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Manufacturing project management in the conglomerate enterprises supported by IDSS

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ABSTRACT

Purpose: of this paper is to summarize the application study of a general framework of intelligent decision support system (IDSS) to collaborative projects in conglomerate enterprises. In some situations, even with the knowledge of how to find right information and which decision making methods to apply, we do not have enough time to make right decisions at the right time. In this paper, the framework of an IDSS system to support real-time collaboration and enable seamless data exchange is presented.

Design/methodology/approach: The important roles of facilitation and organization that the IDSS plays are demonstrated. In the case study, examples of manufacturing projects analysis are given with the known methods, including Analytical Hierarchy Process and Bayes' rule.

Findings: It is demonstrated that IDSS systems can help us to manage information flow, clean data, transform data into knowledge, perform analysis and monitor the effectiveness of manufacturing projects during the whole life cycle.

Research limitations/implications: The functionality of the developed framework is limited by the willingness of management style and culture changes in companies, as well as the level of interoperability between commercial software components. Only the essential components that influence the success of the manufacturing projects are considered.

Practical implications: Project engineers and managers need to adapt to the new IT-based working environment.

Originality/value: New information management model and the framework of IDSS system are proposed. The new collaborative decision making system consists of different parts: management of information flow, preparation of data for decision making, and actual decision making and monitoring of manufacturing projects supported by several methods.

Keywords: Project management; Productivity and performance management; Erp; Intelligent Decision Support System; Project analysis; Data mining

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1. Introduction

Today's competitive marketplace requires that enterprises should be more flexible, innovative and responsive to their customers' needs. Therefore, it poses challenges to small and medium sized enterprises (SME-s) so that their traditional business models should be changed and new ones to facilitate collaboration with suppliers and customers need to be adopted. Next-generation enterprises will form complex collaboration networks in supply chains, which value information sharing in order to reach their respective goals of time, cost, and quality. The availability of information enables the management team to make right decisions at the right time to react responsively according to the individual objectives (e.g. customize a product, provide special services, outsourcing).

Because of the proliferation of Internet and global networks, organizations are increasingly connected to one another, not only for the purpose of business transactions and exchanging data but also for making collaborative or negotiated decisions. In this environment, Enterprise Resource Planning (ERP) systems can serve as platforms for trans-organizational data exchange [9]. ERP systems provide mechanisms for data sharing within organizations and among enterprises. However, the lack of decision support tools significantly reduces the values of data. An integrated information and decision support system will accelerate the adaptation of ERP systems for SME-s and help them to reap the benefits.

In previous work, it is demonstrated how the intelligent decision support system (IDSS) could be used for the optimization of engineering and production planning for collaborative SME-s [17]. In this paper, the IDSS is applied to manufacturing projects. A knowledge management framework and information flow management by IDSS are introduced. A case study for analysis of real-life manufacturing projects is demonstrated.

2. Background

Different decision making tools have been developed for decision making in business environment. As a result, the heavy use of computers and the new decision-making software tools bring changes to white-collar, executive and professional work, similar to the situation when machinery was introduced and blue-collar manual jobs were changed too [8]. Some of the most popular decision-making software includes decision trees techniques [1] and Bayesian belief or causal probabilistic networks [4, 10].

Management of data and knowledge base in manufacturing enterprises has a long history. Recent research efforts have been devoted to the generation and evaluation of alternative process plans and to the enlargement of manufacturing knowledge base [7]. As an important source of organizational knowledge, business and engineering data are constantly collected and archived by manufacturing companies. The huge amount of data is of little benefit unless it can be turned into useful information and knowledge [14]. Recognizing that distributed data with different formats are usually found in most of enterprises, database software companies have implemented some forms of data warehouse to allow bringing these data together and supporting efficient enterprise report and analysis. As key information needs to reach multiple decision makers within an organization, inconsistencies of information and inefficiencies of information exchange will lead to catastrophes when data are distributed and shared across the organization.

