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**Abstract**: The paper presents simulation-based methodology for analysis and optimisation of multi-echelon supply chain planning policies over the product life cycle. It is aimed to analyse an efficiency of a specific planning policy at the product life cycle phases and to optimise the cyclic planning policy at the product maturity phase. Specific 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".

*Keywords:* multi-echelon supply chain, discrete-event simulation, cyclic planning policies, simulation optimisation, genetic algorithm, response surface-based linear search.

## 1. INTRODUCTION

For the last years, 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 from the procurement of raw materials through production to distribution of finished products to the end-customer in order to minimise the total supply chain cost and maximise a customer service level.

There are two different approaches that can be applied to supply chain planning such as *single-echelon* and *multi-echelon* approaches (Merkuryev et al, 2007). The single-echelon approach splits multi-echelon supply chain into separate stages optimising each stage in isolation. In this case, stages account only for their immediate suppliers and customers. However, this approach does not guarantee that optimisation is achieved for the whole supply chain. Moreover, it can lead to suboptimal planning solutions. Nowadays, the multi-echelon approach has become more attractive than the single-echelon approach as it considers managing all the echelons in a holistic way and, thus, optimises the global supply chain performance (Merkuryeva and Napalkova, 2008). A variety of planning policies, which are grouped in *non-cyclic* and *cyclic* ones, can be used within multi-echelon 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 order to improve supply chain planning, an appropriate planning policy should be applied to each of the product life cycle phases, i.e. *introduction*, *maturity* and *end-of-life*. Introduction and end-of-life phases are typically characterised by customer demand variability and uncertainty. Here, non-cyclic policies that are more flexible than cyclic ones are preferable. In contrast to introduction and end-of-life phases, customer demand at the maturity phase is stable and predictable. Therefore, cyclic planning has more practical benefits at this phase, and could provide easy control, reduced administrative costs and safety stocks, and elimination of bullwhip effect (Campbell and Mabert 1991). Determining of necessity of switching between cyclic and non-cyclic planning policies, and optimising cyclic planning policies for mature products are main research objectives of the proposed paper.

This paper is organised as follows. Section 2 presents simulation-based analysis of the optimality gap between supply chain planning policies. The developed software prototype and an illustrative example are provided. Section 3 presents the simulation optimisation methodology and software for multi-echelon supply chain planning. An example that illustrates the methodology is given as well. Section 4 concludes the paper.

## 2. SIMULATION-BASED ANALYSIS OF PLANNING ALTERNATIVES OVER THE PRODUCT LIFE CYCLE

In practice, cyclic planning policies are preferable for a multi-product and a multi-location stock case, as they are easier to control, and reducing administrative costs could reduce higher inventory costs. However, when product demands are dynamic, e.g., in the introduction and end-of-life phases, flexibility in spacing of planning periods can result in lower total costs for the non-cyclic planning policy. Evaluation of the difference between the performance measures of cyclic and non-cyclic planning policies in supply chains gives possibilities to determine efficiency of a specific planning policy at the different phases of the product life and provides a control mechanism for the smooth switching between these planning policies. 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 between performances of cyclic and non-cyclic planning policies in conditions of demand variability and uncertainty.

### 2.1 Methodology

To measure the gap between performances of planning alternatives, the difference in their costs expressed as percentage is applied. For this purpose, ACCS (Additional Cost of a Cyclic Schedule) performance measure is used to describe the gap between cyclic and non-cyclic planning solutions, i.e.:

$$ACCS = \frac{Cyclic\ Solution\ Cost - Noncyclic\ Solution\ Cost}{Noncyclic\ Solution\ Cost} \quad (1)$$

Non-negative nature of this performance measure is proved in literature (Campbell and Mabert, 2008).

Simulation scheme for optimality gap evaluation (Merkuryeva and Vecherinska, 2008) and presented in Fig. 1. Here, cycles and order-up-to levels are used as parameters of cyclic planning policy, while non-cyclic policy is defined by reorder points and order quantities per each supply chain echelon. Simulation experiments are also applied to reveal significant parameters affecting the difference between total costs of cyclic and non-cyclic schedules.

