Optimization of Supply Chain Network using Genetic Algorithms based on Bill of materials

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---*ABSTRACT*---
The integration of genetic algorithms to optimize the networks of value chains could enormously improve the performance of supply chains. For this reason, this paper describes in more detail the application of genetic algorithms in the value chains of the automotive industry. For this purpose, a theoretical model is built up to evaluate whether the application of the model can optimize the value chain. This option is described, analyzed and its restrictions are shown. Instead of looking at the entire network, individual finished goods and their bill of material are used as a basis for optimization, which greatly reduces the complexity of the original problem. The original complexity of the supply chain networks can thus be reduced and considered based on the bill of material.

KEYWORDS: *Supply Chain Network, Genetic Algorithm, Supply Chain Network Optimization*

I INTRODUCTION

As a result of global competitive pressure, companies today are forced to offer higher quality products at lower prices in order to survive in the market. The competitiveness of a company is mainly determined by supply chain efficiency. The reduction of costs and lead times as well as the improvement of customer service play essential roles in this context. Companies can only achieve these competitive advantages by optimizing their entire supply chain. The increasing complexity of supply chain networks due to globalization gets much more complicated. This causes companies to think about their supply chain configuration (Matinrad, Roghanian, & Rasi, 2013, p. 2-4). The supply chain can therefore be seen as a way to meet customer requirements in order to maximize the total value generated. The ability of the supply chain to respond quickly to market changes and customer requirements is considered as a key competitive advantage in today's business environment (Wild & Knoppe, 2018, p. 2-3.).

They need to improve their supply chain capability and integrate and coordinate the full range of end-to-end processes, i.e. sourcing materials or components, converting them into finished products and shipping them to customers through timely delivery processes (Min, 2015, p. 144). It is therefore not enough to improve internal company processes, but the supply chain must be presented as a combination of several units so that the products and services can be delivered to the customer in the desired time, at the desired cost and with the desired quality.

The economy driven by digitization offers a wide range of application possibilities for making value-added networks more efficient. In connection with this change, artificial intelligence is particularly noteworthy. Since the 1950s, artificial intelligence based applications have been researched and developed further, which can now be used due to increasing data availability, more intensive networking and improved computing power. By using artificial intelligence, algorithms can be implemented that have their own problem-solving competence and can thus contribute significantly to the optimization of supply chain networks (Scheuer, 2018, p. 4). Besides the two best known artificial intelligence techniques, such as neural networks and deep learning, evolutionary algorithms are gaining more and more attention (Reiterer, 2006, p. 142). Among the multitude of evolutionary algorithms, genetic algorithms are among the dominant ones in research and application (Nissen, 1997, p. 33-34).

To improve networks, many leading companies have sought to use state-of-the-art decision support tools that diversify their decision alternatives, helping them to achieve the optimization of their business objectives. One of these tools includes the genetic algorithm, which has existed for more than four decades but is not fully exploited in the field of SCM due to a lack of understanding of its usefulness and application potential (Min, 2015, p. 144).

Therefore, this paper investigates whether genetic algorithms can contribute to the optimization of supply chain networks.

II Literature Review

Supply Chain Network

Due to increasing globalization, companies today can no longer act as a single economic entity, making them dependent on cooperation with other companies. As a result, the planning and execution of value-adding activities take place across companies, which means that different partners must interact with each other. For this reason, value creation no longer ends at the company's own boundaries, but goes beyond them. This means that successful companies in today's business environment must work together with their customers and suppliers. In addition, companies are expanding into international markets, which increases competitive pressure. It is therefore essential that companies work both collaboratively with other business partners and in a customer-oriented manner (Kahn & Yu, 2019).

As a result, business partners act both nationally and internationally in value chains known as supply chains. The supply chain can be described as a cross-company value chain consisting of different organizations. These actors interact in a network to manufacture a product and transport it to the end customer (Busch & Dangelmaier, 2004, p. 4).

Thus, the supply chain can be represented as an amalgamation of several units that work in a coalition on the procurement and transformation of raw materials, the production of end products and their distribution and delivery (Radhakrishnan, Prasad, & Gopalan, 2009, p. 33). Accordingly, the supply chain can be described as a beneficial coordination and integration of organizations with individual goals to achieve a common goal (Prasad, Radhakrishnan, & Gopalan, 2009, p. 234). However, it should be noted that the performance of the entire supply chain is directly dependent on the behavior of the individual members. Optimizing the performance of an individual member is important, but to improve the performance of the entire supply chain, it is necessary to look at the supply chain as a whole (Kumanan, Venkatesan, & Kumar, 2005, p. 41).

