Simulation-Based Optimization for the Design of Eco-efficient Supply Chains

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Abstract. The efficient design of supply chains incorporating ecological objectives is a strategic task that is increasingly attracting the attention of companies. This paper introduces a simulation-based optimization approach to eco-efficiently orchestrate a supply chain with a target system consisting of three sub-targets: Costs, energy-efficiency and service level. Regarding a use case from the steel processing industry, an event-discrete simulation model of the corresponding supply chain was configurated. By interfacing the simulation model with a Nondominated Sorting Genetic Algorithm new configurations of decision variables are generated after a set of simulation runs. The evaluation of the experiments and the resulting pareto sets led to the identification of promising eco-efficient configurations and the derivation of corresponding decision variable assignments for the use case which consist of material allocation, reorder point and replenishment level.

Introduction

Rising global demand for energy as well as raw materials pose a major challenge for the manufacturing industry. Due to the scarcity of fossil fuels, sustainability in the industrial sector is becoming increasingly important. Nevertheless, according to the German Federal Ministry of Economic Affairs and Energy, the energy consumption in this sector increases significantly [1]. Efforts at the interface between research and application are necessary to enable companies to counter these contradictory developments.

In the context of supply chain management, ecological goals are increasingly being integrated into corporate decisions. Eco-efficient approaches represent a decisive strategy for the design of sustainable supply chains [2]. In this context, ecological goals have to be integrated into the target system of the value network, and, at the same time, economic efficiency has to be maintained or increased. However, supply chains are highly dynamic and complex systems with multiple dynamic interdependencies. Accordingly, efficient methodological tools are needed that can map and evaluate supply chain interdependencies and achieve improvement in supply chain parameter configurations. The event-discrete material flow simulation is an established tool to digitally replicate and evaluate different control logics and parameter settings of individual entities. Linear optimization models as well as metaheuristics are, among other, suitable for the optimization of value chains [3]. Due to the complexity described above and the associated large solution space of possible design options for a value chain, it is difficult to generate exact solutions for a given modelled problem. Furthermore, a purely mathematical formulation of the model is often challenging due to the large number of objects, dependencies and stochastic uncertainties associated with these problems.

Combining both metaheuristics and simulation utilizes the advantages of both tools [4]. According to the VDI, this so-called simulation-based optimization can be implemented in four different ways [5]. In this paper, an integrative coupling shall be implemented to guide in the decision-making process. The (multi-criteria) simulation results serve as an objective function for a genetic algorithm. According to the VDI, this corresponds to a “Category D” approach. The three-dimensional target value system consists of costs, energy consumption and service level.

A genetic algorithm is used to create new configurations of supply chain input parameters for the simulation model after a series of simulation runs. For this paper, the genetic algorithms used are the „Nondominated Sorting Genetic Algorithms (NSGA)" NSGA-II and NSGA-III.

Through an implemented interface, newly generated configurations are automated and iteratively tested in subsequent simulation runs. Based on the state of the art and to differentiate the approach from previous papers, a specific demonstrative application from the steel processing industry is presented. Based on a sensitivity analysis to narrow the search space to initially preclude deficit solutions, the developed methodology is experimentally tested and the results are evaluated.

1 Simulation-based Optimization for Supply Chains

The use of simulation-based optimization for the orchestration and configuration of supply chains is a broad field of research. This chapter is dedicated to the consideration of current solution approaches of simulation-based optimization, especially for the strategic and tactical design of processes in value networks.

A methodology for a simulation-based optimization with an NSGA-II algorithm of the supply chain of a steel trading company was presented by Rabe et al. in which user-defined action plans, which address inventory parameters and material reallocations, can be designed [6]. The target system includes both cost and service-level, but does not integrate environmental metrics. Furthermore, besides the NSGA-II algorithm a Deep Reinforcement Learning (DRL) approach is used instead of NSGA-III.

Another "Category D" approach by Benyoucef and Xie focusses on a use case in the automotive industry, in which a two-dimensional target system consisting of cost and service level was also considered. Here, the solution space was restricted by limiting configurable parameters such as the order quantity and the reorder point with upper and lower limits in the potential occupancy [7].

