Simulation based Planning and Optimisation in Supply Chains: Application in ECLIPS Project

Galina Merkuryeva, Yuri Merkuryev*

Riga Technical University, Department of Modelling and Simulation,1. Kalku Street, Riga LV-1658, Latvia;
*merkur@itl.rtu.lv

Abstract. The paper presents simulation-based methodology to solving multi-echelon supply chain planning and optimisation problems. It is aimed to analyse an efficiency of a specific planning policy over the product life cycle within the entire supply chain and to optimise the cyclic planning policy at the product maturity phase. Software prototypes and applications are described in the paper. The presented research is funded by the ECLIPS Specific Targeted Research Project of the European Commission 'Extended Collaborative Integrated Life Cycle Supply Chain Planning System'.

Introduction

For the last decade, supply chain planning has become a critical factor in the success and profitability of an enterprise, especially given a global competition, rapidly changing markets and increasing customer expectations.

Supply chain planning can be defined as a process of coordinating and integrating key logistics activities, i.e. inventory management, production planning, warehousing, etc., from the procurement of raw materials through production to distribution of finished products to the end-customer with the goal to minimise total supply chain cost and maximise customer service level [2].

To manage supply chains, two different approaches are used [5] in practice. For years, researchers and practitioners have primarily investigated so called single echelon approach, where a stage or facility in the supply chain is managed. Recently, however, increasing attention has been placed on the performance, design, and analysis of the supply chain as a whole that allows optimising the global supply chain performance. Indeed, almost every product is produced in a chain of successive processes (either in different companies or different departments within the same company). A multi-echelon environment considers multiple processes (e.g. purchasing, production, picking and transportation) and multiple stock points (buffer or storage).

A variety of planning policies, which are grouped in non-cyclic and cyclic ones, can be used within a multiechelon approach. In cyclic planning, fixed processing (i.e. order, production or delivery) interval lengths are applied to all items, while non-cyclic planning assumes that interval lengths can vary over the planning horizon.

In practice, cyclic policies are more preferable for a multi-product and a multi-stock case, as they easier to control, and reducing administrative costs could reduce higher inventory costs [1]. However, when a customer demand is variable and uncertain, e.g. at the product introduction or end-of-life phases, flexibility in spacing of planning periods can result in lower total costs for the non-cyclic policy.

Simulation technology provides an experimental approach [5] to supply chain analysis and optimisation that allows the analyst easily to: 1) introduce into the multiechelon cyclic planning procedure variability of demand, lot sizes and processes lead times; 2) model processes that contain nonlinearities, combinatorial relationships and uncertainties; 3) take into account constraints at different echelons of the supply chain. Moreover, by building a virtual reality out of small components and not requiring a rigid structure of the analytical model, a simulation model provides the great flexibility that allows in the planning procedure: 1) validate different assumptions and planning decisions; 2) estimate consequences of planning decisions in time and by echelon; 3) perform a sensitivity analysis of parameters that influence optimality of the cyclic schedule; 4) define optimal planning parameter for each of supply chain nodes during the product maturity phase; and 5) analyse stability of the optimal production schedule under conditions of uncertain demand and finite capacity.

The ECLIPS Specific Targeted Research Project [13] is addressing both academic and business state-of-the-art in supply chain planning and management. Its abbreviation stands for 'Extended Collaborative Integrated Life Cycle Supply Chain Planning System'.

SNE Simulation Notes Europe – Print ISSN 2305-9974 | Online ISSN 2306-0271
SNE 21(1), 2011, 37-44 | doi: 10.11128/sne.21.tn.10045

The key research is multi-echelon supply chain planning for industries with batch and semi-batch processes on a tactical level spanning the full life cycle of the product. The project is aimed at minimization of total inventories through the whole supply chain, taking into account a product lifecycle, from its introduction into market, through a maturity phase, and finally to an end-of-life phase. In order to achieve this goal, simulation is used intensively in the ECLIPS project [6]. From one hand, it supports supply chain management processes (e.g., optimization and decision making), thus providing conditions for minimization of inventories. From another hand, simulation provides a platform for testing algorithms and tools, being developed within the project. The benefits of the project developments have been proved in practice in the environments of two industrial partners. The results, however, could be exploited to a wide range of industries, e.g., in manufacturing, wholesale and retail sale, and transport.

