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DEVELOPMENT AND APPLICATION OF MULTI-OBJECTIVE SIMULATION-BASED OPTIMISATION METHODS

Summary of Doctoral Thesis

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"Management Information Technology"

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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.

Liana Napalkova…………………………….(Signature)

Date: ………………………

The doctoral thesis is written in English. It consists of introduction, 5 sections, conclusions, bibliography and 4 appendixes. It includes 65 figures and 14 tables. The thesis is printed on 156 pages. The bibliography comprises 205 entries.

GENERAL DESCRIPTION OF THE THESIS

Research motivation

The development of the modern world economy and globalisation tendency has encouraged the appearance of a new class of problems in the field of complex systems and process optimisation. These problems are characterised by multiple and stochastic performance measures and constraints, and a large number of discrete and continuous (mixed) decision variables, which significantly complicates the problem solution process. Therefore, there is a growing need for new optimisation methods and algorithms, which would be capable of solving the outlined problems.

The combination of stochastic simulation and multi-objective optimisation is considered to be one of the most promising research directions related to optimisation of complex systems and processes. A significant contribution to the development of this research direction is made by Syberfeldt, Merkuryev, Amodeo, Prins, Sánchez, Lee, Chew, Teng and Chen [4, 31, 35, 50]. Nevertheless, there are still many research problems to be solved.

First, there is no full agreement on which simulation-based optimisation methods and algorithms should be used to efficiently investigate a search space and its regions at a low number of optimisation iterations. In addition, this problem is complicated by the need to improve the approximation accuracy of a Pareto-optimal front, when analytical estimates of objective functions are not available. Second, an experimental research on the best combination of a global and local search approaches for generating Pareto-optimal solutions is required. Finally, there exists a class of application problems referred to cyclic planning of complex systems, for which powerful optimisation methods should be developed. In the thesis, the research for these problems is predominant.

The goal and the tasks of the thesis

The thesis is aimed at developing methods, algorithms and a prototype of a software environment to solve multi-objective stochastic simulation-based optimisation problems with constraints and mixed decision variables, as well as to apply them to multi-echelon cyclic planning. To achieve this aim, the following tasks are specified:

1) To analyse existent approaches and methods of multi-objective stochastic simulation optimisation in order to formulate the requirements for solving the proposed problem.
2) To develop methods and algorithms, which allow simultaneously providing approximation accuracy and diversity of a Pareto-optimal front while minimising the number of simulation optimisation iterations by integrating evolutionary computation and response surface methodology.
3) To develop main blocks and mechanisms of the genetic algorithm and response surface-based linear search algorithm by combining the advantages of the global and local search approaches.
4) To create a prototype of the software environment that allows analysing input data, developing simulation models and optimising their parameters.
5) To apply developed methods and algorithms in solving supply chain cyclic planning problems.

The object and the subject of the research

The object of the research is multi-objective stochastic simulation-based optimisation with constraints and mixed decision variables.

The subject of the research is the development of methods and algorithms for searching Pareto-optimal solutions with application to multi-echelon cyclic planning.

Research methods

The research is based on using discrete-event simulation, multi-objective optimisation, morphological analysis, statistical analysis, evolutionary computation, response surface methodology (RSM) and supply chain cyclic planning methods.

Scientific novelty

The scientific novelty of the thesis is as follows:

1) Morphological analysis of well-known hybrid multi-objective evolutionary algorithms enabled defining the best combination of their parameters in accordance with the requirements for the proposed problem solving.
2) Two-phase search method is based on the combination of the global and local search approaches, which are aimed at providing

the diversity of Pareto-optimal solutions and increase their approximation accuracy, respectively.

3) Main blocks and mechanisms of a multi-objective simulation-based genetic algorithm are developed including a mechanism for encoding diploid chromosomes, uniform population initialisation mechanism, a penalty-based constraints' handling technique, a dominance-based termination criterion and heuristic rule for decreasing the number of simulation replications.
4) The developed prototype of the software environment enables optimising parameters of the cyclic schedules for supply chain planning.

Practical value

The proposed prototype of the software environment supports the main stages of simulation-based optimisation including a supply chain description in MS Excel format, an automatic generation of the corresponding simulation models, as well as optimisation of simulation model parameters by using the methods and algorithms developed in the doctoral thesis. The implementation of these stages minimises the time and efforts required for creating simulation models and performing optimisation experiments.

The developed methods and algorithms are applied to Huntsman business case in order to define the optimal lengths of process cycles and stock point order-up-to levels during the maturity phase of the product life cycle. They can be also used for solving cyclic planning problems in different complex systems. In comparison with other optimisation tools the search for Pareto-optimal solutions requires less simulation optimisation iterations due to sequential using of global and local search approaches.

Approbation of the obtained results

The results of the thesis have been presented at **11 international scientific conferences**:

1) International Conference "*24th European Conference on Operational Research*" (EURO 2010), Lisbon, Portugal, July 11-14, 2010.
2) RTU 50th International Scientific Conference, Section "*Information Technology and Management Science*", Riga, Latvia, October 14-16, 2009.

3) International Conference "*13th IFAC Symposium on Information Control Problems in Manufacturing*" (INCOM'2009), Moscow, Russia, June 3-5, 2009.
4) International Conference "*European Modelling and Simulation Symposium*" (EMSS'2008), Campora San Giovanni, Amantea (CS), Italy, September 17-19, 2008.
5) RTU 49th International Scientific Conference, Section "*Information Technology and Management Science*", Riga, Latvia, October 13-15, 2008.
6) International conference "*20th International EURO Mini Conference „Continuous Optimization and Knowledge-Based Technologies*" (EurOpt'2008), Neringa, Lithuania, May 20-23, 2008.
7) International Conference "*10th International Conference on Computer Modelling and Simulation*" (EUROSIM/UKsim'2008), Cambridge, Great Britain, April 1-3, 2008.
8) International Conference "*6th EUROSIM Congress on Modelling and Simulation*" (EUROSIM'2007), Ljubljana, Slovenia, September 9-13, 2007.
9) International Conference "*European Modelling and Simulation Symposium*" (EMSS'2006), Barcelona, Spain, October 4-6, 2006.
10) International Conference "*European Conference of Modelling and Simulation*" (ECMS'2005), Riga, Latvia, June 1-4, 2005.
11) RTU 45th International Scientific Conference, Section "*Information Technology and Management Science*", Riga, Latvia, October 14-16, 2004.

The results have been published in **13 scientific papers** including **1** book chapter published by Springer, **1** paper in the International Journal of Simulation and Process Modelling and **11** papers in scientific proceedings of international conferences:

1) Merkuryeva G., Napalkova L. Two-Phase Simulation Optimisation Algorithm with Applications to Multi-Echelon Cyclic Planning// International Journal of Simulation and Process Modelling (IJSPM). - 2010. - Vol.6. - No.1. - p. 7-18 http://www.inderscience.com. Compendex, Inspec.
2) Napalkova L. Hybridisation of evolutionary algorithms for solving multi-objective simulation optimisation problems//

RTU 50th International Scientific Conference. - Riga: Publishing House of RTU, October 14-16, 2009. - p. 9-15 EBSCO, CSA/ProQuest, VINITI.

