Estonian Journal of Engineering, 2009, **15**, 1, 48–60 doi: 10.3176/eng.2009.1.05

Production planning for a supply chain in a low-volume and make-to-order manufacturing environment

Rein Küttner

Department of Machinery, Tallinn University of Technology, Ehitajate tee 5, 19086 Tallinn, Estonia; Rein.kyttner@ttu.ee

Received 22 September 2008, in revised form 30 January 2009

Abstract. Under the pressure of global competition, manufacturing firms are forced to continually improve production efficiency, product quality and delivery responsiveness. This study aims to develop a better understanding of the production planning problems for a supply chain for low-volume production in make-to-order environment. The objectives of this paper are to develop a generic framework for describing the strategic planning process for a supply chain and to model the propagation of uncertainty and variability in it. Focus is on the benchmarking of the performance of a supply chain, understanding the impact of different characteristics (including the sources of uncertainty and variability) to the planning of it and on possibilities of improving the performance of a supply chain.

Key words: supply chain planning, low-volume make-to-order production, two-stage optimal stochastic planning, Pareto-optimal solutions.

1. INTRODUCTION

No company alone possesses all the necessary resources needed to succeed in today's competitive global market. The challenges for production planning lie in managing of the network of cooperating enterprises (supply chain). The strategic role of effective production planning for a supply chain (SC) has been well recognized in recent years. Several researchers have addressed SC planning decisions by employing different optimization models [1,2]. Critical parameters of a SC such as customer demands, prices of products, process times, resource capacities, etc, are quite uncertain, and supply chain managers continually face the problems of efficient planning in a complex SC environment under uncertainty. Stochastic programming techniques are most suitable for planning in supply chain systems, because they address the issues of optimal decision-making under uncertainty and variability [3–8].

The supply chain structure can be viewed as a network of suppliers, manufacturing plants, transporters and customers, organized to acquire raw materials, to convert these raw materials to finished products and to distribute these products to customers.

To match the planning model more closely with the real situation, the problem of planning for a SC is recommended to be decomposed and to use a multi-level task structure. A natural response to the complexity of a supply chain is to manage various SC entities independently, i.e., to allow each entity to use local information and to implement locally optimal management polices. This approach can lead to an inefficient SC. To improve the performance, a coordination of the activities is needed.

It is obvious that hierarchical approach to planning activities raises different engineering problems, sharing of information and coordination of planning tasks of different levels. Each unit of a SC may have different resource arrangement to focus on one or more criteria of performance. There is a need to align the goal of each enterprise with the common objectives of the whole SC. This leads to the multilevel hierarchical optimization scheme.

- *On the lower level, the capacity planning for each enterprise*. We consider that each enterprise is autonomous to develop its resources and to make decisions about the efficiency of resource utilization. The capacity of each enterprise is optimized on the basis of production tasks and the average function of profit for the enterprise, which are determined on the upper level.
- *On the upper level, integrated manufacturing planning for a SC* in order to realize the best coordinated strategy for the whole SC, based on the capacities determined on the lower level.

The resource investment process on a lower level for the machine building industry is characterized by long lead times in investment costs. As a result, these decisions need to be made early, using uncertain long-term demand forecasts and average production system data. They are costly and difficult to change later on. Manufacturers need to be flexible so that they can effectively adapt to variable demands. Investing in resource flexibility is one of the strategies of prime importance in today’s competitive environment [4].

On the upper level, strategic level supply chain planning involves different decisions, with time horizons more than one (a half) year. In this work our focus is on:

1) *configuration decisions* (consider the number, capacity, and technology of the facilities),
2) *production decisions* (consider the aggregate quantities for purchasing, processing and distribution of products).

The intent of this paper is to develop a methodology for manufacturing planning for a SC, and to estimate how SC architecture, manufacturing capacity and variability of SC parameters influence SC performance in a low-volume and make-to-order manufacturing environment. The focus is on the theory of the development of multilevel hierarchical optimization schemes and on the issues of optimal manufacturing planning under uncertainty and variability.