The project scope in the paper focuses on development of simulation-based methodology and tools for optimizing multi-echelon cyclic planning solutions for products at the maturity phase, and analysing cyclic and noncyclic planning policies over the product life cycle in order to prove in practice efficiency of a cyclic schedule or to switch from a cyclic planning policy to a non-cyclic one.

1 Simulation-based Multi-echelon Cyclic Planning and Optimization

Application of the MILP (Mixed Integer Linear Problem) analytical model in multi-echelon supply chain planning and optimisation is limited by assumptions of a constant demand, fixed set-up costs and lead times. These assumptions significantly decrease the complexity of the problem, but still are considered very useful for mature products [3]. In this context, simulation-based planning and optimization techniques are more flexible and do not require a rigid structure of the analytical model. They allow estimating consequences of different planning policies and decisions in time and by echelon; analysing stability of an optimal production schedule received from the MILP analytical model, and define optimal parameters of a multi-level cyclic schedule under conditions of uncertain demand and finite capacity [5].

In the paper, multi-echelon cyclic planning and optimisation at the product maturity phase is based on integration of analytical and simulation techniques [7]. Analytical formulas are used to obtain initial planning decisions under conditions of stochastic demand and constant or stochastic lead time. Simulation techniques extend these conditions to backlogging and capacity constraints. In this case, the multi-echelon cyclic planning problem is formulated as a simulation-based optimisation problem that is aimed to determine optimal parameters of cyclic schedules at different supply chain echelons.

1.1 Network Conceptual Model

The following are main assumptions that define the scope of a network simulation model: (1) Demand is considered to be uncertain, while predicting the demand mean value, its variations are estimated by a standard deviation of the demand per period; (2) Lead times of the processes are considered to be variable and/or stochastic; (3)

Lot sizes of the products are variable; (4) Capacities are limited; (5) Demand is considered to be independent only for customised products; (5) Backorders are delivered in full; (6) Fixed production and ordering costs, and linear inventory holding costs are assumed; (7) Planning is performed for a finite planning horizon.

A network simulation model [7] itself is built as process oriented model with a one-directional flow of goods. It is presented by two types of atomic elements: stock points and processes that are graphically represented by triangles and rectangles, correspondingly (see Figure 1). Any process with a stock point connected with a directed arc defines a stage. A set of stages that belong to the same network level creates an echelon. Input parameters, decision variables and constraints are assigned to atomic elements. The supply chain generic network is constructed from basic sub-networks, such as linear, convergent and divergent. The replenishment and delivery logic for each sub-network is defined.

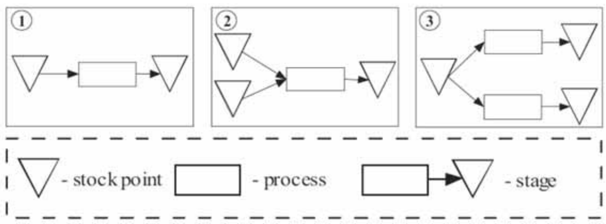

Figure 1. Basic sub-networks of the supply chain.

Average total cost of a cyclic schedule that includes a sum of set-up, ordering and inventory costs is defined as the main network model performance measure. However, in order to avoid unconstrained minimization of the total cost and satisfy customer service requirements, the average order fill rate is introduced as additional performance measure to be analysed in simulation optimisation experiments. It is defined as the percentage of endcustomer’s orders filled from the available inventory. As controllable variables, lengths of replenishment cycles and order-up-to-levels for stock points are defined in the network model. These variables determine the reorder period and quantity to be ordered or produced for each mature product in the network.

