RIGA TECHNICAL UNIVERSITY

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# SIMULATION-BASED ANALYSIS OF SUPPLY CHAIN PLANNING METHODS OPTIMALITY UNDER UNCERTAINTY

**Summary of Doctoral Thesis**

**Rīga 2012**

**RIGA TECHNICAL UNIVERSITY**
Faculty of Computer Science and Information Technology
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# SIMULATION-BASED ANALYSIS OF SUPPLY CHAIN PLANNING METHODS OPTIMALITY UNDER UNCERTAINTY

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DOCTORAL THESIS
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DECLARATION

I hereby confirm that I have developed this thesis submitted for the doctoral degree at Riga Technical University. This thesis has not been submitted for the doctoral degree at any other university.

Olesja Vecherinska …………………………….(Signature)

Date: ………………………

The doctoral thesis is written in Latvian. It consists of introduction, 5 sections, conclusions, bibliography and 1 appendix. It includes 43 figures and 20 tables. The thesis is printed on 143 pages. The bibliography comprises 113 entries.

## GENERAL DESCRIPTION OF THE THESIS

### *Research motivation*

The topicality of the research is related to the priorities within supply chain management field raised in the European Commission 6th and 7th framework programmes. They cover moving from recourse-based approaches towards more knowledge-based ones and integration of European companies in global supply and distribution networks with the aim to serve regional markets efficiently and to achieve cost-optimal production and logistic processes in the future [29,30]. Fast globalisation of the European and world market leads to the deeper investigation of the global supply chain management issues. Furthermore, it is necessary to consider optimality in processes for each supply chain node. Effective planning of the supply chain is the possible solution to achieve proposed requirements.

Traditionally, cyclic and non-cyclic methods are used in the planning process of complex systems like supply chains. However, the utilisation conditions and optimality of the methods have not been thoroughly investigated in multi-echelon supply chains within product life cycle and under uncertainty. Simulation as a technique provides new opportunities for solving that problem. Furthermore, there is a lack of simulation-based procedure for optimality evaluation of supply chain planning methods in scientific literature. The aforementioned aspects emphasize the importance of:

- improvement of complex systems planning process within product life cycle and under uncertainty;
- extended analysis and choice of the planning methods, their optimality introduction and investigation;
- analysis of simulation utilisation in multi-echelon supply chain planning tasks.

### *The goal and the tasks of the thesis*

The thesis is aimed at developing simulation-based optimality evaluation procedure for multi-echelon supply chain planning methods under uncertain conditions. To achieve this goal, the following tasks are specified:

1. To analyse the utilisation of planning approach and methods in supply chains under uncertain conditions.
2. To investigate the essence of optimality gap within supply chain planning and management tasks.
3. To analyse general and simulation-based methods of alternative comparison.
4. To develop simulation-based supply chain planning procedure and switching algorithm within product life cycle.
5. To analyse input data modelling methods for supply chain planning tasks

solving, as well as determine factors that influence optimality of planning policies.
6. To apply the developed procedure in solving multi-echelon supply chain cyclic planning problem.

***The object and the subject of the research***

The object of the research is multi-echelon supply chain planning methods and policies used in the stochastic environment with customer nondeterministic demand as the main factor of uncertainty.

The subject of the research is the simulation-based comparison methods of planning policies and possibility of optimality estimation.

***Research methods***

The theoretical research is based on the analysis of scientific literature to investigate the preferences of supply chain planning policies and their comparison possibilities. Theoretical results are achieved using methods of inventory planning, mathematical statistics and probability theory. Supply chain cyclic and non-cyclic planning methods and discrete-event simulation are used within practical research realisation.

***Scientific novelty***

The scientific novelty of the thesis is as follows:

1. Optimality evaluation procedure is developed. It is aimed at analysis of multi-echelon supply chain planning methods in stochastic environment. Initially, optimality interval utilisation is analysed within the areas of information technology and supply chain management.
2. Simulation-based switching algorithm for supply chain planning methods based on their comparison is developed. It is applied in real supply chain planning problem and allows smooth switching from one planning policy to another within product life cycle.
3. The production rules that determine conformable planning policy are generated, according to the results of optimality estimation procedure.

In parallel with the main scientific novelty after analysing and solving the gaps determined during research, other scientific outcomes are as follows:

1. Modelling methods of stochastic demand are investigated to work with a wide range of demand variability.
2. Simulation-based methods of statistical comparison of alternatives based on confidence intervals are analysed.
3. Sensitivity analysis of the factors influencing supply chain performance measures is performed to run simulation experiments and create production rules.

***Practical value***

Simulation-based optimality evaluation procedure for multi-echelon supply chain planning methods is developed and supports the algorithm of the switching moment determination. The algorithm execution allows improving of supply chain planning process.

The developed procedure is applied in business case study in order to determine a switching point between planning methods after maturity phase of the product life cycle has started.

***Approbation of the obtained results***

The results of the thesis have been presented at ***eight international scientific conferences***:

1. International Conference "*12th International Conference on Computer Modelling and Simulation*" (UKsim'2010), Cambridge, Great Britain, March 24-26, 2010.
2. International Conference "*1st International Conference on Intelligent Systems, Modelling and Simulation*" (ISMS'2010), Liverpool, Great Britain, January 27-29, 2010.
3. RTU 50th International Scientific Conference, Section "*Information Technology and Management Science*", Riga, Latvia, October 12-16, 2009.
4. International Conference "*7th WSEAS International Conference on System Science and Simulation in Engineering*" (ICOSSSE'2008), Venice, Italy, November 21-23, 2008.
5. RTU 49th International Scientific Conference, Section "*Information Technology and Management Science*", Riga, Latvia, October 13-15, 2008.
6. International Conference "*10th International Conference on Computer Modelling and Simulation*" (EUROSIM/UKsim'2008), Cambridge, Great Britain, April 1-3, 2008.
7. RTU 48th International Scientific Conference, Section "*Information Technology and Management Science*", Riga, Latvia, October 11-13, 2007.
8. International Conference "*6th International Conference on Production Engineering*" (PE'2008). Wroclaw, Poland, December 7-8, 2006.

The results have been reported in eight scientific papers in scientific proceedings of international conferences:

1. Merkuryeva, G., Vecherinska, O. Simulation-based Comparison: An Overview and Case Study// The 12th International Conference on Computer Modelling and Simulation (UKsim'2010). – Los Alamitos:

IEEE Conference Publication Service, March 24-26, 2010. – p.186-190 (IEEE CS Digital Library, Scopus, Compendex).

2. Merkuryeva, G., Vecherinska, O. Randomness modelling in supply chain simulation// The 1st International Conference on Intelligent Systems, Modelling and Simulation (ISMS'2010). – Los Alamitos: IEEE Conference Publication Service, January 27-29, 2010. – p.128-133 (IEEE CS Digital Library, Scopus, Compendex).
3. Merkuryeva, G., Vecherinska, O., Hatem, J. Statistical input data analysis for supply chain simulation// RTU 50$^{th}$ International Scientific Conference. – Riga: Publishing House of RTU, October 12-16, 2009. – p.33.-38 (EBSCO, CSA/ProQuest, VINITI RAN).
4. Merkuryeva, G., Napalkova, L., Vecherinska, O. Simulation-Based Analysis and Optimisation of Planning Policies over the Product Life Cycle within the Entire Supply Chain// The 13th IFAC Symposium on Information Control Problems in Manufacturing. – Oxford: "IFAC Publishers", June 3-5, 2009. – p.580-585 IFAC-PapersOnLine.
5. Merkuryeva, G., Vecherinska, O. Development of Simulation-Based Switching Algorithm for Inventory Management in Multi-Echelon Supply Chain// The 7th WSEAS International Conference on System Science and Simulation in Engineering. – Venice: WSEAS Press, November 21-23, 2008.– p.399-404.
6. Merkuryeva, G., Vecherinska, O. Simulation-Based Approach for Comparison of (s, Q) and (R, S) Replenishment Policies Utilization Efficiency in Multi-echelon Supply Chains// The 10th International Conference on Computer Modelling and Simulation (EUROSIM/UKSim'2008). – Cambridge: IEEE Computer Society, April 1-3, 2008. – p.434-440 (Scopus, Compendex, CS Digital Library).
7. Merkuryeva, G., Vecherinska, O. Simulation-based Analysis of Optimality Gap Between Replenishment Policies in Supply Chains// RTU 48$^{th}$ International Scientific Conference. – Riga: Publishing House of RTU, October 11-13, 2007. – p.41-49 (EBSCO, CSA/ProQuest, VINITI RAN).
8. Merkuryeva, G., Timmermans, S., Vecherinska, O. Evaluating the 'Optimality Gap' between Cyclic and Non-cyclic Planning Policies in Supply Chains// The 6th International Conference on Production Engineering (PE'2006). – Wroclaw: Publishing House of Wroclaw University of Technology, December 7-8, 2006. – p.155-162 (CiteSeerX).

The obtained results have been utilised within the following research projects:

1) *Specific targeted research project NMP2-CT-2006-032378 ECLIPS* "*Extended Collaborative Integrated Life Cycle Supply Chain Planning System*" of the EU funded Sixth Framework Programme. RTU coordinator and leader: Dr.habil.sc.ing., Prof. Y. Merkuryev. 2006 - 2009.

2) “*Simulation-based optimisation using computational intelligence*” (a research grant from the Latvian Council of Science). Project leader: Dr.habil.sc.ing., Prof. Y. Merkuryev. 2009 - 2012.

The scientific importance of the procedure and algorithm developed in the doctoral thesis is approved by the Certificate of Significant Academic Contribution issued by MÖBIUS Ltd. in the scope of the task “Switching methodology based on a set of supply chain parameters” within the ECLIPS project. Within this project the author of the thesis has participated with presentations at ten workshops in Riga, Gent, Paris and Brno and is a co-author of three deliverables.

***Structure of the thesis***

The doctoral thesis consists of introduction, 5 chapters, conclusions, bibliography and 1 appendix. The thesis contains 143 pages, 43 figures and 20 tables. The bibliography contains 113 entries. The thesis is structured as follows:

***Introduction*** motivates the research, formulates the research aim and tasks, defines the research object and subject, describes research methods used in the thesis, and explains scientific novelty, practical use and approbation of the thesis.