3) Merkuryeva, G., Napalkova, L. Multi-Objective Genetic Local Search Algorithm for Supply Chain Simulation Optimisation// International Conference on Harbor, Maritime & Multimodal Logistics Modelling and Simulation. – Tenerife: Universidad de la Laguna, September 23-25, 2009. - p. 190-194 Thomson SCI.
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., Napalkova, L. Supply Chain Cyclic Planning and Optimisation. Simulation-Based Case Studies in Logistics: Education and Applied Research. - London: Springer-Verlag, 2009. - p. 89-107 SpringerLink.
6) Merkuryeva, G., Napalkova, L. Two-Phase Simulation Optimisation Procedure with Applications to Multi-Echelon Cyclic Planning// The 20th European Modelling and Simulation Symposium (EMSS’2008). - Genoa: University of Genoa, September 17-19, 2008. - p. 51-58 Thomson SCI.
7) Merkuryeva, G., Napalkova, L. Development of Multi-Objective Simulation-Based Genetic Algorithm for Supply Chain Cyclic Planning and Optimisation// The 20th International EURO Mini Conference “Continuous Optimisation and Knowledge-Based Technologies” (EurOpt’2008). - Vilnius: VGTU Publishing House “Technika”, May 20-23, 2008. - p. 444-449.
8) Napalkova, L., Merkuryeva, G. Theoretical Framework of Multi-Objective Simulation-Based Genetic Algorithm for Supply Chain Cyclic Planning and Optimisation// The 10th International Conference on Computer Modelling and Simulation (EUROSIM/UKSim’2008). – Cambridge: IEEE Computer Society, April 1-3, 2008. - p. 467-474 Scopus, Compendex, CS Digital Library.
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10) Merkuryeva, G., Napalkova, L. Development of Simulation-Based Environment for Multi-Echelon Cyclic Planning and Optimization// The 6th EUROSIM Congress on Modelling and Simulation (EUROSIM’2007). - Ljubljana: EUROSIM/SLOSIM, September 9-13, 2007. - p. 1-9.
11) Napalkova, L., Merkuryeva, G., Piera, M.A. Development of Genetic Algorithm for Solving Scheduling Tasks of FMS with Coloured Petri Nets. International Mediterranean Modelling Multiconference. – Barcelona: LogiSim, October 4-6, 2006. - p. 135-140 Thomson SCI.
12) Merkuryeva, G., Napalkova, L. Applications of NeuroFuzzy Training Algorithms to Simulation Metamodelling// The 19th European Conference of Modelling and Simulation (ECMS’2005). – Riga: Publishing House of RTU, June 1-4, 2005. - p. 745-749 Thomson SCI.
13) Merkuryeva, G., Napalkova, L. Applications of NeuroFuzzy training algorithms to analysis of business processes// RTU 45th International Scientific Conference. – Riga: Publishing House of RTU, October 14-16, 2004. - p. 141-148.

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

1) “*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.
2) *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.

The scientific importance of the methods and algorithms developed in the doctoral thesis is approved by the Certificate of Significant Academic Contribution issued by MÖBIUS Ltd. in the scope of the task “*Maturity phase best practice development*” within the ECLIPS project.

Structure of the thesis

The doctoral thesis consists of introduction, 5 chapters, conclusions, bibliography and 4 appendixes. The thesis contains 156 pages, 65 figures and 14 tables. The bibliography contains 205 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 "Statement of the multi-objective simulation optimisation problem" discusses the main aspects of complex process optimisation including supply chain planning. The chapter formulates the investigated problem as a multi-objective stochastic simulation-based optimisation with constraints and mixed decision variables. The state-of-the-art in simulation optimisation is analysed. Basic approaches to the problem solving are reviewed with respect to the requirements formulated.

Chapter 2 "Analysis of methods for multi-objective simulation optimisation" analyses simulation optimisation methods aimed at searching for Pareto-optimal solutions with respect to the problem requirements specified. Morphological analysis of hybrid multi-objective evolutionary algorithms is then performed to identify the best combination of the values of parameters for the problem solving.

Chapter 3 "Framework of the simulation-based hybrid optimisation method" presents a two-phase search and compromise programming methods, which comprise the simulation-based hybrid optimisation method. The two-phase search method includes the blocks and mechanisms of a multi-objective simulation-based genetic algorithm and RSM-based linear search algorithm. To select a single solution from the Pareto-optimal front, the compromise programming method is used.

Chapter 4 "Multi-objective simulation optimisation for supply chain cyclic planning" investigates the features of a supply chain cyclic planning process and presents a formalised problem statement including variables, performance measures and constraints. Then, it develops a prototype of the software environment for simulation-based optimisation of supply chain cyclic planning parameters.

Chapter 5 "Approbation of the developed methods and algorithms" evaluates the effectiveness of the developed methods

and algorithms based on solving supply chain cyclic planning problems. For that purpose, both simplified and Huntsman business case studies are accomplished.

Results and conclusions of the thesis

Bibliography

Appendixes

SUMMARY OF THESIS CHAPTERS

Statement of the multi-objective simulation optimisation problem

In Chapter 1, an optimisation problem of complex systems/processes is formulated as a multi-objective stochastic simulation-based optimisation problem with constraints and mixed (both continuous and discrete) decision variables. The state-of-the-art in simulation optimisation is analysed with respect to the advantages and disadvantages of existing methods. The requirements for the problem solving are formulated, and a basic problem-solving approach is selected for further investigation.

The optimisation of complex systems/processes plays a vital role in the growth and profitability of modern business companies. In order to perform optimisation of such systems/processes, a link between simulation and optimisation is often indispensable. Due to that, simulation optimisation becomes a central part of many scientific and technological investigations [12, 21].

The main emphasis of the doctoral thesis is placed on the class of "complex management processes" that are typical for supply chain tactical planning and for solving many similar optimisation problems in the separate stages of a supply chain, i.e., procurement, production, distribution and sales. A complex management process is interpreted as abstraction of a dynamic system that adapts to steadily changing and unpredictable environment. In general, this kind of system is characterised by the following six features [57, 58]:

a) a hierarchical network-based structure;
b) a large number of decision variables including both discrete and continuous ones;
c) an emergent behaviour of the system as a whole;
d) a conflicting behaviour of system elements;
e) multiple performance measures; and
f) a stochastic nature.

The hierarchical network-based structure of a system provides that decisions at a given level depend on the decisions made at upstream and downstream levels.

A large number of continuous and discrete decision variables results from a system size and the number of links between system elements, which increases computational complexity of simulation optimisation problem.

The system's emergent behaviour means that it cannot be predicted merely on the basis of understanding the behaviour of the system elements or from understanding interactions between them. In opposite, all these elements working together should be investigated [9, 44].

The conflicting behaviour of system elements can generate conflicting planning decisions.

The multiple performance measures of a complex system encourage searching for a set of the best trade-off solutions instead of a global optimal solution.

Finally, the stochastic nature comes from the dependence of system performance on uncertainty of the behaviour of its environment. This refers to unpredictable changes in values of system environmental variables over time.

The known optimisation methods that use analytical models like mixed integer programming, non-linear programming and stochastic dynamic programming, are not designed to deal with all the above-mentioned features of complex systems. Even if the optimisation problem can be formulated analytically, there could be a lack of an efficient analytic or heuristic solving method. Moreover, in some cases mathematical simplifications introduced in analytical models could result in suboptimal solutions.

In contrast, the simulation technology does not require a rigid structure of the analytical model and provides an experimental approach to a complex system/process analysis [34, 45, 48]; combined with optimisation it is called the simulation optimisation approach. Here, the optimisation module runs a stochastic discrete-event simulation model N times in order to map the model input variables $\mathbf{x}$ into performance measures $\hat{\mathbf{y}}$, where N is the number of simulation replications. At each replication i, the model is executed during T periods (Figure 1).