The main idea of a cyclic schedule is to use fixed order intervals at each stage or echelon while synchronizing these cycles in a multi-echelon supply chain to keep cycle inventory and order costs low. For that, additional cyclical replenishment constraints that define cyclic policy, e.g. power-of-two policy, are introduced.

1.2 Simulation Environment

The simulation environment for cyclic planning and optimisation is built in the ProModel simulation software [4]. It provides automatic generation of the simulation model of a generic network described in the Excel format by using the ProModel ActiveX technology; as well as definition of an initial point for simulation optimization using analytical calculus, and realization of the simulation-based optimization algorithm to find optimal parameters of a multi-echelon cyclic schedule and optimise network simulation model performance measures. Automation capability allows the program to automatically generate simulation models from external applications by using VBA programming language. The ActiveX-based VBA program developed in MS Excel consists of subroutines that provide ProModel operational control and allows accessing the model information, i.e. loading a blank simulation model; definition a title of the model, a path to a graphical library, an animation speed, the simulation length and number of replications; creating entities, locations of stock points and processes, path networks used to establish links between a stock and process points; creating arrays, variables, functions and procedures; and definition of entities arrival schedule, sequence of processes and their operational logic. The simulation environment for cyclic planning and optimisation includes [7] the following components presented in Figure 2:

1. Database component built in the Excel format that contains network and dataset subcomponents. The dataset subcomponent includes basic data about products, costs, capacities, time steps or period in the planning horizon and customer demand.
2. Procedural component by using analytical calculus generates cyclic schedules for different products and contains lot sizing procedures workable under conditions of time-varying demand.
3. Process component where the network is built up and simulated, cyclic schedules are modelled, inventory levels are controlled, and the network performance measures are estimated
4. Optimisation component to find optimal parameters of a multi-echelon cyclic schedule and optimize network simulation model performance measures.

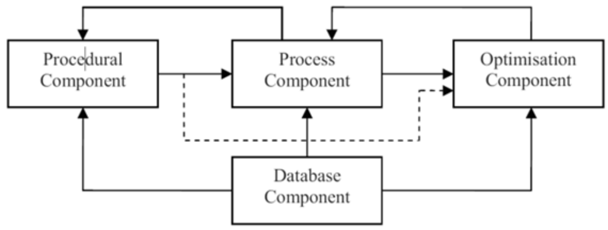

Figure 2. Basic components of simulation environment

Architecture of simulation-based environment, components structure and data exchange processes between these components are described in [8].

1.3 Simulation Optimisation

Within simulation-optimisation component the network simulation model is used in traditional way with a simulation optimiser in negative feedback. Variables controlled in the simulation model, i.e. lengths of replenishment cycles and order-up-to-levels for stock points, define multiple decision variables to be optimised in the problem.

The number of decision variables increases with the number of stock points. As a result, a large number of decision variables in practice could make conducting iterative optimisation experiments difficult. Moreover, two objective functions such the average total costs and the average order fill rate are associated to the network simulation model. As a result, optimisation of multi-echelon cyclic solutions leads to the multi-objective combinatorial optimisation problem. To solve the problem, the simulation-based optimisation algorithm based on the cooperative search of the multiobjective genetic algorithm (GA) and response surface-based method (RSM) is introduced [9]. While a GA is well suited to solve combinatorial problems and is used to guide the search towards the Pareto-optimal front, RSM-based linear search is appropriate to improve GA solutions based on the local search approach. Let us note that metric scales of decision variables have a very different range of possible values. During simulation experiments, 'order-up-to-levels' type variables are calibrated with a discrete step size.