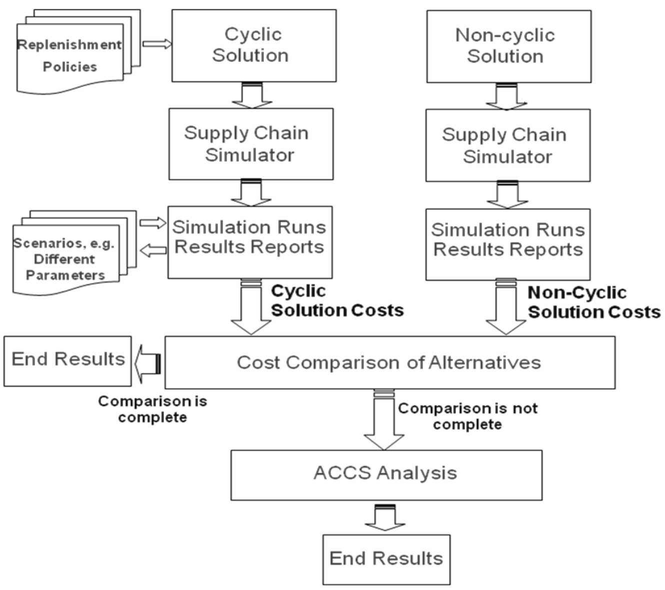


Fig. 1. Simulation-based optimality gap evaluation.

To determine the necessity of switching from one planning policy to another one, simulation-based two-phase algorithm is developed. It allows estimating the difference between the total costs of cyclic and non-cyclic policies and making a decision about application of an appropriate one. The algorithm contains the following phases: (i) cost comparison of planning alternatives based on testing statistical hypotheses in the first phase and (ii) ACCS analysis based on a set of parameters in the second phase. To test statistical hypotheses about the difference between total costs, the Paired-t confidence interval method is used. It is supposed that simulation observations are independent, normally distributed and a number of observations received for two policies are equal.

As input data, parameters of non-cyclic and cyclic policies are determined using either analytical calculus or simulation optimisation techniques. Performance measures of planning policies, i.e. the total costs mean values and correspondent ACCS values, are received from simulation experiments with a supply chain model. To estimate performance measures expected values, multiple observations are used, and the steady-state behaviour of the model is analysed.

#### 2.1.1 Cost comparison of planning alternatives

Cost comparison for planning alternatives is based on estimation of the difference between two mean values of the total costs by using the Paired-t confidence interval method. It is aimed to discover if these two mean total costs values are significantly different.

Two statistical hypotheses, the null hypothesis $\mathbf{H_0}$ and an alternative hypothesis $\mathbf{H_1}$ are formulated as follows:

- $\mathbf{H_0}$**:** $\mu_{Cyclic} - \mu_{Non\text{-}cyclic} = 0$ (or $\mu_{(Cyclic\text{-}Non\text{-}cyclic)} = 0$ for Paired-t notation).
- $\mathbf{H_1}$**:** $\mu_{Cyclic} - \mu_{Non\text{-}cyclic} \neq 0$ (or $\mu_{(Cyclic\text{-}Non\text{-}cyclic)} \neq 0$ for Paired-t notation).

Here, $\mu_{Cyclic}$ and $\mu_{Non\text{-}cyclic}$ define true mean value of total costs of each policy, and $\mu_{(Cyclic\text{-}Non\text{-}cyclic)}$ defines the difference between total costs mean values. Based on testing the above formulated statistical hypothesis, the following conclusions $\mathbf{C_0}$ or $\mathbf{C_1}$ are made.

$\mathbf{C_0}$**:** If the confidence interval includes zero, hypothesis $\mathbf{H_0}$ is failed to reject, and there is no a significant difference between the mean costs for two policies.

$\mathbf{C_1}$**:** If the confidence interval excludes zero, hypothesis $\mathbf{H_0}$ is rejected and $\mathbf{H_1}$ is assumed. There is a significant difference between policies' mean costs.

If the Paired-t confidence interval includes zero ($\mathbf{C_0}$) with a probability 1-$\alpha$, then $\mu_{Cyclic}$ is not significantly different from the $\mu_{Non\text{-}cyclic}$ with $\alpha$ significance level. This leads to a decision: not reject the cyclic policy as the most suitable one. Otherwise, $\mu_{Cyclic}$ is significantly different from the value of $\mu_{Non\text{-}cyclic}$ at $\alpha$ significance level (see $\mathbf{C_1}$). In case of $\mu_{Cyclic} < \mu_{Non\text{-}cyclic}$ cyclic planning policy outperforms non-cyclic one.