2. MODELLING UNCERTAINTIES AND VARIABILITY IN A MANUFACTURING ENVIRONMENT

There are many sources of variability in a SC: variation of dimensions of parts (products), process times, machine failure/repair times, quality measures, set-up times, etc. According to the *variability law* [9] increasing variability always degrades the performance of a production system. It is essential that companies first understand the impact that external changes and variability have on their plans and competitiveness, and then proactively prepare themselves to thrive and grow in this new reality.

Manufacturing systems operate with different levels and diverse sources of variability in the production environment. From an analytical point of view, a SC is a network with the following sources of variability:

- supplier variability,
- manufacturing (product and manufacturing process) variability,
- demand variability.

Because there is no clear analytical way to estimate the influence of uncertainties and variability on a SC performance, firms have traditionally relied on experience and intuition in problem-solving.

2.1. Modelling the product variability

Product variety results in recurrent manufacturing process variations that are related to machine set-ups, cycle times, labour, etc. It is essential to limit the number of options of products and to minimize process variation using the coordination of the product and process variety from both design and production perspective.

We assume that in a production system products are relatively homogeneous and form families of similar products, with a variability of

- product structure,
- dimensions, materials and other features of products,
- volume of orders.

The concept of the generic bill of the material (GBOM) [10] has been used to describe the product families. GBOM is a structure, common to a set of similar products in a family; it represents multiple product elements, variety parameters and their value instances, and various relationships. The GBOM of a product family can be represented in the form of a tree (Fig. 1).

Martin and Ishii [11] developed a method of Design for Variety to estimate the influence of the variety of products on the manufacturing processes.

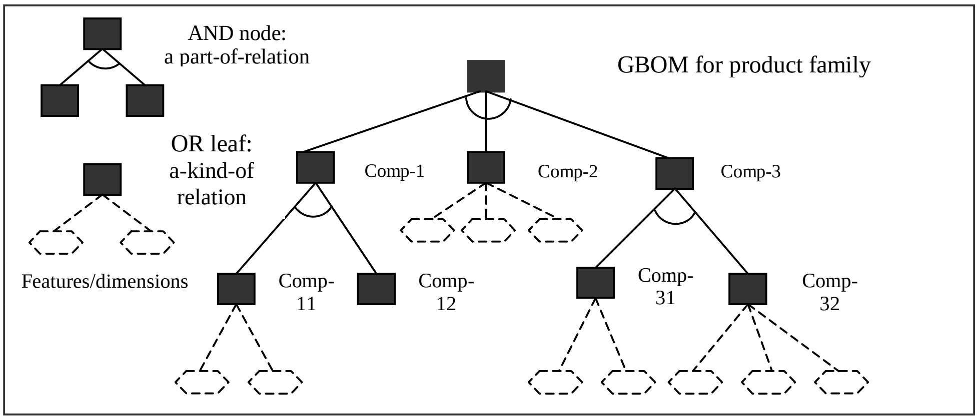


Fig. 1. The model of GBOM in the form of And-Or tree (for each OR leaf probabilities of its occurrence are given).

For each OR leaf, to simulate the variability, the random number generator for a discrete distribution with given probabilities of occurrence of alternative components or features is used.

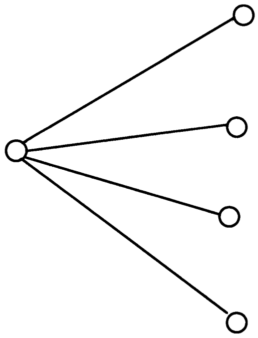
2.2. Modelling the process time variability

The process time, the actual time that is needed to manufacture a part or assemble the product, and consequently the workstation (WS) workload fluctuates as a result of product variety. Process time variability could be introduced in production systems through unequal processing times, random breakdowns of workstations, yield losses, etc. Usually, companies have some estimates for means and standard deviations of the work content of different products, based on historical data or on the analysis of the work content of workstations. To simulate the variability of the process time, the random number generator for normal distribution with a given mean and standard deviation is used.

