Dynamic decision support system for strategic policy making

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Abstract

Strategic policy making in industrial firms is often coupled with inherent uncertainty. Variability in demand, prices and cost, call for effective methodological approaches mainly in case of decisions demanding high investment costs. In such cases, a dynamic decision support system facilitates the decision making procedure.
In this work we contribute to the above research effort. Specifically, we introduce a generic framework for the development of decision support systems for strategic policy making, which is based on System Dynamics. System Dynamics methodological approach has proven its applicability in a wide range of medium and long-term decision making cases reported in the literature. The proposed generic framework is implemented in the evaluation process of an investment plan, suggested by a real-world Greek manufacturer who faces uncertainty especially in the customer orders and the raw materials' price due to volatile currency exchange rates.

Keywords: decision support system, system dynamics, policy making, uncertainty, dynamic business environment

JEL Classification: L60

1. Introduction

Most business activities take place within a stochastic operational environment. Severe demand uncertainty, increased globalization, shorter time-to-market, reduced product lifecycle, make-to-order strategies and pull systems, are only a few to mention trends which force organizations to adopt new ways of doing business (Stefanovic et al., 2009). More than ever before, companies which are not able to revise periodically their strategies and, accordingly, to modify their organizational processes seriously risk to be pulled out from the competitive edge.
To cope with the bids of the new economic environment, manufacturers realized the necessity of well structured tools that will support managers identifying the sources of uncertainty, understand their potential impact on the company's operations and ensure that every decision involves an acceptable risk. This need has forced industry and academia start studying policies and methodologies for the identification and effective response to uncertainty.
During the previous 20 years, many computer-based information systems have been developed to aid operation managers in the decision-making procedure (Otto, 2008). The majority of these systems are complicated information management systems which are best suited for normative decision-making. However, as most firms operate within a complex

dynamic business environment, operation managers tend to follow their intuition rather than rely on computer-based information systems (Crockett, 1992).

System Dynamics (SD) is a well-documented methodological approach in dealing with complexity and uncertainty. SD was introduced by Forrester (1961) to conceptualize, illustrate and simulate the dynamic behaviour of complex industrial management systems. Since the dynamic behaviour may be used to evaluate the performance of a specific managerial policy, SD models can be viewed as decision support systems (DSS) for strategic decisions. The DSS may go one step further and be used for the identification of managerial policies that optimize the system's behaviour under a predetermined objective function. In particular, SD models can be used to analyze various scenarios (i.e. to conduct various "what-if" analyses) thus identifying efficient policies which would holistically improve the performance of a company. SD methodological approach has been successfully implemented in numerous policy analysis and decision making managerial applications (Sterman, 2000, Powell et al., 2001, Yim et al., 2004).

The contribution of the present paper is twofold. Firstly, we provide a generic framework, for developing simple-to-implement SD-based DSS for strategic policy making. Towards to this scope, our research focuses on developing the integration of SD methodological approach with traditional decision support procedures, to provide complementary and synergistic support to operation managers seeking effective ways to attain multiple objectives. The benefits can be even greater for businesses operating within a complex stochastic environment. Secondly, we provide the implementation of the proposed framework for a real-world manufacturer operating within an uncertain business environment, mainly due to fluctuation in customer orders and raw materials price. By using data from the manufacturer, we develop the SD model of the production/inventory system under study. Using the model in conjunction with numerical investigation, we evaluate the profitability of an investment plan suggested by the management of the manufacturing firm and we identify the most efficient business policy regarding the selling price of the finished goods. Since the structure of the proposed DSS provides versatility, it can be used in other companies operating within similar stochastic environments.

The rest of the paper is organized as follows: In Section 2 we present the framework for the development of SD-based decision support systems for strategic policy making. Section 3 demonstrates the implementation of the proposed framework in the real-world manufacturer. The section also provides an extensive numerical investigation for the effectiveness of different business policies related to the selling price of finished goods. Finally in Section 4 we wrap-up with summary and potential future extensions.