*Chapter 1* ***“Analysis of the supply chain planning process under uncertain conditions”*** discusses the planning task within supply chain management under uncertainty. Planning processes and their models are analysed as well. An overview of the planning methods for complex systems and simulation-based planning possibilities is provided. The problem of planning methods analysis within product life cycle is formulated with the possibility of performing switching between different planning alternatives.

*Chapter 2* ***“Optimality analysis within supply chain planning”*** analyses the concept of optimality gap and describes its essence. As a result, optimality gap concept is introduced within the analysed problem. The characteristic of the main effects of the influencing factors is discussed. The optimality estimation approach is proposed for simulation of planning policies for multi-echelon supply chain. The simulation-based alternative comparison methods are analysed; the analysis is supplemented with a case study of statistical comparison methods utilisation in a planning task.

*Chapter 3* ***“Development of the two-phase supply chain planning procedure”*** introduces the simulation-based procedure for optimality gap analysis between cyclic and non-cyclic planning methods that combine several phases within themselves. Switching algorithm based on the analysis of the confidence interval is executed within the procedure introduced. Besides, the input data analysis and their utilisation possibilities within simulation are discussed, in order to choose an appropriate approach to modelling the normally distributed demand.

*Chapter 4* ***„Sensitivity analysis algorithm within the task"*** overviews the sensitivity analysis concept and overall technology to define the simulation based problem within research task. Moreover, optimality gap analysis procedure is extended with sensitivity analysis phase. The implementation of the simulation-based sensitivity analysis allows one to determine the possible values of the influencing factors, at which the opportunity to change the planning alternatives has to be analysed. This provides the switching rule introduction.

*Chapter 5* ***„Approbation of the developed procedure on multi-echelon supply chain model"*** presents the developed procedure and algorithm approbation on supply chain planning problem solving. Here, the three-echelon supply chain and business cases are analysed based on the supply chain of chemical industrial company. The actual results of the procedure, as well as improvement possibilities are analysed.

***Results and conclusions of the thesis***

***Bibliography***

***Appendixes***

## SUMMARY OF THESIS CHAPTERS

### *Chapter 1. Analysis of the supply chain planning process under uncertain conditions*

Chapter 1 presents an overview of materials that cover thesis investigation areas and analysis of the main problems. Here, the solving of planning problem in supply chain management under uncertainty is emphasized, planning and management process is described, and simulation-based planning possibilities are discussed. Planning approaches and methods are overviewed based on the product life cycle, and research problem is formulated.

In the chapter, a supply chain is defined as a complex system that has four characteristic features: integrity, divisibility, relations between elements and their organisation. The changes within one of the supply chain elements affect the whole supply chain and impact the inventory of materials and products, as well as supply chain total costs and service level. Supply chain complexity mainly is influenced by the number of echelons, the number of elements in each echelon, structure of the material and information flows, as well as by integration level and information availability and management mentioned in various researches [4, 12, 19]. The goal of any supply chain is to create suitable flexible environment for a company in order to respond to the alterations of customers' desires. These problems are solved within one of supply chain management branch – supply chain planning. Planning processes and their decisions in supply chains can be divided according to the:

- length of planning horizon – operational, tactical and strategic planning;
- investments profitability;
- plan implementation complexity;
- functional features of planning tasks – material, production, distribution and sales planning;
- forms of collaborative planning – vertical and horizontal control coordination;
- direction of planning processes – upstream and downstream planning.

In Fig. 1 the appropriate planning processes are connected to the main stages of supply chain, i.e. procurement, production, distribution and sales - that are linked to the factors described above as well. The strategic planning aspects were not taken into account during this research, the emphasis is put on the tactical planning and its management.

According to the existing planning processes in supply chain the new approaches need to be developed and used in order to facilitate and improve planning processes in the specific supply chain. Researches in this field are based on the specified models development and analysis using appropriate methods, i.e.:

- *Analytical models* concern dynamic and stochastic environments, and usually are presented by Markov chains, Petri nets or queueing models.

- *Simulation models* provide an analysis of complex dynamic and stochastic processes.
- *Optimisation models* are mostly deterministic, i.e. MILP, optimisation algorithms using computational intelligence and metaheuristics.

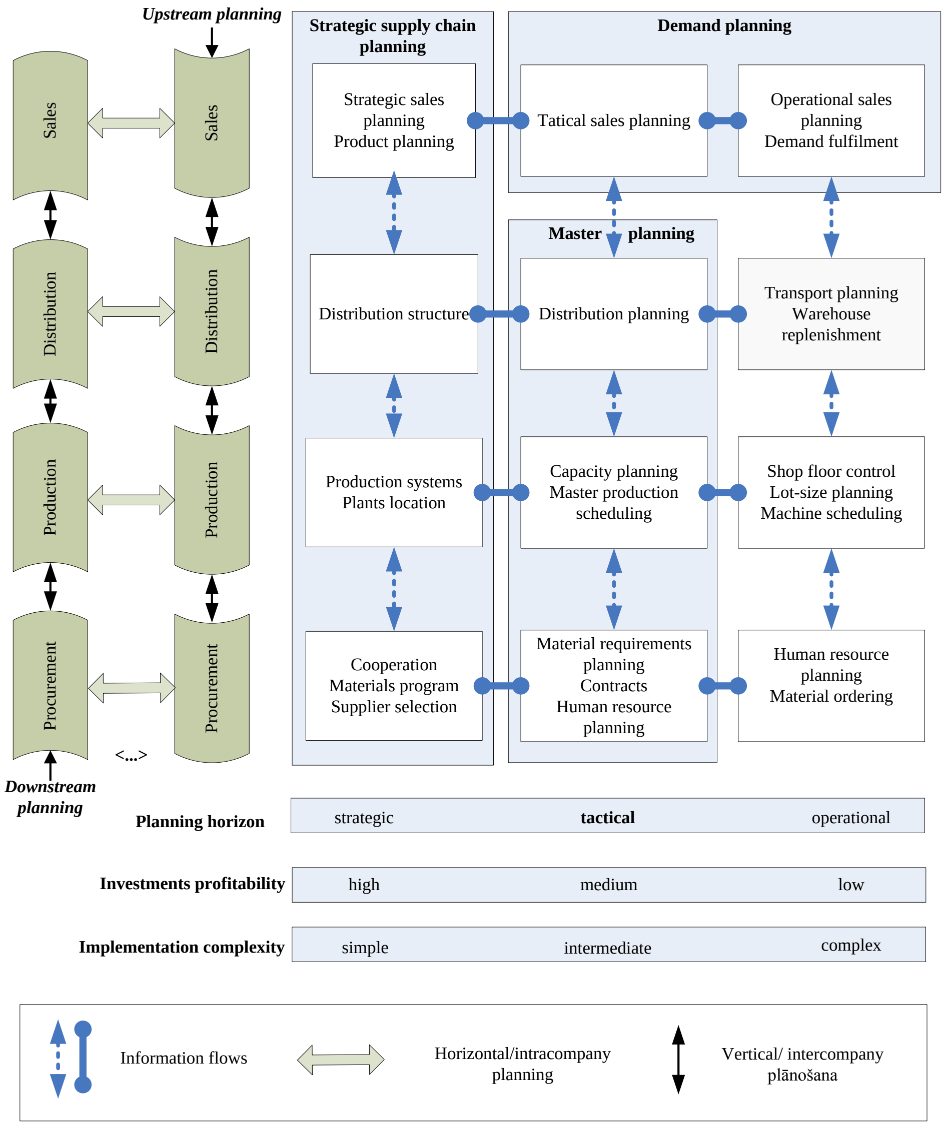


**Figure 1. Planning processes in supply chain**

Supply chain is a dynamic system, where regular changes of the processes influence both the entire set of actions in supply chain and its planning and improvement. Sources of uncertainty involve all types of nondeterministic constrains, changes and fluctuations in supply chain internal and external processes. Researches that cover investigation of production and inventory management systems analyse different sources of uncertainty, i.e. customer demand, lead and production times, processes' quality and profit [20]. But the changes in products and technologies on the market appear with growing speed, less information is analysed during planning process, which, as a result, causes more penalties [10]. Additionally, uncertain lead time of the processes due to production idle time and product defects is investigated [31].

Supply chain is described as a large scale system with hierarchical decision structure, different input data and operations randomness, as well as dynamic interaction between its elements where the modelling methodology is useful for decision making in supply chain. This methodology enables to design supply chains with higher performance and identify and implement innovations in management strategies [21].

The utilisation of the analytical models in comparison with simulation ones makes difficult or impossible solving the problems of multi-echelon supply chain, complex systems and large queuing models. Usually, analytical techniques are used under conditions of dynamic and deterministic demand, but simulation provides a test environment for analytical solutions and allows modelling and optimising planning decisions under demand variability and uncertain conditions. These are commonly known benefits associated with simulation technology, e.g.:

- Simulation and optimisation possibilities for complex systems with stochastic elements.
- Possibility of alternative systems comparison with the aim to find appropriate solution.
- Possibility to tend toward improving of system understanding by analysing interaction of system functions.

Four simulation types for supply chain analysis: system dynamics, spreadsheet simulation, discrete-event dynamic systems simulation and business games – are distinguished within supply chain simulation area [14]. Different researches have concluded [1, 16] that discrete-event systems simulation is powerful tool to work with complex stochastic systems. A combination of simulation technique and spreadsheets is used to define supply chain model structure and the values of parameters.

Within the thesis, the simulation technique is used to analyse and compare multi-echelon supply chain planning methods in the inventory management context and within product life cycle. During the product life cycle the time moments when transitions between phases take place are called switching points. The variability of product demand defines the product life cycle separate phases, as well as switching point from one life cycle phase to another, accordingly from one planning policy to another (see Fig.2). Importantly, supply chain product demand is dynamic and variable; however it is stable during maturity phase of the product life cycle.