Multi-objective genetic algorithm [12] is used to find optimal parameters of cyclic schedules, i.e. cycles and order-up-to levels, in each echelon of the supply chain. Starting with the initialisation of an initial population, the following steps are performed per loop iteration. First, the initial population of the pre-defined size is randomly generated and chromosomes are encoded with respect to power-of-two synchronisation policy. Afterwards, fitness values are assigned to population members using Pareto-ranking approach and discrete-event simulation model. Next, penalty function is applied to infeasible solutions in current population. In order to maintain a diverse population and prevent premature convergence, crowding distances of all chromosomes are calculated. The next step represents the mating selection, where individuals are chosen by means of crowded tournament selection.

Finally, after crossover and mutation the new population is replaced by the union of the best parents and mating pool individuals. The user-interface of the developed genetic algorithm is implemented in MS Excel using ActiveX controls.

RSM-based linear search is used [9] to improve cyclic planning solutions of the genetic algorithm by adjusting order-up-to levels that could result in decreasing the total cost and/or increasing the end-customers fill rate. The algorithm is based on local approximation of the simulation response surface by a regression type meta-model in a small region of independent factors and integrates linear search techniques for optimising stock points' orderup to levels. Finally, the Pareto-optimal front initially generated by the GA is updated including solutions found in RSM-based linear search procedure. Solutions received are reordered according to their fitness values in the increasing sequence.

Numerical example that illustrates simulation optimisation algorithm is given in section 4 of the paper.

2 Simulation-based Comparative Analysis of Cyclic and non-cyclic Policies

Evaluation of the difference between performance measures of cyclic and non-cyclic planning policies in supply chains gives possibilities to determine the most efficient planning policy at the product life cycle different phases, and provides a control mechanism for switching from one planning policy to another one. Simulation is defined as the most suitable technique to reveal significant parameters affecting the difference between costs of cyclic and non-cyclic schedules and to investigate the optimality gap [10] between performances of cyclic and non-cyclic planning policies in conditions of demand variability and uncertainty for switching to cyclic planning.

2.1 Simulation-based Methodology for Comparative Analysis

The following main factors that influence the difference between the cost of the cyclic policy and the cost of the non-cyclic policy are analysed in literature [1, 10]: coefficient of demand variation (CODVAR); capacity utilization; and number of planning periods. It is shown in that the coefficient of demand variation is the key factor affecting an additional cost of a cyclic schedule.

In general, the optimality gap is defined as a percentage or ratio measure to investigate how close a solution is to optimum. To measure the gap between performances of planning policies, usually the difference in their costs is expressed as percentage. For this purpose, ACCS performance measure (i.e. an Additional Cost of a Cyclic Schedule) that describes the gap between cyclic and non-cyclic solutions is used:

$$ACCS = \frac{Cyclic\,Solution\,Cost - Noncyclic\,Solution\,Cost}{NoncyclicSolutionCost}$$

Simulation-based scheme for comparative analysis of planning alternatives over the product life cycle is introduced [11] and presented in Figure 3. It allows estimating the difference between the total costs of cyclic and non-cyclic policies, analysing an additional cost of a cyclic schedule and making a decision about application of an appropriate policy. As input data, parameters of non-cyclic and cyclic policies are determined using either analytical calculus or simulation optimisation techniques.

Here, cycles and order-up-to levels are used as parameters of a cyclic planning policy, while a non-cyclic policy is defined by reorder points and order quantities per each supply chain echelon. For a cyclic planning policy the optimal parameters received from simulation optimisation component are used. Supply chain simulator model behaviour of alternative planning policies, and correspondent performance measures, i.e. the total costs mean values and correspondent ACCS values, are received from simulation experiments. Cost comparison for planning alternatives requires a careful analysis to ensure that the differences being observed are attributable to actual differences in their performances and not to statistical variations. This is done by analysing steady-state behaviour of the network simulation model, performing multiple simulation replications for each planning policy and comparing average results received from replications.

