Optimization Networks for Real-World Production and Logistics Problems

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ABSTRACT

With the continuous advancement of industry 4.0, also in the area of production and logistics optimization, a more holistic consideration of problems is required. Therefore, in contrary to the traditional sequential optimization approach in the area of operations research, in this paper, an integrated solution approach called optimization networks (ON) is presented. In an ON, multiple problem models get connected and optimized by an evolutionary solution algorithm. By having several optimization runs, in which the results of the preceding optimizations are considered, opportunity costs which could arise out of a traditional sequential optimization approach, are avoided.

CCS CONCEPTS

•Theory of computation → Mathematical optimization; Evolutionary algorithms; •Computing methodologies → Genetic algorithms;

KEYWORDS

optimization networks, production and logistics problem models, evolutionary algorithms, opportunity costs, synergy effects

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1 INTRODUCTION

With the development of the fourth industrial revolution, it is tried to realize an increasing interconnection between different fields of action within and between organizations [7]. One of the main goals of this new approach, which is also called industry 4.0, is the achievement of resource efficiency [7]. By connecting (inter-) organizational units, hitherto hidden and unused synergy effects should be detected and utilized [7]. As a result, the approach of industry 4.0 indicates an increasing focus on the holistic consideration of different problems and problem models of organizations.

For the optimization of problems in the area of production and logistics, the typical main objective is gaining quantitative improvements, which also corresponds to an increase of resource efficiency. However, by the sequential execution of optimization models of different departments, high opportunity costs can arise. If two models are optimized sequentially, the result of the first optimization problem could for example bring high savings. Taking this outcome as an input for the next optimization model, the second result's costs could be higher than the achieved savings for the first one. As a consequence, an alternative to the traditional consideration of single problems in the area of operations research (OR) is developed, in which an interconnection of different units is possible. Therefore, opportunity costs should be avoided. The difference between the traditional sequential approach and the new approach of optimization networks is presented in Fig. 1.

In this work, a generic solution approach for multiple problems is presented. Production and logistics problem models are integrated into one optimization network, where they get connected and optimized. With this approach, every integrated problem model is solved by one assigned solution algorithm. An orchestrator is responsible for the data transfer between all nodes of the network. This transfer allows an ongoing data exchange between problem solvers and the so-called meta solver. The meta solver is responsible for the optimization of the calculated overall result out of all single problem model solutions. The result of this optimization is then

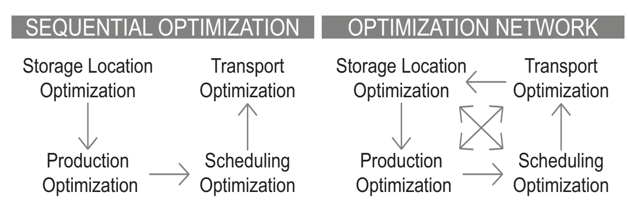

Figure 1: Sequential optimization versus optimization networks.

used to initiate a new optimization run for all single problem models. Thus, solutions of single solvers influence further optimization runs, which was not possible with a sequential approach, where problems are solved once and consecutively. With this approach, opportunity costs should be avoided and so far undetected synergy effects should be made visible and used.

The article is organized as follows. In Sect. 2, related work concerning mathematical optimization is presented. Afterwards, a generic optimization network is illustrated in Sect. 3. Finally, in Sect. 4 a conclusion is provided and directions for further research are given.

2 LITERATURE REVIEW

For the integration of more than one production or logistics problem model or solution technique, different approaches exist within the field of OR. One possiblity is the integration of various problems into one mathematical problem model and the development of a specific algorithm for solving it. An already existing example is the Location Routing Problem (LRP) [9], which consists of the Facility Location Problem (FLP) and the Vehicle Routing Problem (VRP). Matheuristics are a solution approach for integrating different optimization methods, where metaheuristics are combined with mathematical programming. High-quality results show their capabilities [3, 12]. [1, 8] also show the potential of integrating different problem formulations into one optimization. They introduce new algorithmic strategies to be able to combine different problem models and heuristic solution approaches within one optimization.