2.3. Modelling the supply and demand variability

Enterprises are “demand driven”, meaning that, at least in theory, nothing happens until there is a customer order (or demand). In reality, everything must be planned in advance to be able to respond to the demand. Based on the forecast and plan, production facilities are set up, materials and components are staged and everything is ready to respond quickly.

To deal with the stochastic nature of demand and supply, we use the stochastic scenario trees (Fig. 2) [7,12]. Each scenario has some probability ω_i of the occurrence of the demand or supply parameter ξ, which can be an objective measure, derived by statistical information, forecasting methods or a subjective measure of likelihood. Scenarios can be the result of the discretization of a continuous probability distribution $f_p(\xi)$.



$$\xi \le p_1; \omega_1 = \int_{-\infty}^{p_1} f(\xi)\mathrm{d}\xi$$

$$\xi \le p_2; \omega_2 = \int_{p_1}^{p_2} f(\xi)\mathrm{d}\xi$$

$$\xi \le p_i; \omega_i = \int_{p_{i-1}}^{p_i} f(\xi)\mathrm{d}\xi$$

$$\xi \le p_n; \omega_n = \int_{p_n}^{+\infty} f(\xi)\mathrm{d}\xi$$

Fig. 2. Scenario tree for parameter selection, where p_i is the value of the parameter ξ and ω_i is the probability of occurrence of this parameter.

To simulate the variability of the demand and supply, the random number generator for discrete distribution with given probabilities of occurrence for each scenario is used.

3. OPTIMAL PRODUCTION PLANNING

3.1. Model for integrated optimal planning of a SC

In order to understand how different SCs work, we consider a simple, yet representative SC network $\Theta = (N, A)$ (Fig. 3), where N is the set of nodes and A is the set of arcs. The set N consists of the set of suppliers S, the set of manufacturing enterprises E and the set of customers C, i.e., $N = S \cup E \cup C$.

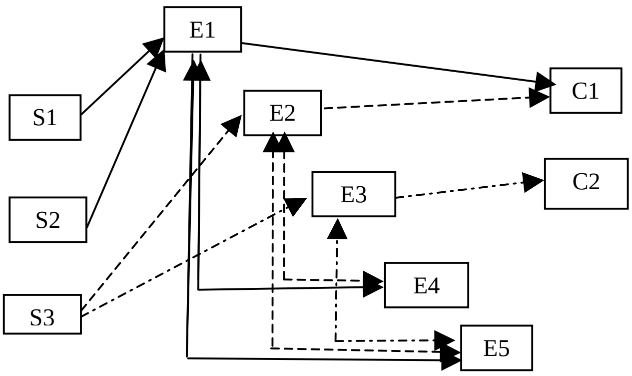


Fig. 3. Schema of a simple supply chain network, where S_i are suppliers, E_j are processing facilities, C_u are customers and arcs represent the material flows for different products.

The manufacturing enterprises $E_i(i=1,n)$ include different workstations (manufacturing centres) M and assembling facilities F, i.e., $E=M\cup F$. Components are purchased by different suppliers $S_j(j=1,m)$, and we suppose that there are different customers $C_u(u=1,l)$.

Let P be the set of products, flowing through the supply chain. We have k products $(p^1, p^2, \dots, p^k)$, which are assembled out of m components. To solve the planning task we need processing/purchasing times $a_{i,j}$ of each component of a GBOM at each enterprise and machining centre. The planning decisions consist of routing the flow of the product $p^k\in P$ from the supplier to the customers. By X_{ij}^k we denote the flow of the product p^k from the node i to the node j of the network, where $(ij)\in A$.

