Simulation Framework for Evaluating Production Networks

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ABSTRACT
The manuscript presents the ongoing development of an agent-based production network simulation framework. The simulation is intended to analyze the high level (strategic and tactical) planning problems decomposed into simple subproblems, similarly to the practical approach applied by the Enterprise Resource Planning (ERP) systems. The background, the goals and the design of the framework are described, and some preliminary experiments with the current phase of the development are shown.

Keywords
Logistics optimization, agent-based simulation, robustness

1. INTRODUCTION
In recent years the shortening product life cycles and the increasing product variety have led to complex production networks with dynamic structure, fluctuating demand, embedded in volatile environments. Handling such complex and uncertain problems with exact mathematical optimization models is time-consuming and usually impractical.

There are two main difficulties in creating practical planning models. On the one hand, some parameters or dynamics are unknown or uncertain, therefore they are only estimated or approximated. For example, the demand curve usually assumes a simple relationship between the price and the demand, and completely disregards other important factors that influence the market, such as sudden changes in customers' preferences. On the other hand, if a model contains too many details, it can result in an *overfitted* solution. In this case the plan might be optimal considering fixed parameters, however, any change in the environment—e.g., a late supply or inappropriate quality—can cause a major change in the execution. Due to these difficulties, the realization usually diverges from the plan or the forecast.

In the industrial practice, commonly the basic planning algorithms that are built into the ERP systems are used. These general algorithms neglect several details of the problem, but usually result in plans that have more room for adaptation and are more flexible to changes. Furthermore, they are readily available, do not require additional software and interface development, and frequently provide comparable results to specialized optimization algorithms [5]. For example, the scheduling algorithm of SAP APO computes the order finish date simply by adding the production time to the start time, where the production time is a sum of the setup time, of the processing time multiplied by the quantity and of the interoperation time [9]. This approach disregards the capacity and the load of the resources, as well as the possibilities of unexpected disturbances.

The goal of our current research is to develop a testbed for studying production networks in a simulated volatile environment. The desired characteristics of the simulation framework are to be general, modular and flexible. It should allow modeling dynamic production networks in uncertain environments, with a wide range of products, both mass produced and customized. The decision problems considered are focused on the strategic and tactical levels. Each node can apply different planning algorithms that are available in ERP systems. The performance of the network and the nodes should be evaluated according to multiple criteria, thus we are going to model various network footprints and strategies (see [6]). The first application of the developed framework is to study the fields of *resilience*, *pricing* and *trust* in production networks.

Resilience corresponds to balancing *robustness* and *agility* in supply chains [1]. Agility is the capability to react to changes, while robustness is resulted by a proactive strategy enabling to cope with turbulences without taking further actions. Monostori [7] introduced measures of structural and operational robustness of supply chains, and described a framework for evaluating robustness, complexity and efficiency. A supply chain simulation for evaluating robustness and coordination is presented in [2].

Two types of uncertainty are especially relevant in supply chains: *stochastic events* and *low probability high impact disruptions* [10]. The former ones can be forecasted based on historic data and/or expert knowledge. These include factors such as demand fluctuation, production and transportation times, as well as raw material and transportation prices. The disruptions, however, are rare, thus traditional forecast-

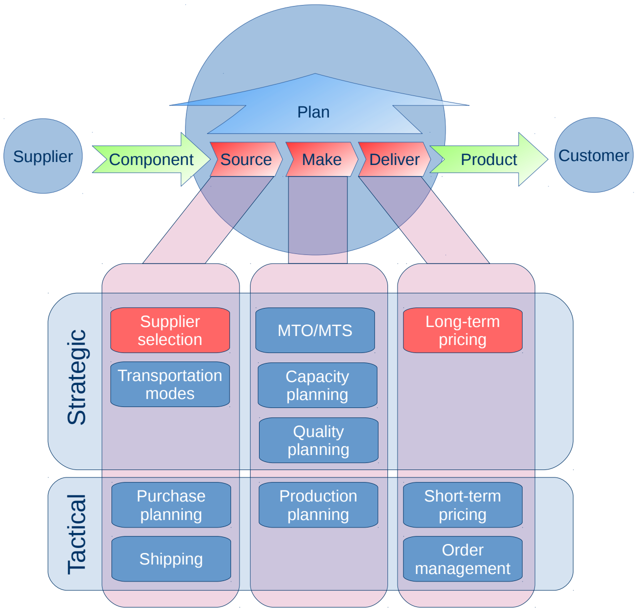

Figure 1: Decision problems at each node of the network.

ing techniques are inappropriate to handle them. These include events such as sudden disturbances at supply chain members, unexpected damages, and natural disasters.

