# Simulation-Based Decision Support: From Experience Towards Knowledge

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## ABSTRACT

*This paper analyzes simulation as a knowledge base for decision support and its' usefulness in application on three cases: 1) post-decision analysis of the reengineering process, 2) warehouse optimization in an uncertain environment, and 3) decision-making process supported by simulation in a laboratory environment. The paper describes the methodological aspect of simulation as part of the anticipative system and the practical application of simulation and interaction between user, simulation model and scenario in the process of seeking for a solution to a managerial problem as decision support in a business system. Results of all three cases show the effectiveness of simulation in decision support and prove simulation to be a powerfull tool in organizational learning.*

**Keywords:** simulation, learning, reengineering, information, warehouse optimization

## 1. INTRODUCTION

The role of simulation methodology in the decision assessment of complex systems is constantly increasing. Human knowledge, simulation model and decision methodology combined in an integral information system offers a new standard of quality in management problem solving. Simulation model is used as an explanatory tool for a better understanding of the decision process and/or for learning processes in enterprises and in schools. Many successful businesses intensively use simulation as a tool for operational and strategic planning and enterprise resource planning (Schniederjans and Kim, 2003; Muscatello et. al, 2003). Experiences described in literature, (Homer, 1996) emphasize that in a variety of industries actual problems can be solved with computer simulation for different purposes and conditions. At the same time, potential problems can be avoided and operative and strategic business plans could also be tested. Currently the most intensive research efforts are concentrated on a combination of simulation methods and expert systems (Dijk et. al, 1996; Coyle, 1996). Although there is a considerable amount of work devoted to simulation methodology, there is a lack of its application in practice especially in small- and mid-sized companies. The reason lies not in the methodology itself; the real reason is rather in the problems of methodology transfer to enterprises and the subjective nature of decision-making. However, there are several problems, objective and subjective, that are the reason why this well established methodology is not used more frequently.

One of the objective problems is model validation, which is very important for any model-based methodology. The validity of the model of a given problem is related to the soundness of the results and its transparency for users. According to Coyle (1996), a valid model means well suited to a purpose and soundly constructed. According to Forrester (1968), it is pointless to discuss validation without reference to a particular situation. There is no way to prove usefulness of the model of complex systems such as enterprises in advance (Forrester, 1994).

The second problem, the subjective one, is related to the transparency of the methodology and data presentation (Kahneman and Tversky, 1979), preferences of the decision-maker to use a certain decision style and poor communication between methodologist and user. The simulation methodology is a paradigm of problem solving where the personal experience of users as well as their organizational culture play an important role (e.g., in transition countries: market economy, ownership, etc.). This article describes tree different cases demonstrating the usefulness of simulation methods for decision assessments in enterprises.

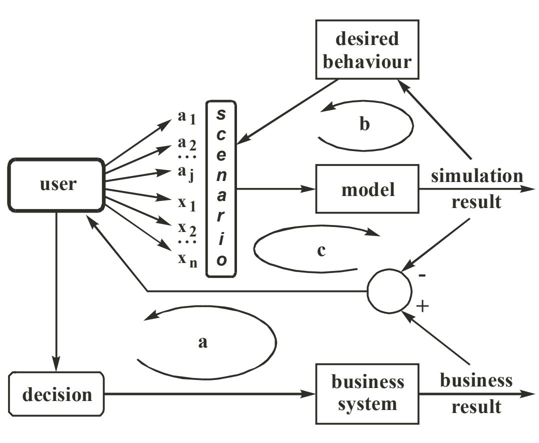
## 2. SIMULATION METHODOLOGY AS A BASE FOR DECISION SUPPORT

Many authors prefer the simulation method as a holistic approach for assessment of decision-making (Gopinath and Sawyer, 1999; Simon, 1997; Sterman, 2000) however; user confidence in it is of crucial importance (Chen and Liaw, 2001). The main problems of each managerial system are the comprehensiveness of information concerning the state and the environment within appropriate time. This means that a mathematical model of the process and a model of the environment are required. However, in enterprises processes due to the complex dynamics resulting from the stochastic interaction and delay it is hard task to get a confident model. Decision-makers though cover a broader perspective in problem-solving than could be obtained solely through simulation. Both simulation interacted with human experience create a new quality at the condition that users is convinced in the value of simulation methodology. The principal representation of the proposed approach is shown in Figure 1 where the principle of interaction between the user, simulation model and scenario interaction is exposed (Kljajić, 1994).