As the real manufacturing systems have stochastic nature and significant variability of parameters, it is necessary to have a mechanism for estimating the activities at each node of a SC in response to the variability in demand, the variability in process times, etc.

We use $\hat{\xi}=(\hat{d}_j,\hat{a}_{i,w})$ to represent the random data vector, while $\xi=(d_j,a_{i,w})$ stands for its particular realization. The resulting formulation (considering the variability of process times and demand as an example) leads to a conceptual planning framework that guides the selection of supply chain strategies seeking higher total profit [13]:

$$\text{Max } \Pi=\sum_{i=1}^{m}\sum_{j=1}^{k}(r_i\times X_i^k-X_{j,i})\times(M_i+c_j^k\times\hat{a}_{i,j})-\sum_{i=1}^{m}\sum_{w=1}^{v}Inv_w^i\times m_w^i,$$

subject to conditions:

1) $\sum_{i\in N}X_{ij}^K-\sum_{l\in N}X_{jl}^k=0;\forall j\in E;\forall k\in K,$ balance of material flow for each product and node;

2) $X_\delta^k\le\hat{d}_{k,\delta},$ random demand for all product variants k and customers δ;

3) $\sum_{i=1}^{m}\hat{a}_{iw}*X_i\le m_w\times F_w,$ for all machines w;

4) $\sum_{i=1}^{m}X_{i,u}\times M_i\le\mu_i,$ for all materials and components (suppliers) u;

5) $X_i\ge 0,$ for all ij,

where

Π	–	objective function, total profit;
r_i	–	revenue from one unit of the sold product p^i;
$\hat{a}_{i,j}$	–	stochastic time required for the processing product i on the machine j;
c_j^k	–	per-unit cost of the processing product k at the facility j (or transporting product k on arc (ij));
F_w	–	capacity of the processing unit (machine) w;
M_i,μ_i	–	cost and resource of the material i;
Inv_w^i	–	investment costs to implement the machine w in the enterprise i;
X_i	–	quantity of the products p_i, produced during the period analysed;

m_w – number of processing facilities (machines) for WS;
$\hat{d}_{k,\delta}$ – stochastic demand for the product k from the customer δ.

The possibilities of outsourcing of production are considered whenever the enterprise is incapable of satisfying the demand.

A prevalent approach for optimization under uncertainty is the multistage stochastic programming, which deals with problems involving a sequence of decisions, reacting to uncertainties that evolve over time [[1,12]]. At each stage, we make decisions based on currently available information, i.e., past observations, and decisions prior to the realization of future events. In our model, the two-staged stochastic optimization approach is used [[6–8]]. The first stage decisions, based on the estimation of an average situation, consist of the configuration decisions (capacity, numbers of machines m_w in enterprises). The second stage consists of product processing from suppliers to customers in an optimal use, based upon the given configuration and the realized uncertain scenario.

The objective of the first stage is to minimize the expected capacity investment costs $E[Q(m^i, \hat{\xi})]$ for each enterprise i.

The optimal value $Q(m, \xi)$ of the second stage problem is a function of the first stage decision variable and a realization (or a scenario) $\xi = (c_j, a_{i,w}, r_i, \mu_u)$ of uncertain parameters.

$E[Q(m, \hat{\xi})]$ is estimated as "a response surface or surrogate" model for solving the second stage problem and using, for example, the regression analysis. The expectations $E[Q(m^i, \hat{\xi})]$ are taken with respect to the probability distribution of $\hat{\xi} = (c_j, a_{i,w}, r_i, \mu_u)$.

We deal with the problem using the SAA (sample average approximation) scheme [[6]]. In the SAA scheme, a random sample $\xi^1, \dots, \xi^N$ of N realizations (scenarios) of the random vector $\hat{\xi}$ is generated (simulated), and the expectation $E[Q(m, \hat{\xi})]$ is approximated by the sample average. For a particular realization $\xi^1, \dots, \xi^N$ of the random sample, the problem is deterministic and can be solved by appropriate optimization techniques. Based on the proposed models, planning tasks are represented as an integer and combinatorial linear programming problems.