At each iteration τ, the optimisation module attempts to improve a solution. Comparing both current and previous estimates of objective function values or performance measures produced by the simulation model, it guides a search toward a near-optimal direction; and these estimates are influenced by stochastic environmental variables $\mathbf{z}^t$ of the model at discrete points of time $t \in [1, T]$, which requires estimating the mathematical expectation $\mathbb{E}[\cdot]$ of objective functions. The optimisation model generates new values of decision variables to approach nearer to optimal solution **x***. These actions are performed until the termination criterion is satisfied.

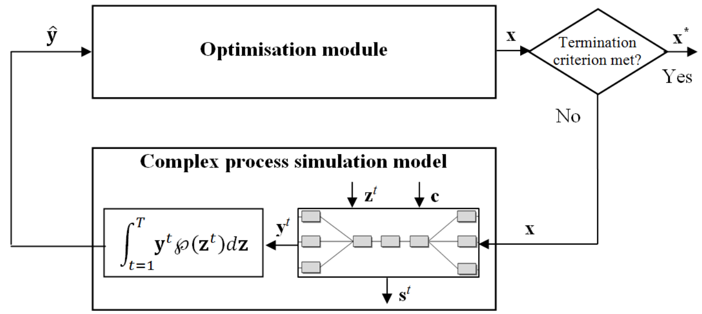


Figure 1.Operational scheme of the simulation optimisation approach

Related variables and parameters of simulation optimisation are specified in the vector form, i.e.:

a) *input vector* **x** of K input variables, $\mathbf{x} = (x_1,..., x_K) \in X$, where the decision space $X \subseteq \mathbb{R}^+$ is defined in a set of positive real numbers. In the context of optimisation, these variables are called *decision variables*;
b) *vector* **c** of B model parameters, i.e., constants, $\mathbf{c} = (c_1,...,c_B) \in C$, where C is the space of model parameters;
c) *disturbance vector* $\mathbf{z}^t$ of D environmental variables, $\mathbf{z}^t = (z_1^t, \dots, z_D^t) \in Z$, where Z is the space of environmental variables, $t \in [1, T]$ is a period, and T is the length of a simulation replication measured in periods (hours, days, weeks, etc.);
d) *state vector* $\mathbf{s}^t$ of R state variables, $\mathbf{s}^t = (s_1^t, \dots, s_R^t) \in S$, where S is the space of state variables. These variables characterise elements of the system and their relations with other elements at $t \in [1, T]$;
e) *output vector* $\mathbf{y}^t$ of M output variables (i.e., performance measures), $\mathbf{y}^t = (y_1^t, \dots, y_M^t) \in Y$, where Y is the objective space. Values of output variables are the responses generated by the simulation model at $t \in [1, T]$.

The optimisation methods that are able to produce solutions by using simulation models instead of analytical expressions are called simulation optimisation methods [7]. Summarising the reviews of Andradottir [5], Azadivar [7], Merkuryev and Visipkov [35], Fu [21], and Ólafsson and Kim [43], the shortcomings of the major optimisation techniques used in the area of simulation optimisation are defined as follows:

- *Response surface methodology (RSM)* provides statistical significance of solutions and reproducibility of regression metamodels, while having a slow convergence to a global solution.
- *Stochastic approximation (SA)* and *sample path optimisation (SPO) methods* require a large number of simulation optimisation iterations.
- *Ranking and selection (RS)* are only applicable to optimisation problems with a relatively small decision space.
- *Heuristics (Hs)* provide a good performance with a high probability on the average, while not guaranteeing that a global optimal solution will be found.

This analysis reveals that simulation optimisation methods have been mainly applied to single-objective optimisation problems [1, 6, 13, 27], whereas multi-objective problems have been often solved by aggregating multiple performance measures into a single one [3, 46]. In addition, a number of single-objective and multi-objective simulation optimisation methods are developed for specific applications, e.g., manufacturing high-technology components for aircraft- and gas turbine engines [50], the kanban sizing [23] and the inventory management [3]. Thus, there is a need for a method, which on the one hand can cope with the above-discussed features of complex systems by using simulation models, but on the other hand is general enough to be applicable to a diversity of these systems.

Here, the optimisation problem is formulated mathematically as a multi-objective stochastic simulation-based optimisation problem with constraints and mixed decision variables:

$$\mathrm{opt}_{\mathbf{x}\in X}\ \hat{\mathbf{y}} = \mathbf{f}(\mathbf{x}) = \int_{t=1}^{T} \mathbf{y}^t \wp(\mathbf{z}) d\mathbf{z} = \mathbb{E}[\boldsymbol{\omega}(\mathbf{y}^T)], \quad (1)$$

$$\text{where } \mathbf{y}^t = \varphi(\mathbf{x}, \mathbf{c}, \mathbf{z}^t, \mathbf{s}^t),$$

$$\text{subject to } X\text{: } \begin{cases} \mathbf{g}(\mathbf{x}) = \mathbb{E}[\boldsymbol{\gamma}(\mathbf{y}^T)] \geq 0, \\ \mathbf{h}(\mathbf{x}) = \mathbb{E}[\boldsymbol{\eta}(\mathbf{y}^T)] = 0, \end{cases} \quad (2)$$

where **f** : $X \to Y'$ is a vector of objective functions, which links values of a decision vector $\mathbf{x} \in X$ with corresponding expected values of an output vector $\hat{\mathbf{y}} \in Y'$, where Y' is an approximate objective space;

$\mathbb{E}[\cdot]$ denotes the mathematical expectation;

$\wp$ is a probability density function of a random vector of environmental variables;

φ represents a mapping that results from a simulation algorithm;

g, **h** define vectors of inequality and equality constraints;

ω, **γ**, **η** present vectors of stochastic sample response functions.

Based on the state-of-the-art of simulation optimisation and the problem statement (1)-(2), the following requirements to the optimisation method are specified:

R1. minimise an Euclidean distance d between the true $\mathcal{PF}^*$ and approximate $\widetilde{\mathcal{PF}}^*$ Pareto-optimal fronts:

$$\min d(\mathcal{PF}^*, \widetilde{\mathcal{PF}}^*); \tag{3}$$

R2. maximise a diversity δ^i of the Pareto-optimal solutions $\mathbf{x}^i \in \widetilde{\mathcal{PF}}^*$ to have a wide range of variety:

$$\max \sum_{i=1}^{|\widetilde{\mathcal{PF}}^*|} \delta^i, \tag{4}$$

where $|\widetilde{\mathcal{PF}}^*|$ is the number of solutions in the Pareto-optimal front $\widetilde{\mathcal{PF}}^*$; i is an index of a solution;

R3. minimise the number ρ^τ of non-dominated solutions that are lost during the transition from iteration τ to iteration τ+1:

$$\min \sum_{\tau=1}^{\tau^*} \rho^\tau; \tag{5}$$

R4. minimise computational costs defined as a total number τ of simulation optimisation iterations;

R5. generate discontinuous Pareto-optimal fronts;

R6. use both continuous and discrete decision variables;

R6.1. use global search methods for exploring the large space of discrete and continuous decision variables;

R6.2. use local search methods for exploring small regions around continuous decision variables to approach Pareto-optimal solutions as close as possible;

R7. include the uncertainty of system environmental variables in the search process.

The general problem solving process is composed of two stages:

1) *the search stage* aimed at generating the approximate Pareto-optimal front $\widetilde{\mathcal{PF}}^*$;
2) *the selection stage* aimed at choosing a single solution **x*** for the implementation in practice.

Depending on how these stages are combined, three basic approaches can be indicated, such as selection before search, selection during search and selection after search. Analysis of these approaches determines selection after search as the most preferable one for solving the problem formulated in the thesis. The advantage of this approach is that it is compatible with single-objective methods that should be executed several times with different settings in order to obtain the approximate Pareto-optimal front, and with multi-objective optimisation methods that require only a single execution.

