knowledge, as in the first case. The automatic procedure analysed all records, looking for every single possible correlation between any couple of variables, and at the end it selected the model that best fitted database structure. The time required for all these computations was quite long and the resulting connections came out to be different from the ones manually imposed. However the final configuration was a singly-connected network providing almost the same results of the first network, but in a significantly lower time.

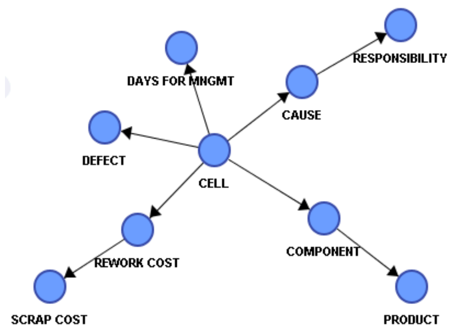


Fig. 5. Alternative Bayesian network. The second network was obtained automatically from the software, linking the variables according to the database frequencies.

Many times, the resulting configuration doesn't match with that manually built, but, as a matter of fact, this can be an important opportunity to bring to enlighten hidden correlations that nobody else would ever suppose or even would look for. Moreover, a simpler structure means an unique and certain information flow that guarantees goods results, regardless of the database structure used.

V. DISCUSSION

In the previous section we've seen how the Bayesian model was built starting from the corporate database. In this section we're going to see which are the benefits of this application and what are the drawbacks. First of all, let's focus on the BN operation. BN is extremely easy to understand: if we have an evidence concerning any event represented in the network, we'll assign to the corresponding node a percentage of 100% to the verified status and 0 to all the others (see Figure 6). In this way, the change in the node probabilities will instantaneously trigger the inferential computations and the following change of all the probabilities associated to every other node status.

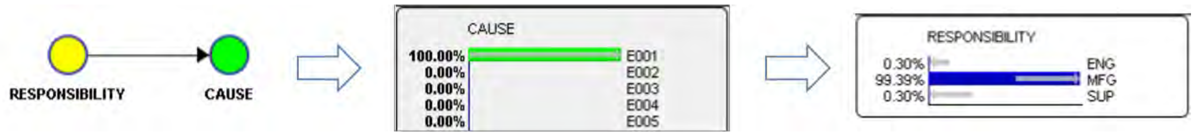


Fig. 6. Operating principle of a network. An evidence of a “cause” node means that a percentage of 100% must be assigned to the certain status and 0 to all the others. This means that all the probabilities of the states of each node are immediately recalculated and updated by the system. In the picture this concept is applied to a sample network of two nodes: if you know what caused a NC, then you can determine the responsible department.

Of course, the ability to get an immediate synthesis of database data and an intuitive graphical representation of the problem are elements of primary importance when you choose to use a BN, but, as a matter of fact, other data analysis tools can provide the same results. Actually, BNs have another important distinguishing feature: in fact they’re not strictly bound to the data contained in the database; they can go beyond the bare data representation and can represent reality, thanks to their capability to include additional information. This means that the built BN is able to provide answers that describe reality better than the only database can do, and this is possible thanks to the forecasting capacity and the expertise coding.

A. BN validation

In order to test the BN value as a forecasting tool, after an initial verification phase in which the compliance between the resulting structure with the actual reality, it was time for a validation activity. A new BN was built, using the same database, with the exception of 25 records. Then, the network was inquired on the extracted records verifying their adherence to the BN.

Answers obtained have shown good results, which were obviously more accurate for more frequent cases. Increasing population in database will certainly determine correct answers even for less distributed events. However, the predictive capabilities of the network have been verified

B. Expertise Coding

The second important feature that distinguishes BNs from other similar tools, is the expertise coding that consists the capability of modifying a BN through the introduction of new information that could not be extrapolated from database since they come out of human experience or from anywhere else. Looking at our process, we could observe something that affects non conformity generation and that could never be encoded in any information system, since it’s not a feature strictly related to each single nonconformity. This means that we will never find this element in our database and its influence would never be taken into account. On the contrary, BNs allow coding into our process both knowledge and experience by simply modifying the network with the addition of new nodes and arcs, thus improving the results coming from database analysis with a very little effort.

C. Node Addition

Another very positive aspect of the Bayesian modelling, is that whenever a new factor occurs in the process, it can be easily encoded in the model by simply adding a new node and connecting it to one or more nodes already present. This naturally implies also the need of filling the new conditional probability tables: the values to be inserted, once again, result either from historical data or from people experience, but any database query is not necessary in this case.

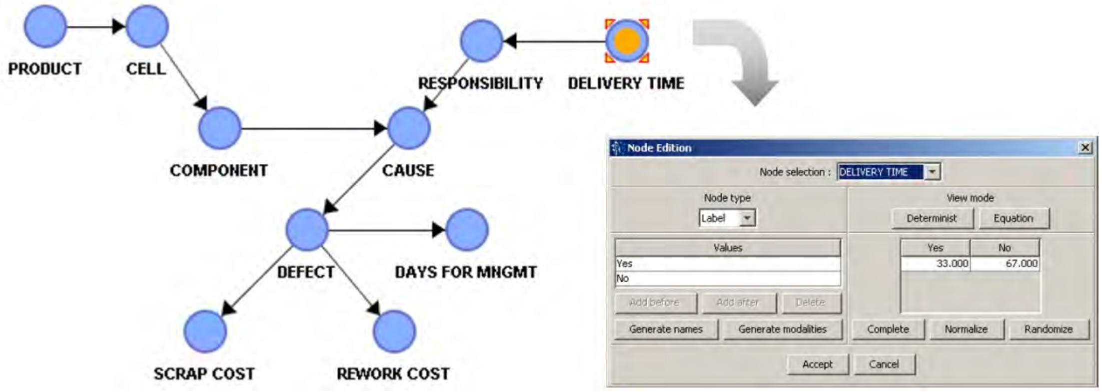


Fig. 7. Node addition. The network shown in the figure has been modified by adding a node that connects the time of delivery of the order with the other elements of the network. This element is not part of the company's database, but was added considering the actual company operations.