Intelligent data processing tools are necessary to extract useful information from data. Among different mechanisms, artificial neural networks (ANNs) have been proved their applicability in various data mining applications [21]. They are generally used for function approximation, classification, and pattern reorganization problems [19]. An ANN, just like a human being, learns by means of training. ANN has been demonstrated to be a powerful tool for pattern recognition and pattern classification in engineering and financial problems with its nonlinear nonparametric adaptive-learning properties. In certain situations, neural networks may produce significantly better prediction accuracy than classical statistical techniques [13].

The capabilities to support reasoning and decision-making are highly desirable given a large amount of information is available in today's enterprises, especially when uncertainties are present and the degree of truth for the given information is unknown. Bayesian belief network (BBN) is an effective tool for explicitly addressing uncertainties and utilizing data from multiple sources. It has been widely used in different areas, such as on-line alert systems to detect fault and abnormal behaviour in production plants. [16], marketing [24], computer aided process planning [20], diagnostics of process variations [23], supply chain diagnostics and reasoning [11]. Bayesian network can be used as a general decision support tool for reasoning accompanied with knowledge base.

Decision support system (DSS) is a concept of integrating reasoning capabilities with data analysis and knowledge acquisition. Recently the benefits of using DSS are reviewed and an empirical study to gather the views of DSS adopters about such benefits [23]. Subsequently, eight evaluation metrics to measure DSS benefits were proposed, including the overall cost effectiveness of DSS, overall user satisfaction with DSS, degree to which a DSS enhances a company's competitiveness, degree to which a DSS enhances the communication within an organization, degree to which a DSS enhances user's productivity, degree to which a DSS provides time savings, and degree to which a DSS reduces costs [23]. To maximize the benefits of a DSS, it needs to be integrated with a knowledge base which contains native information. The relatively unified, consistent, common, real-time knowledge repository resulting from ERP implementation is a foundation to reap these decision-support benefits [9]. To manage risks with the consideration of uncertainties, a methodology for the ranking of decision alternatives in a DSS has been developed in order to support policy makers to make a strategic selection among different options. The methodology consists of an uncertainty analysis and a ranking procedure based on significance of the difference between output distributions [3].

In this paper, we use BBN as the core reasoning tool in our IDSS for manufacturing project management in conglomerate enterprises, where children SME-s work collaboratively on projects over computer networks.

3. IDSS in the collaborative network of enterprises

As World Wide Web is becoming an infrastructure of groupware applications, many companies apply groupware technologies to increase business-to-business collaborations among stakeholders in the supply chain over intranets and extranets. These include synchronous video conferencing, presentation, chatting, as well as asynchronous workflow management, document repository, wiki publication, etc. In a conglomerate company, information flows among children SME-s can be divided into two main circles: internal and external.

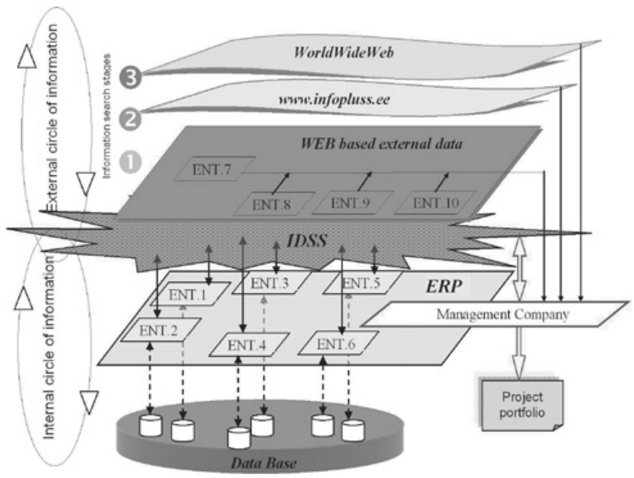

Fig. 1. Information flow model in the collaborative network of enterprises

The proposed information flow model is illustrated in Fig. 1. Internal circle represents the internal environment of the concern including all SME-s (further *an internal enterprise*). Annually these enterprises prepare the sales forecasts for the coming year in a standard form for assessment. An external circle has three levels of information with different availabilities: information about companies that SME-s are familiar to or have collaboration experiences with; information about new companies that are found from a national companies' database (for instance, *www.infopluss.ee* in Estonia); and information about totally unknown companies (domestic or abroad) with unknown technology.