Analysis of methods for multi-objective simulation optimisation

Chapter 2 analyses multi-objective evolutionary algorithms (MOEAs) and compares them with the other simulation optimisation methods and algorithms, such as RSM, SA, SPO, RS and Hs. Then, a hybrid combination of the properties of the known simulation optimisation methods and algorithms is determined in order to satisfy the requirements *R1 ÷ R7*.

The analysis reveals that RSM-based, SA and SPO methods are used to optimise only continuous decision variables, whereas these methods and also heuristics cannot generate discontinuous Pareto-optimal fronts.

In contrast, the MOEAs [14, 20, 25, 29, 47, 55, 56] are able to evolve a set of non-dominated solutions instead of a single one and to explore a large search space with continuous and discrete decision variables. However, their essential disadvantage is that they are often unable to simultaneously provide a high approximation accuracy and diversity of the Pareto-optimal front at a small number of simulation optimisation iterations.

The comparison of the simulation optimisation methods and algorithms shown in Table 1 demonstrates that none of them satisfies all the requirements *R1 ÷ R7*. This table also indicates that the most rational way of solving the problem (1)-(2) is to compose a method based on determining the best combination of MOEAs with other methods and algorithms.

Recently, a number of different hybrid schemes have been proposed in the literature [18, 22, 28, 32, 52]. However, most of them have been restricted to the benchmark of deterministic multi-objective optimisation problems that are formulated analytically. The hybrid schemes are also implemented in commercial simulation optimisation tools such as SimRunner® and OptQuest® that aggregate multiple performance measures into a single one or keep them as constraints. Thus, there is currently a lack of hybrid multi-objective EAs in combination with simulation models, which are able to generate Pareto-optimal fronts. In order to fill this gap, the technique of morphological analysis [2] is used to investigate possible configurations of hybrid algorithms and elicit the final one that best satisfies the given requirements (*R1* ÷ *R7*).

Table 1

Comparison of simulation optimisation methods and algorithms

Requirements \ Methods and algorithms	RSM	SA	SPO	RS	Hs	MOEAs
R1 + *R2*	-	-	-	-	-	-
R3	-	-	-	-	-	+
R4	+	-	-	-	+	-
R5	-	-	-	-	-	+
R6	-	-	-	+	+	+
R7	+	+	-	-	-	-

As shown in Figure 2, seven parameters of hybrid algorithms are identified and relevant values are defined for each of these parameters. The total number of configurations in a morphological field resulted from these parameters is equal to $M = m_1 \cdot m_2 \cdot \cdot \cdot m_7 = 128$, where m_i is the number of relevant values for i-th parameter ($i = 1, 2, \ldots, 7$). Each configuration $A_k = (a_{1j}^{(k)}, \ldots, a_{7j}^{(k)})$ defines a certain hybrid algorithm, where $a_{ij}^{(k)}$ denotes the j-th value of the i-th parameter in the k-th morphological configuration [40].

In order to reduce the morphological field to a smaller set of consistent configurations, hybrid multi-objective evolutionary algorithms known in literature are examined [15, 16, 24, 26, 30, 33, 42, 49, 51, 53]. These algorithms are divided into subsets corresponding to five morphological configurations *A1* ÷ *A5*. According to the above requirements (*R1* ÷ *R7*), two-phase algorithms corresponding to the morphological configuration $A_4 = (a_{12}, a_{32}, a_{41}, a_{51}, a_{61}, a_{71})$, i.e., the hybrid EA [51] and hybrid elitist non-dominated sorting genetic algorithm (hybrid NSGA-II) [15], are selected as the most suitable for simulation optimisation. Here, EA is

used at the first phase to obtain an approximate Pareto-optimal front and to keep a uniform distribution among the solutions, whereas the local search algorithm improves an approximation accuracy of the Pareto-optimal front at the second phase. In case of simulation optimisation, such hybrid algorithms can be less computationally expensive than, for instance, simple multi-objective genetic local search algorithm (S-MOGLS) [26] and memetic Pareto-archived evolution strategy (M-PAES) [30], because they apply a local search only after a genetic search is completed. In addition, they don't require parallel runs of simulation models and can be easily implemented on a single computer.

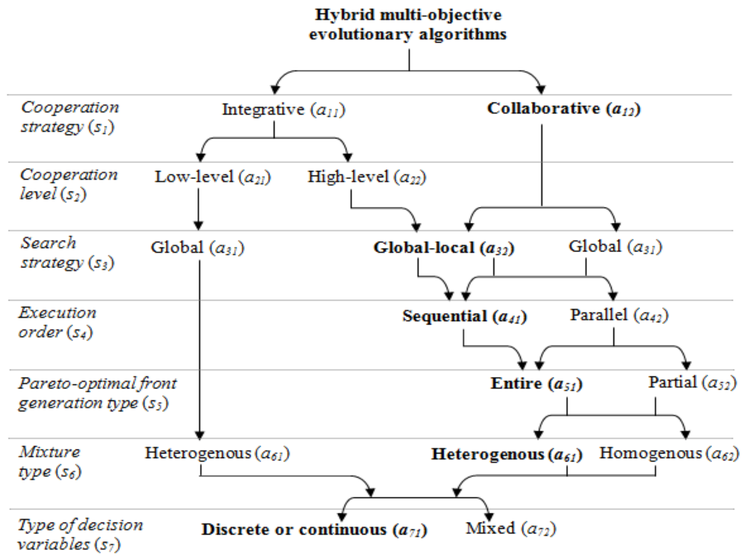


Figure 2. The links between the parameters of hybrid algorithms

At the same time, it is concluded that the hybrid EA and hybrid NSGA-II require modification due to ineffective use of a global and local search in case of operating with mixed decision variables and stochastic output variables, which are typical features of the outlined problem. For this reason, the configuration $A^*_4 = (a_{12}, a_{32}, a_{41}, a_{51}, a_{61}, a_{72})$ that is the nearest to the above configuration A_4 (see Figure 3) is selected for the development of the hybrid algorithm required and differs only by the last parameter. While selecting this configuration, it is taken into account that hybrid analogues such as hybrid EA and hybrid NSGA-II have additional disadvantages as follows:

- a fixed number of optimisation iterations, which is defined as a termination criterion in the hybrid EA, doesn't permit to measure the algorithm's convergence level;
- local search algorithms used in both hybrid algorithms are not powerful enough to perform a local improvement of Pareto-optimal solutions in case of simulation optimisation;
- local search algorithms require aggregating multiple objective functions into a weighted sum, which can cause a search in wrong directions.

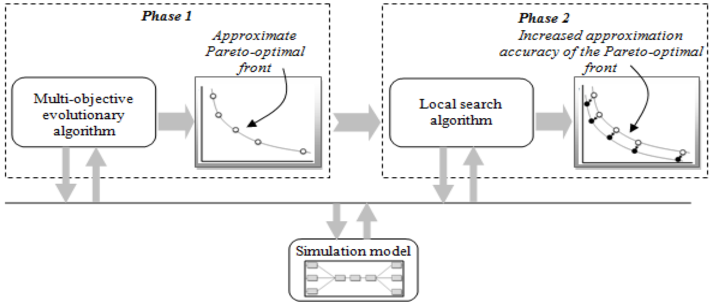


Figure 3. General scheme of the algorithm based on the configuration A_4

Thus, the modification of the selected hybrid analogues and a removal of the above-mentioned disadvantages can provide a new framework resulting in new method of solving the problem.