The supply chain is not just a group of actors responsible for meeting customer requirements, but rather a supply network. These include, for example, production facilities, warehouses and carrier cross docks, large distribution centers, ports and intermodal terminals, whether owned by the company, suppliers, carriers, external service providers or the end customer (Danalakshmi & Kumar, 2015, p. 31). Supply chains are characterized by decentralized decision-making in connection with the various economic actors. Therefore, any formalism aimed at modeling supply chains and providing quantifiable insights and measures must be system-wide and network-based. In fact, issues as critical as the stability and resilience of supply chains, and their adaptability and responsiveness to events in a global environment of increasing risk and uncertainty can only be examined from the perspective of supply chains as network systems. Supply chain networks provide the critical infrastructure for the production, distribution and end use of goods in today's globalized economies and societies (Varasteh, 2007, p. 1).

Consequently, the optimal network structure or the best supply chain network design should be found to maximize profit. The selection of partners in the SCN forms the basis for the cooperation of the members on the upstream, midstream and downstream level. When designing a supply chain, economic decisions must be made about

- the number, size and location of supply chain nodes,
- the number and location of the production facilities,
- the capacity at each location,
- the assignment of each market region to one or more locations and
- the selection of suppliers for components and materials (Meixell & Gargeya, 2005, p. 538-542).

Supply Chain Network Design is of great importance for companies to achieve cost efficiency and competitiveness and have a significant impact on logistics costs (Matinrad, Roghanian, & Rasi, 2013, p. 5-7.).

Above all, the growing global competition makes the supply chain network continuously more complex. Another major challenge faced by most supply chains are conflicting goals between the end customer and the supply chain. To guarantee competitiveness, costs incurred in the supply chain must be reduced. In return, the ability to deliver must always be guaranteed so that the dynamic demand of customers can be adequately met. In addition, products on the markets experience ever shorter product life cycles, which leads to greater demand uncertainty and increases supply chain complexity. Effective planning, control and management of the supply chain has become unavoidable due to the significant increase in service levels (Prasad, Radhakrishnan, & Gopalan, 2009, p. 234).

In summary, the supply chain network is a strategic configuration of the supply chain and therefore a key factor influencing the tactical and operational levels and therefore the entire company in the long run. This increases the importance of the supply chain netzwork problem. It covers a broad spectrum of formulations, ranging from simple single product types and linear deterministic models to complex non-linear stochastic multi-product models (Douiri, Jabri, & El Barkany, 2016, p. 866).

Genetic Algorithms

Genetic Algorithms (GA) were developed by John Holland at the University of Michigan in the 1960s. Holland's original goal was not to develop algorithms to solve specific problems, but to formally study the phenomenon of adaptation as it occurs in nature and to find ways to import the mechanisms of natural adaptation into computer systems (Mitchell, 1999, p. 3). The genetic algorithm is therefore characterized by some important features of biological evolution (Deepa & Sivanandam, 2008, p. 20). These principles can be transferred to an optimization approach of GA:

- The environment is defined by the problem to be treated.
- Chromosomes represent candidate solutions to the problem.
- The genotypes encode the candidate solutions for the problem. The genotype-phenotype translation determines how the chromosomes should be interpreted to obtain the actual candidate solutions.
- The fitness of individuals depends on different factors of the problem, so that more adaptable individuals are more likely to survive.
- A population of individuals develops, into which new individuals enter and others disappear.
- New individuals emerge as a result of the recombination and/or mutation of previous individuals, whereby the fitness increases steadily (Garcia-Martinez, Rodriguez, & Lozano, 2018, p. 431-436).

Each population contains a predefined number of chromosomes. The genetic algorithm thus works with a variety of possible solutions, with each chromosome representing a potential solution. By modifying the population in each iteration step, better solutions are to be found continuously. The principle of natural selection is used, which should help to find the optimal solution. The basic procedure of a GA is illustrated in the following figure (Weicker, 2015, p. 24-26).