The IDSS system is responsible for the management of information flows in the collaborative network of enterprises and enabling secure data transfers. The IDSS can enhance the effective usage of information available in the database of an ERP system. It also helps to archive and manage external information to make more reliable decisions. It is an intelligent system that can be trained towards the user's needs and preferences based on historical data [18].

The system consists of two parts. One is responsible for structured decision support, and the other provides support for analysis of non-structured information. The structured decisions of IDSS are based on the parameters specified by a Management Company. The Management Company estimates the required resources for certain projects such as budget, time consumption, human resources, applicable technology and so forth. Non-structured decisions can be made in the way of modelling and analysis.

Based on stored information, several methods can be used for reasoning and decision making such as Bayes' rule [1], AHP [12, 13], or optimal planning solver [17]. A system interface will help the user to find out the right methods and to collect the results. The three types of explanations that contribute to the overall explanatory power of an intelligent interface: rule traces, strategic knowledge, and deep justifications [8].

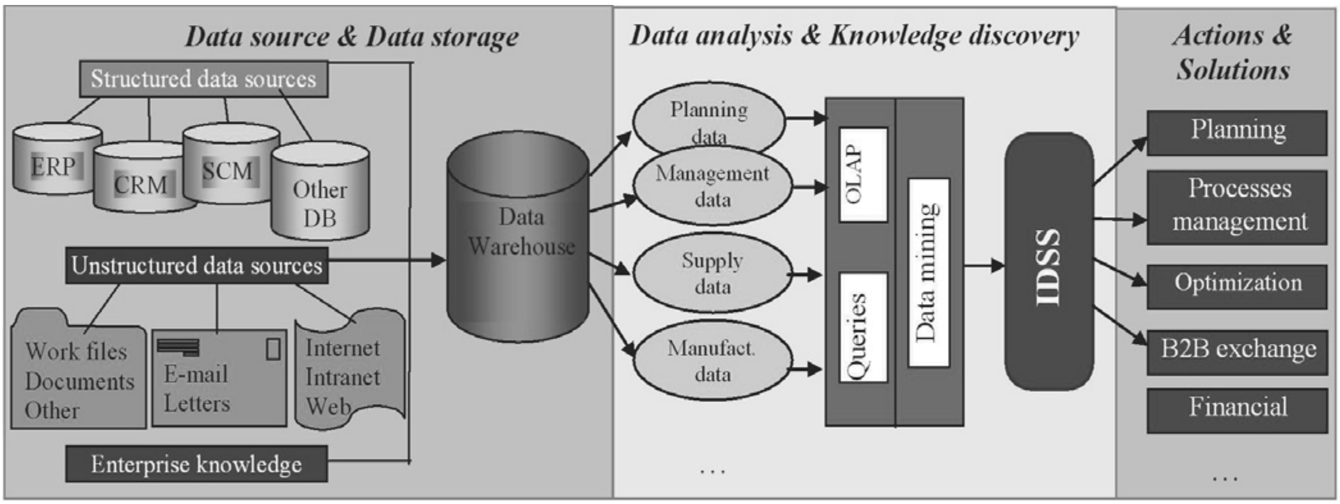

Fig. 2. Decision support and knowledge management activities

4. Knowledge discovery for decisions making

As shown in Fig. 2, there are various components in a decision-making environment, including collection of data, storage of data, data analysis and knowledge discovery. The associated knowledge management activities include different analysis processes and process monitoring. Data from internal and external sources, spread across operational databases and data warehouses, are accessible by decision makers using tools for OLAP (online analytical processing), data mining, and queries. Decision makers, through the experience of using such tools and techniques, gain new knowledge pertaining to the specific problem area. The decision-making process itself results in improved understanding of the problem and the process, and generates new knowledge. In other words, the decision-making and knowledge creation processes are interdependent. Proper integration of decision support and knowledge management will not only support the required interaction but also provide new opportunities for enhancing the quality of support provided by the system [2]. Specific decision support systems are usually built based on data extracted from various data sources and decision making models extracted from various knowledge sources (Fig. 3).