2. Development of SD-based decision support systems

The focal point of the proposed strategic policy making procedure is System Dynamics methodological approach. SD is a computer-aided approach for analyzing and solving complex problems with a focus on policy analysis and design (Yuan and Ashayeri, 2009). It is based on control theory, systems theory and continuous simulation techniques. For more than 40 years SD has proven its applicability in a wide range of real-world social and physical problem domains including economic development, ecology, psychology, energy policy, public management, corporate planning and policy design as well as in biological and medical modeling problems. For a comprehensive presentation of the most representative fields related to the SD research agenda we refer

to the papers of Lebel (1981), Sastry and Sterman (1993), Angerhofer and Angelides (2000) and Größler et al. (2008). SD has been successfully employed in numerous problems to provide managers with insights about market behavior when evaluating alternative policy scenarios. Pasaoglu Kilanc and Or (2008) develop a SD model to better understand and analyze the decentralized and competitive electricity market dynamics in the long run. Tatari et al. (2008) evaluate investments related to integrated information management systems in the construction industry. Qi et al. (2009) analyze the Chinese mobile carriers' competition strategies under alternative investment options. Suryani et al. (2010) establish a system dynamics framework for forecasting demand and evaluating capacity expansion policies. Georgiadis and Athanasiou (2010) investigate the impact of various product and market characteristics on the optimal policies regarding expansion and contraction of collection and remanufacturing capacities in a reverse supply chain.
In the present work we establish a generic framework, for developing SD-based practically applicable DSS for strategic policy making in manufacturing systems. The proposed framework consists of the following sequential decision and action levels (see Figure 1):

1. Set the objectives of the decision support system
2. Define the system boundaries
3. Identify the sources of uncertainty
4. Develop the causal loop diagram
5. Develop the mathematical model
6. Design and conduct simulation experiments
7. Evaluate the managerial decisions

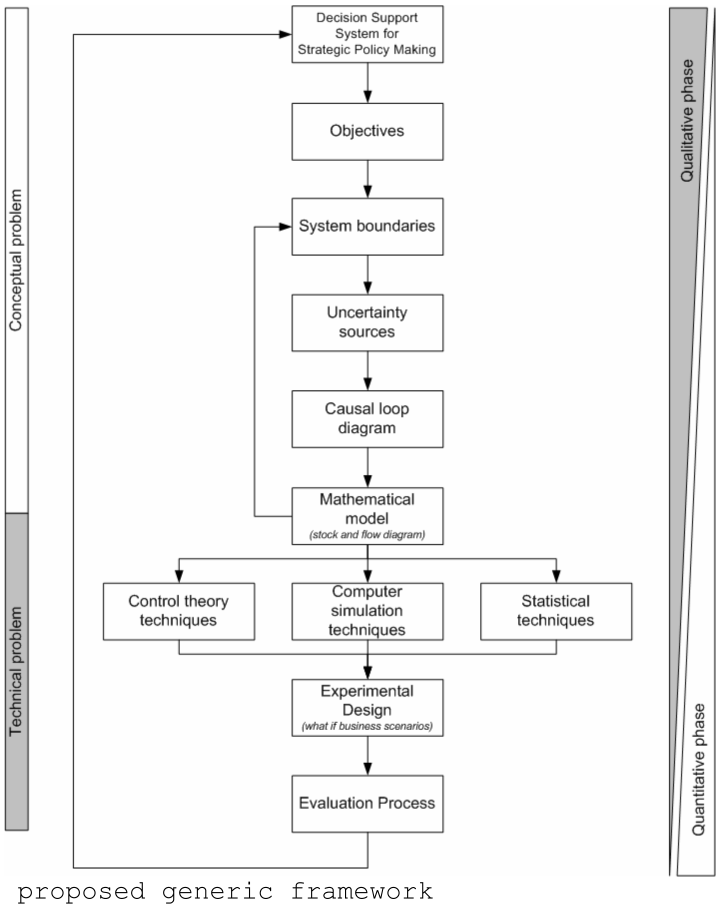

Figure 1. The proposed generic framework

The above mentioned steps of the proposed framework are discussed in detail in the following subsections.

Set the objectives of the decision support system

The first step towards the development of SD-based DSS, is to identify the corporate' objectives. Objectives set out what the business is trying to achieve. Setting objectives is not an easy process but once set they provide a useful benchmark from which the development needs are identified and performance is monitored and supported over a period of time. Since objectives communicate the corporate management's desired outcome, they should be achievable, realistic and measurable. Setting managerial decisions and strategic policies for achieving profit targets, increased shareholder value and high customer satisfaction are examples of such objectives.