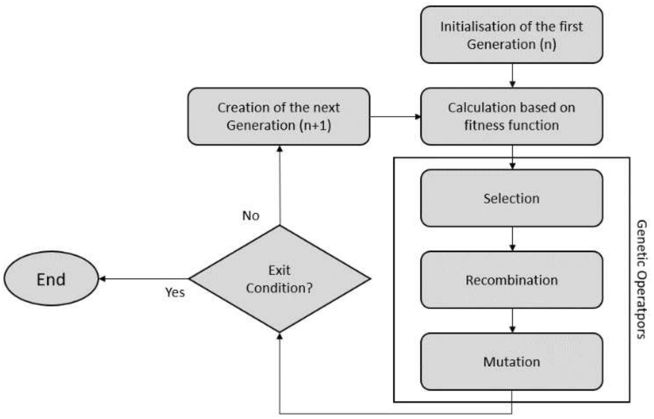

Figure 1. Genetic Algorithm Flow Chart

At the beginning of the presented optimization process the population is initialized. This includes both the parameterization and the creation of the initial population. If previous knowledge about the solution candidates of the initial population is available, the results of previous optimization processes can be used. In all other cases the initial population is initialized randomly and equally distributed in the solution space (Pohlheim, 2000, p. 8-10). If a heuristic initialization is performed, this can help to find an adequate solution faster. On the other hand, this makes the global search for the optimum more difficult, since there is a lack of diversity in the population, which means that only a small part of the search space is explored depending on the heuristic method (Mitsuo, Runwei, & Lin, 2008, p. 9-11). The starting population can be initially evaluated at creation, i.e. each solution is validated by a fitness function.

III Fitness function

The evaluation of each generation is done by the fitness function. The quality of each chromosome is calculated to identify the best chromosomes of a generation. In addition to quantitative indicators, such as transport costs, storage costs or delivery reliability (which can be integrated into the fitness function by penalty costs), qualitative indicators must also be taken into account. Qualitative key figures are collected, for example, through interviews, questionnaires, opinion polls etc. in order to subsequently present them in the form of corresponding characteristic values (Glazinski, 2004, p. 88). Consequently, an individual rule must be developed for each qualitative indicator in order to evaluate and segment the characteristics. Typical qualitative indicators for supply chain networks are the flexibility of a value chain participant, the intensity of the economic relationship or the capabilities of the economic operators.

The fitness function significantly influences the quality of the genetic algorithm. When setting up the fitness function, there is always a compromise between the consideration of all influencing factors and the performance. Each additional influencing factor that is taken into account in the fitness function is reflected in a deteriorated performance. Therefore, it must be determined individually for each application how to deal with this.

Genetic Operators

As soon as a previously defined termination condition is met, the individual with the best fitness can be output. If no abort criterion is met, new generations are created cyclically and the evolutionary cycle begins. This includes three genetic operators: selection, recombination and mutation.

The selection is based on the evaluation by the fitness function. By this a value is calculated for each individual or chromosome, which reflects the quality. This evaluation process aims at comparing one chromosome with another chromosome in the population. Thus, this information can be used in the selection mechanism to identify the best chromosomes (Garcia-Martinez, Rodriguez, & Lozano, 2018, p. 438). The selection process can be based on different selection algorithms.

After a stochastic selection process has selected the corresponding chromosomes, the recombination - also called crossover - takes place. New chromosomes are generated from two chromosomes of the so-called parent generation, in which the genes of the parents are copied and passed on. This enables the optimization within the solution space (Deepa & Sivanandam, 2008, p. 13). Also, for the recombination operator there are different procedures that can be used. As stated by Sourirajan et al. 2009, empirical studies on network design problems show that the uniform recombination strategy outperforms the one-point recombination strategy (Sourirajan, Ozsen, & Uzsoy, 2009, p. 220). The crossover operator as the driving force of a genetic algorithm has the task of generating better solutions, if possible, by constantly recombining genetic material already present in the population (Pankratz, 2002, p. 121).

The selection algorithm of selection promotes the survival of the traits of individuals of higher quality / fitness. Thus, the chromosomally represented properties of adequate solutions outweigh the properties of poorer individuals in the course of some recombination cycles. To counteract the associated risk of premature genetic algorithm convergence due to genetic impoverishment of the population, the mutation operator occasionally introduces new or already lost allele values into the population. In this context, the mutation operator plays a complementary role in genetic algorithms (Pankratz, 2002, p. 121). The mutation is a so-called background operator, which makes individual changes on different chromosomes. In contrast to crossover, however, mutation is usually performed by modifying the gene within a chromosome. In this process, no new chromosomes are created, but single alleles within an existing chromosome are manipulated (Iris & Asan, 2012, p. 203-209) The mutation rate or probability to manipulate a chromosome can be defined initially. If a gene is to be manipulated, a new random value is assigned to the corresponding allele (Gerdes, Klawonn, & Kruse, 2004, p. 40f.)