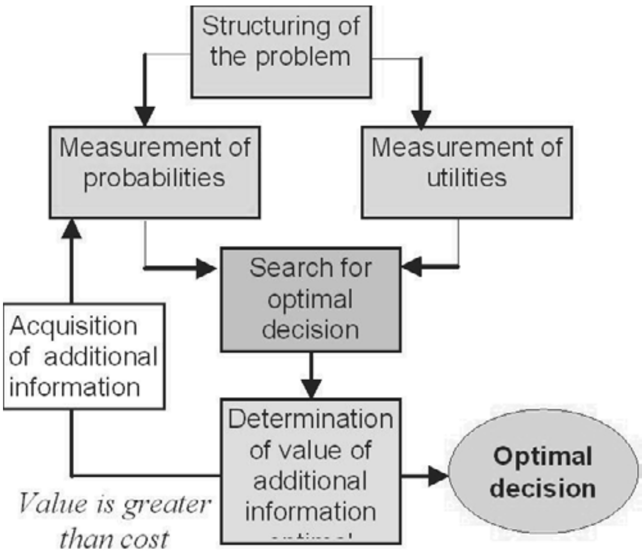

Fig. 3. Searching of optimal decision

5. Decision theory

Efforts in decision theory may be divided into five categories [16]:

- Decision makings under certainty are those in which each alternative action results in one and only one outcome and where that outcome is sure to occur.
- Decision makings under probabilistic uncertainty are those in which one of several outcomes can result from a given action depending on the state of nature, and these states occur with known probabilities. There are outcome uncertainties, and the probabilities associated with these are known precisely.
- Decision makings under probabilistic imprecision are those in which one of several outcomes can result from a given action depending on the state of nature, and these states occur with unknown or imprecisely specified probabilities. There are outcome uncertainties, and the probabilities associated with the uncertain parameters which are not all known precisely.
- Decision makings under information imperfection are those in which one of several outcomes can result from a given action depending on the state of nature, and these states occur with imperfectly specified probabilities. There are outcome uncertainties, the probabilities associated with uncertain parameters, as well as imperfections in knowledge of the utility in various event outcomes.
- Decision makings under conflict and cooperation are those in which there is more than a single decision maker, and where the objectives and activities of one decision maker are not necessarily known to other decision makers. The objectives of the decision makers may also differ.

We take a BBN approach to help make decisions. The decision maker is concerned with determining the likelihood that a hypothesis (H_i) is true. Bayesian interface is the technique for interfering the probability (P_i) that a hypothesis (C) is true, from evidence (E_j) linking the hypothesis to other observed states of the world. The approach makes use of Bayes' rule to combine the various sources of evidence. The Bayes' rule states that the posterior probability of hypothesis H_i given that evidence E_j is present, or $P(H_i|E_j)$, is given by the equation:

$$P(H_i \mid E_j) = \frac{P(E_j \mid H_i)P(H_i)}{P(E_j)} \tag{1}$$

where $P(H_i)$ is the probability of the hypothesis being true prior to obtaining the evidence E_j, and $P(E_j \mid H_i)$ is the probability of obtaining the evidence E_j given that the hypothesis H_i is true. Eq. (1) predicts the probability that that the projects will be successful if we achieved the information:

P(project is successful)=
P(project is successful|information is available)P(information in general)
+P(project is successful|no information is available)P(no information in general) (2)

When the evidence E_j consists of multiple states $E_1, E_2, \ldots, E_n$, each of which is conditionally independent, the Bayes' rule can be expanded into the expression:

$$P(H_i \mid E_j) = \frac{\prod_{j=1}^{n} P(E_j \mid H_i)P(H_i)}{P(E_j)} \tag{3}$$