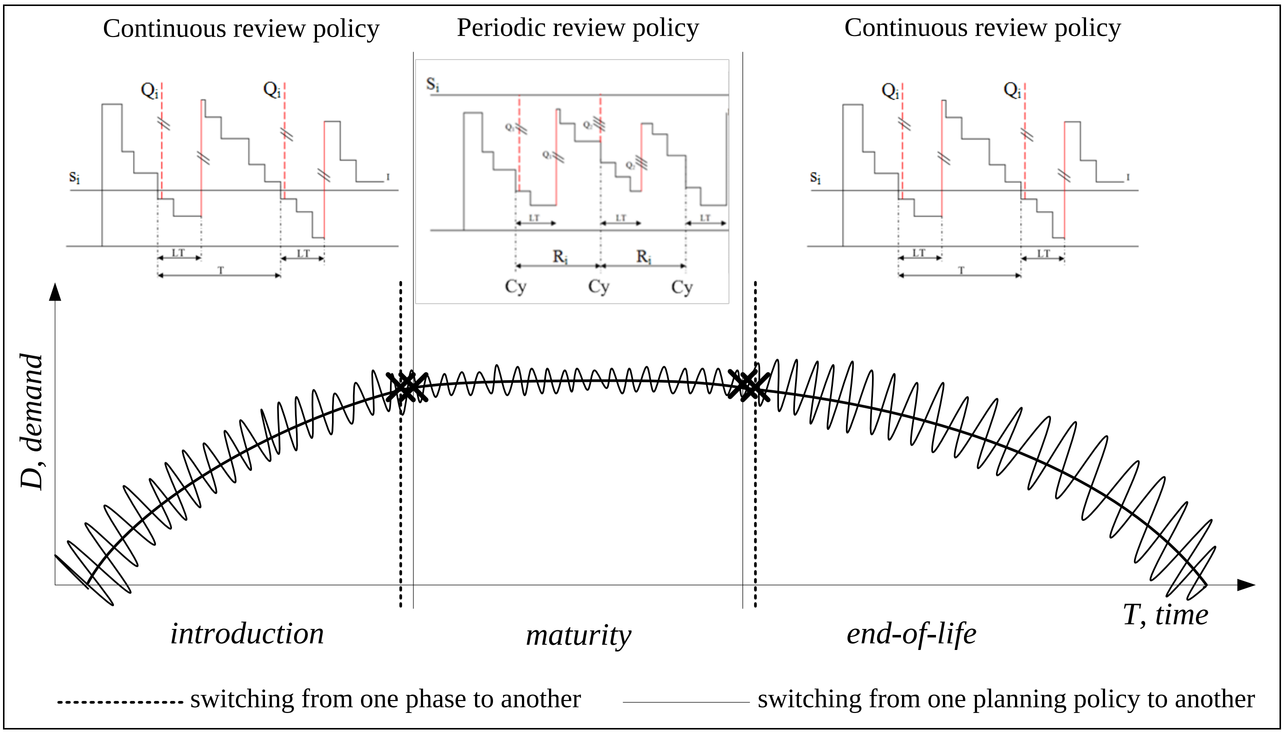


**Figure 2. Switching points based on product life cycle**

Within product life cycle supply chain planning is based on the continuous review and periodic review policies that have non-cyclic and cyclic behaviour accordingly. In case of cyclic planning, further *POR*, that is used during stable demand (Fig.2.), the constant order intervals are implemented for all product units, parameters $R_i$ – cycle length and $S_i$ – maximal stock level are determined. But, in non-cyclic planning (further *ROP*), order intervals are variable within planning horizon and for constant parameters $s_i$ – re-order point and $Q_i$ – order quantity. In this case, the fixed inventory level is determined by taking into account product demand changes. This triggers constant order initialisation for inventory replenishment, and the order time varies. When the stock level reaches the fixed point reorder level ($s_i$), a replenishment order is placed. Here, order quantity ($Q_i$) is fixed. LT denotes the lead time interval starting with order initialization and finishing with order arriving and stock level increasing by $Q_{i.}$ T represents the time period between orders, whose length varies from one cycle to another for this system [27].

In the supply chain planning process, only one, cyclic or non-cyclic plan, is typically implemented in supply chain stages, both production and inventory. The cyclic planning methods can be defined as subset of non-cyclic methods, where cyclic one is determined as non-optimal. Its total costs are higher than total costs of non-cyclic plan. From the management point of view, the cyclic plan is preferred when the non-cyclic one has more complex realisation that can be less effective in practice. In Fig. 3 the possible dynamics of the costs changes based on the product demand is presented, where non-cyclic costs are depicted with straight lines, but cyclic costs – with striped ones. By planning cyclically, the long-term benefits are highlighted and reached if demand variability is insignificant. The benefits can exceed inventory and setup costs minimisation by reducing handling cost and time, planning and administration costs, buffer inventories, as well as the complexity of the detailed planning [7].

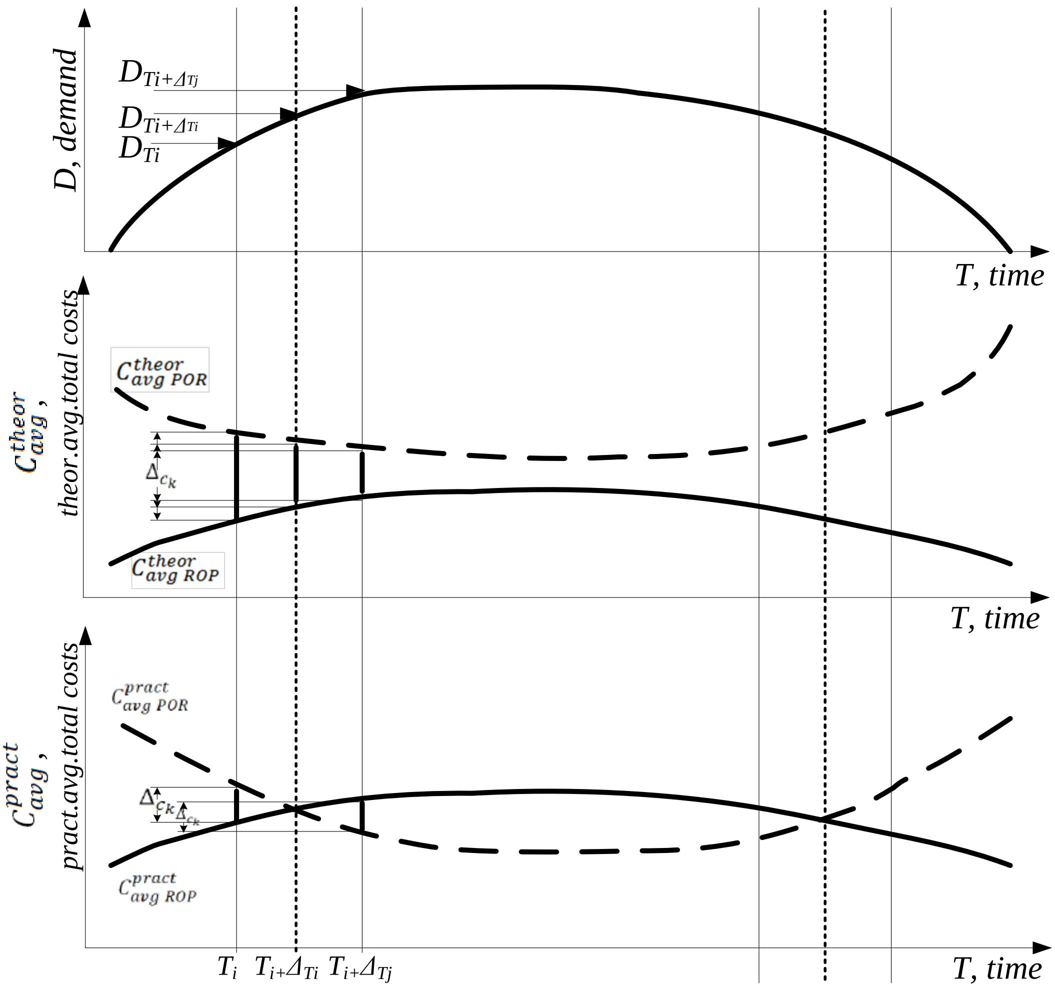


**Figure 3. Costs change dynamics depending on the product life cycle and demand**

After evaluation of all aspects analysed in this chapter: supply chain complexity and its management tendencies, different sources of uncertainty, product life cycle observation and features of planning methods – there is a need to create a procedure for optimal planning policy selection. The switching point has to be determined when it is possible to replace the multi-echelon non-cyclic planning with the cyclic one. It means that the developed procedure checks the possibility of using a cyclic plan within multi-echelon supply chain.

The main conclusions are as follows:

- the increase in supply chain planning process complexity within product life cycle shows the need of planning procedure improvement;
- simulation model with its ability to analyse stochastic elements ensures holistic view on the supply chain and is able to present significant supply chain features especially in many echelons;

- switching between different planning methods is not analysed sufficiently and as a result has no algorithm that propose the mechanism for the evaluation of switching point between planning methods.

***Chapter 2. Optimality analysis within supply chain planning***

In Chapter 2 the optimality gap concept is analysed and its essence is described. As a result, it is introduced in the context of the described problem. Optimality gap is usually utilized in optimisation tasks (see Fig.4a). In mixed integer programming it means the difference between the best known solution and the worst example of the best possible solutions calculated as absolute or relative value [26]. In optimisation tasks, for example, sample average approximation method, optimality gap is used as a *termination point for the optimal solution searching algorithm* [15, 25]. In the linear programming this concept is utilized in the *sensitivity analysis of models* in order to define the intervals of the equation coefficients values whose changes do not influence found optimal solution [28]. Optimality gap is used in the model *validation* to estimate the solution quality and approve that provided solution is an appropriate candidate for optimal solution.

In the thesis, *optimality gap is the ratio of the investigated alternatives – planning methods – estimations that determines the difference and significance of the compared alternatives* (see fig.4b).

*Additional costs of cyclic solutions or ACCS* criterion [6] is introduced in order to compare supply chain cyclic and non-cyclic planning methods. *ACCS* is determined as a relative ratio between total costs of *POR* and *ROP* cases, i.e. $C_{POR}$ and $C_{ROP}$:

$$ACCS = \frac{C_{POR} - C_{ROP}}{C_{ROP}} \tag{1}$$

Based on the theoretical comparison and previous researches, the *ACCS* is characterised with positive values.

The following performance measures are used to compare planning alternatives:

- *ACCS* average value and its confidence interval;
- The averages and variances of the cyclic and non-cyclic solution cost;
- The confidence interval of the costs difference between solutions.