There is a potential source of difficulty in solving the proposed problem: an evaluation of the objective function $E[Q(m^i, \hat{\xi})]$ involves computing the expected value of the discrete value function $Q(m^i, \xi)$. This might involve solving a large number of linear programming tasks of the second-stage problem, one for each scenario of the uncertain problem parameter realization. For example, as a result, we have for E_2 the function for estimating $E[Q(m^2, \hat{\xi})]$:

$$E[Q(m^2, \hat{\xi})] = a_0^2 + a_1^2 \times m_{21} + \dots + a_n^2 \times m_{2,n} = 987.1 - 100\,m_{21} - 100\,m_{22} - 20\,m_{23}.$$

The tool for identifying effective and robust policies in the face of variability and randomness is statistical simulation combined with multiple sources of variability. In Figs. 4 and 5 some examples of the variability of decisions are presented.

To manage the production in the presence of variability, enterprises use different approaches: keep a little extra material (so called "safety stocks"),

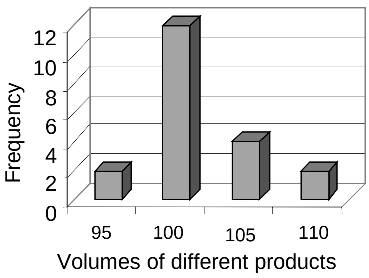


Fig. 4. Distribution of production volumes E_1.

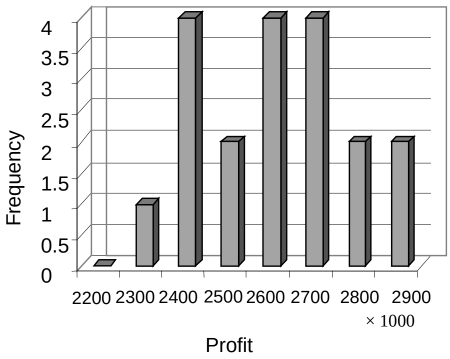


Fig. 5. Distribution of total profit.

improve machine reliability, speed up equipment repair, use shorter set-ups, minimize operator outages, etc. Many of the potential savings come from the "tuning" process, adjusting the SC for a better performance.

Analytical techniques and simulation can help to estimate the influence of different sources of variability, to determine the robustness of planning decisions and to tune a supply chain. Pooling variability is, for example, one strategy to reduce the effect of the variability and to increase the robustness of decisions. Considering the *variability pooling* [[9]], one may expect a less variable demand for products from several customers than from any single customer. An analogous effect is encountered with the subcontracting of production between different enterprises (Fig. 6), etc.

In our academic example, about 99% of acceptance of the total customer demand was received (with a minimal capacity of enterprises determined from the capacity planning task, see Section 2.2.). According to the Pareto-optimal decisions, implementing three additional machines, we can receive 100% of acceptance of the possible product demand.

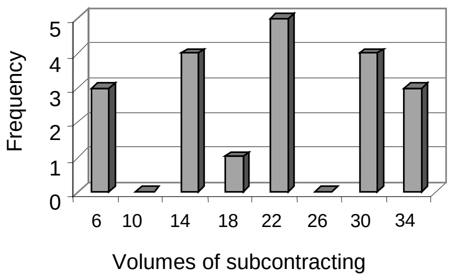


Fig. 6. Distribution of volumes of subcontracting.

One possible way to "tune the variability" is to allow a possibility of increasing the acceptable time for workstations via the use of overtime. For instance, in our example, to satisfy a minimum demand the overtime is not needed; for average demand about 143 hours and maximum demand about 311 hours of overtime is needed. An analogous situation is also related to the use of extra orders for materials and components, in addition to the average volumes of orders specified at the beginning of the planning period.