A Bayesian network contains three elements: nodes, arrows between nodes, and probability assignments. A finite set of nodes together with a set of arrows (directed links) between nodes forms a mathematical structure called a directed graph. The Bayesian network can be considered as a directed acyclic graph in which nodes represent random variables, where the random variables are usually discrete, with a finite set of mutually exclusive states which themselves can be categorical, discrete or continuous. The computational architecture of Bayesian networks computes the effect of evidence on the states of the variables. The architecture

- updates probabilities of the states of the variables, on learning new evidence;
- utilises probabilistic independence relationships, both explicitly and implicitly represented in the graphical model, to make computation more efficient.
- The human mind is good in selecting those features of reality that are important but poor at aggregating the features. Human experts are good in building the model, but they are not so good in reasoning through the model. A computer program is not good in building the model, but if is very good in performing calculations. It is acknowledged that Bayesian networks do not describe how the human mind works. It is claimed that only in simple cases, they provide intuitively reasonable answers, and that they are better than human minds in performing some even more complex reasoning tasks [22].

6. Analysis framework for manufacturing orders supported by IDSS

Management of manufacturing projects can be widely applied in creation of new products, facilities, services, and events, in organizational changes and restructure, or recovery from natural or man-made disasters. Projects have starting and ending points in time and progress through a number of life cycle phases. In this case study is given the illustration of how IDSS system is able to support selection and planning of manufacturing projects [18]. IDSS system will help to gather required information, then it will help to analysis information received and estimate if selected projects will be successful. After manufacturing projects are started it will be possible to monitor the present situation and respond quickly if new information is received.

Step 1 - Collection of the required information.

The collection of the required information about quoted manufacturing projects from children companies (see Fig. 4).

Children companies (D/companies) propose quoted manufacturing projects for future period. Since every company has its own distinctive development strategy, therefore a number of projects and their attributes are different as well. All this information (project description, feasibility study, etc.) is delivered from companies to the managing company that is engaged in verification, agreement, and further deployment of these projects.

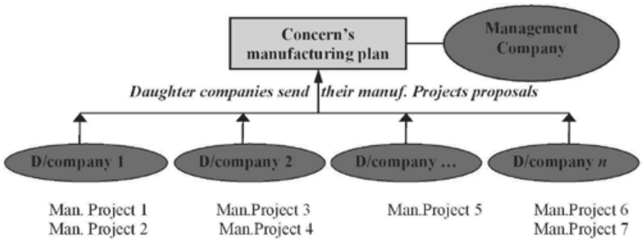

Fig. 4. Collection of quoted manufacturing projects

Step 2 - Project description.

This process requires a significant number of resources and knowledge of the project structure [15]. At the moment all collaboration is performed manually. IDSS must be able to support this process. Common format for all internal enterprises is developed and should be filled automatically by IDSS (Fig. 5).

Project: ***Forge workshop modernizing***			
NN	Parameters/ criterions (planned):		
1	*Start*	15-Jan-07	
2	*Finish*	16-Aug-07	
3	*Budget*	$ 1.500.000	
4	*Goal*	Revenue growth	
5	*Net profit value*		
6	*Internal rate of return*		
7	*Volume*	20000 year	
8	*Cost of equipment*	$ 400.000	
9	Risk of the manuf.proj.	....	

Fig. 5. Fragment of a project describing file

The input of process will be collection of internal enterprise common files. Output will be the whole concern consolidated file. This file will be used for further step.

Step 3 - Preliminary planning of single projects.

At this stage all projects should be planned in detail. Firstly is necessary to estimate all the projects on the base of corresponding criterions [5,6]. IDSS will use common project template which includes tasks and steps: designing; manufacturing; installation; inspection. It is possible to include as much tasks and steps as necessary (see Fig. 6).