Simulation-based experiments approve the critical importance of the coefficient of demand variation (*CODVAR*) and its affect on additional costs of cyclic planning solution [23]. The coefficient is defined as a ratio between demand standard deviation $s_i$ and average demand $\bar{x}_i$ of the product *i* estimated in percentage:

$$CODVAR_{i\,\%} = \frac{s_i}{\bar{x}_i} * 100\% \tag{2}$$

The more customer demand fluctuates, the more coefficient of demand variation increases. In situations like that, the benefit of non-cyclic planning appears – a more flexible planning than using the cyclic one.

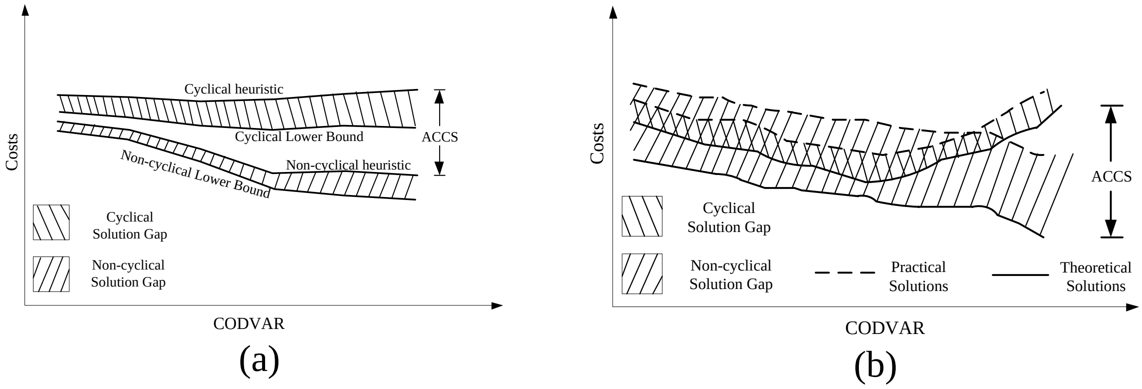


**Figure 4. The interpretation of the optimality gap within optimisation tasks (a) and comparison of planning alternatives (b)**

In the thesis the set of the factors' significant effects is analysed that influences the bounds of optimality gap, i.e. capacity utilization (*CAP*), number of supply chian echelons and periods, setup and lead times and different type of costs. A detailed summary of practical researches [5, 6, 7, 8] that describes different factors and the significant effects of their interaction is given in Table 1.

Table 1

**Characteristic of the factors significant effects**

| Effect | Factors | Description of effects |
|---|---|---|
| Main effects | *CODVAR* | *ACCS* increases as *CODVAR* increases because of the reduction of non-cyclic solution costs. |
| | *CAP* | Higher capacity utilization results in larger *ACCS* values. The effect is less strong than that of *CODVAR* for *ACCS*. |
| Interaction effects | *CODVAR* and *CAP* | Higher *CAP* makes stronger *CODVAR* effect to *ACCS*. Both factors combination makes it difficult to determine a solution close to lower bound. |
| | Setup time and *CAP* | Lower setup times have the effect similar to higher levels of *CAP*. The effect of setup times is greater at the higher *CAP* level. |
| | *CODVAR* and time between orders | The larger order intervals at small *CODVAR* result in lower *ACCS* values. |
| Combined effects | Ordering cost, holding cost and *CODVAR* | The interaction effect of ordering cost and holding cost becomes more significant with the increase of *CODVAR* that results in the increase of*ACCS* value. |

An analysis of the existed researches shows that comparison and choice of planning policies previously was applied for production planning in one-echelon supply chains by different heuristics utilisation.

To determine the efficiency of any planning policy or method, in the thesis different techniques are grouped in four general approaches, i.e. theoretical optimality proof by costs comparison, optimality evaluation from the complexity perspectives, optimality evaluation by implementation guaranty, and optimality evaluation through simulation experiments. Theoretical optimality proof supposes [3, 7, 9, 23, 24] existence of the *lower bound* of average cost over feasible policies used to determine the best solution. Optimality evaluation from the complexity perspectives is based on estimation of the number of iterations or computational times [2, 22, 23] of solving method. Additionally, expert conclusions are used to compare the alternatives [23, 24]. But, simulation-based experiments allow planning alternatives estimating and decision about appropriate policy implementation in conditions of demand variability and other uncertainties that are closely related to the multi-echelon supply chain dynamics and its stochastic performance. Moreover, simulation-based sensitivity analysis allows learning possible effects of supply chain factors on optimality gap influencing.

Here, optimality estimation apporach is based on the supply chain simulation using alternative planning methods (see, Fig.5), designed to receive performance measures estimates at different values of input parameters and factors. The comparison of planning alternatives is presented in separate step as significant and decisive for optimality gap estimation.

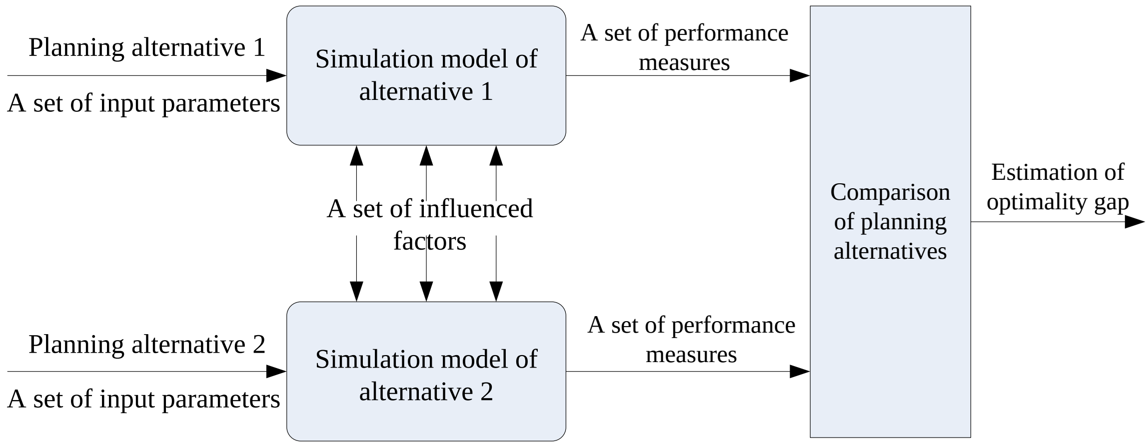


**Figure 5. Simulation-based optimality gap estimation**

Three sets of methods for simulation-based comparison of alternatives are analysed in the research, i.e., simple comparative analysis, graphical comparison and statistical comparison [18]. Statistical comparison methods, i.e. *hypothesis tests* and *confidence intervals*, are used under uncertainty. Both methods combination provides an objective comparison of the models performance measures. The difference between average values of performance measures is estimated by confidence interval, but alternative statistical hypotheses are used to check the significance of the estimated difference. For example, if the estimated confidence interval with assumed level of confidence includes zero value, the conclusion about non-significant difference between average values of the analysed alternatives is made (see Fig.6a).

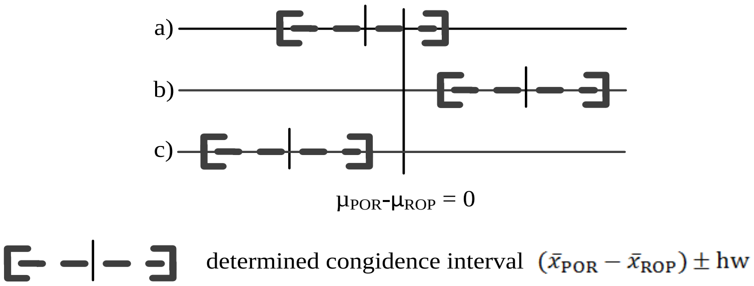


**Figure 6. The position of confidence interval regarding zero point**

Moreover, the confidence interval and its quantitative bounds characterize the uncertainty of modelling outcomes. It is desirable to have a small interval with high confidence that ensures more useful and meaningful models comparison. The width of the confidence interval with a given level of confidence is affected by the number of observations and the output data variance. Variance reduction techniques are used to reduce the width of the confidence interval within simulation [16].

Two statistical techniques are used for simulation of comparable systems [13]: independent sampling and correlated sampling, where the second method is also called the CRN (*common random number*) method. In the last case the equal string of random numbers is used to simulate both systems within one replication. In practise, the utilisation of this technique decreases the variation of the estimated difference and provides an accurate estimation of the difference value at the defined sample size.

Methods based on the confidence interval estimation for statistical comparison of two alternatives, i.e. Welch and pared-t confidence intervals, require the independence of the model outputs between alternative samples and normally distributed data within each sample. When using the paired-t method, the analysed samples cannot be independent, but equal sizes of both samples are required. The utilisation of the common random numbers is possible. But, Welch method allows working with different sizes of samples with an assumption that there is no correlation between output data of planning alternatives. The number of degrees of freedom and their calculation process differs for these methods.

In the case of planning alternatives comparison, the confidence interval between the two means of the average total costs at the defined level of significance $\alpha$ is

$$P[(\bar{x}_{POR} - \bar{x}_{ROP}) - hw \leq \mu_{POR} - \mu_{ROP} \leq (\bar{x}_{POR} - \bar{x}_{ROP}) + hw] = 1 - \alpha, \qquad (3)$$

where $(\mu_{POR} - \mu_{ROP})$ - the difference between mean values of total costs of the alternatives; $(\bar{x}_{\mathrm{POR}} - \bar{x}_{\mathrm{ROP}})$ - the difference between average values of total costs of the alternatives; *hw* - the half-width of the confidence interval.

Here, half-width *hw* of the *paired-t* confidence interval is calculated by formula (4):

$$hw = \frac{\mathrm{t}_{(\mathrm{n}-1,\alpha/2)} * s_{(\mathrm{POR}-\mathrm{ROP})}}{\sqrt{\mathrm{n}}}, \tag{4}$$

where $\mathrm{s}_{(\mathrm{POR}-\mathrm{ROP})}$ - standard deviation for average total costs difference that estimates true standard deviation $\sigma_{(\mathrm{POR}-\mathrm{ROP})}$; n - the number of replications; $\mathrm{t}_{(\mathrm{n}-1,\alpha/2)}$ – Student's *t* distribution value for α/2 level of significance and degree of freedom *n-1*;

But, half-width *hw* of *Welch* confidence interval is calculated by formulae (5):

$$hw = \mathrm{t}_{\mathrm{df},\alpha/2}\sqrt{\frac{\mathrm{s}^2_{\mathrm{POR}}}{\mathrm{N}_{\mathrm{POR}}} + \frac{\mathrm{s}^2_{\mathrm{ROP}}}{\mathrm{N}_{\mathrm{ROP}}}}, \tag{5}$$

where *df* - degree of freedom, $N_{POR}$ un $N_{ROP}$ - the number of replications for comparative POR and ROP planning alternatives and $\mathrm{s}^2_{\mathrm{POR}}$ un $\mathrm{s}^2_{\mathrm{ROP}}$ – corresponding sample variance.