The following three basic loops are emphasized:

a) The causal or feed-back loop, representing the result as a consequence of former decision-making, and being a part of management experience and history of the system. From the learning aspect this loop could be named "learning by experience".
b) The anticipative or intellectual feedback loop, which provides the feed forward information relevant for decision making. This loop consists of the simulation model of the system, criteria function and scenarios. The simulation scenarios consist of two subsets: a subset of input that anticipates the state of nature

*Figure 1. The principle diagram of the simulation methodology for decision support in enterprises*



(exogenous scenarios) – and a subset of alternatives (endogenous scenarios). They give the answer to the basic question concerning the problem situation for which the answer is being sought. In literature it is known as the *what-if* analysis. The generation of scenarios of the simulation system that responds to the *what-if* is based on different scenarios anticipating future impacts of the environment on the system.

c) The *a posteriori* information loop represents the pragmatic validation of the model concerning model applicability and former decision-making. This loop represents the pragmatic validation of the model. A comparison of prior information concerning the simulated impact of the selected strategy on system behaviour with the actual results allows us to evaluate the value of the model and improve it. In this way learning is enabled on the basis of *a priori* assumptions on the model and not just on the basis of empirical experiences.

Loops a) and b) are the basic ones for learning and knowledge acquisition for improved decision-making. Loop c represents the pragmatic validation of the model which supports users' confidence in the simulation methodology.

## 3. POST-DECISION ANALYSIS OF PRODUCTION LINE SELECTION BY SIMULATION METHODS

Described methodology was applied in a medium-sized factory, a manufacturer of concrete goods, for the purpose of reengineering process assessment. Due to the increased demand for a specific article and better quality requirements of products, the firm's management considered investing in a new production line. The decision assessment has been organized at two hierarchical levels. The model at the top level is used for the assessment of the enterprise's strategy (continuous simulation). At the bottom level the model is used for discrete event simulation (DES), necessary for operation planning and testing production performance. The system structure of the simulation model consists of entities connected in a flow diagram in Figure 2. The diagram is sufficiently abstract to allow understanding of the problem and precise enough to provide valid experimentation on the model. As soon as one becomes satisfied with the "picture" of the process, he/she proceeds to the building of the simulation model. From the decision-making aspect the state equation of the simulated system is described by Equation (1):

$$y(k+1) = f(y(k)\ x(k)\ a)\quad k = 0,1,2,..N \tag{1}$$

where $y \in Y$ represents the vector of state variables such as inventory, cash, income, liabilities, backlog, etc., $x_i \in X$ represents the system input: market demand, and $a_j \in A$ represents the control variables (alternatives). The decision strategy was defined as: choose the alternative $a_j$ for the market demandy $x_i$ and its probability $p_i \in P$, which satisfies the performance function reflected by the manager's preferences. Performance of alternatives $a_i \in A$ in Equation (1) was obtained through DES as shown in Figure 2. Two criteria were considered:

Maximal expected value (EV) (of profit) defined by Equation (2):

$$\max E\ (a_j) = \sum_i C_j\, p_i \tag{2}$$

where $C_j$ represents the values of the i-th input at j-th alternative, and linear weighted sum of multiple criteria defined by Equation (3):

$$\max J(a_j) = \sum_{r=1}^{m} w_r J_r(a_j) \tag{3}$$

where $w_r$ represents the weight of the $r$-th objective, which reflects the decision-maker's business policy preference. The individual objective $J_r = q(y,x,a)$ in Equation (3) is a function of the state of the system, the state of the market and the chosen alternative in achieving the goal. The multiple criteria and its weighting for the evaluation of scenarios were defined by the decision group using the group support system. Saaty's AHP method (1990) was used to determine the relative importance of the objectives $w_r$ and a pair-wise comparison of alternatives $a_j$ for the $r$-th objective. The alternatives $a_i$ in Equation (1) represents suppliers of the new production line, which were considered in the decision-making besides the existing technology. The suppliers denoted as alternatives: $a_i = a_1, a_2, a_3, a_4$ and their costs in monetary units as: $c_i$= 0, 371, 392, 532, respectively. Experts estimated the market demand $X_i$ and its probability $p(X_i)$ for the next 5 years. For a detailed description of alternatives one should look at Kljajić et al. (2000). The financial aspect of reengineering was modelled as the continuous simulation model. The block diagram in Figure 2 shows the main material, financial and information flows of the manufacturing system. Net income is represented as an element dependent on different supplier options simulated on DES. This approach provides a unique framework for integrating the functional areas of management – marketing, production, accounting, research and development, and capital investment. An expert group determined Unit Sale Price and Market Demand Function necessary for different production scenarios. The scenarios are defined as a combination of: Unit Sale Price, Unit Production Costs, Market Demand and Other Operating Expenses. Market demand is defined on the basis of current orders and future estimation, which was determined by the company's expert group. The production plan forms the input for DES with the purpose of evaluating the utilization and capacity constraints of the considered alternative. The simulator of the business system allows us to make an analysis of the investment effects, depreciation plan, risk of drop in sales, delivery time and change in sale prices. The model is used for predicting financial and production system efficiency. Four scenarios representing the market demand were simulated for each alternative. The EV of the payoff for alternatives for the 8-year period were computed according to Equation (2).

Several other requirements for the new technology were additionally imposed: Quality of Products, Net Profit, Risk of Company Ruin, Market Demands and Flexibility of Technology. The decision group consisting of enterprise experts carefully determined the relation between the key criterions.

As a result of the decision-making and final judgment, alternative $a_3$ was chosen. It scored first rank, evaluated by the EV and multicriteria evaluation, considering the period of an 8-year horizon. The longer time period, however, proposed as the best solution alternative $a_4$, which had been seriously considered for the final judgment.

Data obtained from the production of concrete goods over the past four years, which is a reasonable period for post-decision analysis, were used for the model validation of the decision process. Validation was carried out by comparing the business outcomes with the anticipated responses of the business model according Figure 1. Figure 3 represents EV of Net Income of the selected alternative $a_3$ (Curve 1), the actual Net Income (Curve 2), and the estimated Net Income in case decision makers would have selected alternative $a_4$ (Curve 3) in time (from 0 to $t_0$ the first four years, and from $t_0$ to 96 months the future four years).

We see that the curves 1 and 2 correlate, both staying in the average region of positive performance of the analysed production process. The observed increase at the beginning in Curve 2 (actual Net Income) is due to one year loan moratorium. However the predicted value of Curve 2 (from $t_0$ on) is slightly below EV. These results can be explained by lower demand, which should reflect in lower Net Income. Curve 3 represents estimated Net Income in case decision makers would have selected $a_4$. It is characterized by a fully automated production pro-

*Figure 2. Causal loop diagram of the simulation model for decision assessment*

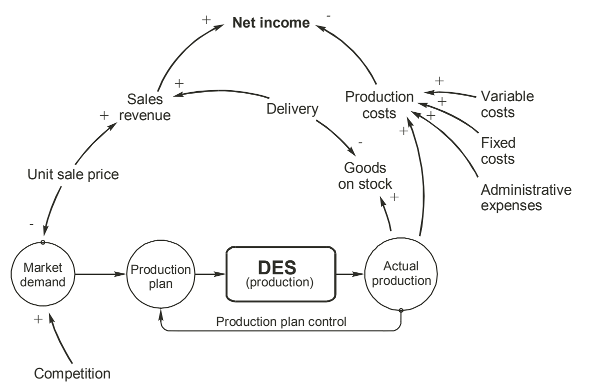


*Figure 3. EV of Net Incom (Curve 1), realized Net Income (Curve 2) and predicted Net Income of the alternative $a_4$ (Curve 3)*