#### 2.1.2 ACCS Analysis

The final decision is made, based on ACCS analysis that is compared with its critical value $ACCS_{cr}$ by using IF-THEN production rules. Here, $ACCS_{cr}$ defines the maximum allowed ratio between two policies' average total costs difference and an average total cost of a non-cyclic policy. ACCS critical values assigned by an application expert and refined within simulation-based analysis are used as a threshold for making a final decision.

### 2.2 Software Prototype

The software prototype that allows analysing efficiency of planning policies and determining the switching moment from one policy to another is developed using ProModel, MS Excel and VBA integration possibilities (Fig. 2).

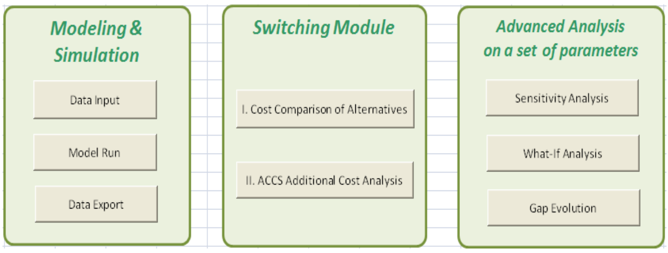


Fig. 2. The main window of the prototype.

The prototype includes the following main blocks:

1. *Modeling & Simulation* that controls inputs of the model parameters and policies; initialise ProModel-based model run; export simulation output data to the MS Excel.

2. *Switching Module* that recognises switching moment from one policy to another by performing cost comparison of planning alternatives and ACCS additional cost analysis.

3. *Advanced Analysis on a Set of Parameters* that provides sensitivity analysis of parameters influences ACCS values; What-If Analysis and off-line gap investigation.

### 2.3 Illustrative example

The results of simulation-based analysis for a generic network are presented in Fig. 3 and 4. Fig. 3 shows that the average cost per period and its confidence interval increase as demand variability CODVAR increases. Here, process lead times are assumed to be constant, and confidence intervals are estimated with 95% of confidence. The difference between costs of cyclic and non-cyclic policies always stays negative. Analysis of the ACCS results (see, Fig. 4) leads to conclusion that in this case the cyclic solution is more preferable then non-cyclic one.

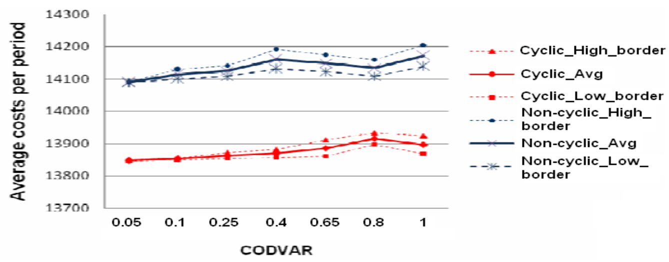


Fig. 3.The average cost value per period as a function of CODVAR.

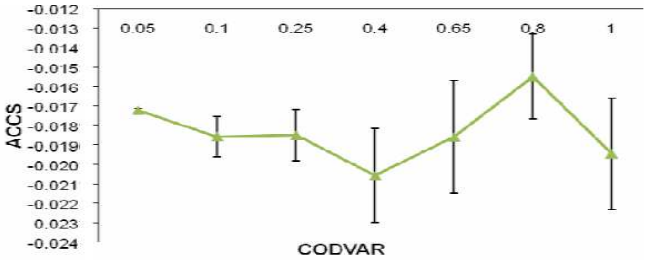


Fig. 4.The ACCS as a function of CODVAR.

## 3. SIMULATION-BASED CYCLIC PLANNING OPTIMISATION

Optimisation of multi-echelon cyclic planning policy at the product maturity phase is based on integration of analytical and simulation techniques. Analytical techniques 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. The multi-echelon cyclic planning problem is formulated as a simulation optimisation problem aimed to determine optimal parameters of cyclic schedules at different supply chain echelons.