A case study is done to investigate the utilisation of statistical comparison methods for planning alternatives analysis, where three-echelon supply chain is simulated using cyclic and non-cyclic planning methods (Fig.7).

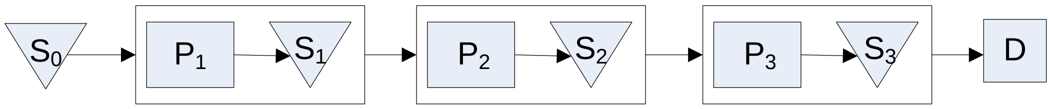


**Figure 7. The structure of simulated supply chain**

The coefficient of demand variation is set as follows *CODvar*=30%. The performance measure is average total costs of period. 20 simulation replications are performed for each alternative. The level of significance is set as α = *0,05*. *The paired-t* confidence interval method, *Welch* confidence interval method with equal and unequal samples sizes, as well as *t*-test for comparison of averages of two independent samples are employed. Relative standard error values of both samples are $s_{\bar{x}\%_{POR}} = 0{,}18\%$ and $s_{\bar{x}\%_{ROP}} = 0{,}35\%$, which shows the appropriate accuracy of analysed data. The critical and de facto values of the *t*-test are $t_{crit} = 2.05$ and $t_{fact} = 17.41$, accordingly. As $t_{fact} > t_{crit}$, the difference between period average costs values of planning alternatives is determined as significant. The same conclusion is made after confidence interval methods utilisation, based on hypotheses testing and confidence interval of analysed alternatives costs difference estimating. At the equal samples sizes, the length of *the paired-t* confidence interval is smaller (see Table 2).

Table 2

**Numerical estimates of the case study**

| **Statistical comparison methods** | **Half-width $hw$ of the confidence interval** | $\mu_{(POR-ROP)} \in [\underline{\mu}, \overline{\mu}]$ |
|---|---|---|
| Paired-t confidence interval method | 1255 | [10083;12593] |
| Welch confidence interval method *with equal samples sizes* | 1332 | [10006;12670] |
| Welch confidence interval method *with unequal samples sizes* | | |
| Experiment 1 | 1380 | [10069;12829] |
| Experiment 2 | 1197 | [10192;12585] |

The confidence interval methods are useful for estimation and comparison of performance measures of supply chain planning methods based on simulation. The common random number implementation and equal samples sizes limit the choice of the possible confidence interval to use.

The main conclusions are as follows:

- *ACCS* criterion is applicable for estimating the difference between costs of cyclic and non-cyclic methods. This ratio is defined as optimality gap;
- external factors and parameters influence the difference of performance measures. The choice of planning method can be made to realise based on the factors and parameters changeable values as a decision making critical point;
- simulation provides an opportunity to make a decision about implementation of certain planning method based on the hypotheses testing according to the confidence interval calculation. *The paired-t* confidence interval method is defined as appropriate for utilisation within the discussed problem.

### *Chapter 3. Development of the two-phase supply chain planning procedure*

In this chapter the procedure for optimality gap analysis between cyclic and non-cyclic planning policies is described. The developed procedure consists of these steps:

- *presimulation quantitative analysis* of parameters and external factors of planning alternatives, i.e. cyclic and non-cyclic plan;
- *simulation* of supply chains with alternative plans;
- *analysis of* the simulation models *performance measures;*
- *decision making* about efficient policy utilisation;
- *production rule generation* to support planning decisions.

In the presimulation step, the values of simulation initialisation and models influencing factors and input parameters are determined by analytical-quantitative calculus utilisation. The parameters of the cyclic and non-cyclic alternatives are calculated in order to determine safety stocks at the desired service level.

Simulation warm-up period and the number of replications are taken into account to adjust the accuracy of models and to work with confidence intervals.

Simulation is used as an experimental approach in the task of planning alternatives comparison. In parallel, models of the cyclic and non-cyclic planning are run that have previously defined performance measures as an output.

A comparative analysis of the results is performed after simulation. *ACCS* criterion estimates indicate practical effectiveness of the alternative plans and preferable switching moment from one plan to another. Inventory levels and reached service levels of planning policies are analysed within this step as well. As a result, decision about preferable planning alternative is made.

The aim of production rules is to control planning processes of product life cycle based on the set of supply chain influencing parameters values. The sets of analysed factors values are combined to scenarios. The defined set of production rules forms the switching rule that allows automatically selecting the appropriate planning alternative within predefined scenarios.

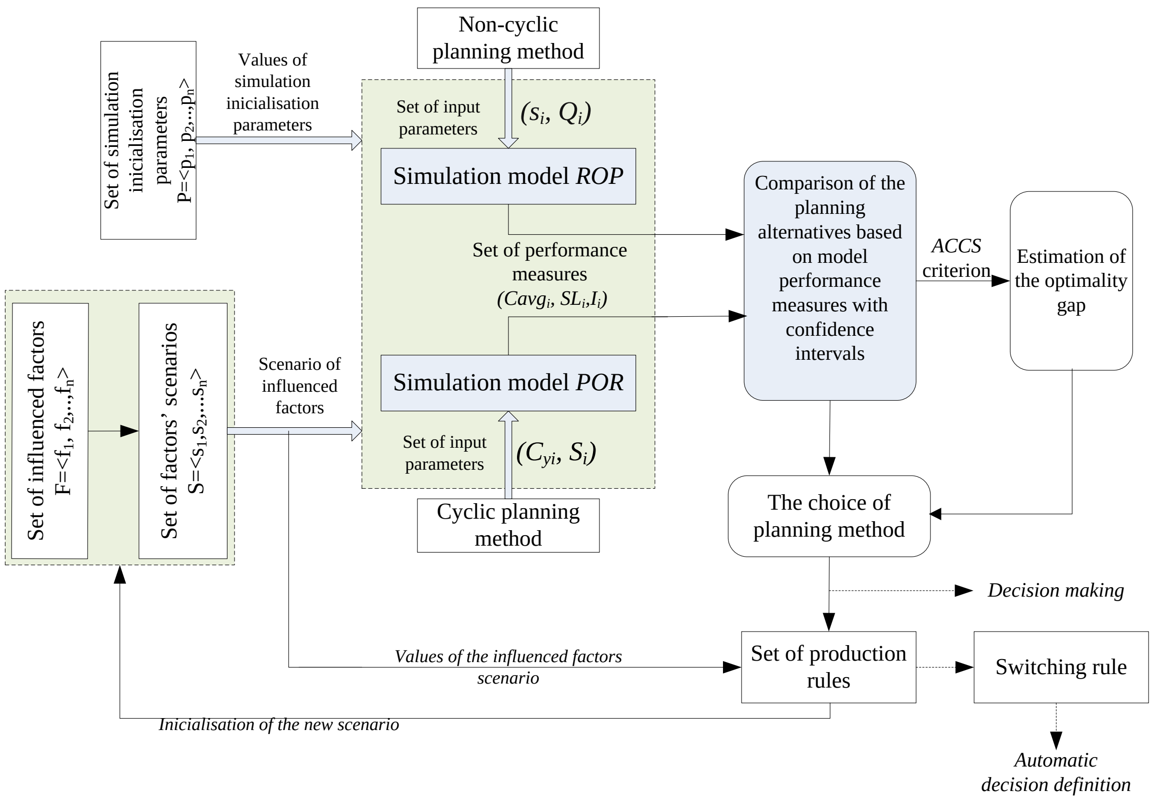


**Figure 8. Simulation-based procedure of optimality gap analysis**

The research procedure (Fig.8) of the optimality gap analysis provides: (1) a set of simulation initialisation parameters and models input parameters definition; (2) a set of influenced factors scenarios definition; (3) simulation of the alternative models at the determined values of parameters and factors; (4) a comparative analysis of performance measures using confidence interval method; (5) analysis of ACCS criterion value and its change; (6) choice of the recommended planning method; (7) production rule definition and adjusting.