Define the system boundaries

A system is composed of interacting parts that operate together to achieve the predefined objectives. The system "absorbs" inputs, process them and produce outputs. These outputs are the measures of the system's ability to achieve the objectives. In order to understand the relationship between inputs, outputs and processes, it is necessary to understand the environment in which all of these activities take place. The environment represents everything that is important to understand the functioning of the system, but is not part of the system. In general, the environment can be ignored in the analysis except for its interaction with the system.
A major issue in developing a DSS is distinguishing what the system should include from what it should not include, according to the current objectives. This distinction is given by the system's boundaries; the definition of correct boundaries is a function of the problem under consideration and henceforth it is important to be completed before the DSS is developed.

Identify the sources of uncertainty

After establishing the boundaries of the system, the next step is to identify the sources of uncertainty, potential risks, threats to assets and vulnerabilities of these assets, and document the unwanted incidents as well. There are many sources of uncertainty for businesses to consider. There are sources that can be planned for but not controlled like strikes. Others can be more directly controlled such as production techniques or methods. However, the key uncertainty sources on the manufacturing sector derive mainly from the production and marketing processes; financial markets, project failures, legal liabilities, credit risk, accidents, natural causes, and disasters as well as deliberate attacks from an adversary are typical examples of such uncertainty sources.

Develop the causal loop diagram

SD represents a problem situation in terms of processes, information flows, feedback and delays, boundaries and strategies/policies. The modelling process comprises of several (iterative) steps, forming a loop rather than a linear progression (Richardson and Pugh, 1981, Sterman, 2000). A SD model is based upon a set of diagrams, known as causal loop diagrams that are built during the conceptual modeling phase. A causal loop diagram maps the major system feedback mechanisms. These mechanisms are either negative (balancing) or positive feedback (reinforcing) loops. A negative feedback loop exhibits a goal-seeking behavior: after a disturbance, the system seeks to return to an equilibrium situation. In a positive feedback loop an initial disturbance leads to further change, suggesting the presence of an unstable equilibrium.

Develop the mathematical model

The next step of the proposed framework includes the development of the mathematical model, usually presented as a stock and flow diagram that captures the model structure and the interrelationships among the variables. Stock variables are the accumulations within the system (i.e. Backlogged Customer Orders, Work in Process, Finished Products Inventory); they thus capture the state of the system. Flow variables represent the flows in the system (i.e. Incoming Customer Orders, Production Orders, Production Rate, Delivery Rate, Completed Customer Orders), which are the output of the decision-making process. The stock and flow diagram is translated to a system of differential equations, which is then numerically solved via simulation. Nowadays, high-level graphical simulation programs (such as i-think®, Powersim®, Vensim®, and Stella®) support such an analysis.

Design and conduct simulation experiments

The proposed procedure is rather typical for simulation projects; thus, includes the generation of multiple system instances using the appropriate random number generators and the statistical analysis of the results to obtain the distribution characteristics of the variable under study.

Evaluate the managerial decisions

In order to assess the impact, effectiveness, and/or outcomes of the alternative managerial decisions, the numerical results are evaluated, with respect to the system’s objectives. The evaluation process involves the measurement of business growth by both quantitative and qualitative measures. In case of poor performance of a managerial decision, an alternative policy is selected and the evaluation process is repeated.

3. Implementation of the generic framework

The proposed framework is implemented in the evaluation process of an investment plan, suggested by the management of a real-world manufacturer. The manufacturer, which produces tailor-made refrigeration bodies for commercial vehicles, currently operates in a single manufacturing shop located in the region of Central Macedonia in Northern Greece. In an effort to increase its market share, the manufacturer plans to expand its operations by establishing a new production facility in Central Greece.
The new production facility characteristics, i.e. the number and type of workstations, the required open-air and covered surfaces, and the necessary personnel (workers and administrative employees) have been defined based on relevant studies (capacity/facility planning and workforce planning). More specifically, the manufacturing operations will take place in a network of four workstations while in a fifth workstation the finished bodies will be fitted to the vehicles. The estimated investment cost is 1200000 €.

The production procedure initiates whenever a new customer order arrives at the shop. Customer orders are translated into production orders and are backlogged in a job pool, waiting to enter the shop floor. According to the adopted order release mechanism, production orders enter the shop floor and join the queue in front of the first workstation indicated by the routing. The production rate of each workstation is defined by considering the operational parameters (routing, scheduling, sequencing, batching, etc), product specifications and is constrained by both production capacity and in-process inventories availability. After the completion of the required processes at the last workstation, the vehicles are moved to the finished vehicles depot where they remain until being delivered to the customers. Each time a vehicle is delivered to the customers, an equivalent order is withdrawn from the job pool depleting the backlog level. The production process assumes infinite work in process buffers and infinite finished vehicles depot capacity.
The causal loop diagram of the production system under study, along with the cost structure, is presented in Figure 2.