To determine the most efficient planning policy at a specific phase of the product life cycle, simulation-based switching algorithm is developed that contains the following phases: cost comparison for planning alternatives based on testing statistical hypotheses in the first phase, and ACCS analysis based on a set of supply chain parameters in the second phase. Cost comparison for alternative policies is based on estimation of the difference between their total costs mean values through simulation experiments by using the Paired-t confidence interval method. It is aimed to discover if two mean values are significantly different. Confidence level is defined at least at 95%. Two statistical hypotheses, i.e. the null hypothesis H0 and an alternative hypothesis H1, for making these comparisons are intro duced and tested. The null hypothesis supposes that there is no a significant difference between total costs mean values for two policies.

Let μ_{cyclic} and $\mu_{non\text{-}cyclic}$ define the true mean value of total costs for cyclic and non-cyclic policy, correspondingly, and $\mu_{cyclic} - \mu_{non\text{-}cyclic}$ *or* $\mu_{(cyclic\text{-}Non\text{-}cyclic)}$ defines the difference between mean values of total costs for two policies. In Paired-t notation these statistical hypotheses are formulated as follows: H0: $\mu_{(cyclic\text{-}Non\text{-}cyclic)} = 0$ and H1: $\mu_{(cyclic\text{-}Non\text{-}cyclic)} \neq 0$. While testing statistical hypotheses, it is supposed that simulation observations are independent, normally distributed and a number of observations received for two policies are equal. Based on testing of statistical hypotheses H0 and H1, the following conclusions are made.

If the Paired-t confidence interval excludes zero with a probability 1-7, then μ_{cyclic} is significantly different from the $\mu_{non\text{-}cyclic}$ with 7 significance level (Figure 4, position (b) and position (c)). In case of $\mu_{cyclic} < \mu_{non\text{-}cyclic}$ (Figure 4, position (c)) the cyclic planning policy outperforms non-cyclic one. Otherwise, if the Paired-t confidence interval includes zero (Figure 4, position (a)) with a probability 1-7, the null hypothesis H0 is failed to reject, and there is no a significant difference between the mean costs for two policies, i.e. μ_{cyclic} is not significantly different from the $\mu_{non\text{-}cyclic}$ with 7 significance level. In this case, the final decision is based on the ACCS analysis.

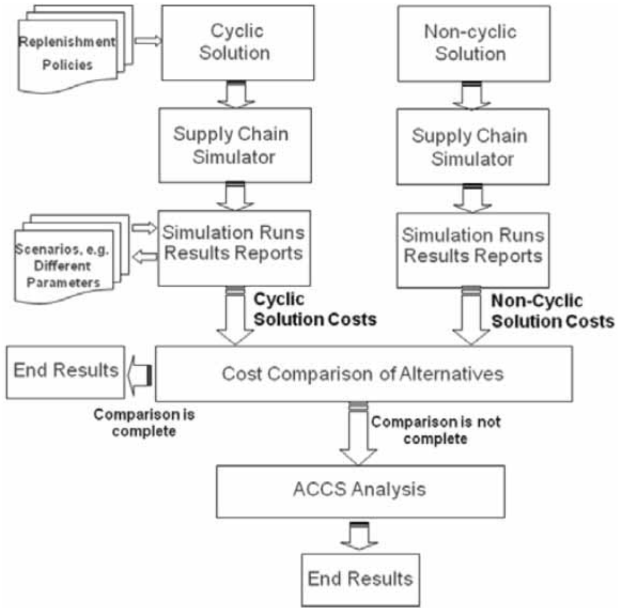

Figure 3. Comparative analysis of planning alternatives through simulation experiments

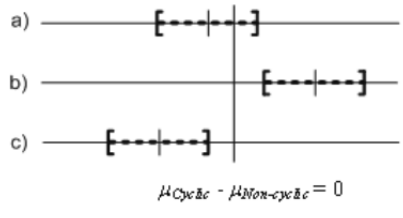

Figure 4. Hypotheses testing using Paired-t confidence intervals.