### 3.1 Problem Statement

The simulation optimisation problem can be symbolically represented in compact form as:

$$\text{Min } E[\mathbf{f}(\mathbf{x})] = E[f_1(\mathbf{x}),\ldots, f_M(\mathbf{x})], \qquad (2)$$

subject to: $\mathbf{g}(\mathbf{x}) = E[\mathbf{r}(\mathbf{x})] \le 0$ and $\mathbf{h}(\mathbf{x}) \le 0$,

where $E[\cdot]$ is a mathematical expectation; $\mathbf{x} = (x_1,\ldots x_K) \in X$, $\mathbf{f} = (f_1,\ldots,f_M) \in Z$; $K$ is a number of decision variables; $M$ is a number of objective functions; $X$ is the decision space; $Z$ is the objective space; $\mathbf{x}$ is a vector of decision variables; $\mathbf{f}$ is a vector of objective functions; $\mathbf{g}$ is a vector of stochastic constraints; $\mathbf{h}$ is a vector of deterministic constraints on the decision variables; $\mathbf{r}$ is a random vector that represents several responses of the simulation model for a given $\mathbf{x}$. Proceeding from (2), the solution of multi-objective optimisation problem is a vector of decision variables $\mathbf{x}$ that satisfies all feasible constraints and provides the best trade-off between multiple objectives. To describe the objective vector function, one could use traditional methods of aggregating multiple objectives into a single objective. The main strength of this approach is a computational efficiency and simple implementation. The weakness is the difficulty to determine a value of the weights that reflect a relative importance of each criterion. Therefore, this paper applies the Pareto dominance concept for finding trade-off solutions.

The trade-off solution $\mathbf{x}^* \in X$ is said to be Pareto-optimal (or non-dominated) if there does not exist another $\mathbf{x} \in X$ such that $f_i(\mathbf{x}) \le f_i(\mathbf{x}^*)$ for all criterions $i = 1,\ldots,M$ and $f_j(\mathbf{x}) < f_j(\mathbf{x}^*)$ for at least one criterion $j$. Finding the Pareto-optimal set is a necessary condition for selecting trade-off solutions. Note that if some objective function $f_i$ is to be maximised, it is equivalent to minimise the function $-f_i$.

Regarding the problem of cyclic planning within multi-echelon supply chain environment, two objective functions are introduced. The first one is to minimise the average total cost represented by sum of inventory holding, production and ordering costs in accordance with the following equation:

$$\text{Min E}[TC] = \sum_{t=1}^{T}(\sum_{j=1}^{J} CP_{jt} + \sum_{i=1}^{I} CO_{it} + \sum_{i=1}^{I} CH_{it}), \quad (3)$$

where $TC$ denotes the total cost, $CP_{jt}$ denotes production cost in process $j$ per period $t$, $CO_{it}$ is ordering cost at stock point $i$ per period $t$, and $CH_{it}$ is inventory holding cost at stock point $i$ per period $t$; $I$ and $J$ correspond to the number of stock points and processes, and $T$ defines the number of periods in the planning horizon. The second objective function is to maximise customer service requirements specified by the order fill rate.

$$\text{Min E}[FR] = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{k=1}^{K} QC_{ikt} \Bigg/ \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{k=1}^{K} D_{kit}, \quad (4)$$

where $QC_{ikt}$ is a fraction of orders provided by stock point $i$ to end-customer $k$ in time period $t$, $D_{kit}$ is actual demand of end-customer $k$ to stock point $i$ in time period $t$. Controlled in optimisation experiments, the second performance measure is introduced to avoid unconstrained minimisation of the total cost. The decision variables are lengths of cycles and order-up-to levels, which are considered as discrete and continuous type variables, respectively.

The main idea of cyclic planning is to use cyclic schedules at each echelon and synchronise them with one-other to keep cycle inventory and total supply chain costs low. For that, additional cyclical constraints are introduced to define cyclic policy, e.g. power-of-two policy (Roundy, 1986).

## 3.2 Supply Chain 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) Capacities are finite; (4) Demand is considered to be independent only for customised products; (5) Full backlogging is allowed; (6) Planning is performed for a finite planning horizon.

A network simulation model 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 (see, Fig. 5). 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. The supply chain generic network is constructed from basic sub-networks, such as linear, convergent and divergent. The replenishment and delivery logic for sub-networks is defined.


Fig. 5. Basic elements of supply chain network model.

## 3.3 Simulation-Based Environment

The simulation-based environment for multi-echelon supply chain planning optimisation is built in the ProModel simulation software. It provides automatic generation of the simulation model of supply chain network described in the MS Excel format by using the ProModel ActiveX technology; as well as definition of an initial point for simulation optimisation using analytical calculus, and realisation of the simulation optimisation algorithm. The environment includes the following four components (Fig. 6):

1. *Database component* built in the MS 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 optimise network simulation model performance measures.