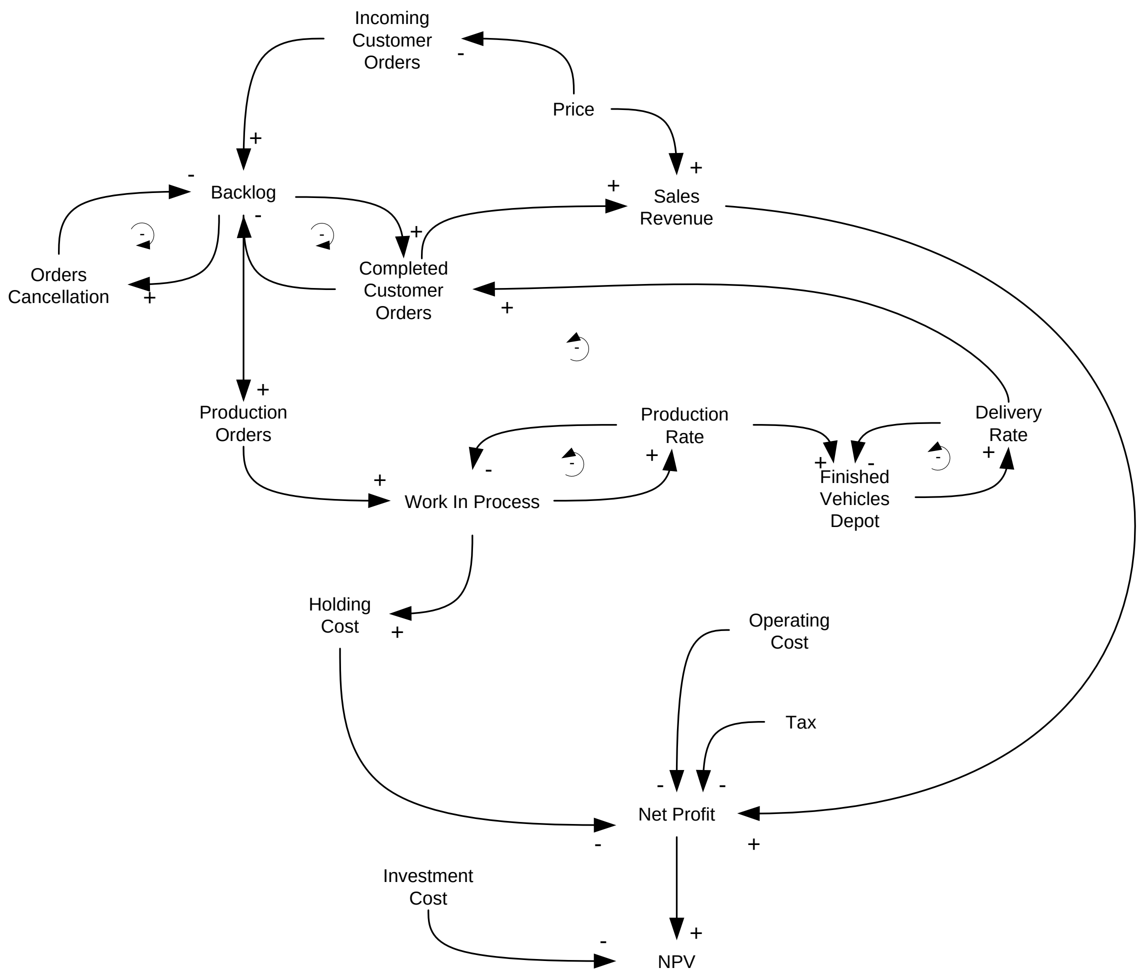

Figure 2. Causal loop diagram of the decision support system

Despite the effort made for accurate estimation of the system parameters, there is a number of parameters of major importance for the efficiency of the investment option, the values of which are either time dependent or uncertain. These parameters that may considerably affect the profit of the entire production process are the incoming customer orders and the raw materials' price.