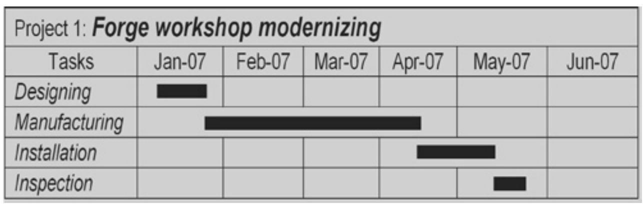

Fig. 6. Gantt chart for a certain project life-cycle

Step 4 - Calendar of manufacturing projects.

IDSS will include the calendar of all manufacturing projects in a consolidated fashion. Here users can see and compare all projects on the same screen (see Fig.7).

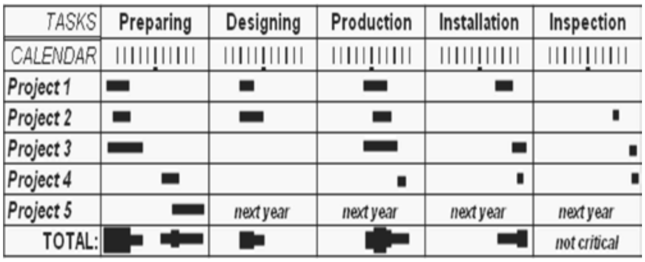

Fig. 7. Project calendar within the year

Step 5 - Establishing the priorities.

The IDSS takes into account all important aspects, and users can propose some logical solutions based on the result of data analysis. This process is based on AHP or Bayes' rule. The AHP will be used if there is no exact information about future manufacturing projects. The Bayes' rule can be used when there is enough information to select the most profitable or the less risky projects [10].

Step 6 - Optimisation of manufacturing project calendar.

If some resources are overloaded, the IDSS system will propose to re-plan resource usage backward. The projects with lower priorities will be postponed. It is possible to make this operation manually. It is also possible to track the solution methodology if required and will optimize the collaborative work.

Step 7. Estimation of success of selected manufacturing projects.

During the project start-up stage the Bayesian network was constructed. Bayesian networks create a very efficient language for building models of domains with inherent uncertainty. Fortunately, software tools which can do the calculation job for us are available [10].

For this research the Microsoft Belief Networks (BSBNx) software is used. For estimation of success of manufacturing projects the Bayesian network was constructed based on prior probabilities. This is what is known about projects, market situation and company information before the project is started. It is known that success of our manufacturing projects depends on such factors as: stable product price; stable product cost; availability of resources; stability of our subcontractors and stability of our market share. Then it could be seen that availability of resources depends from: availability of labour and availability of machine resources. Stable product cost related with the stability of components costs and the stability of the labour cost. Component prices depend on such parameters as: increase of material prices on the market; increase of transport cost and increase of handling cost.