IV Genetic Algorithms in Supply Chain Network Optimization

Coding the original problem so that the genetic algorithm can work with it, is one of the biggest challenges in the application of genetic algorithms.

General Approach

The conversion of a phenotype (decoded variable) into a genotype (coded variable) plays a crucial role in the efficient search for the optimum. The coding of a solution possibility has direct influence on the fitness calculation and therefore contributes to the quality in the solution space. Since fitness is calculated based on the encoded chromosomes, it is important to determine a suitable coding. There are different coding methods. On the one hand, there is the method of representation (binary coding, real number coding, integer / literal permutation coding, general coding) and on the other hand, there is the conversion method, i.e. the rule by which the decoded solution possibilities can be converted into coded ones. As a rule, there is a dependency between the representation method and the conversion method (Mitsuo, Runwei, & Lin, 2008, p. 6-8). The coding depends mainly on the properties of the problem.

Due to the complexity and size of the supply chain network problem, the chromosome representation usually consists of several parts that describe and represent the assignment between the supply chain participants. There are numerous possibilities for coding (Iris & Asan, 2012, p. 210-215). The individual chromosomes each represent a potential path to fulfill all customer requirements in one supply chain network. The number of genes required in a chromosome is determined by the depth (number of steps) of the value chain as well as by the number of customer (Lin, Xiaoguang, & Mitsuo, 2007, p. 6).

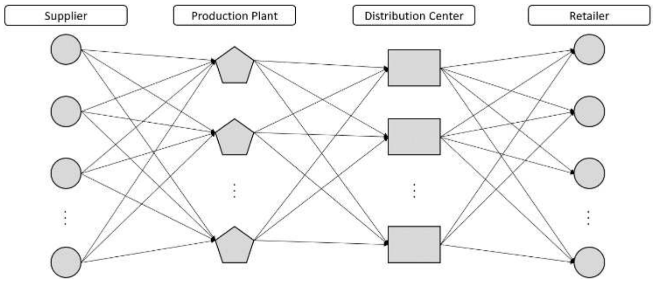

Figure 2. Simplified supply chain network

In this case the chromosomes could be represented for example by the following logical representation form:

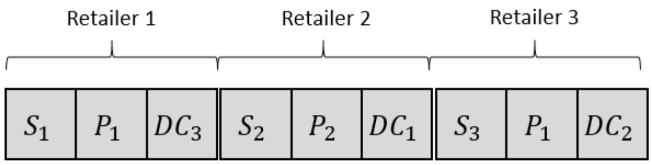

Figure 3. Coding of Chromosomes with Route explanation

In the picture above Retailer 1 will be deliverd by Supplier 1, Production Plant 1 and Distribution Center 3. To be able to work mathematically with the chromosomes, they are represented as integer strings:

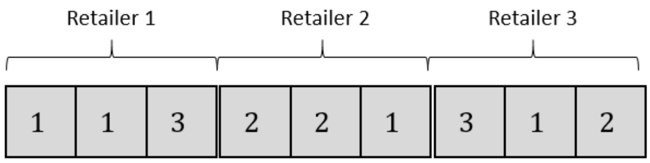

Figure 4. Coding of Chromosomes

This simple representation allows the delivery route to be determined already in the coded chromosome, which greatly reduces the computing time of the genetic algorithm (Lin, Xiaoguang, & Mitsuo, 2007, p. 6). After the coding, the generation of the initial population, the initialization, takes place directly. With the supply chain network problem the initial population is usually generated randomly, in order not to limit the solution space. In the example above, each gene (supply chain per customer, here retailer) is given a randomly generated supply chain (Iris & Asan, 2012, p. 215). After calculating the fitness function, those chromosomes are selected which have the best target function value. If no termination condition is met, the genetic operators are used to determine the next generation. In the optimization of supply chain network, it can happen that a chromosome is mainly characterized by a very strong participant within the network, so that other participants are no longer considered. For this reason, the mutation plays a particularly important role in the optimization of supply chain network. All three genetic operators therefore have a considerable influence on both quality and performance and must be applied in the best possible way. The performance of a genetic algorithm depends on the population size, number of generations (iterations), recombination rate, mutation rate and termination criteria. The lack of parameter optimization for supply chain network problems indicates a potential research area. The population size of the genetic algorithm is related to the search efficiency of the algorithm. If the population size is too small, the genetic algorithm may not be able to explore the solution space sufficiently to find good solutions and thus converge quickly. In contrast, too large a population size can cause the algorithm to get lost in the search space, the computation time to increase sharply, and the genetic algorithm to become inefficient. For this reason, each problem type should be treated separately.