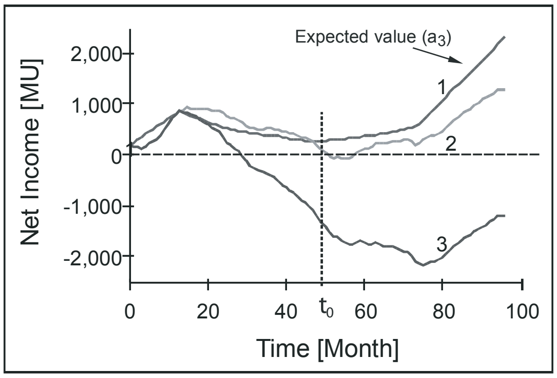
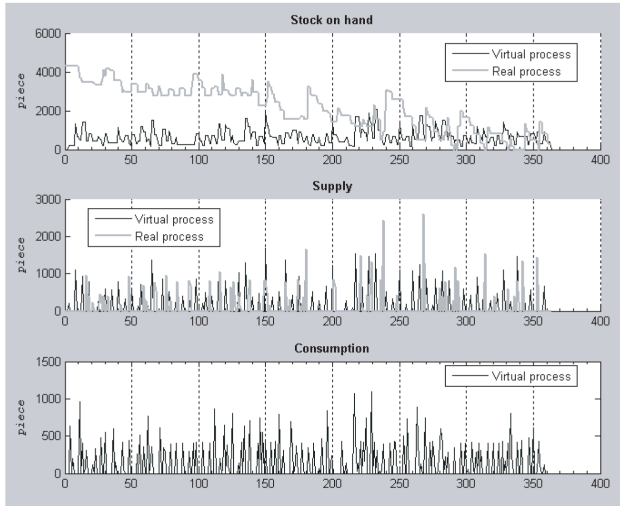



*Figure 4. Stock, supply and consumption dynamics for the observed case*




cess, which can ensure a high quality and quantity of products and was seriously considered for purchase.

One can learn from this lesson what would happen if we had chosen alternative $a_4$ instead of $a_3$. At the anticipated ratio of demand on the market sales it could not cover the financial burden of such volume. This means that the company would suffer a financial crisis shortly after the implementation of such technology.

## 4. WAREHOUSE OPTIMIZATION IN AN UNCERTAIN ENVIRONMENT

In this case, we were dealing with a typical warehouse for storing products for further build in. The consumption of products depends on a production plan, which can be predicted with a certainty for six weeks. Lead time, for every product, is not variable. The problem occurs at defining the ordering quantity, because we have to consider the past orders and the variable consumption of a specific product. Long lead times also represent a problem, because they are usually much longer than the time period in which the production plan can be predicted with a certainty. The main goal of optimization was to rationalize warehouse ordering process, this means determining the interval between orders and the quantity to be ordered, so that the warehouse will operate with minimal common costs.

From control point of view, our problem can be described with the difference equation:

$$x(k+1) = x(k) + d(k) - p(k)\ , k = 0,1,2..n \qquad (4)$$

$$x(0) = x_0$$

where *x(k)*, represents stock variable, *d(k)* material delivery and *p(k)* production process. The delivery function *d(k)* is delayed for an average time of an order *o(k)*. Time delays are stochastic.

$$d(k) = o(k - \varphi(\tau_d)) \qquad (5)$$

where $\varphi(\tau_d)$ represents discrete uniform probability density function *(pdf)*. In order to compensate the stochastic delivery delay, the order policy *o(k)* has to be defined as:

$$o(k) = f(x(k)\ d(k - \varphi(\tau_d)), p(k + \tau_p) \qquad (6)$$

where $\tau_d$ represents the time delay and $\tau_p$ the production plan. It is necessary to find such *o(k)* to minimize the following cost function:

$$J(o(k) = \sum_0^n q(c\ x(k)\ h\ d(k)), k = 0,1,2,..n \qquad (7)$$

for $x\min \le x \le x\max$. In equation (7) *c* and *h* represents the cost of units of material on stock and its transportation.