Pricing is also important in influencing the market demand, and eventually, the profitability of the companies [11].

There are several approaches for collaboration in production networks decreasing the undesirable effects such as double marginalization or the bullwhip effect, see e.g., [12]. However, identifying the benefits of collaboration is still a challenge in supply chain management, and particularly in supply chain simulation [8]. Trust is a precondition of successful collaboration, but it is rarely considered formally in decision models, because it consists of a complex belief of dependability, competence and integrity. One of the few exceptions can be found in [4], where trust in a supplier is measured as its average order fill rate, i.e., the number of supplied goods divided by the number of ordered goods. The authors have observed that using trust based supplier selection, the robustness of the supply chain network increases.

2. THE SIMULATION FRAMEWORK

The simulation model is intended to be as general as possible. We consider a network consisting of nodes that are similar in the sense that each of them creates products, consumes components and has the same decision problems illustrated in Fig. 1. However, the specific products, components and applied decision algorithms can be different. This characterization of the nodes is based on the high level model of the Supply Chain Operations Reference (SCOR) and the supply chain planning matrix, see [3]. The dynamic nature of the network is also taken into consideration, i.e., nodes can enter and exit, choose different sources of materials, therefore changing the network structure.

As Fig. 1 shows, our model considers the higher strategic and tactical planning levels and does not include operational problems such as shop floor control. These long- or medium-term plans are more exposed to the uncertainties that are in the focus of our study. The strategic problems usually consider a one period planning horizon, oftentimes a year. This is then divided into shorter periods for the tactical decisions, where the horizon usually consists of multiple shorter periods, e.g., weeks. The main decisions considered in our model include capacity investment, supplier selection (including single and dual sourcing), transportation modes (e.g., air, water, land), Make-to-Stock (MTS) or Make-to-Order (MTO) production, pricing, quality control, order management, inventory control and procurement decisions. It is assumed that these decisions are made sequentially and not simultaneously, which is often the case in the practice. This is also true along the supply chains, where it is common to assume Stackelberg-games, i.e., when the leader decides first, then the follower reacts. The two strategic tasks indicated in the figure with red color are the ones we have started to implement and study first.

Most decision problems have the minimal cost or the maximal profit as their objective. But besides cost, there are usually multiple important criteria that are considered in practice, such as resource utilization. We consider three types of Key Performance Indicators (KPIs) that cover the most important aspects of the performance. The first type includes *financial* indicators, such as profit and total cost, which describe the economic sustainability. The second type is related to the *manufacturing efficiency*, e.g., the Overall Equipment Effectiveness (OEE). The last type measures *supply chain related* indicators, including service level, item fill rate, inventory turnover and lead time between order placement and delivery.

The description of the network is based on data generally available in Enterprise Information Systems (EIS). The first type of the data consists of information about the resources, i.e., the network nodes. These include for example the location of the nodes, their capabilities, costs and available transportation modes. The second type is related to the materials, including bills-of-materials (BOMs), demand forecasts, inventories and prices. The third type describes the process, such as the production times and costs. Finally, the fourth type is related to the operations, e.g., the realized demand or the purchase orders.

The simulation includes uncertainties in form of stochastic variables such as demand, component quality, production and transportation times, material and transportation prices. Besides, it also allows to generate sudden disturbances like perished shipments, resource outage and other unexpected events.