Other approaches exist that incorporate emission values in two-dimensional target systems [8] or elaborations that implement other metaheuristics, such as a Particle Swarm Optimization (PSO) [9].

An up-to-date and detailed review of the current research of simulation-based optimization for value networks can be found in the paper by Tordecilla et al. [10].

From this, it is particularly clear that the target size system of the use case considered in this paper, with its three dimensions of cost, service level and energy efficiency, represents a differentiation from previous works.

2 Use Case Description

The use case for this paper is a supply chain of a steel processing service provider with several distribution and processing centers. The service provider offers services in which standard sizes of steel products are transformed to customer-specific dimensions and shapes by various processing machines. For this purpose, a pool of processing machines is available at various locations. The supply chain consists of five distribution centers and 25 customer regions. A simplified form is shown in Figure **1**.

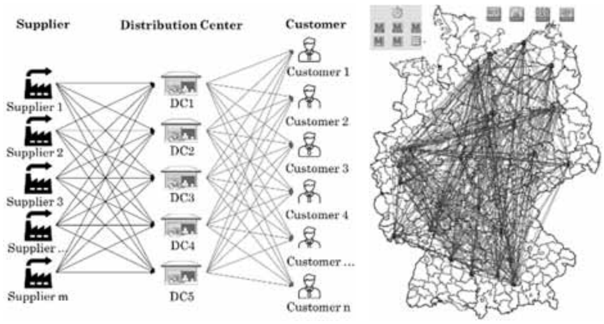

Figure 1: Representation of the supply chain of the service provider.

2.1 Procurement, Production and Distribution in the Use Case

In the following the basic processes of procurement, production, and distribution within the supply chain of the service provider are shown, which are integrated into the mechanisms of the simulation model.

Incoming customer orders are first divided into order lines. Based on the stock levels in the distribution centers, these are checked to determine whether the order can be accepted. Due to individual material allocations, scenarios may exist in which not all standard sizes are stocked in all distribution centers. In the case that several distribution centers store the material of an order in sufficient quantity, a distance-based allocation is made so that the distribution center accepts the order that is geographically nearest to the customer region of the ordering customer. If there is not enough material in the supply chain, the order is rejected. This must be considered accordingly in the service level.

The monitoring of the distribution centers' stock levels is thus an integral part. The service provider operates with an order point stock level strategy, called (s, S)-order policy [11]. If, within the scope of this ordering policy, a stock level falls below a defined reorder level s, the service provider triggers a purchase order with the supplier, which replenishes new standard sizes to a maximum target stock level S, defined individually for each product.

The production process represents the customized processing of existing standard sizes or residual sizes from previous machining processes. A distinction is made between the sawing of profiles and beams and the cutting of sheets (seen in Figure **2**). The times of the respective sawing and cutting processes depend on the cross-section of the material to be cut as well as the sawing or cutting speed of the machine. In addition, the feeding rates as well as loading and unloading times of the machines are included in the total processing time. Each distribution center has an individual pool of machines with different attributes regarding processing speed, capabilities for processing specific materials and energy consumption.

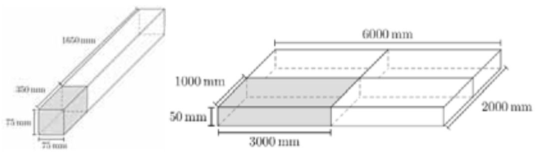

Figure 2: Example processing operations of the service provider.

On the distribution side, order picking and loading is based on the weight and volume of the finished products and the maximum quantity and volume capacity of the transport trucks. They depend on the customer's desired deadline, as well as route minimization. In addition to the company's own trucks, there is also the option of calling a shipping agent.

2.2 Target System of the Use Case

An important aspect is the ability to quantify the individual components of the target system consisting of cost, energy consumption and service level.

Costs. As the first objective function of the target system, the total costs are calculated, which consist of the sum of the transport costs, the order costs, the inventory costs, and the backorder costs.