Framework of the simulation-based hybrid optimisation method

Chapter 3 describes the simulation-based hybrid optimisation method developed for solving the problem in accordance with the approach of selection after search and the configuration A^*_4. This method integrates the two-phase search and compromise programming methods. In particular, the two-phase search [38] applies evolutionary computation and response surface methodology. A multi-objective simulation-based genetic algorithm (MOSGA) is used for a global search of Pareto-optimal solutions, whereas a RSM-

based linear search algorithm allows local improving of the solutions. To select a single solution from the Pareto-optimal front, a compromise programming method is employed.

A general scheme of the simulation-based hybrid optimisation method is shown in Figure 4. The scheme operates starting from the MOSGA algorithm that is used to find near-optimal values of discrete and continuous decision variables in Phase 1 of the search stage. In Phase 2, the RSM-based linear search algorithm improves the values of continuous decision variables, and an output of this phase is the approximate Pareto-optimal front $\widetilde{\mathcal{PF}}^*$. In the selection stage a single Pareto-optimal solution $\mathbf{x}^* \in \widetilde{\mathcal{PF}}^*$ is determined by using compromise programming that measures deviations of all found solutions from an ideal (utopian) point predefined by a decision maker.

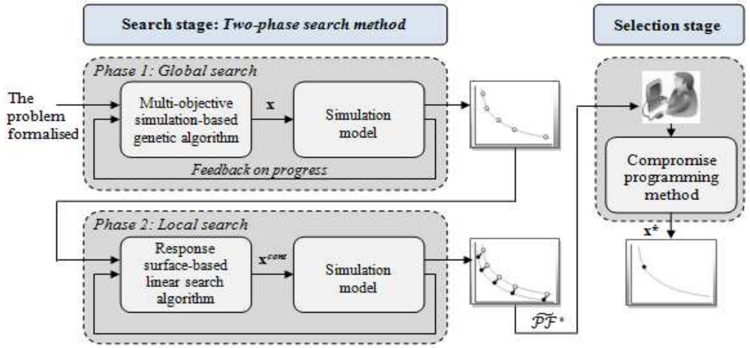


Figure 4. General scheme of the simulation-based hybrid optimisation method

Being a modified version of NSGA-II [14], the MOSGA algorithm [41] contains a mechanism for encoding diploid chromosomes consisting of two sets of chromosomes, a heuristic rule for reducing a computation time, a mechanism for generating uniform populations, ranking-based fitness assignment and estimation mechanisms, a diversity preservation mechanism, a penalty-based constraint handling technique, a crowded-two tournament selection mechanism, uniform crossover and mutation operators, an elitist mechanism, as well as a domination-based termination criterion. Formally, it can be described as follows.

Let $P^{\tau MOSGA} = \{a^{n1}, a^{n2} | n = \overline{1,N}\}$ be a population that consists of N diploid chromosomes. Each diploid chromosome in $P^{\tau MOSGA}$ is represented by two binary strings, such as:

$$a^{n1} = \left(a^{n1}{}_{\ell_1-1} a^{n1}{}_{\ell_1-2} \dots a^{n1}{}_1 a^{n1}{}_0\right) \in \{0,1\}^{\ell_1}, \qquad (6)$$

$$a^{n2} = \left(a^{n2}{}_{\ell_2-1} a^{n2}{}_{\ell_2-2} \dots a^{n2}{}_1 a^{n2}{}_0\right) \in \{0,1\}^{\ell_2}, \qquad (7)$$

where n is the number of a string; ℓ_1 and ℓ_2 are lengths of strings; a_k^{n1} and a_k^{n2} are genes at locus k.

Binary strings a^{n1} are used in order to encode discrete decision variables $x_i^{n,discr}$ measured on a time scale by using a modified binary encoding, such as:

$$a^{n1} = \phi\left(\log_2\left(\frac{x_i^{n,discr}}{t}\right)\right), \qquad (8)$$

where ϕ is an encoding algorithm; i is an index of a solution; t is a basic period or the minimal available value of $x_i^{n,discr}$.

Binary strings a^{n2} are intended for continuous decision variables $x_i^{n,cont}$, and they are developed by using classical binary encoding procedure.

The performance of the MOSGA algorithm is controlled by the genetic operator $\mathcal{G}$ that implements iterative transitions between populations according to:

$$P^{\tau MOSGA+1} \sim \mathcal{G}(P^{\tau MOSGA}), \qquad (9)$$

where $\sim$ is an equivalence relation.

This operator is composed of four operators, such as the crowded-two tournament selection ($\mathcal{A}_s$), the uniform crossover ($\mathcal{A}_c$), the mutation ($\mathcal{A}_m$) and the reproduction ($\mathcal{A}_r$) so that:

$$\mathcal{G} = \mathcal{A}_s \circ \mathcal{A}_c \circ \mathcal{A}_m \circ \mathcal{A}_r; \qquad (10)$$

The crowded-two tournament selection operator $\mathcal{A}_s$ maps the n-th string into multiple copies of itself according to its dominance depth and crowding distance. The dominance depth r^n defines a dominance degree of a certain solution, where the value "1" corresponds to non-dominated solutions. The crowding distance δ^n estimates the density of solutions surrounding the n-th solution, where the value "∞" indicates the less crowded area.

The values of r^n and δ^n are estimated based on the values of the performance measures $\hat{\mathbf{y}}^n$ that are obtained from simulation experiments. In order to reduce a computation time, the evaluation of solution feasibility is performed after the first simulation replication

based on $f_j(\mathbf{x}^n) < \gamma_j$, where γ_j is a lower bound of the j-the performance measure. If the solution $\mathbf{x}^n$ is infeasible, then further simulation replications are not performed.

After applying the uniform crossover $\mathcal{A}_c$ and mutation $\mathcal{A}_m$ operators, the new population $\mathcal{P}^{\tau MOSGA+1}$ is replaced with the union of the best parents $P^{\tau MOSGA}$ and mating pool $\mathcal{M}^{\tau MOSGA}$ (reproduction operator $\mathcal{A}_r$) in order to avoid the loss of non-dominated solutions during the search. Dominance depths of chromosomes are updated in the combined population $P^{\tau MOSGA} \cup \mathcal{M}^{\tau MOSGA}$. First N solutions are gathered for the next population $P^{\tau MOSGA+1}$, and the above-described operations are repeated.

The MOSGA algorithm is automatically terminated, when a number $d_{\tau_{MOSGA}}$ of populations with a stagnant non-dominated set is equal to the predefined value d^*, which is defined as:

$$d_{\tau_{MOSGA}} = d^*; \qquad (11)$$

Since the MOSGA is a stochastic algorithm, it could produce different solutions for different random number seeds. This issue is supported by performing several independent optimisation experiments based on using different random number seeds. Then, a composite set of best non-dominated solutions is created.

The flowchart of the developed algorithm is shown in Figure 5.

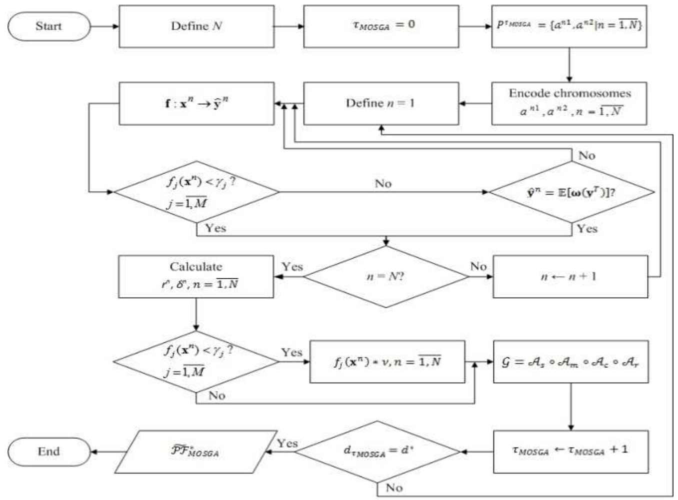


Figure 5. Flowchart of the MOSGA algorithm

The RSM-based linear search algorithm applied to simulation optimisation illustrated in Figure 6 presents an iterative procedure [36] that in each iteration m includes the following steps:

- a local approximation of a response surface function by a regression-type metamodel;
- checking the fit of a metamodel;
- a linear search in steepest descent direction.