The described method provides a quickly comprehensible and efficient integer string to map the supply chain network problem. Based on the coding, the fitness function can then be set up. As already mentioned, both qualitative and quantitative factors must be taken into account, which can lead to considerable problems and unanswered questions due to the ambiguity. Due to the increasing competitive pressure in various industries, which is mostly cost-driven, many companies are faced with the question of whether they should rely on long-term supplier or customer relationships and thus possibly accept higher costs or not enter into relationships with business partners in order to save costs. In order for the algorithm to be able to take such influencing factors into account in the calculation, this problem must also be represented on a corresponding scale. These facts often cannot be expressed by mathematical formulations. This is due, for example, to the intensity of the business relationship. Short-term relationships are cost-oriented, whereas long-term relationships aim at common goals and in crisis situations (e.g. bottlenecks, shortage of raw materials) stick together and prioritize each other.

In summary, coding and setting up the fitness function are the two most essential parts of genetic algorithm in supply chain network and contribute significantly to quality and performance.

The general form and application of genetic algorithms in supply chain networks can therefore be illustrated as following:

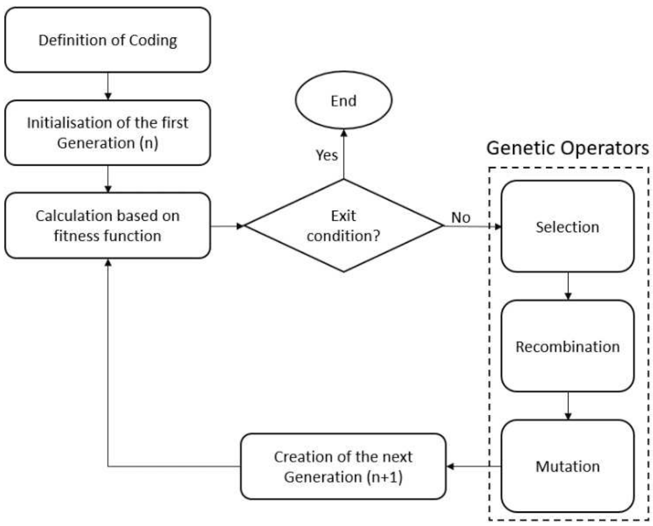

Figure 5. Typical Genetic Algorithm Flow Chart

Bill of Material Approach

Particularly in the automotive industry, customer-supplier relationships within the supply chain are usually based on long-term contracts and relationships that are characterized by special features such as just-in-time, just-in-sequence, customer-specific shipping labels or electronic data interfaces and are therefore irreplaceable. The parties thus work together in an integrative manner and their cooperation has matured over the years. Through many years of cooperation these could be matured and optimized. Due to the maturity of the supply chain of the automotive industry, it is even more important to consider qualitative factors in the fitness calculation. In addition to measurable costs, soft factors in the value chain of automobile manufacturers are therefore much more important than in other industries. Therefore, as already mentioned, all qualitative factors must be assigned to penalty costs.

In the automotive industry, the qualitative key figure of the customer-supplier relationship is of great importance: *The longer the customer-supplier relationship exists, the lower the penalty costs. Accordingly, the penalty costs decrease with increasing duration of the customer-supplier relationship.*

Accordingly, suppliers who already operate in the existing network are assigned lower penalty costs compared to potential new suppliers. This is intended to compensate for the opportunity costs of training and qualification of new suppliers. The qualification of new suppliers means not only the validation of quality and other key figures such as delivery times, delivery reliability, etc., but also the integration into the company's own business processes. This requires the coordination and agreement with new suppliers as well as a high expenditure of time and personnel.

The assemblies of a car require many individual parts that must be assembled along the value chain. The associated complexity of the supply chain network is reflected in the coding of the original problem of genetic algorithms. Thus, the application of genetic algorithms to supply chain networks is enormously complicated. For this reason, the standard application, described in the previous chapter, of genetic algorithms in supply chain networks is not recommended.