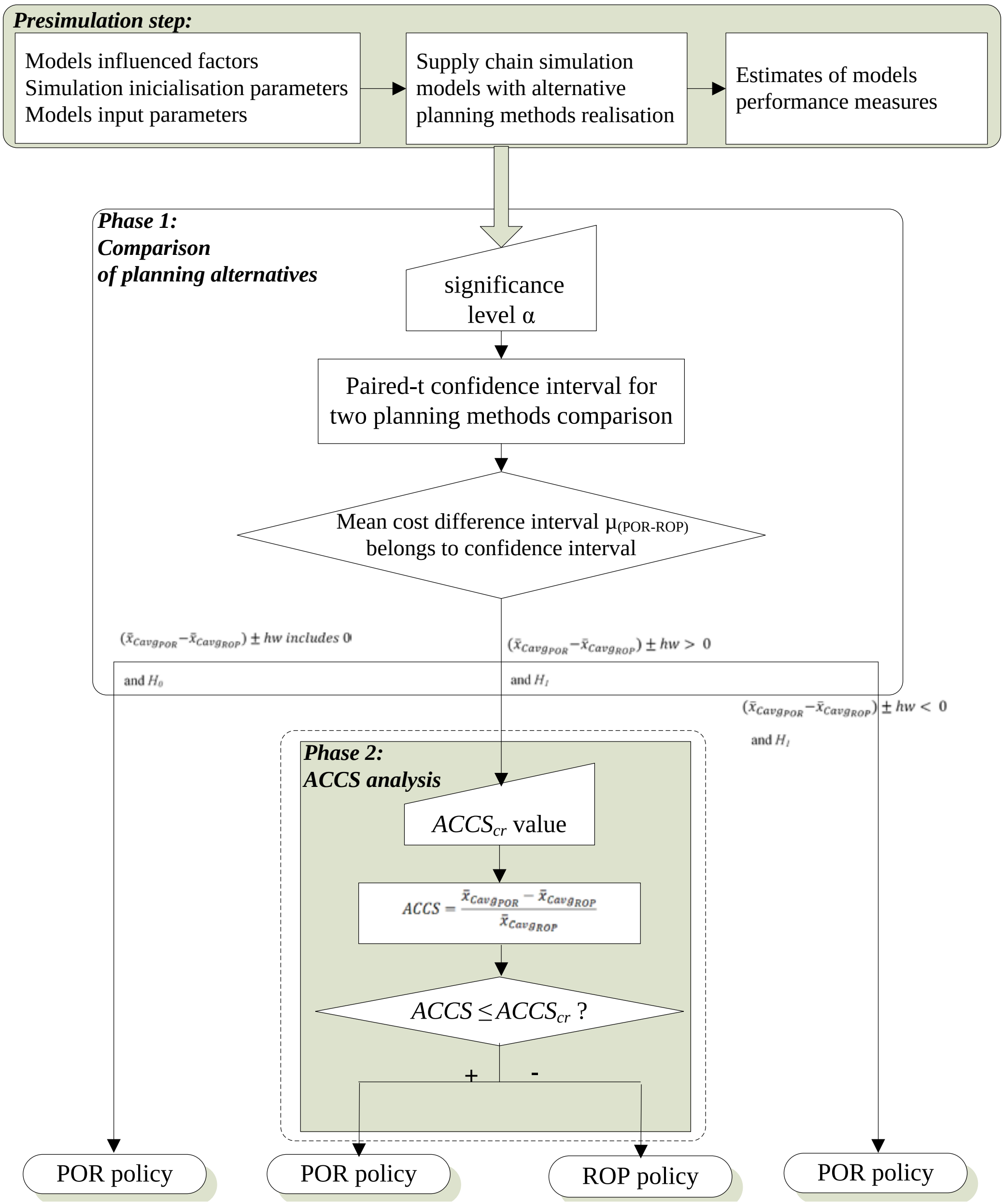


**Figure 9. Two-phase switching algorithm**

Furthermore, a comparative analysis of the simulation models performance measures and choice of the planning methods are made by, the so-called switching algorithm (see Fig.9.). Against the point estimation, the *paired-t* confidence interval is used to estimate the difference between sample means of alternative plans performance measures. By analysing the *paired-t* confidence interval value, the defined hypotheses about non-significant difference between alternatives are assumed or rejected. If the hypothesis is not rejected, the cyclic plan is chosen. Otherwise, if the hypothesis about two alternatives non-significant difference at the defined level of significance is rejected, but confidence interval is situated on axle's right side according to zero (see Fig.6), *ACCS* analysis compares it with $ACCS_{cr}$ values and performs the choice of appropriate alternative. Here, $ACCS_{cr}$ determine the relative difference that according to expert opinion is considered optimal. For example, in literature it is defined as $ACCS_{cr}$ = 4.7% [7].

In practice, CRN utilisation and relative standard error estimation limit the large variation of models output data sets [16]. When the confidence interval contains zero value, the analysis of ratio between interval negative and positive parts is preferable. It allows a deeper analysis of the decision about cyclic plan implementation, if the alternative difference is non-significant. The valid $hw_{cr}$ value determines the allowed variance from average value of the difference and is defined as $hw_{cr} = k * (\bar{x}_{POR-ROP})$, where coefficient $k=1.05$. For the further analysis criterion $A$ is introduced:

$$A = \frac{|a_{neg}|}{a_{pos} - a_{neg}} * 100\%, \tag{6}$$

where $a_{neg}$ – maximal negative value of confidence interval, $a_{pos}$ – maximal positive value of confidence interval.

No difference exists between cyclic and non-cyclic methods when the confidence interval is symmetric to zero value and, accordingly, $A$ = 50%. The smallest relative difference is estimated, the largest part of the interval lies in the positive side. It means that the probability that cyclic costs outperform non-cyclic ones increases.

Within the procedure of the optimality gap analysis, i.e. in calculus of *ACCS* and *paired-t* confidence interval, normally distributed demand is assumed. Moreover, the fluctuations of the demand from inessential to decision influenced are taken into account, which leads to the obtaining of demand negative values in the distribution generation phase. This requires an analysis of the input data modelling approaches and methods with the aim to choose suitable method within simulation modelling under uncertain conditions. A comparison of input data modelling methods based on simulation researches context and input data availability is given in Table 3.

Table 3

**Comparison of the input data modelling methods**

| Method | Advantages | Disadvantages |
|---|---|---|
| **Theoretical distribution choice** | Data representation in compact mode. Smoothing of sample data. Generation of the values outside a sample range. | No theoretical distribution fits a sample data. |
| **Empirical distribution construction** | Utilisation when no theoretical distribution fits the data. | Irregular distribution composition for small data samples. Impossible generation of values outside the range of data. Inconvenience to incorporate large data set in simulation. |
| **Trace data utilisation** | Efficiency in model validation. | Reproduction of only historical behaviour. |
| **Bootstrapping** | Usefulness for a small sample of data. | Data outside the range of the trace generation impossibility. |
| **Expert estimations** | Utilisation when input data points are not available. | Lack of accuracy. |

Within the research, the normal distribution is used, based on the customer demand historical data analysis. If the coefficient of demand variation is sufficiently large (e.g. *CODVAR=1*), the random generation of the demand negative value does not allow to correctly use normal distribution for customer demand generation in simulation model. To deal with normally distributed demand within the research, the following techniques are investigated [17]:

- iterative transformation of normally distributed demand,
- introducing truncated normal distribution, and
- utilisation of alternative distribution.

Iterative transformation of normally distributed demand that exclude receiving of the demand negative values is made by this formula (Ms *EXCEL)*:

$$x_i = x_{i-2} + x_{i-2} * \frac{x_{i-2}}{\mu} * (SIGN(x_{i-2} - \bar{x}_{i-2}) * (\frac{CODVAR}{CODVAR_{i-2}} - 1)), \quad (7)$$

where $x_i$ and $\bar{x_i}$ –the point estimate of the demand transformed distribution and its average value in iteration *i*, accordingly; $\mu$ – mean value of the normally distributed demand; $CODVAR$ and $CODVAR_{i-2}$ – coefficient of demand variation, accordingly, for normal and transformed in the iteration *i-2* distribution. The received average and standard deviation values of the iteratively transformed distribution (Fig.10) match theoretical distribution, but at CODVAR=1 de facto value of $\chi^2_{\text{de facto}}$ exceeds the critical value $\chi^2_{\text{Crit}}$, i.e. $\chi^2_{\text{de facto}} > \chi^2_{\text{Crit}}$.

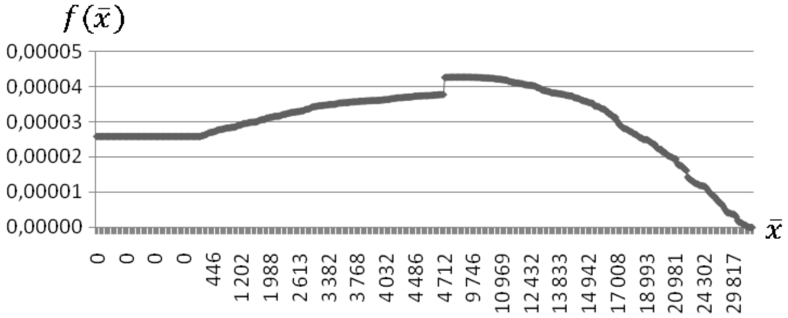


**Figure 10. Probability density function of the transformed normal distribution with CODVAR = 1**

Truncated normal distribution parameters μ and σ are calculated in the *MathCAD v.13* software using formulas (8) – (10):

$$\mu_e = \mu + c\sigma \frac{1}{\sqrt{2\pi}} exp(-\frac{1}{2}(\frac{\mu}{\sigma})^2), \quad (8)$$

$$\sigma_e^2 = \sigma^2 - \mu_e(\mu_e - \mu), \quad (9)$$

$$c = \frac{1}{1-\Phi(-\frac{\mu}{\sigma})}, \quad (10)$$

where $c$ – rationing multiplier; $\mu$ – sample mean of truncated normal distribution; $\mu_e$ – sample mean of initial normal distribution; $\sigma^2$ – sample variance of truncated normal distribution; $\sigma_e^2$ – sample variance of initial normal distribution. The different values of the average and standard deviation for initial normally distributed demand and truncated one are received. That is why, *CODVAR* values of the distributions are not equal. Probability density functions of two normal distributions with *CODVAR* equal to 0.5 and 1, and the truncated distribution are illustrated in Fig.11. Wasted area in the left from zero (i.e. truncated point) grows as the negative demand area of the normal distribution grows when the *CODVAR* tends towards 1 and more. In these cases, it could become impossible to find parameters for a corresponding truncated normal distribution. Moreover, the truncated normal distribution has to be constructed as an empirical distribution. This makes the input modelling phase time and capacity consuming.

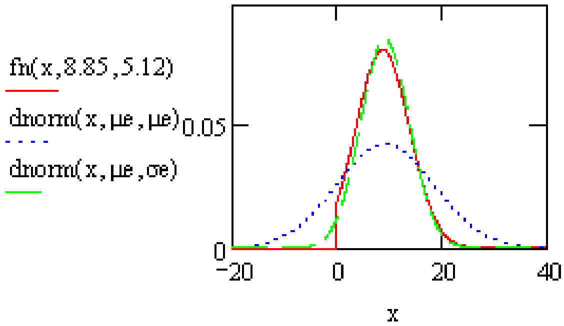


**Figure 11. Probability density functions of normal distribution with different parameters representations**

Parameters $\mu_L$ and $\sigma_L$ of alternative lognormal distribution [32] are calculated when the parameters $\mu$ and $\sigma$ for normal distribution are known.

$$\mu_L = e^{\mu+\sigma^2/2}; \tag{11}$$

$$\sigma_L^2 = e^{2\mu+\sigma^2}(e^{\sigma^2} - 1)\ . \tag{12}$$

But, formulas (X13) un (X14) allow calculating the values $\mu$ and $\sigma$ for normal distribution, if the parameters of lognormal distribution $\mu_L$ and $\sigma_L$ are known:

$$\mu = \ln \mu_L - (\sigma^2/2)\ ; \tag{13}$$

$$\sigma = \sqrt{\ln(1 + (\sigma_L/\mu_L)^2)}. \tag{14}$$

The lognormal distribution can be chosen for modelling randomness in supply chains, because as a standard theoretical distribution commonly represented in simulation software, satisfies the normality condition and does not have the areas of negative values. But, lognormal distribution operates with small values of parameters, that is why the original normal distribution parameters need to be scaled and accordingly converted during simulation.