The algorithm starts from using a linear metamodel in a small region of independent factors. The metamodel describes main effects of input factors as follows:

$$y^m = b_0^m + \sum_{k=1}^{K} b_k^m \xi_k^m + \varepsilon^m , \quad k = 1,\dots, K , \qquad (12)$$

where y^m is a response variable; ξ_k^m is a coded input factor k; b_0^m and b_k^m are a constant and a regression coefficient of the input factor k, respectively; ε^m is a statistical error of a regression model (or residual); K is the number of input factors. In order to fit the metamodel, the Plackett-Burman experimental design [39] is created in which response values are received from simulation experiments.

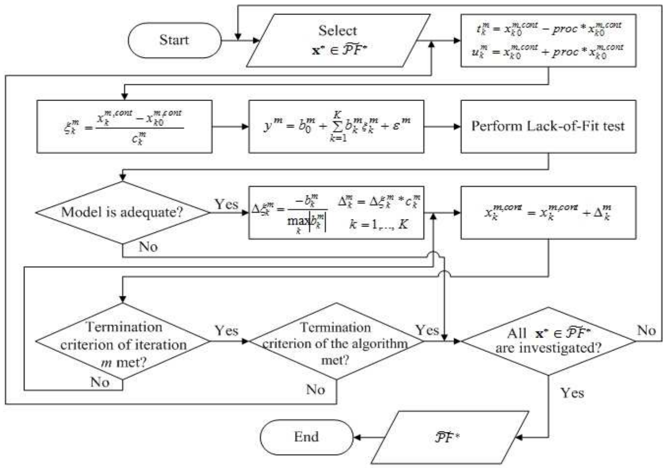


Figure 6. Flowchart of the RSM-based linear search algorithm

If the metamodel is adequate, then a local response surface is sequentially investigated by using a linear search in the steepest descent direction in order to improve the values of continuous input factors. The steepest descent direction is defined by regression coefficients b_0^m, b_2^m,…, b_K^m starting from the center point of the experimental region. The search direction is chosen as the negative of the gradient. The local search is performed for input factors that correspond to significant regression coefficients (p-value < 0.05). If the metamodel is not adequate or further improvement is impossible, then the RSM-based linear search algorithm is terminated.

In the selection stage, the Pareto-optimal front $\widetilde{\mathcal{PF}}^*$ is analysed in order to select a single solution that could be most suitable for the implementation in practice. For that, the compromise programming method [54] is used. It is based on identifying an ideal trade-off solution, for which optimal values of objectives are usually given by the decision maker. Then, the task is to find a solution that is closest to the ideal one. To calculate the degree of closeness, the following distance metric L_p is used:

$$L_p\!: \ \rho(\hat{\mathbf{y}}^{norm}, \mathbf{z}^{norm}) = \left(\sum_{j=1}^{M} \left|\hat{y}_j^{norm} - z_j^{norm}\right|^p\right)^{1/p}, \qquad (13)$$

where $\hat{y}_j^{norm}$ is a normalised value of the jth performance measure in the Pareto-optimal front $\widetilde{\mathcal{PF}}^*$; z_j^{norm} is a normalised ideal value of the jth performance measure; ρ is the distance between the ideal and Pareto-optimal solution measured on the objective space; p is a power parameter ranging from 1 to ∞.

Multi-objective simulation optimisation for supply chain cyclic planning

In Chapter 4, as a test bed for checking the efficiency of the developed methods and algorithms, the multi-echelon cyclic planning is investigated, and the corresponding optimisation problem is formulated. A prototype of the software environment is developed for solving the formulated problem.

Multi-echelon supply chain planning can be interpreted as a complex process, wherein various business entities (i.e., suppliers, manufactures, distributors, and retailers) work together in order to acquire raw materials, convert these raw materials into specified final products, and deliver these final products to end-customers. To plan and control this complex process at the product maturity phase, cyclic planning policy can be used. It provides the following main benefits: the implementation simplicity, the reduction of administrative costs and the decrease of safety stocks between echelons [34].

The basis of cyclic planning policy constitutes the coordination to be combined with the synchronisation of sub-processes over the time [10, 19]. Here, coordination consists in making trade-off decisions on the basis of arranged interactions among system elements [58]. The synchronisation enables planning every process in the supply chain on a repetitive, “cyclic” basis and fitting the process cycles together, while accounting for the lags of lead times between periods of process initialisation and completion (see Figure 7).

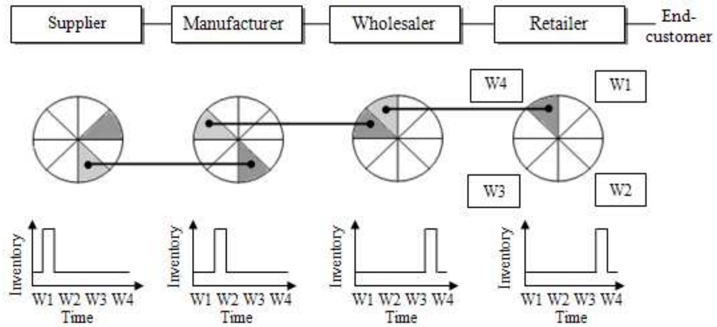


Figure 7. Synchronisation of planning wheels in multi-echelon supply chain [37]

In literature, the parameters of synchronisation policies are optimised by using analytical models [8, 10, 11, 17]. At the same time, simulation technology provides possibilities for more realistic modelling of supply chain operation and extends conditions of analytical models to backordering and model-specific constraints [34].

The problem [37] is to determine near-optimal values of cyclic planning parameters (i.e., process cycles Cy_i and order-up-to levels OUL_i) for each of supply chain stock points $i = \overline{1,I}$ such that the vector of performance measures represented by total cost TC and fill rate FR is optimised with respect to the imposed constraints. Consequently, two objective functions are introduced in the problem. The first one is to minimise the average total cost $\mathbb{E}[TC]$ represented by a sum of production, setup and inventory holding costs, i.e.:

$$\text{Min } y_1 = \mathbb{E}[TC] = \mathbb{E}[\tag{14}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{J} QP_{jt} * CP_j + \quad (\textit{production costs})$$
$$\sum_{t=1}^{T}\sum_{j=1}^{J} (T/Cy_{i\in j}) * CS_j + \quad (\textit{setup costs})$$
$$\sum_{t=2}^{T}\sum_{|S(i)|=0} \frac{H_{it}+H_{it-1}}{2} * CH_i \ + \quad (\textit{holding costs of the last echelon})$$
$$\sum_{t=1}^{T}\sum_{|S(i)|\neq 0} H_{it} * CH_i \ ], \quad (\textit{holding costs of other echelons})$$

where H_{it} is on hand inventory at stock point i at the end of period t; QP_{it} is a production order made by stock point i in period t; CP_j is unit production cost in process j; CS_j is setup cost in process j; CH_i is unit inventory holding cost at stock point i; $S(i)$ indicates a set of stock points immediately succeeding the stock point i; T is the number of periods in the planning horizon; I is the number of stock points, J is the number of processes.