More specifically, based on market analysis and historical data retrieved from the existing production facility, the arrival rate of new customer orders is found to follow a Poisson distribution, with mean value $1/\lambda=\mu$. Furthermore, a time-series analysis of company’s sales revealed a seasonal behavior in the arrival pattern, with the mean value μ being increased by 30% during the summer months and decreased by an equivalent percentage during the winter months. Additionally, the estimation for the mean value μ is that it will increase almost linearly in the following five years. Hence, we formulate the mean value μ of incoming customer orders by the following additive seasonal model:

$$\mu_t=b_1+b_2t+L\sin(P\cdot t)+\varepsilon_t \qquad (1)$$

where, b_1 is the base signal (initially equal to zero), b_2 is the linear trend component (slope), L is the magnitude of the seasonal term (30% of the mean value μ), P is the season period (52 weeks) and ε_t is a random error component which follows a normal distribution with constant parameters. We assume b_2 to follow a uniform distribution with fixed upper and lower limits. Furthermore, stochastic equipment availability and processing times are also contributing to the establishment of an uncertain business environment. In particular, equipment availability is subject to machine failure rate, expressed in terms of failure probability and mean repair time, while processing times are uniformly distributed.

An additional parameter that requires attention is the price of the raw materials. The bill of materials includes solid polymeric isothermal panels and stainless steel frames, while a number of extra secondary components are also used according to the individual customer needs and technical specifications. The majority of the required raw materials are imported from non Eurozone-member countries. Therefore a high volatility in exchange rates is observed, which consists a threat for the profit of the entire investment plan. Based on historical data (five years) about the currency exchange rates, the price of raw material follows a uniform distribution, with limits x1 and x2.

An important parameter which defines in major the profitability of the production system is the products’ selling price. In effort to assess a higher market share, the selling price will be initially set equal to A €/unit, which is C% below the average market selling price (U). We assume that the lower is the initial selling price (A), the higher is the incoming customer orders rate. The initial discrepancy however, between the manufacturer’s price and the average market price will be progressively eliminated by the gradual adjustment of the selling price to the average market level, according to the employed adjustment policy. Figure 3 illustrates three different selling price adjustment policies, namely aggressive (K1), normal (K2) and conservative (K3).

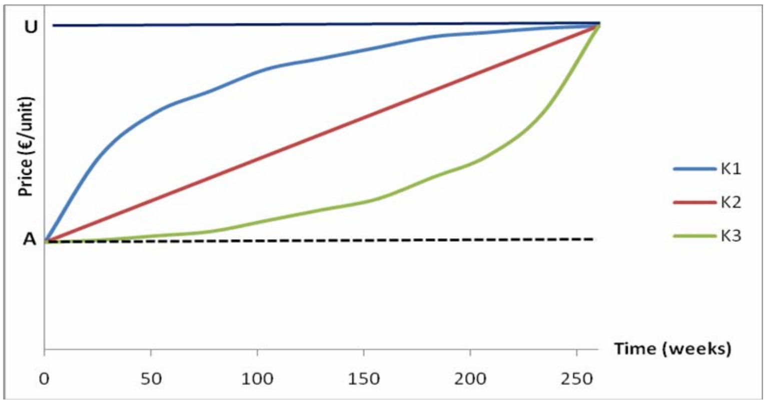

Figure 3. Selling price adjustment policies

However, changes in selling price have an impact in the arrival rate of customer orders. The specific business sector shows an inelastic behavior with the price elasticity of demand (PED), that is the ratio of the percentage change in quantity demanded to the percentage change in price, being equal to 0.66. Therefore, an increase in selling price by 10% is expected to decrease mean customer orders by 6.6%.

To evaluate the investment plan, we developed a SD model of the system under study. The SD model represents in detail the new manufacturing facility characteristics (number of workstations, routing, sequencing and capacity), in order to define the various cost elements including the operations expenses, the holding costs, the investment depreciation and the profit taxes, along with the income from sales.

We use the simulation model in an extensive numerical investigation, to examine the effectiveness of the different price setting policies regarding the ***initial selling price*** (A) and the ***selling price adjustment policies*** (K1, K2, K3). We employ the maximization of Net Present Value (NPV) of the total profit over a five-year planning horizon as the optimization criterion. The NPV of the investment is calculated by assuming a constant cost of capital equal to 6%.

The numerical investigation consists of a full factorial design with 24 combinations of the two selling price policies (initial selling price and selling price adjustment). In more detail, for each selling price adjustment policy (K1, K2 and K3), a set of eight different initial selling prices (A=3950,4000,4050,4100,4150,4200,4250,4300 €/unit) are examined. Each combination was simulated 1000 times to test for alternative generators of random number concerning the processing times, the raw material price and the slope b_2, increasing the number of simulation runs (instances) to 24 x 1000 = 24000. The simulation horizon is 260 weeks and the integrating time step is 1 day. Figure 4 depicts the evolution of Net Present Value of an instance for the case of A=3950 €/unit and aggressive selling price adjustment policy (K1). The mean values of NPV for the eight different values of initial selling price (A) and under the three alternative selling price adjustment policies (K1, K2 and K3) are illustrated in Figure 5.