In order to create an environment for cooperative behaviour, it is recommended to conduct negotiations between enterprises for the development of the SC performance, based on additional performance measures of enterprises. To choose different measures of performance for different enterprises of a SC, it is useful to estimate them. We define, for example, three key performance indicators to measure the efficiency of performance for any enterprise [9]:

- throughput TH efficiency E_{TH} in terms of whether the output is adequate to satisfy the demand, $E_{TH} = \dfrac{\min(TH, D)}{D}$, where D is the average demand rate for a product;
- utilization efficiency E_u is the fraction of time the workstations are busy, $E_u = \dfrac{1}{n}\sum_{i=1}^{n}\dfrac{TH(i)}{r^*(i)}$, where $r^*(i)$ is the ideal rate of the workstation i (not including detractors);
- cycle time efficiency E_{CT} as the ratio of the best possible cycle time to the actual cycle time, $E_{CT} = \dfrac{T_0^*}{CT}$, where T_0^* is the raw process time (not including detractors).

Performance of an ideal manufacturing system requires that all efficiency measures are equal to 1.0. For real enterprises the efficiency measures are less than 1.0.

Data used in our academic example are shown in Table 1.

Table 1. Efficiency measures of different enterprises

Efficiency measures	E_1	E_2	E_3
	Enterprises		
E_{TH}	0.80	0.76	0.67
E_u	0.55	0.65	0.54
E_{CT}	0.69	0.56	0.85

3.2. Strategic capacity planning for enterprises

There are several issues to address the strategic capacity planning:

1) to what extent and when capacity should be added?
2) what type of capacity should be added?

We assume that a reasonable set of technology options can be generated and that cost, capacity and variability parameters can be estimated for each option.

To frame the capacity-planning problem at the plant level, we use the so-called "modern views of the role of capacity". The traditional view is based on the single question whether there is enough capacity to meet a manufacturing task, and the answer is either yes or no. A modern view is more realistic and consistent, providing that cycle times (CT) and work in process (WIP) levels grow continuously with an increasing capacity utilized (Figs. 7 and 8).

That means that for capacity planning we must consider other measures of performance in addition to the cost and processing times, e.g. WIP, mean CT, and CT variance, which are affected by capacity decisions.

The resulting formulation of a capacity planning task for an enterprise is a bi-criterial non-linear integer planning task: find the number of machines $m_1^i, m_2^i, \ldots, m_n^i$ for each enterprise i and for each workstation that will give

$$\text{Min}\begin{cases} E[Q(m^i,\xi)] = a_0^i + a_1^i \times m_1^i + a_2^i \times m_2^i + \ldots + a_n^i \times m_n^i, \\ \sum_{j=1}^{n} CT(m_j^i) = \sum_{j=1}^{n} \left(\dfrac{c_a^2 + c_e^2}{2}\right) \times \left(\dfrac{u^{\sqrt{2(m+1)}-1}}{m_j(1-u(m_j^i))}\right) \times t_e + t_e, \end{cases}$$

subject to constraints

$$u(m_W^i) = \frac{\sum_{j=1}^{n} X_j \times t_{e,j}}{m_w \times F_w} \le [u_w], \text{ for } w = 1, n,$$

$$m_{ji}^i \ge 0, \text{ and } m_j^i \text{ are integer for } j = 1, n.$$

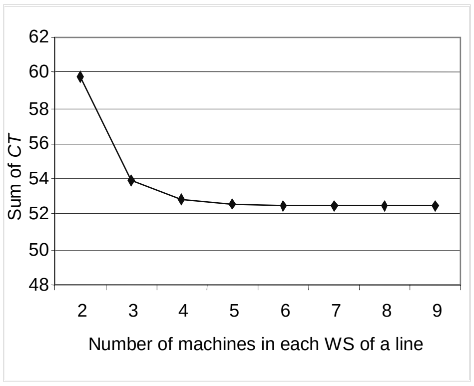


Fig. 7. Dependence of total CT of a line on the number of machines.