In order to improve the stock control problem, a simulation approach has been chosen where heuristics and fuzzy control algorithm were tested.

The experiment was performed with the actual historic data for seven years provided by the observed company. The results for one case (product) are presented. The company has confirmed the simulation inventory level dynamics based on the above-mentioned data. They have also confirmed the validity of the costs the simulation model has calculated. The model was changed in the "ordering" module to try out new ordering strategies. A Monte Carlo simulation was used for variation of consumption unreliability. Fifty simulation runs for every strategy on new simulation models were run, using only consumption data. On the basis of these simulation runs, average costs and average stock-outs were calculated. With several simulation runs and a calculation of average values, we have tried to minimize the influences of the random generator, which represents the stochastic environment.

Figure 4 presents results for the Real Process and Virtual Process. The Real Process is represented by the brighter line and the Virtual Process is represented with a darker line. The first graph presents stock level dynamics, the second delivery dynamics and the third the consumption dynamics throughout simulation time (time unit is weeks). The results shown in Figure 4 can be used to indicate similarities or differences between the two processes. The supply dynamics graph indicates some similarities in the ordering strategy – some peaks (representing order quantity) are very similar but with some time delay. However, the simulation results of ordering have produced much lower costs than the Real one for the 65%.

The simulator also allows us to compare two methodologies used in the ordering process: heuristics of the warehouse operator and algorithm based on simulation and fuzzy logic. From the Figure 4 one can observe, from the stock variable, the operators' "learning by experience". Namely, starting from high stock value, the operators' ordering strategy slowly improves over time approaching optimal strategy obtained by simulation. From the obtained results we can deduct about the usefulness of simulation method for the operator training for new ordering strategy.

## 5. DECISION-MAKING SUPPORTED BY SIMULATION MODEL AND GROUP FEEDBACK INFORMATION

The goal of the conducted experiment was to acquire knowledge of the group decision process supported by the system dynamics (SD) model and influence of feedback information. A model of the business system was applied at the experiment with decision groups. The model consists of: production; workforce and marketing segments that are well known in literature (Hines, 1996; Sterman, 2000 and Škraba et. al, 2003). Model shows that Product Price ($r_1$) positively influences Income. However, as prices increase, Demand decreases below the level it would otherwise have been. Therefore the proper pricing that customers would accept can be determined. If Marketing Costs ($r_3$) increase, Demand increases above what it would have been as a result of marketing campaigns. The production system must provide the proper inventory level to cover the demand, which is achieved with the proper determination of the Desired Inventory value ($r_4$).

The experiment considered the task of strategy determination with an explicitly defined multicriteria function. The optimal criteria function value (CFV) was determined at $J = 1.5$.

Experiment was conducted under three experimental conditions: $a_1$) determination of business strategy without application of a formal model, $a_2$) determination of the strategy with application of a formal SD model and, $a_3$) determination of the strategy with application of a formal SD model with subjects interaction supported by the group feedback information. 147 senior university students participated in the experiment. We hypothesized that the model application and group feedback information positively influence the convergence of the decision process and contribute to higher criteria function values.

The results of the decision process conducted under experimental conditions: $a_1$) ($N_1$=52), $a_2$) ($N_2$=55), and $a_3$) ($N_3$=40) presented as deviation of CFV from the optimal CFV, are shown in Figure 5.