An additional cost of a cyclic schedule is estimated by the mean ACCS value. The width of the ACSS confidence interval is used to indicate accuracy of the ACCS estimate.

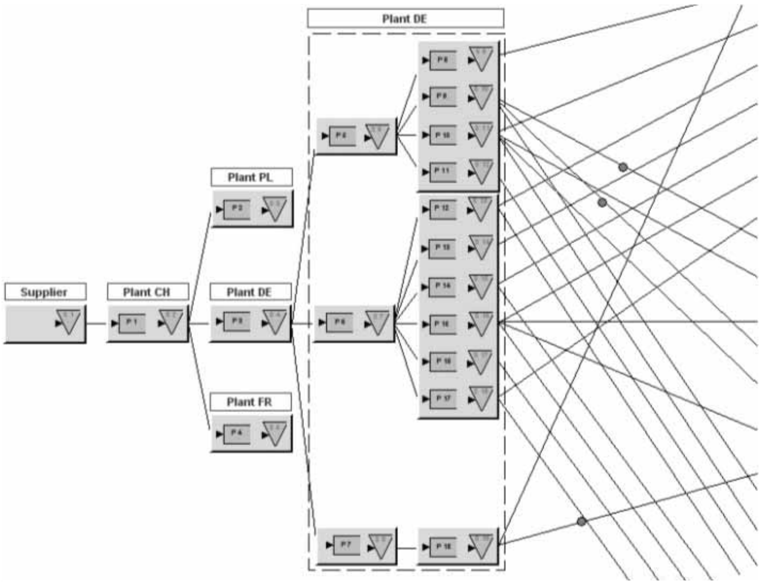

Figure 5. Simulation model screenshot

The mean ACCS value received from simulation experiments is compared with the critical one (or the maximum allowed) by using IF-THEN production rules. ACCS critical values are fixed by an application expert, refined within simulation-based analysis and used as a threshold for final decision making.

2.2 Software Prototype

The developed software prototype that allows analysing efficiency of planning policies and determining the switching from one planning policy to another is developed using ProModel, MS Excel and VBA integration possibilities. It includes the following main blocks:

- *Modelling & Simulation* module controls the input of initial parameters of the simulation model and planning policies; initialize the simulation model run within ProModel Software and export the output data from the simulation model to the MS Excel format. The network simulation model itself consists of three sub modules that simulate two alternative planning policies and estimate ACCS performance measure.
- *Switching Module* recognizes the switching moment from non-cyclic to cyclic policy by performing two types of analysis, i.e. Cost Comparison of planning alternatives by using Paired-t confidence interval method, and following ACCS analysis on a set of parameters.
- *Advanced Analysis* on a Parameter Set performs sensitivity analysis of parameters influences ACCS values; What-If Analysis and off-line gap investigation.

3 Application

The application itself is aimed to find an optimal cyclic plan of a chemical product, i.e. liquid based raisin, in order to minimise inventory holding, ordering and production costs, and maximise end-customers fill rate. As a test bed, the chemical manufacturing supply chain is used. The main operations occurred in the supply chain network are the following. In the plant CH (see, Figure 5), the raw material is converted to the liquid based raisin.

It is then either sourced to direct customers or shipped to the plant DE, where other components are added to make different products. From that plant, the end-products are shipped to different customers. The ProModel-based network simulation model is generated automatically using a simulation-based environment described in Section 2.2.

The end-customer demand is normally distributed; and cycles are defined according to the power-of-two policy. Cycles are presented in weeks as follows, 7, 14, 28, 56, where 56 days is the maximal cycle that corresponds to one full turn of a planning wheel. Initial stocks are equal to order-up-to levels plus average demand multiplied by cycle delays. Stock point 1 has infinite on hand stock and is not controlled by any policy. Backorders are delivered in full.