Fig. 2 shows an overview of the system architecture. The network model is given in an SQLite database which represents the different information systems containing the available data. The simulation model is automatically built, which then provides the run-time behavior of the network, including disturbances. The decision making functions are implemented separately, in a modular way. This enables the customization of the simulated system and also facilitates

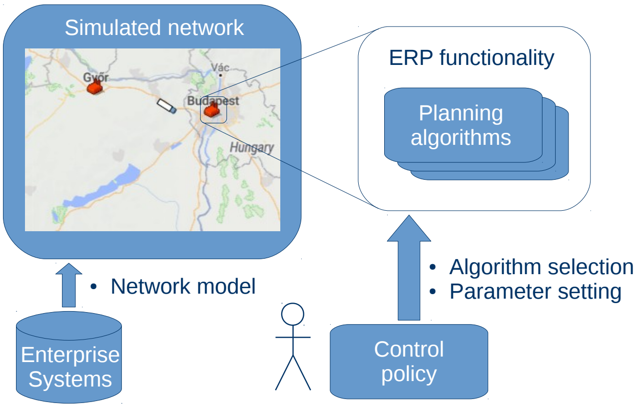

Figure 2: Overview of the architecture.

changing, analyzing and comparing different planning and optimization rules. This way it can be used to find trade-offs between different KPIs, such as cost and service level.

The simulations help to visualize and evaluate the consequences of the decisions in the network, and to analyze typical scenarios, such as a new product introduction. The simulation system is being developed with the AnyLogic tool [13], which provides the possibility of applying any optimization algorithms implemented in the Java language.

3. SUPPLIER SELECTION AND PRICING PROBLEMS

In the following the notations for the formal decision problems are introduced. The models are assumed to be deterministic, but in the simulation most of the parameters can be randomized in order to investigate the impact of the different kinds of uncertainties. Furthermore, since this study focuses on two strategic level decision problems, we omit the parts of the model that are not required for these tasks, such as the time-dependent prices and the transportation modes. We also simplify our trust model for this study.

Let N_i $(i = 1..n)$ denote the nodes in the network and ρ_{ij} is the distance between N_i and N_j. The transportation cost between N_i and N_j is $\rho_{ij}C^{(t)}$. The transportation mode and quality level (Q_i) are considered to be already given, since these optimization problems are ignored here.

The materials are denoted by M_k $(k = 1..m)$. The production portfolio is described by Y_{ik}, which equals 1 if N_i produces M_k, otherwise 0. The relationship between the materials is described by the BOMs: B_{kl} is the number of M_l directly required for producing one unit of M_k. The same material can be viewed as a product and as a component by different nodes of the supply network (see Fig. 1). Unit price of M_k at N_i (as the supplier) is P_{ik}. The $C^{(p)}_{ik}$ is the unit production cost of M_k at N_i. In this study we assume MTO production throughout the network, therefore we omit the input (components) and output (products) inventories from this description. The time required for the production of one unit of M_k is $T^{(p)}_k$.

For each required component one or more supplier(s) should be selected. Let Z_{ijk} denote the ratio of the component demand for M_k that N_j orders from N_i. The total demand for a component should be divided among its selected suppliers, i.e., $\forall j, k : \sum_{i=1}^{n} Z_{ijk} = 1$. This way a node can decide that a component should be supplied by only one supplier (single sourcing), two suppliers with 50%-50% share, or any other possibility. The set of the selected suppliers is called the *supplier basis* of the node. For each supplier in the basis a $C^{(b)}$ one time cost occurs that can represent the cost for building the connection between the nodes, e.g., sharing product designs or connecting data interfaces.

The demand of M_k at N_i at time t is modeled with the isoelastic function $D_{ikt} = D_k P_{ik}^{-r_k}$, where $r_k > 1$ is the price elasticity and D_k is the maximum demand of M_k.

The supplier selection is based on the cost of the purchase and the trust towards the suppliers. The cost consists of the distance-based transportation cost and the price paid for the components[1]. This latter assumes already known unit prices of the components, i.e., the suppliers should decide about the prices first. However, the demand for the components can only be estimated without the knowledge of any downstream pricing or supplier selection decisions. The trust is considered in a simplified way for this study: if the node does not trust in the suppliers, it chooses the dual sourcing strategy instead of the single one.