The simulation optimisation algorithm itself is based on integration of a multi-objective genetic algorithm (GA) and RSM-based linear search (Merkuryeva and Napalkova, 2008). 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.

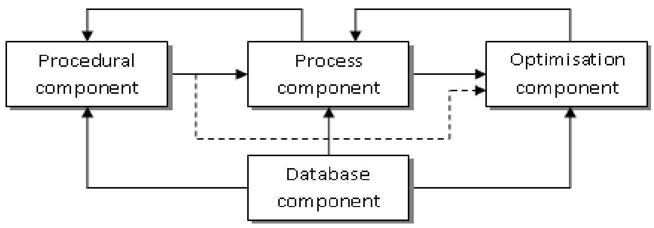


Fig. 6. Basic components of simulation-based environment.

## 3.4 Simulation Optimisation Algorithm

Here, multi-objective genetic algorithm 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 (Table 1). 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 (see, Fig. 9).

**Table 1. Main loop of the genetic algorithm**

| | |
|---|---|
| *Input:* | $N$ population size<br>$Z$ number of generations with a stagnant non-dominated set |
| *Output:* | $v_{TC}$ fill rate's lower bound<br>$X^*$ approximate Pareto-optimal set |
| *Step 1:* | *Initialisation*: Generate an initial population $P_N$. |
| *Step 2:* | *Solutions encoding*: Codify chromosomes using a modified binary encoding procedure, which allows satisfying power-of-two synchronisation policy. |
| *Step 3:* | *Fitness assignment*: Estimate total cost and fill rate for chromosomes in $P_N$ through discrete-event simulation, for which the replication number, length of a warm-up period and simulation length define. Calculate fitness values, i.e. domination depth $r_n$, of each chromosome $n$ using Pareto-ranking approach. |
| *Step 4:* | *Constraints handling*: Apply penalty function to chromosomes, which produce a fill rate below the pre-defined lower bound. |
| *Step 5:* | *Diversity preservation*: Calculate crowding distance $d_n$ of each chromosome $n$ in $P_N$. |
| *Step 6:* | *Selection*: Perform crowded tournament selection to fill the mating pool. |
| *Step 7:* | *Crossover and mutation*: Apply uniform crossover and one-point mutation operators to the mating pool. |
| *Step 8:* | *Elitism*: Use ($\mu + \lambda$) – selection to generate the new population. |
| *Step 9:* | *Termination*: If the pre-defined number $Z$ of generations with a stagnant non-dominated set is achieved, then Stop, else go to Step 3. |

RSM-based linear search is used 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' order-up-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.

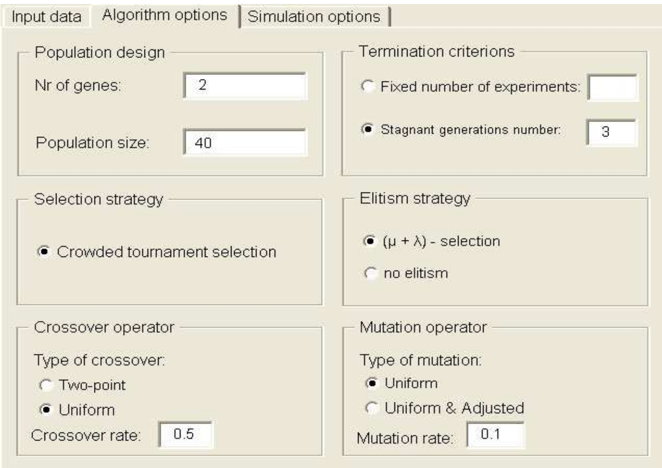


Fig. 7. Example of the GA interface.

3.5 Illustrative Example

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, Fig. 8), 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.