The objective function thus results in:

$$ZF_1 = C_t + C_o + C_{inv} + C_{bo} \tag{1}$$

where:

- C_t : transport costs [in €]
- C_o : order costs [in €]
- C_{inv} : inventory costs [in €]
- C_{bo} : backorder costs [in €]

The cost positions transport costs and order costs are also divided into a fixed and a variable portion. Fixed transport costs are incurred once for a transport. A distinction is made between the fixed costs for a forwarding agent and the fixed costs for transporting a company truck. This applies analogously to the variable transport costs. A different cost rate is used for the shipping agent compared to the company's own trucks. Variable costs are calculated on an hourly basis depending on the duration of a tour. This stems from the total distance of the tour divided by the average speed of a truck.

Ordering costs are always incurred if a stock level falls below a predefined reorder level and an order for the respective material is then placed with the supplier.

The variable order costs of an order result from the multiplication of the order quantity with a variable order cost rate. In addition, a fixed cost rate is added for each purchase order. Inventory costs are always variable costs.

For each storage unit, the individual storage period is the basis for calculating the inventory costs. This is multiplied by the daily inventory cost rate to determine the inventory costs. Finally, the shortage costs result from multiplying the number of the order lines, which couldn't be fulfilled, by the corresponding backorder cost rate. The total costs are to be minimized in this optimization problem.

Energy Consumption. The second objective is to minimize the energy consumption of the sawing and cutting machines (measured in megajoules [MJ]). The processing times, feed rates and technical conditions of the individual machines play an essential role in the calculation. To determine the energetic power consumption of a saw, it is assumed that energy is only consumed by a saw when a workpiece is in its feed or the saw is busy machining a workpiece. For the machines, the drive powers of these two actuators are in the unit kilowatt [kW].

Based on the process times for the feed as well as the machining of an order position and the drive powers of both actuators of a specific saw, it is possible to determine how many kilowatts are consumed for the machining of the respective order.

By multiplying the respective machining times, the energy consumption can thus be determined in kilowatt hours. For the machining of a product of an order line, the following formulation is used to calculate the energy consumption:

$$P_{OL} = \frac{t_{TotFor}}{3600\,{}^{s}/_{h}} \times P_{For} + \frac{t_{TotSaw}}{3600\,{}^{s}/_{h}} \times P_{Saw} \qquad (2)$$

where:

- P_{OL} : power consumption of a saw from the processing of an order line [in kWh]
- t_{TotSaw} : total sawing time of an order line [in s]
- t_{TotFor} : time for the feed of all workpieces of an order line through the sawing machine [in s]
- P_{For} : drive power of the actuator for controlling the feed of the workpieces [in kW]
- P_{Saw} : drive power of the actuator for the sawing process [in kW]

By multiplying with the factor 3.6 MJ/kWh, the kilowatt hour is converted into megajoules. Since an order is divided into individual order lines and these may be processed in different distribution centers, the sum of the power consumed by positions ($i = 1, \dots m$) must be used to determine the energy consumption for an order:

$$ZF_2 = \sum_{i=1}^{m} P_{OL_i} \times 3{,}6\, MJ/kWh \qquad (3)$$

Service-Level. The third dimension of the target system is the degree of service-level and the delivery readiness achieved, respectively. This is a logistical indicator that provides information on the average delivery capability of a company within a given period. In principle, there are various calculation bases for calculating the degree of readiness to deliver. In the context of the use case, the so-called β-Service-Level is sued to quantify the delivery capability. From a practical stand point, this is used as the preferred performance criterion because the amount of a shortfall is included in the calculation basis [11].

Mathematically, this is defined as follows:

$$\beta = \frac{Fulfilled\ orders\ per\ time\ period}{Period\ demand} \qquad (4)$$

The calculation of the β-Service-Level implies that the best performance is achieved with a value of $\beta = 1$, since in this case any period demand could be met. In terms of optimization, the value is to be maximized accordingly. Since the other two objective functions are to be minimized and a combination of minimization and maximization is more difficult to realize with multicriteria metaheuristics, the counter probability of the degree of readiness to deliver is minimized. Mathematically, the third objective function thus results in:

$$ZF_3 = 1 - \beta \qquad (5)$$

3 Decision Variables and Solution Space

As described in the previous chapter, the company's target system consists of the three components cost, energy consumption and service level. To optimize this multicriteria target system, variations of logistic parameters are investigated, which represent the decision variables of the system. The parameters to be studied are the reorder point s per product p in distribution center j, the target stock S per product p in distribution center j, and the allocation of products to specific distribution centers in the form of material reallocation strategies:

- S_j^p : target stock for product p in distribution center j in days $\in \mathbb{Z}^+$
- s_j^p : reorder point for product p in distribution center j in days $\in \mathbb{Z}^+$
- l_j^p : binary material allocation for product p in distribution center $j \in [0{,}1]$

To address the initially shown problem of the large solution space, a sensitivity analysis of the supply chain to different inventory parameters was performed before coupling the simulation with the metaheuristic in order to limit the search space to promising possible combinations of reorder points and target inventories. This analysis technique is used to determine the sensitivity of the target functions as a function of the input parameters [12].

For this purpose, the average demand quantities per product were converted into inventory ranges and all potential combination possibilities up to a defined upper limit were evaluated iteratively in automatically triggered simulation runs. For this, all combination possibilities were equally distributed among the distribution centers. Figure **3** shows the total costs of the network depending on the parameter settings.

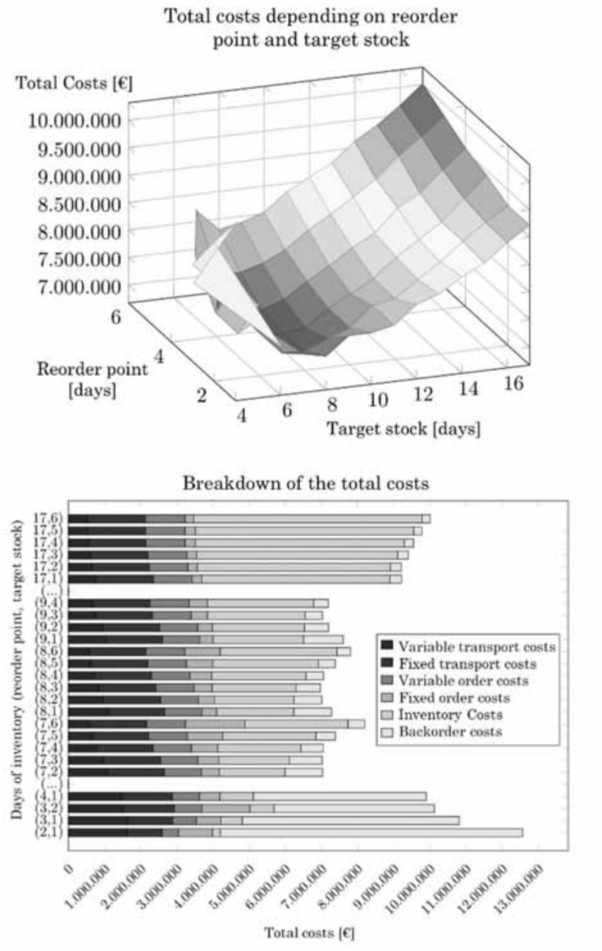

Figure 3: Sensitivity analysis of the total cost of the network as a function of the inventory parameters.

The cost function takes a convex form, at least for the parameters tested. This is a good implication that the local minimum found is also a global minimum.

To achieve a better interpretation of the results regarding the costs achieved, the subsumed total costs are also broken down in Figure **3**. This shows that the most significant differences occur in the shortage costs and the inventory costs.

This finding can be attributed to a classic trade-off effect in inventory management, in which high inventories lead to high capital commitment costs, whereas low inventories lead to shortage costs. With low reorder and target stocks, the risk of incurring a high sum of shortage costs is therefore higher. By contrast, minimizing this risk leads to high inventory costs.

These sensitivity analyses were also conducted for the target variables energy consumption and service level. These analyses showed that the service level settles at a value close to 100% even at quite low ranges, which is associated with low shortfall costs. The quality of the values for energy consumption correlates strongly with the service level. This effect can be explained by the fact that for the sensitivity analysis, only the first tow decision variables were rudimentarily examined for the time being and no material reallocations are integrated. Accordingly, products can only be processed, and energy consumed if products are available in stock. Through this sensitivity analysis of the first two decision variables, a corresponding metaheuristic search space for the inventory parameters could already be defined, which limits deficient solution candidates.