The second objective function is to maximise the average product fill rate $\mathbb{E}[FR]$ calculated as the fraction of demand that can be satisfied directly from the inventory. The product fill rate expressed as a percentage is calculated as the sum of order quantities shipped to end-customers during the planning horizon divided by the total end-customers demand and multiplied by 100, i.e.:

$$\text{Max } y_2 = \mathbb{E}[FR] =$$
$$= \mathbb{E}\left[100 * \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{k=1}^{K} QC_{tik} \Big/ \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{k=1}^{K} D_{tik}\right] \tag{15}$$

where D_{kit} is actual demand of end-customer k to stock point i in period t; QC_{ikt} is the sum of orders delivered by stock point i to end-customer k in period t; K is the number of end-customers.

Feasibility of multi-echelon supply chain cyclic planning solutions is evaluated by using the following stochastic and deterministic constraints:

$$Cy_i = 2^p\tau \quad i=1,...,I, \tag{16}$$
$$Cy_{min} \leq Cy_i \leq Cy_{max} \quad i=1,...,I, \tag{17}$$
$$H_{it} \geq CAP_i \quad i=1,...,I, \tag{18}$$
$$\mathbb{E}[FR] \geq FR_{min} \quad i=1,...,I. \tag{19}$$

Cyclic planning constraint (16) is introduced to synchronise cycles in accordance with the *power-of-two policy*, wherein process cycles are power-of-two multiples $2^p\tau$ in relation to a basic planning period τ, where p is a nonnegative integer; decision variables constraint (17) imposes lower (Cy_{min}) and upper (Cy_{max}) bounds on process cycles Cy_i; capacity constraint (18) defines that on hand stock H_{it} at the end of period t is not allowed to exceed the storage capacity CAP_i of stock point i; fill rate constraint (19) defines that the average fill rate must be higher or equal to a pre-defined lower bound FR_{min}.

The prototype of the software environment (see Figure 8) designed for solving the multi-echelon cyclic planning problem includes four components [34], such as (i) database component, (ii) procedural component, (iii) process component and (iv) optimisation component.

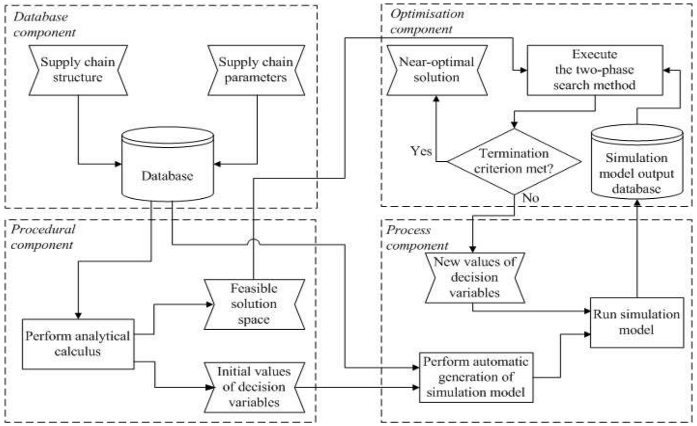


Figure 8. The prototype of the software environment for simulation-based optimisation

Database component is used to store supply chain structure and parameters. Based on these data, procedural component calculates analytically initial values of cyclic planning parameters. Process component (i) automatically generates supply chain simulation model from the data obtained from procedural and database components; and (ii) runs the model for estimating the values of supply chain performance measures. Optimisation component is used to find near-optimal values of multi-echelon cyclic planning parameters.

The components are developed by using MS Excel, Microsoft Visual Basic for Applications (VBA) and ServiceModel Professional 7.0 simulation environment. Data exchange between MS Excel and ServiceModel is supported by ProModel ActiveX Automation capability.

Approbation of the developed methods and algorithms

In Chapter 5, the developed methods and algorithms are applied to simulation optimisation of multi-echelon cyclic planning parameters.

In case study 1, *three-echelon linear supply chain* is analysed as a simplified example. The ServiceModel-based simulation model is generated automatically using the developed software environment. The following assumptions are introduced in the model. The end-customer demand is normally distributed. Process cycles are presented in days according to the power-of-two policy, i.e.: 1, 2, 4, 8, 16, 32, where 32 is the maximal cycle value that corresponds to one full turn of the "planning wheel". Process lead times are considered to be normally distributed. Stock point 1 has infinite on hand stock and is not controlled by any policy. Backorders are delivered in full. The length of one simulation replication comprises 192 periods or 4608 hours (192*24), which allows modelling six full turns of the "planning wheel".

Case study 1 includes five scenarios (1.1-1.5). In Scenario 1.1, the approximation accuracy is evaluated based on measuring the difference between the true and approximate Pareto-optimal fronts and is equal to 98.40%:

The true Pareto-optimal front $\mathcal{PF}^*$ is obtained by using the exhaustive enumeration, whereas the approximate Pareto-optimal front $\widehat{\mathcal{PF}}^*$ is generated by the MOSGA algorithm. As a result, the MOSGA found four of five true Pareto-optimal solutions after five independent executions of the algorithm (see Figure 9).

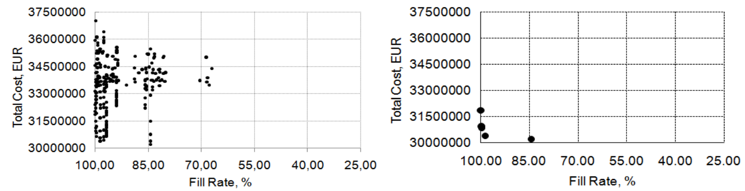


Figure 9. The search space (on the left) and the approximate Pareto-optimal front (on the right)

In scenarios 1.2-1.5, the quality of solutions and the number of optimisation iterations required by the two-phase search method are compared with those received by SimRunner® and OptQuest® optimisation software. This commercial software (Scenario 1.2 and

1.3) finds only a single solution instead of the Pareto-optimal front. Moreover, SimRunner® and OptQuest® require 790 and 435 iterations, respectively. However, the developed method generates the approximate Pareto-optimal front in only 49 iterations, out of which the numbers of iterations of the MOSGA algorithm and the RSM-based linear search algorithm are equal to 42 and 7, respectively. As a result, four trade-off solutions are found that simultaneously provide significant decreasing of total cost and increasing of product fill rate (see Table 3).

Table 3

Comparison of results for Scenarios 1.2-1.4

Scenarios	Solution No.	*TC*, €	*FR*, %	τ
SimRunner®	1	33,521,268	88.18	790
OptQuest®	1	33,656,637	87.36	435
The two-phase search method	1	30,651,322	100.00	49
	2	30,579,657	98.64	
	3	30,445,235	97.55	
	4	30,307,412	91.73	
	5	29,972,845	87.09	
	6	29,923,670	79.09	

The compromise programming method is applied to define which of scenarios provides a solution that is closest to the ideal one. For experiments conducted, the average total cost and average fill rate of an ideal solution **z** are taken as *TC* = €29,000,000 and *FR* = 100.00%, respectively. Hence, the distance values are estimated by the distance metric (13) as applied to solutions obtained by scenarios 1.2-1.4. As a result, it is indicated that the third solution (ρ = 0.332) of the two-phase search method is the most closest to the ideal point.

Case study 2 is aimed at optimising cyclic planning parameters in *five-echelon generic supply chain*. Manufacturing plants of a chemical company “Huntsman Advanced Materials” denoted conditionally as DE and CH are located in Germany and Czech Republic, respectively. Customers come from Spain, Germany and United Kingdom. Raw materials are first converted to the liquid based raisin in the plant CH. Then, they are either delivered to direct customers in Frankfurt and Pamplona or shipped to the plant DE, where other components are added in order to make different chemical products. Finally, the end-products are shipped to

customers connected with this plant. The layout of supply chain simulation model is shown in Figure 10.