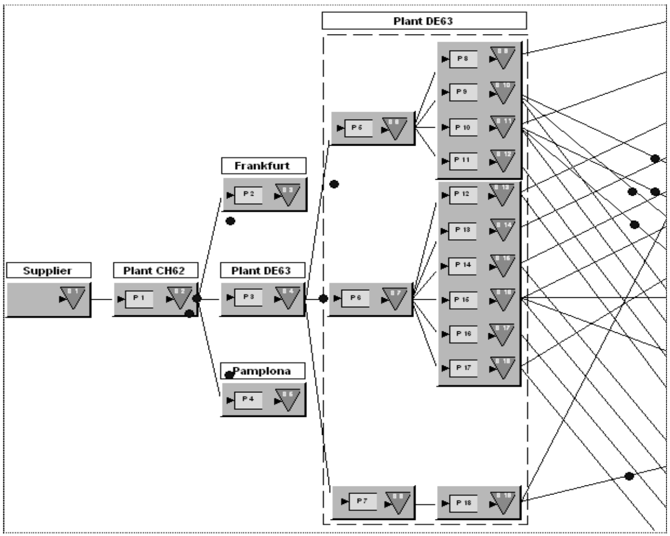


Fig. 8. Example of generated network simulation model.

The ProModel-based simulation model of the above-described supply chain network is generated automatically using a simulation-based environment presented in Section 3.3. 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 non-domination set is equal to 3, the GA is terminated. Fig. 9 shows solutions received from final population. Fig. 10 and 11 illustrate execution of the GA. The average total cost and fill rate of parent chromosomes are plotted against the generation step. The GA makes quick progress in the beginning of the evolution that is typical for genetic algorithms. Then, there are phases when it hits the local optimum before mutations further improve its performance. Finally, the GA finds 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.

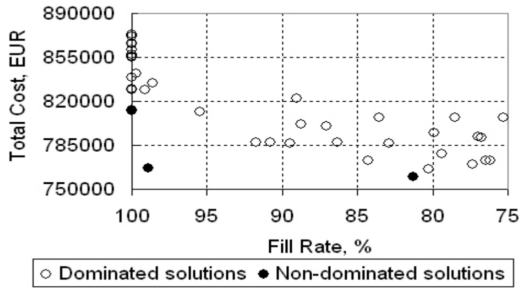


Fig. 9. Final GA population mapped in the objective space.

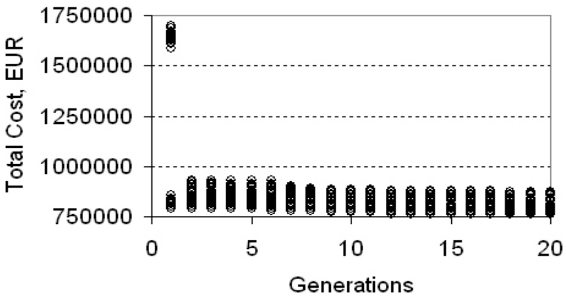


Fig. 10. The GA's convergence subject to total cost.

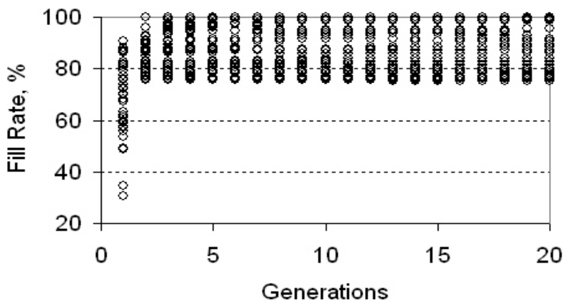


Fig. 11. The GA's convergence subject to fill rate.

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. Finally, the average total cost and average fill rate are equal to EUR 756,178 and 98.88%, respectively. The updated Pareto-optimal front is given in Fig. 12. There are three non-dominated solutions found by the GA, where the second solution is improved by the RSM-based linear search algorithm.

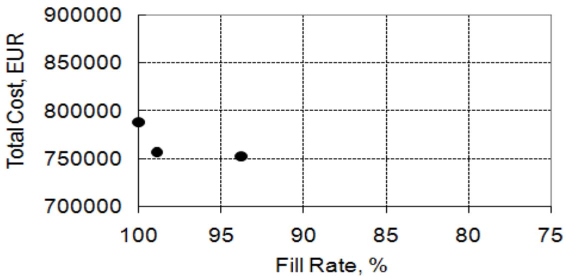


Fig. 12. The approximate Pareto-optimal front.

## 4. CONCLUSIONS

The paper describes simulation-based methodology for analysis and optimisation of planning policies over product life cycle within the entire supply chain. Simulation-based switching algorithm provides a control mechanism to switch between cyclic and non-cyclic planning policies and improve product life cycle management. Simulation optimisation is used to define the optimal parameters of cyclic planning policies for mature products by integrating the GA and RSM-based linear search. The achieved results clearly demonstrate the applicability and efficiency of the proposed methodology.

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