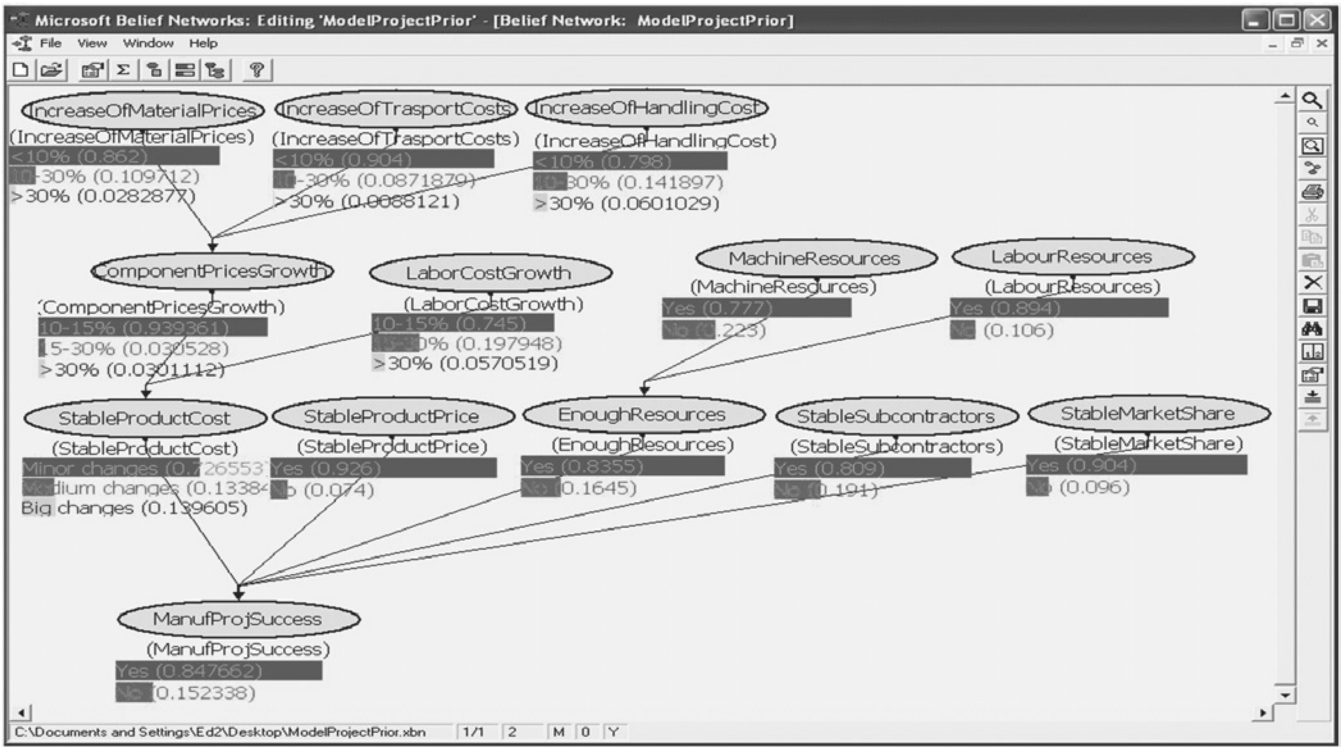

Fig. 8. Bayesian network for estimation of Manufacturing projects Success

Assessment (Model: ModelProjectLast3, Node: ComponentPrices)

Parent Node(s)			ComponentPrices			
IncreaseOfMaterialPrices	IncreaseOfTrasportCosts	IncreaseOfHandlingCost	10-15%	15-30%	30% and Up	bar charts
<10%	<10%	<10%	1,0	0,0	0,0	
		10-30%	0,95	0,05	0,0	
		>30%	0,9	0,05	0,05	
	10-30%	<10%	0,95	0,05	0,0	
		10-30%	0,9	0,05	0,05	
		>30%	0,85	0,08	0,07	
	>30%	<10%	0,9	0,05	0,05	
		10-30%	0,85	0,08	0,07	
		>30%	0,8	0,1	0,1	
10%-30%	<10%	<10%	0,85	0,1	0,05	
		10-30%	0,8	0,12	0,08	
		>30%	0,883	0,09803	0,01897	
	10-30%	<10%	0,8	0,12	0,08	
		10-30%	0,75	0,15	0,1	
		>30%	0,7	0,2	0,1	
	>30%	<10%	0,7	0,2	0,1	
		10-30%	0,65	0,25	0,1	
		>30%	0,6	0,28	0,12	
>30%	<10%	<10%	0,05	0,25	0,7	
		10-30%	0,02	0,23	0,75	
		>30%	0,015	0,235	0,8	
	10-30%	<10%	0,02	0,18	0,8	
		10-30%	0,08	0,12	0,85	
		>30%	0,03	0,12	0,85	
	>30%	<10%	0,01	0,04	0,9	
		10-30%	0,005	0,045	0,95	
		>30%	0,0	0,0	1,0	

Fig. 9. Assessment of nodes relations

The information about increase of material prices on the market; increase of transport cost and increase of handling cost is possible to achieve from previous periods and market research through organized data mining process. IDSS system is able not only to organize the dataflow and collection of information. It is possible to use all this information to achieve the new knowledge. In this case it is necessary to control if selected projects will be successful. ERP system can help by providing required information about resources, sales forecast and market prices. Based on known project related information the Bayesian network is constructed and it could be estimated what is the probability of the selected manufacturing orders success (see Fig. 8). It is possible to assess how different parameters are related to success of our project (see Fig. 9).