The subsequent application of genetic algorithms for the optimization of supply chain networks is therefore based on bill of material (BOM). This will be described in more detail:

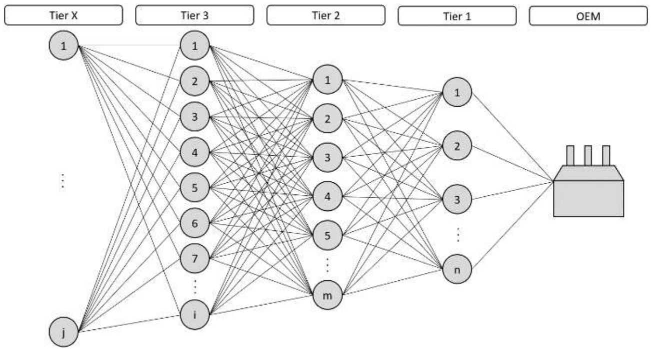

Figure 6. Illustrative supply chain network

Since the original equipment manufacturer (OEM) produce only a small number of different finished products (several product variants of vehicles), many individual parts and modules are built into these products. Therefore, the network constellations of all materials must be considered in the fitness calculation. Consequently, coding and decoding should not be performed based on the OEM and its general supply chain network structure, but per material or per module. Thus, not the entire network per OEM (retailer) is optimized, but the supply chain constellation per bill of material and material. This is illustrated with a fictitious Bill of Material of Modul xyz:

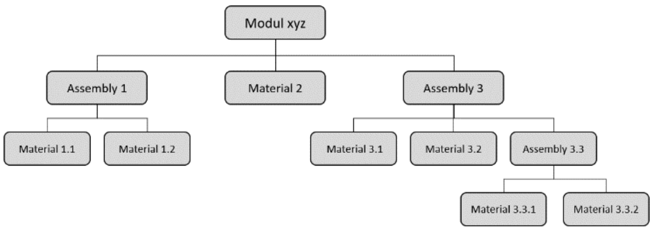

Figure 7. Fictive Bill of Material for Modul xyz

The above figure shows a bill of material for any module xyz, which the OEM procures from a Tier 1 supplier. The coding for this module is based on the BOM explosion and is done successively from the BOM header to the individual parts. The corresponding chromosome in the genetic algorithm can therefore be represented as follows:

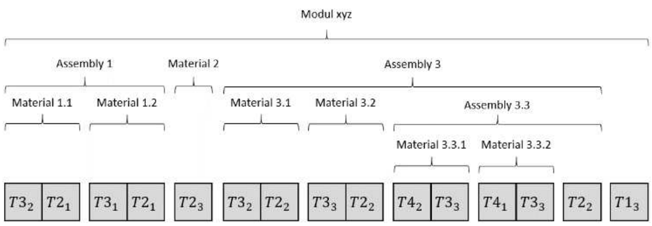

Figure 8. Chromosome-Coding of BOM

The origin, i.e. the corresponding supplier, is assigned to each individual part, which allows the traceability to be mapped in the chromosomes. In the above example, material 1.1 is procured from tier 3 supplier 2 and material 1.2 from tier 3 supplier 1. Assembly 1 is procured by the tier 1 supplier from tier 2 supplier 1. This coding can be illustrated as follows.

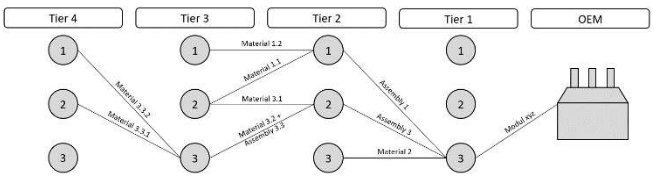

Figure 9. Supply chain network of Modul xyz

This coding allows to display different chromosome constellations per module in order to determine the best supply chain network structure. When initializing the initial population as well as when applying genetic operators, it must be taken into account that the materials and the modules are supplier-dependent. This means that not every supplier can produce every single part or module. Therefore, before the genetic algorithm is run through, a supplier-part matrix must be worked out, which determines which materials can be obtained from which suppliers in order to expand the solution space. This helps the genetic algorithm to calculate the possible combinations and has to be considered when using the genetic operators. After the recombination has been run through, the supplier-part matrix has to be integrated into the programming of the mutation in order to calculate only logically meaningful combinations. Due to the modular structure of chromosomes it is thus also possible to optimize only parts of the supply chain structure of a module or assembly.