Simulation run length is equal to 224 periods. This allows modelling of four full turns of the planning wheel, i.e. 4*56 periods. Number of simulation replications is equal to 5. The GA is executed with the following parameters: the population size is 40; crossover and mutation probabilities are 0.5 and 0.1, correspondingly; a tournament size is equal to 2. The GA works with 66 decision variables assigned to network stock points. Initial values of order-up-to levels are calculated analytically. When the number of generations with a stagnant nondomination set is equal to 3, the GA is terminated.

Figure 6 shows solutions received from the final population that includes three non-dominated solutions with performance average measures 1) total cost = 787,431, fill rate = 100.00; 2) total cost = 766,669, fill rate = 98.88; and total cost = 752,300, fill rate = 93.76.

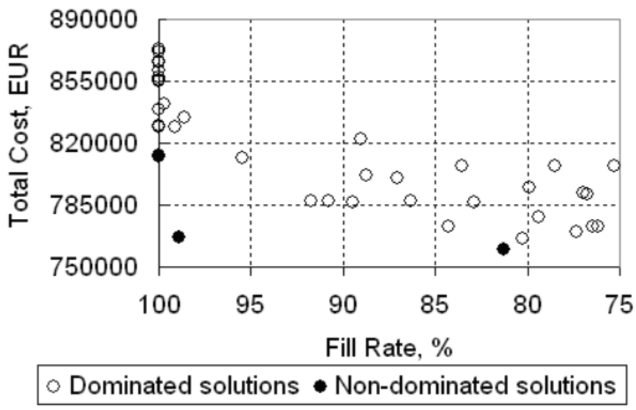

Figure 6. Final GA population mapped in the objective space.

RSM-based linear search algorithm is used to adjust order-up-to levels of three non-dominated solutions received with the GA while fixing stock points' cycles. The updated Pareto-optimal front contains three non-dominated solutions found by the GA, where the second solution is improved by the RSM-based linear search algorithm with the average total cost and average fill rate equal to EUR 756,178 and 98.88%, respectively.

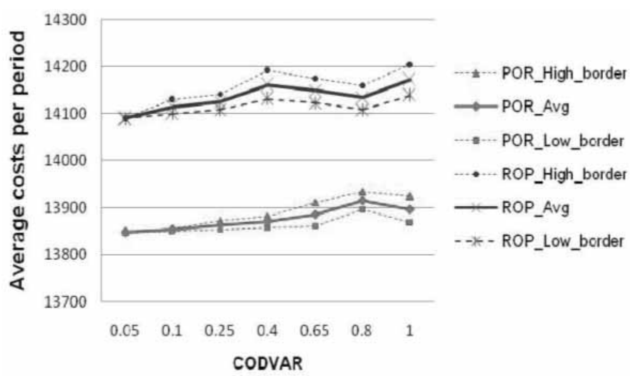

Figure 7. The average cost values per period as function of CODVAR.

The results of simulation-based analysis of performances of multi-echelon cyclic and non-cyclic planning policies are presented in Figure 7 and show that the average total cost per period and its confidence interval increase as demand variability CODVAR. Here, CODVAR coefficient is limited by 1.

Here, process lead times are assumed to be constant, and confidence intervals are estimated with 95% of confidence. The difference between total costs average values for cyclic and non-cyclic policies always stays negative and leads to conclusion that in this case the cyclic solution is more preferable then non-cyclic one.

4 Conclusions

The paper describes simulation-based methodology and tools for analysis and optimisation of planning policies over product life cycle within the entire supply chain. Simulation optimisation is used to define the optimal parameters of cyclic planning policies for mature products by integrating the multi-objective genetic algorithm and RSM-based linear search.

Simulation-based comparison analysis provides estimating the difference between the total costs of cyclic and non-cyclic policies, analysing an additional cost of a cyclic schedule and allows determining the most efficient planning policy at the product life cycle different phases, providing a control mechanism for switching from one planning policy to another one and finally improving the product life cycle management.

The application described and presented results demonstrate efficiency of the proposed methodology.

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Submitted: March, 2010
Accepted: December 10, 2010