The variation of the material allocation to the distribution centers is now to be investigated in more detail, as it is suspected to be a major lever for minimizing the energy consumption. To reduce the computational calculation time a logical correlation was applied to the material reallocation. To investigate different assignments of product and distribution center, a percentage of material reallocations to be performed can be defined before the start of an optimization run. In the initial population and with each mutation of the genetic algorithm, a material is randomly reallocated to on ore more distribution centers according to this ratio.

4 Description of Methodology and Tools

Following the definition of the decision variables and the objective function, the methodological configuration must be designed. Two so-called "Nondominated Sorting Genetic Algorithms" (NSGA-II [13] and NSGA-III [14]) are used as metaheuristics in different experiments, which are based on the principle of genetic algorithms. According to them, the core building blocks are selection, recombination, and mutation.

In contrast to classical evolutionary methods, the two algorithms are particularly suitable for application to discrete multicriteria optimization problems and are accordingly equipped with mechanisms that enable the determination of a Pareto ranking.

Although the NSGA-III, in contrast to NSGA-II, is equipped with a lot of normalization for distance calculation and a Niching mechanism, it does not provide better results for every application. For a more detailed explanation of the algorithms, it can be referred to the corresponding literature.

The metaheuristics are implemented in the Python programming language and coupled to the Tecnomatix Plant Simulation software from Siemens, in which the simulation model was created, using the Component Object Model (COM) interface. The interface makes it possible to control Tecnomatix Plant Simulation from other programs so that they can, for example, start simulation runs, change model parameters and record results.

After the generation of solution candidates in the metaheuristic in Python, these are transferred to the simulation model and then a simulation run is started from Python. The termination of the simulation is communicated via an event in the COM interface, after which the results of the simulation model are transferred to Python.

To increase the computing speed, an additional parallelization of simulation runs on several cores of the CPU was realized. Figure **4** shows the process flow of the simulation optimization roughly by means of a process diagram.

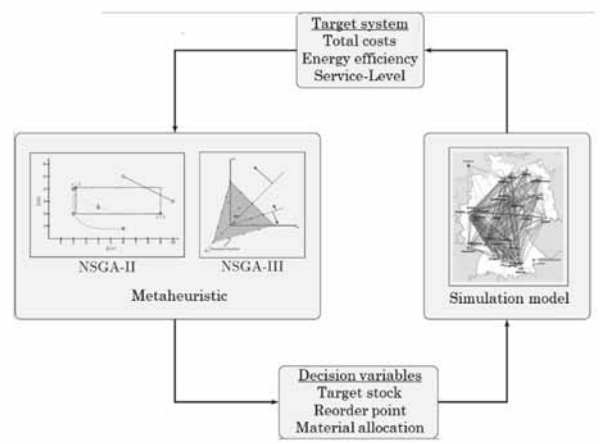

Figure 4: Process diagram of the simulation-based optimization.

5 Results of the Experiments

An experimentation plan was developed for the different algorithms with varying configurations. The design consists of four experiments that investigate the quality of the different algorithms as well as the different proportions of material reallocations (MR) for a given population size (PS). The plan can be found in Table 1.

Experiment	ID	Algorithm	MR	PS	Generations
Experiment 1	EXP 01	NSGA-II	33 %	50	50
Experiment 2	EXP 02	NSGA-II	0 %	50	50
Experiment 3	EXP 03	NSGA-III	33 %	50	50
Experiment 4	EXP 04	NSGA-II	66 %	50	50

Table 1: Experimentation plan.

In this simulation study, a metaheuristic terminates after 50 generations. This results in 2,500 possible solutions from one metaheuristic. To account for stochastic significance, two replications are performed for each experiment. Thus, 5,000 possible solutions need to be evaluated for one experiment. The simulation period is one year per simulation run. The results are shown in a scatter plot in Figure **5**.

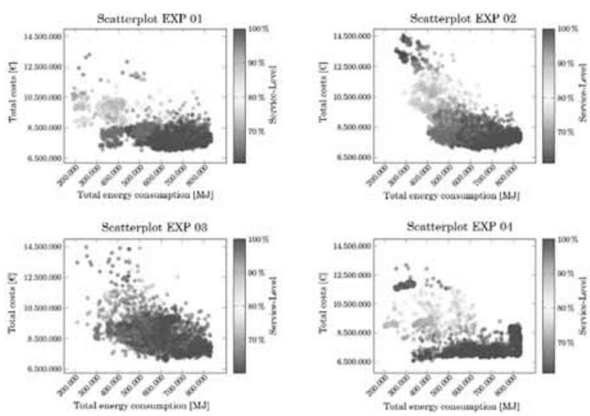

Figure 5: Scatter plots of the objective function values.