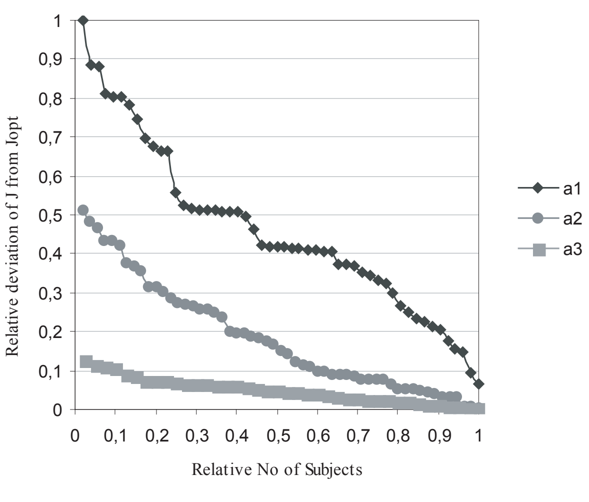
The lowest deviation values were obtained in experimental condition $a_3$) where group information feedback was applied. Results marked $a_2$) and $a_3$) were gathered with the aid of the SD model, and the results marked $a_1$) where assessment was done without a formal model, were gathered by writing them in a paper form. The single factor ANOVA showed that there are highly significant differences in CFV among groups on a $p = .000$ level of confidence. Therefore, the hypothesis that the model application and group feedback information positively influence the convergence of the decision process and contribute to higher CFV was confirmed.

The anticipative value of information using Shanon - Harkevič equation can be measured:

$$I(a_i) = k \log(p(a_i) / p_0) \qquad (8)$$

where $p_0$ and $p(a_i)$ represent the probability of achieving a goal without or with information, respectively, and a $k$ constant. In practice, it is impossible to get a probable released goal in advance. This problem derives from the nature of the

*Figure 5. Normalized deviations of CFV from the optimal CFV for experimental conditions $a_1$), $a_2$), and $a_3$)*




decision process. However, the simulation model of the process and anticipation of possible future impact from the environment can provide useful information to management. In our case, it is obvious and can be observed in Figure 5. Let us suppose that objective function equation can take each value from the unit square interval with equal probability if the experimental subject has no knowledge of the goal. The probability $p_0$ is then reciprocal to the unit square area of $P0 = 1$. In our case it means maximal entropy of the experiment. With experimental condition $a_1$), $a_2$) and $a_3$) we introduced information proportional to the area of reduction. By estimating the area $P1$=1/2, $P2$=1/4, and $P3$= 1/16 and taking its reciprocal value we obtained the probability of $p(a_i)$. Using equation (8) we can estimate the information content of the experimental condition. In the tested case, based on equation (8) where $k = 1$, the following is noted: $I(a_3) = 4$, $I(a_2) = 2$, $I(a_1) = 1$, and $I(a_0) = 0$ bit. (Note that due to the normalization of the area in Figure 5 and $P0$=1, reference is being made to the relative value of information obtained through experiments $a_1$, $a_2$ and $a_3$, where generality is not being affected).

## 6. CONCLUSIONS

This paper analyzes simulation as a knowledge base for decision support and its' usefullness in application.

Four years of experience in a concrete production company, where new production line was chosen by employing simulation methodology, was analyzed. The predictive validation of the simulation model as well as simulation methodology for decision assessment was done by comparing actual data with those predicted of the chosen alternative in four years period. A comparison showed that the gained predictions were a relevant estimation of future company development after the reengineering process was completed. More over, post decision analysis showed how good was the rational decision of alternative $a_3$, comparing to the competing alternative $a_4$.

Warehouse optimization in a production company by simulation methodology was studied. The simulation model was validated on a company's historic data. The results also show how the operators' ordering strategies improved in time as he/she learned from experience. The same experiences one could aquire by experimenting on a model in shorter time.

Influence of the SD model and group feedback information on a decision-making process was analyzed in a laboratory setting. Hypothesis that the model application and group feedback information positively influence the convergence of the decision process and contribute to higher CFV was confirmed.

The basic advantage of the described approach lies in the interactivity and transparency of the model representation. By experimenting on a simulation model, the user enhances knowledge about the studied process and improves judgment about alternatives. In this way the range of *bounded rationality* in decision-making could be enhanced.

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