[5] describe in their survey the so-called multilevel decision-making optimization. The described techniques follow the leader-follower principle of Stackelberg's game theory [13], where the follower decides on the basis of the leader's decision. However, the leader's decision-making process is implicitly influenced by the included assumption of the reaction of the follower. A widespread application is the bilevel optimization. Within two decision levels, the leader (first optimization level) has to decide about his variables and the follower (second optimization level) has to take the decision variables of the leader into account [6]. Solution approaches for bilevel optimization are amongst others metaheuristics und genetic algorithms [6]. In the area of production and logistics, it can for example be seen that the focus of solution approaches is on the individual development of algorithms for the overall problem, such as ant colony optimization methods [2] or particle swarm algorithms [6].

3 A GENERIC OPTIMIZATION NETWORK FOR PRODUCTION AND LOGISTICS PROBLEM MODELS

As already stated in Sect. 1, there is a growing need for an integrated consideration of multiple planning problems in the field of production and logistics. If more than one planning problem is considered, there are different possibilities of problem modeling and solving, as presented in Sect. 2. With a desired integration of two or even more real-world problem models into one (multilevel) optimization problem, every single modification in one affected business area leads to a change of the developed mathematical problem model. Moreover, the whole algorithmic solution approach for the developed model has to be varied every time, one unit demands an adjustment.

However, within the consideration of real-world applications, a solution approach does not only have to combine different problem models out of different departments. It rather has to have short reaction times on changing requests of a unit, since operational activities normally can only be stopped for a short time. Subsequently, a new solution approach for the combination of production and logistics problem models is presented. Within an optimization network (ON), single problem models are integrated with their single solution mechanisms. After every model has been solved, all solutions are merged. This overall result is optimized by a meta solver and another optimization run is initiated to achieve the best possible solution. By taking single problem models and their assigned solution mechanisms into account, requested modifications of one business area should not lead to a change of the whole solution approach but only to an adaptation of the affected part of the network.

3.1 Structure and Operating Principle of an Optimization Network

With the structure and the operating principle of an ON, the traditional, sequential optimization procedure and the related arising opportunity costs described in Sect. 1 should be conquered. The single sequences within an optimization network are connected to each other. They continuously exchange information and therefore get optimized with every optimization run.

The structure of an optimization network is composed of two stages. Within the first stage, the *model splitting*, problem models have to be defined and appropriate solution approaches have to be found. The second stage, the *solution merging*, unites calculated results of single problem models. New combination strategies for the single solutions have to be developed to be able to have multiple optimization runs which lead to improved solutions.

The operating principle of an optimization network is divided into three different sectors. Problem solvers, a meta solver and an orchestrator, which are described hereinafter.

Problem Solvers. For every business unit, which is taken into account, a problem model has to be defined and a solution algorithm has to be assigned.

- Depending on the complexity of the problem and the problem instances, it can be an already existing exact or an evolutionary solution approach.
- After all problem models are optimized, one optimization run is finished and the overall result can be calculated.

Meta Solver. The meta solver is an algorithm, which optimizes the overall result. The method of this optimization is decisive to be able to find a better solution within the next run of the ON.

- The meta solver takes the overall result of all optimized problem models into account and tries to find optimized parameter configurations for the problem instance. With the variegated problem data configurations, a new optimization run is started, which should bring a better overall solution.
- A changed problem instance of course involves non-realistic input data for the optimization. Therefore, the variegated

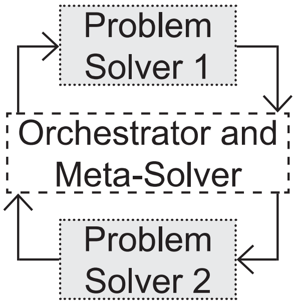

Figure 2: Operating Principle of an Optimization Network.

problem data is only used for the first problem solver. The solution of problem 1 is then converted to the original input data. This means that the optimized decision variables of solution 1 are given to problem solver 2 after they have been provided with original input data. The exact mechansim of this return process is explained in 3.2.

Orchestrator. The orchestrator is the central control point within the optimization network. It tries to reduce opportunity costs by integrating all nodes of the network. Moreover, it is responsible for the transfer of the problem instance data to and between the different parts of the ON.