The pricing decision depends on whether the product has a market demand or used as a component for another product. In case of a market product, the profit—disregarding the constant transportation costs—is $D_{ikt}(P_{ik} - C^{(p)}_{ik} - C^{(a)})$, where $C^{(a)}$ denotes the total value of the consumed components determined by the previous supplier selection. Using the isoelastic demand function, the optimal price can be derived and is given by $P^*_{ik} = r_k(C^{(p)}_{ik} + C^{(a)})/(r_k - 1)$. In case of pricing a component, the demand should be estimated in the same way as for the supplier selection problem. Then the price is determined that provides a desired percent of profit rate considering the estimated demand, the production price, the total value of the components and the total transportation cost.

4. PRELIMINARY EXPERIMENTS

In the preliminary experimental study a simple network has been analyzed in order to evaluate the simulation framework. Only the supplier selection and the pricing decisions are included in the study, thus the other decisions are not implemented or only simple rules are applied, such as the lot-for-lot ordering policy. Five nodes are considered: one end product manufacturer and four component suppliers—two suppliers for both of the two components required for the product. Each material is produced only to orders, i.e., no inventories are included. The quality of the production in a node is considered to influence the production time: with probability Q_i the produced goods have acceptable quality, otherwise additional rework is needed increasing the production time.

[1]Note that in practice sometimes an even simpler rule is applied considering only the component prices.

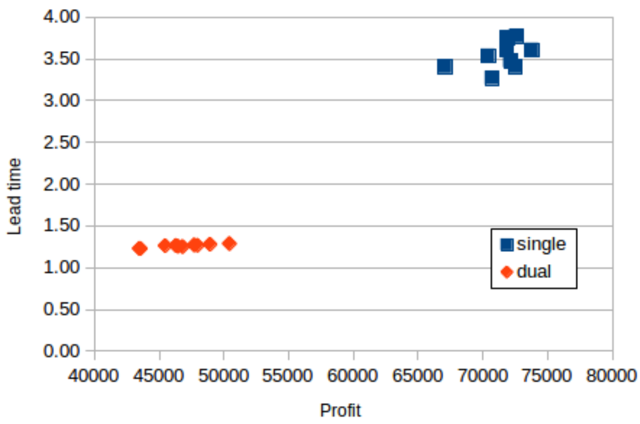

Figure 3: Performance using different sourcing strategies.

The trust is included in a straightforward way: the end product manufacturer either trusts the suppliers and has a single supplier for each component, or does not trust them and applies dual sourcing. In both cases the decision about the supplier basis depends on the estimated transportation and purchasing costs described in the previous section.

The KPIs considered are the average lead time—i.e., the time between receiving a customer order and satisfying it—and the total profit. Both indicators are computed during simulation runs over a one year horizon.

Fig. 3 illustrates the KPIs of the end product manufacturer during 20 runs, half of them using single, the other half dual sourcing strategies. The analysis shows the inversely proportional relationship between the costs and the lead times. Purchasing only from the most inexpensive suppliers results in lower costs, which leads to a lower product price, higher demand and eventually, higher profit. However, dual sourcing performs better regarding to the lead time: the lower component demand is further divided between the suppliers who work in parallel, thus the components are available more quickly reducing the lead time. The simulations support human decision makers to estimate the effects of their decisions on the KPIs, which is even more important when multiple complex decision problems are considered and the performance of the network is hard to be analyzed exactly.

5. CONCLUSION AND FUTURE WORK

The paper reports an ongoing work of developing a simulation framework for analyzing the robustness of production networks. The simulation model considers the common strategic and tactical decision problems at each node. Preliminary experiments are also demonstrated focusing on the supplier selection and the product pricing problems.

The next step of the development is to implement several basic decision making algorithms for each problem. The framework then will be used for evaluating these algorithms in different scenarios, e.g., new product introduction. Furthermore, by implementing simple contract types such as buyback or quantity discount, the effects of supply chain collaboration can be analyzed.

The simulation system will be also deployed at our experimental smart factory. That highly digitized production environment allows us to run simulations based on real data available from the Manufacturing Execution System (MES). The demonstration use case will enable analyzing the resilience and efficiency of the network consisting of the factory and its component suppliers.

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