The main conclusions are as follows:

- provided procedure of the optimality gap analysis allow analysing of two planning alternatives in order to determine switching point between them;
- switching rule supports the automatical decision making process based on the changes of influenced factors;
- investigated iterative transformation of normally distributed demand

provides the unchangeable distribution parameters values and is assumed as more suitable for simulation as it helps to avoid generation of distribution negative values.

### *Chapter 4. Sensitivity analysis algorithm within the task*

The character of the influencing factors changes is important in supply chain control within the product life cycle that influences the selection of implemented planning policies methods. Moreover, simulation based sensitivity analysis implementation in the developed procedure (Fig.8) and its realisation enables determining possible values of influenced factors which have to integrate in switching rules and to analyse the possibility of changing the planning policy.

Within the research, the problem of sensitivity analysis is formulated as follows. The choice between two planning alternatives $A = <A_{por}, A_{rop}>$ has to be made by taking into account certain situations of selection and the features of planning alternatives. The set of different factors $F = <f_1,f_2,...,f_n>$ influences the advantage of one or another alternative in every situation. Two simulation models $M = <M_{por}, M_{rop}>$are available to model planning policies and solutions. This provides the opportunity to calculate total average costs, *ACCS* and others criteria values that are define as performance measures of the simulation models K = $<k_1,k_2,...,k_n>$. By determining the problem with input-output function, the input data vector $F= [f_1,f_2,...,f_n]$ accordingly influences output data vector $K = [ k_1 , k_2 ,..., k_n] =[k_1(f_1,f_2,...,f_n), k_2(f_1,f_2,...f_n),..., k_n(f_1, f_2,..., f_n)]$.

To provide sensitivity analysis, the investigated factors need to be determined to estimate the system reaction on the factors alteration. During investigation of the systems without analogues, all its input factors can be checked to determine the factors whose changes influence the values of performance measures. Within the research, an analysis of the factors influenced the supply chain planning policy choice is performed, where the set of analysed factors is created of the factors that have major influence within the researches of other specialists.

The sensitivity analysis component and its collaboration with planning procedure phases are depicted on generalized scheme (see, Fig.12). The component of planning of experiments manages the experimental plan generation, if the set of influenced factors is not defined, and provides the input data during optimality gap analysis procedure realisation. In cases, when the set of possible performance measures influencing factors is not known, the *OAT* (*one-at-time*) method is implemented. This method utilisation allows determining the individual influence of each factor on the simulation model realisation. *OAT* method is used during optimality gap analysis procedure as well, where by changing each parameter with the predetermined step the switching rule is defined.

The integration of this method with sensitivity indexes investigation allows estimating the system sensitivity to the changeable factors, analysing the influence of factors between each other, ordering of the factors based on the sensitivity index, as well as extracting inessential factors. The used sensitivity index is calculated by formula [11]:

$$SI_f = \frac{K_{fmax} - K_{fmin}}{K_{fmax}}, \tag{15}$$

where $K_{fmax}$ and $K_{fmin}$ are the models output values according to the maximal and minimal values of input factor.

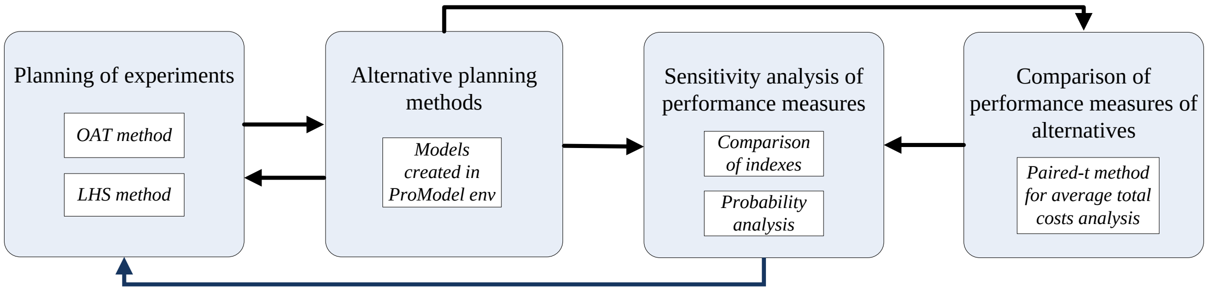


**Figure 12. A general scheme of sensitivity analysis for optimality gap analysis procedure**

Besides an analysis of indexes, the possibility of using probability indicators based on factors values is analysed in the research. This enables analysing each experiment within one set of factors values, to determine the probability of decision change as compared to the decision based on the analysis of all experiments within a separate set.

To present sensitivity analysis, *LHS* (Latin Hypercube) method is approbated to estimate the set of influencing factors. This method is useful when the limitation on experimental time exists that directly is depended on experiment amount. This method allows covering the same range of the factors values by smaller amount of experiments comparing with *OAT* method. To achieve the goal of the research, i.e. to develop optimality gap analysis procedure and define production rules, it is hard to adjust and interpret the *LHS* received results for the investigated problem. That is why, the OAT method has to be used repeatedly.

Based on the results of sensitivity analysis problem investigation, in the thesis the sensitivity analysis algorithm is developed in order to determine the set of influenced factors and scenarios. The utilisation of probability indicator of switching decision change is prescribed in the component of planning alternative choice, when the decision about used planning policy is made based on the particular values of the factors. If the set of influenced factors is known in the beginning, manipulations with the predefined set of factors are made within the sensitivity analysis component.

The main conclusions are as follows:

- sensitivity analysis unit is implemented in the scope of optimality gap analysis procedure to define a set of factors influencing the choice of planning method;

- the set of influenced factors and planning of the experiments realisation allows switching rule generation;
- the *OAT* experimental planning method is suitable to achieve the aim of the optimality gap analysis procedure.

### *Chapter 5. Approbation of the developed procedure on multi-echelon supply chain model*

The developed procedure is applied to the three-echelon supply chain model and the model of European chemical industrial company’s supply chain, where in parallel cyclic and non-cyclic submodels are run (see, Fig.13).

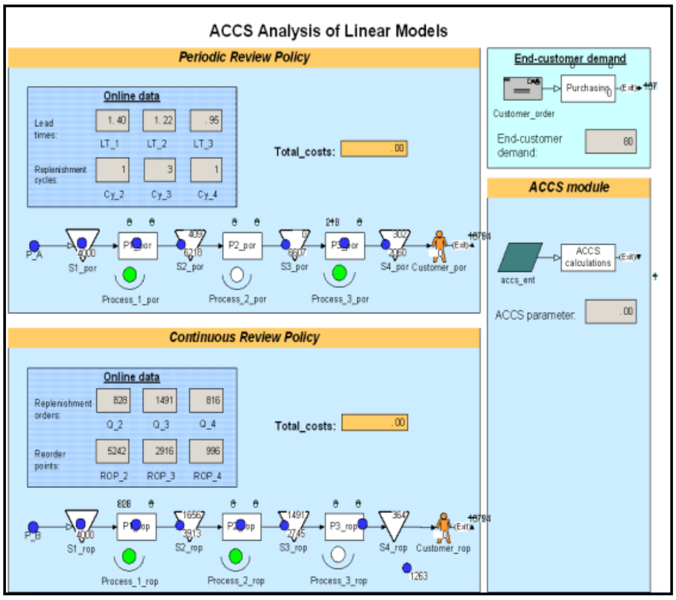


**Figure 13. Supply chain three-echelon simulation model**

Within analytical calculus the input data and planning factors values are defined, i.e. demand average value and its standard deviation, order lead times with its standard deviation, setup times, holding, ordering and other costs, as well as decision variables for cyclic and non-cyclic planning alternatives that firstly can be optimised.

In this case, the two influenced factors are determined, i.e. coefficient of demand variation (*CODvar*) with the main influence, and coefficient of lead time variation (*LTvar*). Both factors vary between 0.1 and 1 with the step 0.1. As the main *performance measure* the period average total costs are chosen. Additionally, the average inventory level and service level could be analysed.

For the procedure approbation on three-echelon supply chain the $ACCS_{cr}$=4.7% is set, but for chemical industrial company the $ACCS_{cr}$ value is revised and increased till 8%. In Fig. 14, the average difference of period average total costs based on the determined factors and received form simulation is illustrated. The costs of cyclic planning policy are higher than those of non-cyclic at all *CODvar* values, but the analysed difference increases as the values of factors increase. Within each planning method, the gradual increase in *LTvar* factor is observed.