Basically, the genetic algorithm works on two different levels: the coding space and the solution space or the genotype and phenotype space. In each iteration activities take place on both levels. In the genotype space (coding space) recombination and mutation are performed, whereas fitness calculation and selection take place in the phenotype space (solution space). Selection is the link between the encoded chromosomes and the performance of the decoded solutions. The assignment of the genotype to the phenotype space has a significant influence on the performance of the genetic algorithm. With this assignment, it may happen that some chromosomes correspond to a decoded solution that cannot be realized. When programming this type of coding, the inadmissibility of solutions must therefore be taken into account.

However, due to the coding method used, there is a risk that invalid offspring may be calculated by the applications of the recombination and mutation operators. To avoid this, it is not enough to use penal techniques, but repair techniques must be used. This involves converting illegal chromosomes into legal ones or excluding illegal solutions before the fitness calculation. In addition to these two approaches, both recombination and mutation can be adapted in such a way that the application of both operators results in exclusively legal solutions. The adjustment of the recombination refers to the recombination point. Thus only allowed genes can be passed on to the successors. The following example in the Figure below shows two fictive solutions for the supply chain network structure of the module xyz. Based on these two solutions, it is described which recombination points can be used.

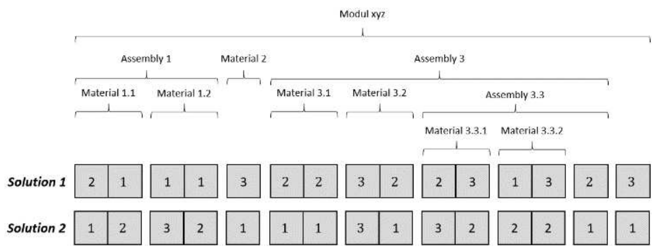

Figure 10. Two examples of possible solutions

In order to avoid invalid solutions, the individual parts and modules must be understood as an independent compound gene, since there are large dependencies within the encoded chromosome: for example, in solution 1, assembly 1 must be sourced from tier-2 supplier 1, since tier-2 supplier 1 sourced material 1.1 from tier-3 supplier 2 and material 1.2 from tier-3 supplier 1. If the supplier of assembly 1 is changed, the network structures of the previous materials must also be adjusted accordingly. Provided that this is to be avoided, there are only two potential recombination points for the solutions shown in following figure.

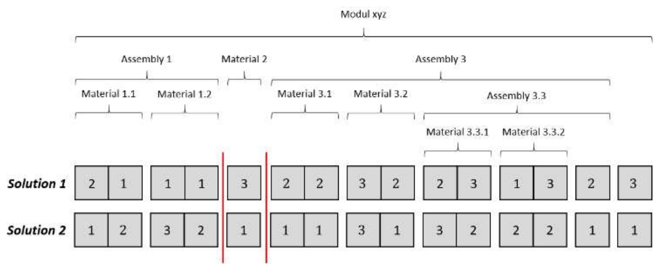

Figure 11. Recombination Point in Chromosomes

Thus, the number of possible recombination points depends on the first piece list level. If further BOM levels are to be considered as well, the mutation must be coupled to the recombination, so that no invalid solutions are generated. This is explained in more detail using assembly 1 as an example.

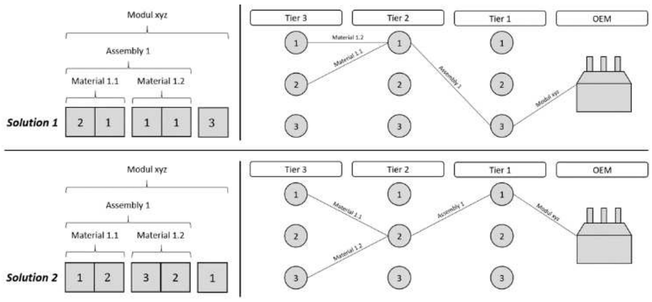

Figure 12. Supply chain network of both possible solutions of assembly 1

A possible recombination point for assembly 1 would be between the two parts. This would lead to the following result:

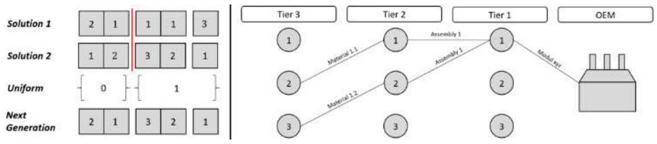

Figure 13. Recombination Point to combine both solutions

This recombination results in an unacceptable offspring, which now has to be converted into an acceptable solution by a corrective mutation as material 1.1 and 1.2 are not procured by the same tier 2 supplier. In addition to the previously defined supplier parts matrix, the costs must also be taken into account in this process in order to obtain an acceptable solution at the lowest possible cost.