- The orchestrator gives the problem instance to the problem solvers and to the meta solver. It is concerned with the initialization of the single optimizations, the solution splitting, and with the data transfer between the solvers.
- After every optimization run, the solution merging process is started. The orchestrator calculates the overall result and gives it to the meta solver. Then it waits for the problem instance, which is optimized and therefore changed by the meta solver. Next, it gives this changed instance to the first problem solver. With this action, a new optimization run is started.
- The orchestrator is also concerned with the return transfer of the changed problem data to its original one. Hence, it is guaranteed that the overall solution of the optimization network is always valid and therefore corresponds to the original real-world input data.

In Fig. 2, the operating principle of an optimization network with two problem solvers is presented. A detailed explanation and a real-world example, especially including the ongoing change of problem input data, is given in Sect. 3.2.

3.2 Procedure and Execution of an Optimization Network

The procedure of an optimization network is explained with the exemplarly Capacitated Location Routing Problem (CLRP) [9]. It consists of the Capacitated Facility Location Problem (CFLP) [10] and the Capacitated Vehicle Routing Problem (CVRP) [11]. In the literature of operations research, these problems are, among others, considered by the integrated mathematical modeling approach of the LRP [9], als already explained in Sect. 2. Subsequently, the solution approach of an optimization network is applied to the CLRP. Besides the described procedure for the ON of a LRP, an illustrative quantified example is given for every explained step of the procedure with italic letters.

Initialization. *Original input data and objective of the CFLP:*

- *Input Data: Potential depots* $n = 3(j = 1, .., n)$ *with coordinates; depot capacities* $s1 = 11$*;* $s2 = 10$*;* $s3 = 10$*; depot opening costs* $f1 = 100$*;* $f2 = 110$*;* $f3 = 100$*; customers* $m = 6(i = 1, .., m)$*; customer coordinates* $i1\{1; 1\}$*;* $i2\{1; 2\}$*;* $i3\{1; 3\}$*;* $i4\{1; 4\}$*;* $i5\{1; 5\}$*;* $i6\{1; 6\}$ *(distances* c_{ji} *from depots to customers are calculated out of coordinates); customer demands* $d1 = 2$*;* $d2 = 3$*;* $d3 = 1$*;* $d4 = 4$*;* $d5 = 3$*;* $d6 = 2$*.*
- *Decision Variables and Objective:* $y_j = 1$ *or* 0 *if a depot is opened or not and* $x_{ij} = 1$ *or* 0 *if a customer is supplied by a depot or not. The objective is the minimization of depot opening costs and delivery costs from depots to customers.*

Original input data and objective of the CVRP:

- *Input Data: One depot* $u = 0$ *with coordinates; vehicles* k*; vehicle capacity* q*; vehicle fixed costs* kf*; customers* w $(u = 1, .., w)$ *with coordinates; customer demands* de_u*; distances* di_{uv} *from all nodes to all nodes.*
- *Decision Variables and Objective:* $z_{uvk} = 1$ *or* 0 *if one node is served after another one and which vehicle is used. The objective is to minimize distances and vehicle fixed costs.*

The orchestrator starts the optimization network. A random solution (first overall result of the ON) is generated.

ON Part 1. The overall result of the first optimization run is given to the meta solver. The meta solver is equipped with an evolutionary approach, the CMA/ES [4]. For the CMA/ES, a specific amount of generations and a population size has to be assigned. Generations correspond with the number of allowed optimization runs of the ON and the population size complies with the amount of generated solutions per optimization run. This evolutionary algorithm optimizes the problem input data for problem 1 (CFLP) by considering the overall result. The objective of the alteration is to achieve a better overall result after the next optimization run. It has to be decided which parts of the input data are changed. Three different examples for such a changing strategy are *the change of customer coordinates, the change of depot coordinates and the change of depot opening costs.* The development and application of the changing strategies are crucial for the solution of every optimization run. Therefore, several strategies and also the combination of different strategies can be tested for an ON. However, in this example, the first strategy is pursued, which means that the meta solver optimizes and therefore generates new customer coordinates after every optimization run. The orchestrator stores the relationship of original coordinates per customer and its new, assigned coordinates out of the CMA/ES. The new, optimized customer coordinates correspond to a real-vector, which is sent to problem solver 1 together with the rest of the original problem input data.