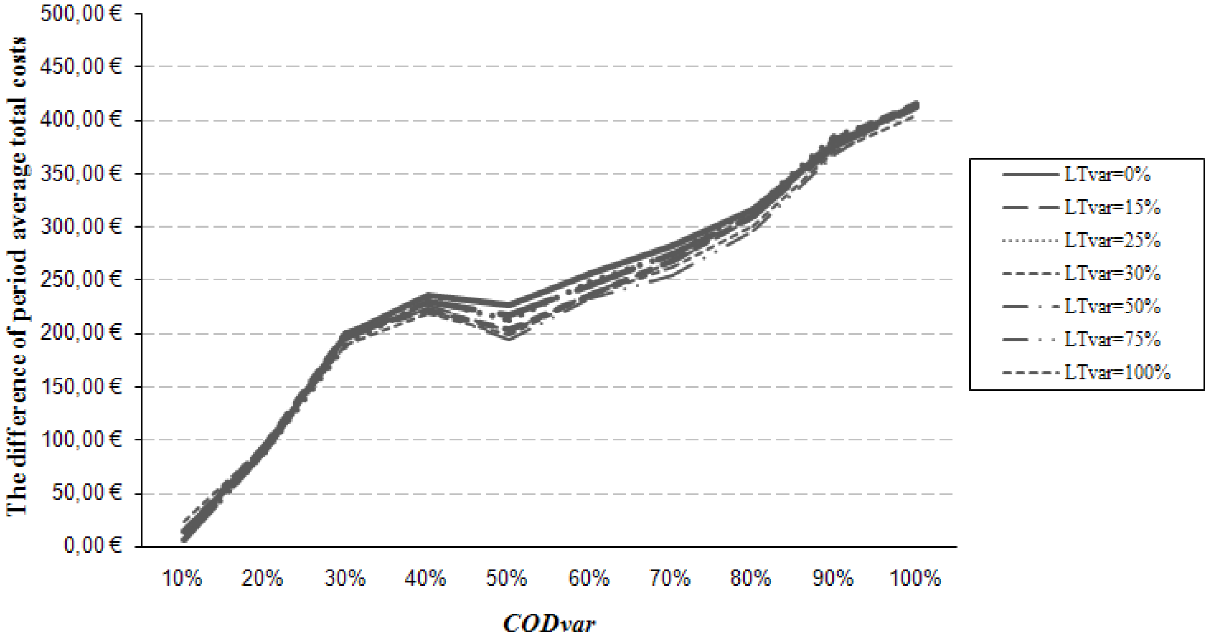


**Figure 14. The average difference of period average total costs based on the influencing factors (the test model)**

Based on the procedure results, the summary table is created (see Table 4) that represents the trend of *ACCS* criterion changes based on the influenced factors values. Based on it, the switching rules with production rules are created. The analysis of factors influence to performance measures allows adjusting the critical values of the criterion. In case when the *LTvar* value changes at the same *CODvar*, *ACCS* value does not change essentially, but the largest value of *ACCS* is estimated at the constant *LTvar* value. In Table 4 with grey colour the factors values are marked where estimated *ACCS* value does not exceed the $ACCS_{cr}$ and decision about cyclic planning *(POR)* is made, in other cases the non-cyclic planning utilisation is introduced. By analysing the developed algorithm, the hypothesis $H_0$ is not rejected at the *CODvar* = 0.1, and it is conclude that there is no significant difference between two planning policies. Due to that, the implementation of cyclic planning is preferred. At the *CODvar* = 0.2, hypothesis $H_0$ is rejected, but $H_1$ is assumed where the conclusion about significant difference between planning policies is made and estimated with *ACCS* criterion. At this *CODvar* the *ACCS* value lies in the interval $ACCS \in [2.62\%; 2.82\%]$ with average value $ACCS_{vid} = 2.73\%$ that not exceed critical value $ACCS_{cr} = 4.7\%$. Based on this analysis, the decision about cyclic planning utilisation is made. At the higher *CODvar* values the hypothesis $H_1$ is assumed as well, but ACCS values overtake its critical value that is why starting with *CODvar* = 0.3 the non-cyclic planning is advisable for realisation.

Table 4

**_ACCS_ criterion estimation based on values of influencing parameters (the test model)**

| | *CODvar* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *LTvar* | 0,1 | 0,2 | 0,3 | 0,4 | 0,5 | 0,6 | 0,7 | 0,8 | 0,9 | 1 |
| 0% | ***0,44%*** | 2,73% | 6,17% | 7,35% | 7,05% | 7,94% | 8,74% | 9,79% | 11,67% | 12,68% |
| 15% | ***0,18%*** | 2,65% | 5,72% | 6,67% | 6,30% | 7,04% | 7,83% | 8,71% | 10,34% | 11,16% |
| 25% | ***0,21%*** | 2,62% | 5,52% | 6,73% | 6,16% | 7,12% | 7,82% | 8,86% | 10,53% | 11,15% |
| 30% | ***0,44%*** | 2,80% | 5,83% | 6,44% | 5,89% | 6,78% | 7,66% | 8,72% | 10,48% | 11,24% |
| 50% | ***0,38%*** | 2,70% | 5,79% | 6,57% | 5,85% | 6,82% | 7,59% | 8,65% | 10,38% | 11,16% |
| 75% | ***0,41%*** | 2,82% | 5,70% | 6,48% | 5,62% | 6,66% | 7,24% | 8,28% | 10,04% | 11,17% |
| 100% | ***0,68%*** | 2,76% | 5,52% | 6,33% | 5,75% | 6,73% | 7,41% | 8,39% | 10,08% | 10,83% |
| *Average* | 0,39% | 2,73% | 5,75% | 6,65% | 6,09% | 7,01% | 7,76% | 8,77% | 10,50% | 11,34% |

Switching rules with production rules are generated for the developed in the thesis procedure with the aim to manage switching algorithm for supply chain on the set of values of influenced factors. In Table 5, a list of production rules, i.e. switching rule for three-echelon supply chain is depicted.

Table 5

**Production rules for three-echelon supply chain model**

| CODvar | LTvar | Switching phase | Planning policy |
|---|---|---|---|
| ... | ... | ... | ... |
| 0.2 | 0% | Nē | ROP |
| 0.3 | 0% | Jā | POR |
| ... | ... | ... | ... |
| 0.2 | 15% | Nē | ROP |
| 0.3 | 15% | Jā | POR |
| ... | ... | ... | ... |
| 0.2 | 25% | Nē | ROP |
| 0.3 | 25% | Jā | POR |
| ... | ... | ... | ... |
| 0.2 | 30% | Nē | ROP |
| 0.3 | 30% | Jā | POR |
| ... | ... | ... | ... |
| 0.2 | 50% | Nē | ROP |
| 0.3 | 50% | Jā | POR |

The influence of production rules on product life cycle is analysed by calculating total costs of the different product life cycle scenarios. As influence of *LTvar* factor is insufficient, it is taken as constant for this analysis. The forecasted costs for different scenarios are presented in Table 6. Based on the developed procedure, the switching is recommended at the *CODvar* = 0.3. The total costs depend on the product life cycle where the maximal difference of costs between all analysed product life cycle scenarios is 11 505 € at the relative ratio of the maximal and minimal costs equal to 3.5%. This analysis shows the ability to reestimate the $ACCS_{cr}$ value based on the product life cycle structure.

Table 6

**Switching moment influence on total costs for different product life cycle scenarios**

| Switching moment CODvar value | Life cycle scenarios | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| only POR | € 337 619 | € 338 461 | € 339 680 | € 339 472 | € 340 947 | € 340 672 | € 340 766 |
| only ROP | € 336 124 | € 334 260 | € 333 451 | € 332 405 | € 331 133 | € 330 536 | € 329 261 |
| 1 | -- | -- | € 339 265 | -- | € 340 533 | -- | -- |
| 0,9 | -- | -- | € 338 886 | -- | € 340 153 | -- | -- |
| 0,8 | -- | -- | € 338 569 | -- | € 339 837 | -- | -- |
| 0,7 | -- | -- | € 338 287 | -- | € 339 272 | € 340 108 | -- |
| 0,6 | -- | -- | € 337 774 | € 338 960 | € 337 991 | € 339 083 | € 340 253 |
| 0,5 | -- | -- | € 337 321 | € 338 280 | € 336 859 | € 337 724 | € 339 574 |
| 0,4 | -- | € 337 754 | € 336 850 | € 337 102 | € 335 680 | € 335 839 | € 338 396 |
| 0,3 | -- | **€ 336 361** | **€ 335 855** | **€ 335 111** | **€ 333 690** | **€ 333 848** | **€ 332 423** |
| 0,2 | -- | € 335 456 | € 334 498 | € 333 302 | € 331 880 | € 331 134 | € 329 710 |

The developed procedure is applied to the multi-echelon supply chain model that represents chemical industrial company. In this model the difference between planning methods costs increases, but ACCS values decrease. A conclusion is made about cyclic planning utilisation even at the *CODvar*=1. But, hypothesis $H_0$ is not rejected up to *CODvar*=0.25 and the diffecence between planning methods is not sufficient. At the higher *CODvar* values the ACCS criterion is estimated that does not exceed $ACCS_{max}$ = 3.85% during the experiments.

The main conclusions are as follows:

- the supply chain structure and features substantially influence the results of the planning analysis;
- the critical value of the estimated criterion has to be defined based on the expertise of analysed supply chain and prospects;
- during the approbation, the analysis of planning methods utilisation based on the total costs of the product life cycle proved to be useful.

## RESULTS AND CONCLUSIONS OF THE THESIS

The multi-echelon supply chain optimality gap analysis procedure for planning alternatives is developed. The aim of the procedure is to determine the switching point between planning alternatives. It is based on the simulation, as appropriate technique, utilisation. The developed procedure provides the control mechanism for switching, as a result, the product life cycle management in the supply chain improves.

The procedure is based on the switching algorithm for planning methods where decision making is based on the statistical comparison process and *ACCS* criterion analysis. The analysis of optimality gap allows improving of planning process and supporting flexible choice of planning method. Switching rule is generated to realise automatic switching between planning methods. It is based on the costs comparison algorithm influenced by supply chain parameters like coefficients of demand and lead time variation.

Based on the tasks of thesis the results are the following:

- Optimality gap analysis procedure is developed. It is aimed at analysis of multi-echelon supply chain planning methods in stochastic environment. The research is based on the analysis of optimality interval utilisation task within supply chain management field.
- Simulation-based switching algorithm for supply chain planning alternatives based on their comparison is developed. It is applied in real supply chain planning problem and allows smooth switching from one planning alternative to another within product life cycle.
- Based on the results of switching algorithm, the optimality gap analysis procedure is extended with switching rule that is based on the set of production rules and provides the choice of planning method according to the specific factors influencing the system.
- Within the research, modelling methods of stochastic demand are investigated to work with a large range of demand variability, as well as simulation-based methods of statistical comparison of alternatives are analysed.
- Sensitivity analysis of factors influenced supply chain performance measures is performed as well as their main effects are analysed to run simulation experiments and create a switching rule.

The research ends with the developed procedure approbation where models based on the supply chains of chemical industrial companies are analysed. During the approbation, conclusions are made that the supply chain structure and features substantially influence the results of the planning analysis, but the critical value of the estimated criterion should be defined based on the expertise of the analysed supply chain.

The developed procedure can be adapted to the simulation-based alternative comparison in other industrial sectors.

Based on the research results, possible ways for the improvements can be the following: a) a comparative analysis of planning methods based on the full product life cycle; b) an analysis of before- and after switching planning issues to avoid unforeseen downtimes; c) increasing the number of alternatives and their features within optimality gap analysis procedure; d) improvement of sensitivity analysis for a more careful generation of switching rule.

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