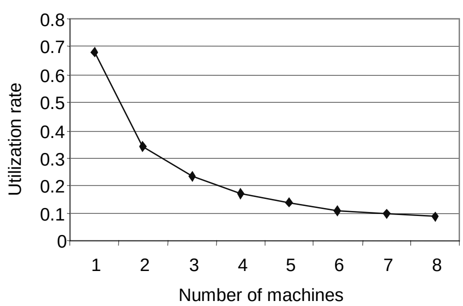


Fig. 8. Dependence of the utilization of a line on the number of machines.

Here t_{ei} is mean effective process time for a machine, including outages, set-ups, rework and other routine disruptions, c_e is effective coefficient of variation of the machining time, excluding gages, set-ups, rework and other routine disruptions, c_a is coefficient of variation of the time between arrival to a WS, F_w is resource of time for the WS_w and $[u_w]$ are recommended values of utilization of a WS.

The relative importance of the objectives is not generally known for the whole SC until the system's best performance is determined and the trade-off between the objectives is understood. The problem can be solved using the Pareto-optimal approach and estimating the Pareto-optimal curve (Pareto-front) [14] (Fig. 9). In Fig. 10 is represented, as an example, the optimal configuration of a technology line for main production and subcontracting.

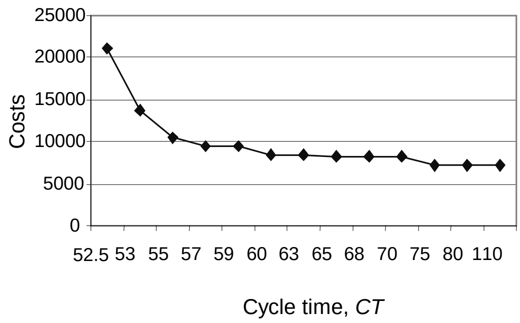


Fig. 9. Example of the Pareto-optimal curve for capacity costs and *CT* for enterprise E1.

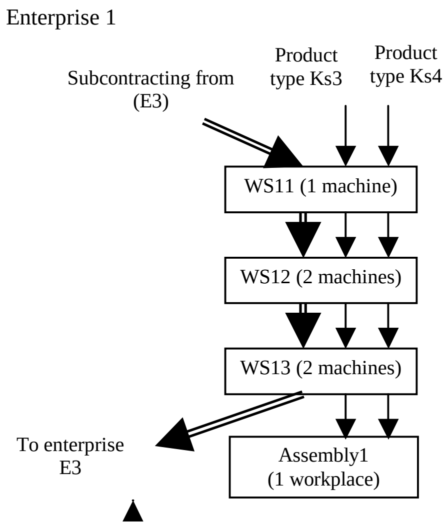


Fig. 10. Optimal configuration of enterprise 1.

4. CONCLUSIONS

New solutions, such as an integrated production system SC development, are to be used by companies that are producing complex products in the make-to-order production environment. Through cooperation between companies it is possible to achieve optimal resource allocation and to share technological resources to reach an optimal use of the resources for the whole SC.

In this study we have developed a model and a methodology for planning product manufacturing for a supply chain. Supply chain planners face a significant amount of uncertainty, particularly during the strategic planning phase. For a stochastic set-up we considered different variability and uncertainties. The proposed stochastic approach is based on statistical simulation and on the use of a sample of an average approximation scheme. The approach proposed is acceptable in the case of higher variability and multiple resources of uncertainty in the supply chain planning in the make-to-order environment. The bi-criterion optimization framework was implemented to obtain the trade-offs between responsiveness and economics of the capacity planning model.