Especially in the experiments with a low proportion of material reallocations (experiments 1-3), a roughly linear dependency between the target variables can be seen.

This result can be attributed to the fact that a lower service-level is associated with the fact that the desired production quantity was not achieved and therefore the machines consumed less energy due to less total production quantities. Since shortage costs are integrated into the cost function in addition to transportation, ordering and inventory costs, such candidate solutions incur correspondingly high costs due to poor delivery service with low energy consumption.

With a higher proportion of material reordering, promising solution candidates can be identified that achieve low costs and energy consumption with a good service level. This is possible because distribution centers vary in energy efficiency. Therefore, material reallocations with efficient inventory parameters are identified so that the materials are produced both close to the customer and at energy-efficient locations.

Furthermore, a large spread of resulting points occurs in the cluster for experiment 3. This can be explained by a different selection operator of the NSGA-III algorithm compared to NSGA-II. The pareto sets of the experiments in Figure **6** provide an even more explicit way of interpreting the results.

The most promising pareto set tends to be generated in Experiment 4. Compared to the pareto sets from the remaining experiments, several candidate solutions have both better delivery efficiencies, energy consumptions and overall costs. Many candidate solutions from the pareto set in experiment 4 would dominate large portions of the remaining pareto sets.

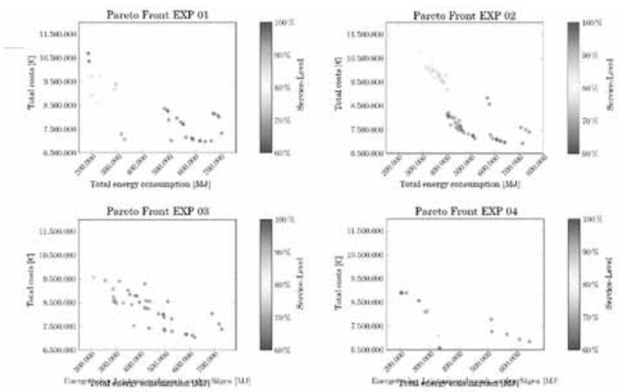

Figure 6: Pareto sets of the experiments.

As anticipated, a single best solution which dominates all three objective functions was not found due to the various trade-off effects within a supply chain.

Nevertheless, recommendations for a course of actions can be derived from the generated pareto sets, depending on the individual weighting of the target system. Experiment 4 delivered solution candidates with total costs of about 6.5 million Euros, a power consumption of about 330,000 MJ and a supply readiness level of about 99 %. Solutions with better energy consumption exist, but the selection of these solutions significantly worsens the service-level as well as the total costs.

Unless individual preferences in the use case overprioritize energy consumption and perfect delivery performance, this underlying combination of decision variables is an extremely eco-efficient configuration for the use case at hand.

6 Summary and Conclusion

The simulation-based optimization for the configuration of eco-efficient supply chains presented in this paper represents a high-performance tool for the generation of target system specific pareto sets. The integration of the target value energy efficiency into a three-dimensional target system supplemented by the dimensions cost and service level in combination with the chosen algorithms and simulation tools represents an innovative approach that stands out from the previous state of the art. Within the evaluation of the experiments, promising eco-efficient configurations could be identified and corresponding assignments of the decision variables for the use case regarding material reallocation, order point and target inventory could be derived. The experiments also made it clear that the NSGA-II algorithm was able to identify better solution candidates than the NSGA-III in the consideration of this use case.

Further research needs to address other methods like reinforcement learning instead of metaheuristics chosen in this paper. Furthermore, the choice of a different simulation tool (e.g., SimPy), which completely avoids animations, could allow a more performant simulation-based optimization. This could potentially generate faster solution candidates. Furthermore, it is possible to integrate additional components of energy consumption, e.g., caused by transportation, into the target system.

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