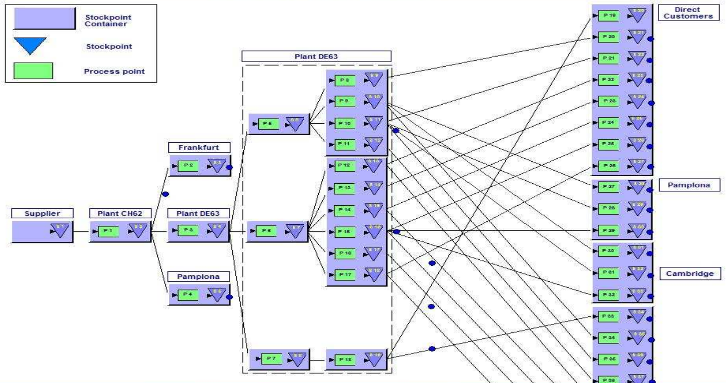
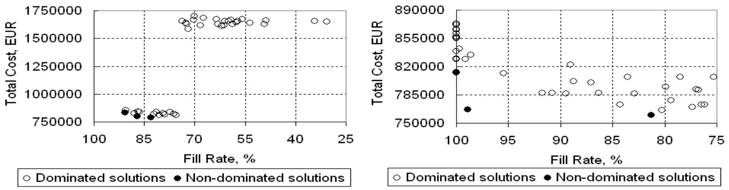


Figure 10. Layout of supply chain simulation model

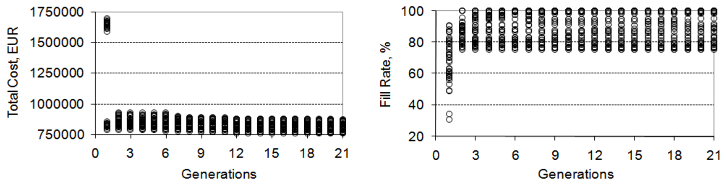
The corresponding ServiceModel-based simulation model is described as follows. It is represented by 42 stages decomposed into 42 stock points and 41 processes. Stock points 20-27 that refer to direct customers are not controlled by any policy. Thus, the number of stock points with parameters to be optimised is equal to 33, and the corresponding number of decision variables is 66. The minimal process cycle is equal to 7 days, and the maximal cycle is equal to 56 days, which corresponds to one full turn of a “planning wheel”. Initial stocks at end-customer echelons are equal to order-up-to levels plus average demand multiplied by cycle delays. The length of one simulation replication is defined by 224 periods or 5376 hours, which allows modelling four full turns of the “planning wheel”.

Scenarios 2.1-2.3 are organised similarly to scenarios 1.2-1.4. In particular, the following results are obtained by the two-phase search method. In Phase 1 the MOSGA works with 66 decision variables. Initial values of order-up-to levels are calculated analytically, and values of process cycles are generated randomly. Figure 11 shows examples of initial and final populations in a specific execution mapped in the objective space. Figure 12 shows the convergence of the MOSGA to solutions with lower total cost and higher fill rate. The Pareto-optimal front received in generations 19-21 contains three solutions with the following expected values of performance measures: (i) *TC* = €787,431, *FR* = 100.00%; (ii) *TC* = €766,669, *FR* = 98.88%; (iii) *TC* = €752,300, *FR* = 93.76%.



a) Initial population b) Final population

Figure 11. Solutions mapped in the objective space



a) Total cost b) Fill rate

Figure 12. The MOSGA performance graphs

In Phase 2 the RSM-based linear search algorithm is used to adjust order-up-to levels of three non-dominated solutions received with the MOSGA while fixing process cycles. Finally, the average total cost *TC* and average fill rate *FR* of the second solution are equal to €756,178 and 98.88%, respectively. The updated Pareto-optimal front is shown in Figure 13.

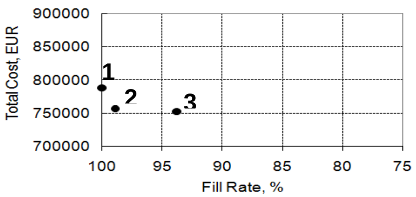


Figure 13. The approximate Pareto-optimal front obtained in Phase 2

In the selection stage, the ideal solution is defined by *TC* = €700,000 and *FR* = 100.00%. As a result, the second solution from the Pareto-optimal front in Figure 13 (ρ = 0.276) is selected by using the compromise programming method.

RESULTS AND CONCLUSIONS OF THE THESIS

The aim of the doctoral thesis was to develop the method and algorithms for solving multi-objective stochastic simulation-based optimisation problems with constraints and mixed decision variables, and to apply them to multi-echelon supply chain cyclic planning.

The results and conclusions of the thesis are the following:

1) Analysis of the state-of-the-art of simulation optimisation and the multi-objective optimisation problem statement allowed formulating the requirements to the problem solving techniques. The main requirements claimed for minimising the Euclidean distance between the true and approximate Pareto-optimal fronts; maximising the diversity of the Pareto-optimal solutions; minimising the number of non-dominated solutions that could be lost during the transition from one optimisation iteration to the other; minimising the total number of simulation optimisation iterations; generating the discontinuous Pareto-optimal fronts; using mixed decision variables, and including the uncertainty of system environmental variables into the search process.
2) Analysis of multi-objective evolutionary algorithms showed that these algorithms are able to satisfy most of the optimisation problem requirements. They, however, cannot simultaneously ensure high approximation accuracy and diversity of the Pareto-optimal front, and require a large number of iterations in order to generate this front.
3) Morphological analysis of hybrid multi-objective evolutionary algorithms allowed defining the best combination of their parameters in order to satisfy the formulated requirements. At the same time, the existing algorithms, such as hybrid EA and hybrid NSGA-II corresponding to the revealed best combination required modification due to ineffective use of a global and local search in case of operating with mixed decision variables and optimising stochastic objective functions.
4) The simulation-based hybrid optimisation method was developed that integrates the two-phase search and compromise programming methods. The proposed two-phase search method allows combining the advantages of global and local search approaches, simultaneously increasing an approximation accuracy and diversity of the Pareto-optimal front, as well as

decreasing the number of simulation optimisation iterations. The compromise programming method was applied for selecting a single solution from the Pareto-optimal front for its implementation in practice.

5) The developed multi-objective simulation-based genetic algorithm includes blocks and mechanisms for encoding diploid chromosomes, uniform population initialisation mechanism, the penalty-based constraint handling technique, the dominance-based termination criterion and a heuristic rule for reducing a computation time. The combined use of these blocks and mechanisms allowed, on the one hand, examining unvisited regions and generating solutions that differ from previously observed ones, and, on the other hand, exploring more carefully the portion of the search space that seems to be more promising.
6) The created prototype of the software environment unifies and integrates modelling, simulation and optimisation of the cyclic schedules for multi-echelon supply chain planning. It supports the main stages of simulation-based optimisation procedure including a supply chain description in MS Excel format, an automatic generation of supply chain simulation models, and optimisation of simulation model parameters by using the developed methods and algorithms.
7) The developed methods and algorithms were applied for cyclic planning in a linear supply chain and a generic supply chain of the chemical manufacturing company. The results obtained demonstrated high approximation accuracy of the Pareto-optimal front that is equal to 98.4 %. In addition, sequential using of global and local search approaches in case studies allowed significant decreasing of the number of simulation optimisation iterations in comparison with commercial software such as SimRunner® and OptQuest®.

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