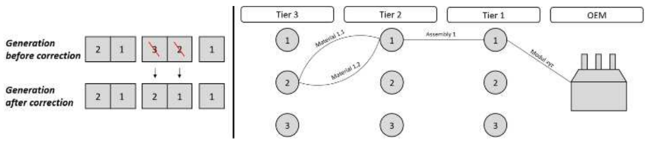

Figure 14. Mutation of Chromosome of assembly 1

After the corrective mutation the 'real' mutation can be performed to identify global optima and extend the solution space.

V Results and Discussion

The genetic algorithm focuses on the optimization of the entire network structures. The multidirectional and global search of genetic algorithms based on a population of possible solutions that are adapted and improved from generation to generation are the main reasons why genetic algorithms can be a suitable optimization method for the supply chain network. Although genetic algorithms aim to efficiently compute global and optimal solutions, their population cannot be infinitely large. Therefore, its final solution may be biased due to the finite sampling of potential solutions. Furthermore, population size does not usually improve the performance of a genetic algorithm in terms of speed of solution finding. It should be considered that the genetic algorithm belongs to the group of metaheuristics, which are general and not problem-specific heuristic optimization methods based on the principle of local search. Metaheuristics, especially the genetic algorithm, have the following advantages:

- **Adaptability**
  The genetic algorithm has no special mathematical requirements for the optimization problems. Due to its evolutionary character, the genetic algorithm looks for solutions within a certain solution space. Objective functions and constraints do not significantly influence the genetic algorithm, so it can be applied to a wide range of problems.
- **Robustness**
  The genetic algorithm is characterized by the application of genetic operators. These make it very effective in performing global searches. Other conventional heuristics usually perform local searches. However, many studies have shown that the genetic algorithm is more efficient and robust in finding the optimal solution and reducing the computational effort than other conventional heuristics (Mitsuo, Runwei, & Lin, 2008, p. 4-6).

- **Flexibility**
  Due to its enormous adaptability, the genetic algorithm is also very flexible. This enables the genetic algorithm to be efficiently implemented for a specific problem.
- **Parallelism**
  GA are fully parallelizable. Thus, for example, each chromosome of a generation can simultaneously pass through the selection algorithm. The same applies to all other process steps of the algorithm

The genetic algorithm is therefore a common optimization method in the field of operations research, which can be adapted and applied to a wide variety of problems. As already mentioned, the genetic algorithm is not a problem-specific algorithm. Therefore, especially in the optimization of supply chain networks, there are other algorithms that can calculate better solutions. This also includes exact procedures like linear optimization, which is already used in supply chain planning, but genetic algorithm has significant advantages in its applicability. This can be seen in the described procedure for the application in the supply chain network of the automotive industry. The coding was done by means of assemblies and modules, which makes it possible to optimize only parts of the supply chain network. The calculation of the entire supply chain network would result in performance problems most likely, because the enormous complexity of the problem has a negative impact on the calculations. However, this also depends on the hardware. Supply chain networks can benefit above all from global supplier availability and can therefore be optimized accordingly. However, genetic algorithms will probably find little or no application in supply chain networks because their approach to computation is not efficient enough due to the limited performance. Nevertheless, only parts of an entire supply chain network can be considered. Companies could limit themselves to one assembly and use the genetic algorithm to compare different supplier constellations without affecting existing supplier relationships.

In summary, business processes are increasingly supported or even replaced by artificial intelligence. The potential for improvement through the application approaches is enormous. The implementation of artificial intelligence is becoming increasingly easier due to the increasing availability of data. As an evolutionary optimization method, genetic algorithm also belongs to the class of artificial intelligence. Accordingly, the number of applications in practice will probably increase in the future. However, this is uncertain, because there are much better optimization methods. genetic algorithm remains a very adaptable and flexible algorithm, which can calculate a good solution for many problems without high implementation effort.

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