Step 8 Monitoring of projects based on Bayesian network.

Small change in situation can affect the on-time completion of non profitable manufacturing project. So what is the feature of the IDSS the enterprises are need. How it possible to respond quickly on all this factors? Today efficient report systems are used, but still it takes time to analyze the reports. And it is common situation that required information is received too late and enterprises faced with the fact that profit is lower than it was planned. Here the IDSS will be able to respond quickly to changed situation. It is possible to use IDSS system analytical mechanism to respond to the information received in real time. It is only required to show to IDSS system the resources, where information could be searched for. The Bayesian network is able to support decision making for corrective actions. In this case the additional information achieved in relation to the manufacturing project in process.

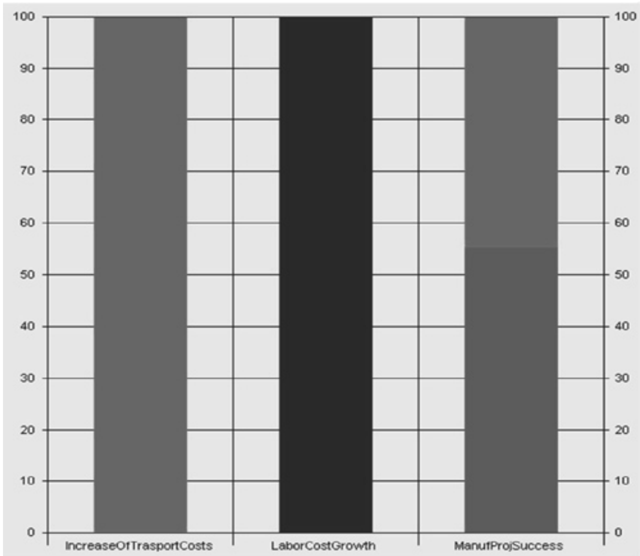

Fig. 10. The evaluation of manufacturing project success based on the last information received

The information that the transportation cost on the market is increased for 30% and the salary of our labour was increased for 31% is received. We want to assess how it will affect our project's success. System is able to make real time analysis of project success based on new information (see Fig.10). The information received will be new posterior probability from the Bayesian network. In this way the system will hold under control our manufacturing projects and it is possible to establish deep analysis of system sensitivity to different inputs changes. The user is just need to respond to this knowledge .In such situation we can estimate what parameters are possible to improve and to estimate how it will be reflected on projects success. It is possible to try to buy more machines to decrease the number of working stuff. And may be it is required to join some partners to combine the transportation cost. The efficient tool can be used, which is able to receive the answer to what if situation in dynamic way, and it is possible to make much more effective decisions.

7. Description of achieved results - General remarks

There are several advantages to use IDSS for project selection and management. In this case study, several benefits are presented, including the increased number of alternatives examined; fast response to unexpected situations; improved communication; control; cost savings; scale savings; better decisions; more effective team work; time savings; making better use of data resource; integrated risk assessment; logical selection of manufacturing projects.

8. Conclusions

The Intelligent decision support system is able to extend the use of the information stored in the database of ERP system. The Intelligent decision system will support and manage the information flow of internal and external cycles. It enables the fast and convenient collection of required information, it helps to select the appropriate analytical tool for better decision making, and it also enables users to systematically study non-structured problems.

Bayesian network can help to transform information into knowledge. Integrated approach saves time for company management. IDSS enables the tracking of decision making process, which enables users to study and to better understand the made decision. Now it is possible to see how the latest information reflects on our projects and how it is possible to perform more effective decision. It is possible to simulate and assess in which directions the work must be made. This paper gives new knowledge about the framework how the IDSS and ERP systems can be used together to collect information, clean and analyze it, assess and track manufacturing projects.

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