The meta solver's optimization of the first overall result leads to changed input data: The new customer coordinates for the CFLP are $i1\{1; 2\}$*;* $i2\{1; 4\}$*;* $i3\{1; 7\}$*;* $i4\{1; 9\}$*;* $i5\{1; 8\}$*;* $i6\{1; 10\}$*.*

ON Part 2. Problem solver 1 solves the CFLP with the variegated customer coordinates. For small problem instances, the problem can be solved to optimality within a very short time. Therefore, an exact solver, such as IBM ILOG CPLEX[1] can be connected to the ON. Solution 1 is sent back to the orchestrator.

The changed input data leads to the following solution.

- *Depot 1* $y1 = 1$ *is opened with* $i2\{1;4\}$*;* $i3\{1;7\}$*;* $i4\{1;9\}$.
- *Depot 2* $y2 = 1$ *is opened with* $i1\{1;2\}$*;* $i5\{1;8\}$*;* $i6\{1;10\}$.

ON Part 3. The orchestrator takes solution 1. It considers the stored correlation of fictional coordinates and original, real coordinates per customer. It takes the customer assignment per depot out of solution 1 and converts the customer coordinates back to its original coordinates on basis of the stored correlation of 'ON Part 1'. These converted customer coordinates, and therefore original ones, are given to problem solver 2 per opened depot $y_j = 1$. All other necessary input data, such as vehicle capacities, are taken out of the CVRP original input data. As CVRP are only solveable to optimality for up to 50 customers [11] for most problem instances, a genetic algorithm is selected for solving the CVRP.

The orchestrator gives the information of opened depots 1 and 2 to the CVRP. Moreover, it gives the new customer assignment of 'ON Part 2' to the CVRP, but with the original customer coordinates.

- *Solve one CVRP for* $y1 = 1$ *with* $i2\{1;2\}$*;* $i3\{1;3\}$*;* $i4\{1;4\}$.
- *Solve one CVRP for* $y2 = 1$ *with* $i1\{1;1\}$*;* $i5\{1;5\}$*;* $i6\{1;6\}$.

Within problem solver 2, all CVRP are optimized. Then, the result is transferred to the orchestrator, which calculates the overall result out of solution 1 and 2. It sums up depot opening costs f_j for all $y_j = 1$ out of solution 1 and distance costs di_{uv} and vehicle fixed costs kf out of solution 2 (for all $z_{uvk} = 1$). Based on this second overall result, the meta solver's algorithm, the CMA/ES, again optimizes the problem input data by assigning a new real vector with different customer coordinates. Another optimization run is initiated. The whole process is repeated, until the maximum number of allowed generations of the CMA/ES is reached.

In the case of an ON, the above described continous information exchange should lead to the detection and utilization of synergy effects. If one only considers a CFLP, low depot costs could lead to very high routing costs for a CVRP. However, it could be the case that higher depot opening costs lead to less routing costs and therefore to a better overall result. First preliminary results, where an ON is applied to the Location Routing Problem and its solutions are compared with another generic solution approach, a mathematical optimization solver called Local Solver[2], show that this new solution approach is promising.

4 CONCLUSION

In the literature, in multilevel optimization applications in supply chain management, new solution algorithms are developed for the whole multilevel decision problem, as for example shown in [2] and [6]. In this work, a new solution approach for the simultaneous optimization of multiple production and logistics problem models has been proposed. Within an optimization network, problem solvers, a meta solver and an orchestrator are integrated. When problem models are solved, the meta solver and the orchestrator are responsible for the evolutionary variegation of the problem input data by considering the overall solution quality and exchanging input data and results. By the introduction of new optimization runs every time the input data has been changed, existing synergy effects between different problem models and therefore between different production and logistics real-world departments, should be detected and utilized. Moreover, different problem models of different departments are regarded separately per problem solver. Thus, demanded real-world modifications only concern one problem solver and not the whole solution approach.

First results are promising, as stated in Sect. 3.2. However, the solution approach has to be tested on several problem models to be able to find out more about its methodogical quality. Furthermore, it is suggested that another future challenge is the development of efficient strategies for the evolutionary solution approach of the meta solver as described in Sect. 3.2. These intelligent changing strategies are crucial for the solution quality of the single optimization runs and therefore for the quality of the overall result of the network.

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