Entering into the merit of our application case, the defect generation process, it was noticed that, before delivering the final products, the process of NCs imputation to departments undergoes some changes, due to efforts made to avoid delays and penalties. In details, the last functions of the supply chain are strongly in hurry since they are the final opportunity to recover all the delay and assure on time delivery. For this reason, when the delivery date is approaching, the majority of NCs are charged to internal production, as well as to external suppliers, rather than to other departments, such as engineering or sourcing, which are at the beginning of the supply chain.

Despite its relevance, this aspect will never be encoded in any database, because it can't be linked to a specific defect. However, the use of a BN can help to take account of this aspect and this can be made by adding a new binary node, such as the "Delivery time" of Figure 7, has allowed to introduce a new element which makes the model more similar to reality, influencing the results which will be much closer to the real outcomes.

D. *Arc Addition*

Also the addition of new arcs, inherent to Bayesian networks, was particularly useful in our modelling of NC management, in particular for those networks automatically created by the software algorithm, because it gives us the possibility to fix certain relations that the software doesn't catch due to data structure or consistency. Actually, when considering simple structures such as the one in Figure 8, adding only few arcs would not significantly change the results because, in most cases, they would just close a triangular connection without changing the main information flow through the network elaboration. Nevertheless, in some other cases, the arc addition activity may directly point out relations that could really move the results.

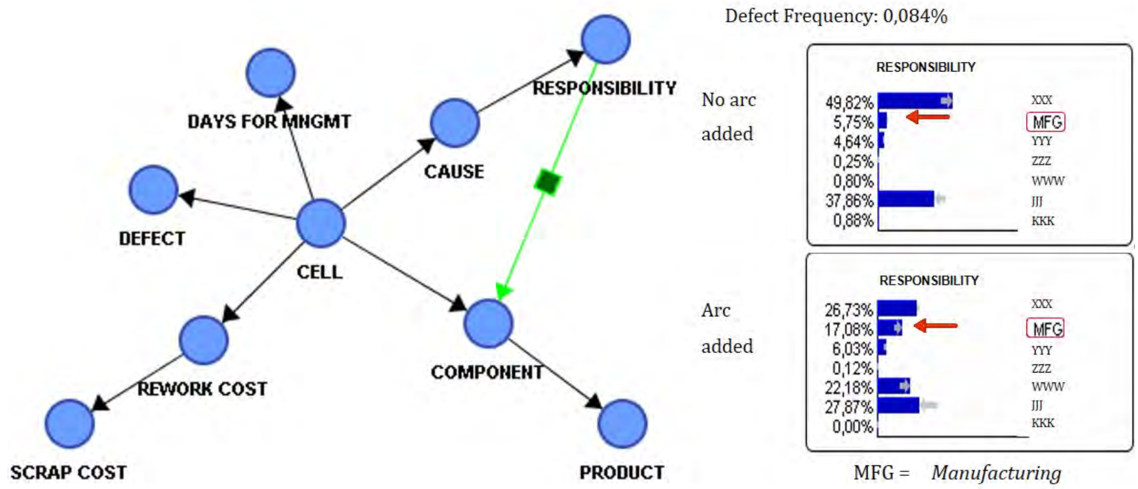


Fig. 8. Arc addition. The Bayesian network allows you to add relationships, in the form of arcs connecting two nodes, when some links have not already been included in the graphical structure of the network.

VI. CONCLUSIONS

The great flexibility and potential of Bayesian networks make them easily applicable to many different contexts. In the present work, they have been applied to a specific field: the management of NCs of a large manufacturing company. In this case study, was much appreciated the graphic and intuitive representation of the problem structure and the chance to provide an instantaneous scenario analysis.

Also, two other main reasons have distinguished BNs from other approaches [24] and, in particular, from the database driven usual applications. First of all, it was very much appreciated the ability to continuously refine the network, combining new historical data with unstructured knowledge of experts. Once realized, the network is far from being frozen but it can be easily modified in order to reflect more and more faithfully the considered process.

The second reason is the perfect intersection of inferential complexity with the ease of the user interface: though the modelling theory behind BNs is surely complicated, the common commercial tools are absolutely easily exploitable by any process engineer thanks to their user-friendliness and to intuitive interfaces that don't require users to be statistical experts.

From inspectors in shop floor to process engineers, anyone involved in the NCs management process can inquiry the network leading different analysis and gaining simple, clear and operational results. Therefore the aspect probably more useful is the ability to make applicable a sophisticated tool also from the more technology reluctant employees. This is for sure one of the most important aspects that can assure to BN a full application.

The main limitation found in the application of Bayesian networks to the case study, is the need to have a large amount of data to build the network and populate the CPTs. Furthermore, if the nodes have a too high number of possible states, the computation time increases, as well as the number of necessary data. Then, before applying BN to industrial management problems, we suggest to conduct an exploratory analysis, such as that proposed in this study, able to show the actual comprehensiveness of the data.

Finally, although the network is a understandable graphical model, it is necessary that at least one element of the team conducting the study is well prepared theoretically on BNs, in order to manage the common modelling problems of engineering problems.

A possible development of the research presented in this paper, is given by the application of BN to other areas of industrial interest, such as maintenance management and safety controls in the workplace. It will be possible to evaluate, in this way, if in these different fields of application the qualities and defects of the BNs are still verified.

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