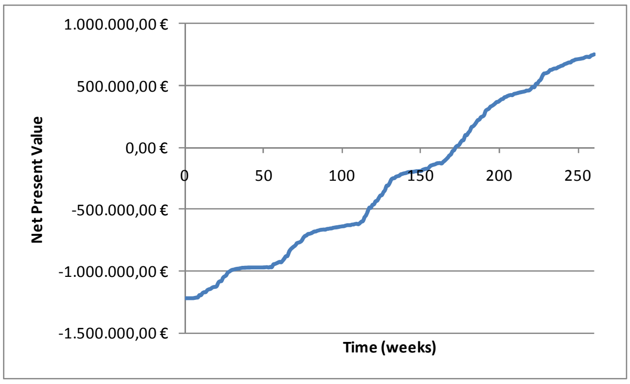

Figure 4. Evolution of NPV for the case of A=3950 €/unit and aggressive selling price adjustment policy (K1).

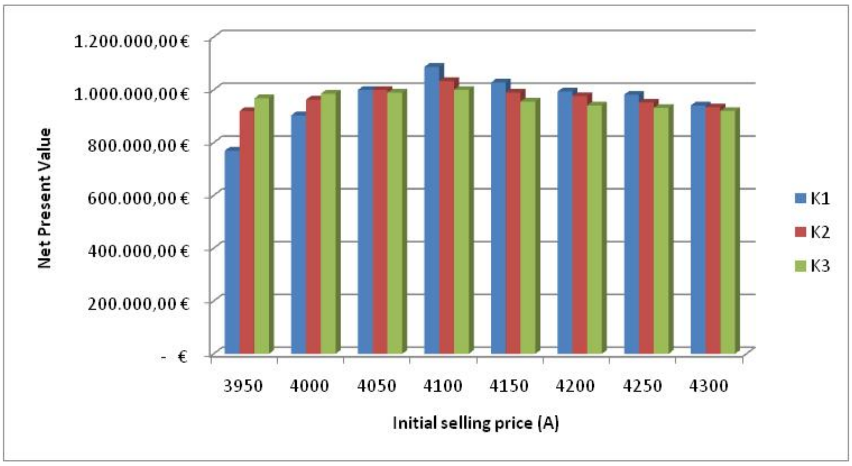

Figure 5. Mean values of NPV for eight different initial selling prices (A) under the three selling price adjustment policies (K1, K2 and K3).

The joint examination of the results shown in Figure 4 and Figure 5, and the analytical numerical results, not presented for brevity, leads to the following observations regarding the evaluation of the investment plan and the effectiveness of the suggested selling price policies:

- The investment plan is profitable regardless of the selling price policy. The higher estimated profit (higher mean value of NPV) is achieved in the case of initial selling price (A) equal to 4100 €/unit.
- The NPV under the normal and conservative selling price adjustment policies (K2 and K3), appear to be insensitive to the initial selling price (A). On the other hand, the aggressive selling price adjustment policy (K1) appears to affect significantly the profitability of the investment plan. In particular, when the initial selling price is substantially lower than the average market selling price (U), the aggressive selling price adjustment policy leads to lower incoming customer orders rate and thus to lower profitability, when compared to the cases of K2 and K3.

4. Summary and potential future extensions

In this paper we proposed a generic framework for developing SD-based decision support systems for strategic policy making. The developed DSS allow the comprehensive description and analysis of complex system operations taking into account shop characteristics (number of workstations, routing, scheduling, capacity), and product specifications as well. We implemented the proposed framework in the evaluation process of an investment plan, suggested by the management of a real-world manufacturer. Furthermore, we used the developed DSS in an extensive numerical investigation to examine the effectiveness of the different business policies regarding the selling price of finished goods. The results documented the best policy which the company should adopt.

However, the suggested generic framework is not confined within the boundaries of the specific manufacturer, but can be employed in other businesses facing similar uncertainties or risk environments. In particular, the suggested framework can be implemented in the evaluation process of alternative policies adopted by corporate managements to insure against specific risks and uncertainties. Trading futures and options to hedge risk of currency fluctuations and price increases for commodities or buying insurance against several other types of risk are typical examples of such policies.

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