REFERENCES

1. Sousa, R. T., Shah, N. and Papageorgiou, L. G. Supply chains of high-value low-volume products. In *Supply Chain Optimization*. Part II. (Papageorgiou, L. G. and Georgiadis, M. C., eds.). Wiley-VCH Verlag, 2008, 1–27.
2. Lapide, L. Supply chain planning optimization: just the facts. http://www.e-optimization.com/resources/amr/9805scsreport/9805scsstory1.htm
3. Dormer, A., Vazacopoulos, A., Verma, N. and Tipi, H. Modeling & solving stochastic programming problems in supply chain management using XPRESS-SP. In *Supply Chain Optimization* (Geunes, J. and Pardalos, P. M., eds.). Springer, 2005, 307–354.
4. Bish, E. K. Optimal investment strategies for flexible resources, considering pricing. In *Supply Chain Optimization* (Geunes, J. and Pardalos, P. M., eds.). Springer, 2005, 123–144.
5. Mo, Y. and Harison, T. P. A conceptual framework for robust supply chain design under demand uncertainty. In *Supply Chain Optimization* (Geunes, J. and Pardalos, P. M., eds.). Springer, 2005, 243–263.
6. Santoso, T., Ahmed, S., Goetschalcky, M. and Shapiro, A. A stochastic programming approach for supply chain network design under uncertainty. *Europ. J. Operat. Res.*, 2005, **167**, 96–115.
7. Alfiery, A. and Brandimarte, P. Stochastic programming models for manufacturing applications. In *Design of Advanced Manufacturing Systems. Models for Capacity Planning in Advanced Manufacturing Systems* (Matta, A. and Semeraro, Q., eds.). Springer, 2005, 73–119.
8. Shah, N. Process industry supply chain: advances and challenges. *Comput. Chem. Eng.*, 2005, **29**, 1225–1235.
9. Hopp, W. J. and Spearman, M. L. *Factory Physics*, 2nd ed. Irwin McGraw-Hill, 2001.
10. Tseng, M. M. and Jiao, J. Fundamental issues regarding developing product family architecture for mass customization. *Integrated Manufact. Syst.*, 2000, **11**, 469–483.
11. Martin, M. V. and Ishii, K. Design for variety: a methodology for development product platform architectures. In *Proc. 2000 ASME Design Engineering Technical Conferences DECT2000*. Atlanta, 2000.

12. Puigjaner, L. and Guillen-Gosalbez; G. Bridging the gap between production, finance, and risk in supply chain optimization. In *Supply Chain Optimization* Part I (Papageorgiou, L. G. and Georgiadis, M. C., eds.). Wiley-VCH Verlag, 2008, 1–44.
13. Küttner, R. Optimal planning of product mix for subcontracting companies. In *Proc. 4th International DAAAM Conference "Industrial Engineering"*. Tallinn, 2004, 249–252.
14. You, F. and Grossmann, I. E. Optimal design and operational planning of responsive process supply chains. *Supply Chain Optimization* Part I (Papageorgiou, L. G. and Georgiadis, M. C., eds.). Wiley-VCH Verlag, 2008, 107–134.

Tootmise planeerimine tarneahelatele tellimustele orienteeritud väikesemahulise tootmise tingimustes

Rein Küttner

On käsitletud tootmise optimaalset planeerimist ettevõtete koostöövõrgule (tarneahelale). Tootmise mudeli koostamisel arvestatakse tootmise sisendite muutlikkust, mis tingib stohhastilise planeerimise meetodite kasutamise. Planeerimise ülesannnet on käsitletud kahetasandilisena: tootmise planeerimine kogu tarneahelale ette antud ressursside tingimustes ja ressursside planeerimine igale ettevõttele. Ressursside planeerimise ülesannet on käsitletud mitme kriteeriumiga ülesandena. Kasutades täisarvulise mittelineaarse planeerimise mudelit, leitakse igale ettevõttele soovitatavatest lahenditest nn Pareto front. Kogu tarneahela tootmise optimeerimisel lähtutakse nendest soovitatavatest lahenditest. On hinnatud tootmissüsteemi sisendite muutlikkuse mõju tootmisele.