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Research Article

Empty Container Management at Ports Considering Pollution, Repair Options, and Street-Turns

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International trade imbalances make the management of empty containers within shipping networks an important economic and ecological problem. While import-dominated ports accumulate large amounts of empty containers, export-dominated ports need them as transport resources, requiring a repositioning transportation of empty containers on the sea and land side. Acknowledging the importance of the problem, plenty of respective literature has appeared. Since periodic review inventory management systems allow to model the inherent stochasticity of empty container transportation, they have emerged as a major solution approach in the domain. Nevertheless, existing approaches often omit crucial economic and ecological real world conditions determining the success of empty container management. Pollution, repair options, and street-turns are important aspects in this context. In this work, we present new stochastic review policies incorporating a realistic allocation scheme for empty container emissions, realistic maintenance, and repair options as well as street-turns. We analyze the optimality of the proposed polices and evaluate them in a simulation model with metaheuristic parameter search based on extensive real-world data from a major global shipping company operating in Latin America. Results provide insights for academics and practitioners about the economic and ecological impact of the distinct empty container management polices within a shipping network.

1. Introduction

Greenhouse gas (GHG) emissions in maritime shipping have received much attention in recent years and are widely seen as a major constraint for sustainable growth in worldwide trade among researchers and practitioners of the field. Due to the trade imbalance, for example, between Asia and Europe, a significant share of global container movements are movements of empty containers. Current empirical studies estimate a percentage between 20 and 30 per cent empty container movements in maritime shipping and even up to 50 per cent in the hinterland [1]. Empty containers are therefore responsible for a significant part of emissions produced in maritime transport. Since empty containers, in contrast to full containers, need to satisfy an internal demand of the shipping company, there may be more space for emission integrated planning approaches in empty container transport. Though the connection between emission models in maritime shipping and empty container repositioning has been drawn [2], there remains lack of respective models on all planning levels of empty container management.

One way to address the problem of empty container repositioning is inventory management approaches applied to manage orders and stock levels of empty containers in ports. For instance, Li et al. [3, 4] have introduced a heuristic for repositioning policies based minimum and maximum numbers of empty containers at ports, and more recently, Dang et al. [5] have presented a simulation-based optimization approach for demand dependent positioning of empty containers between ports and between depots of ports. Although the importance of emissions caused by empty containers has been well understood [2], little effort has been made to extend existing models to multiobjective formulations incorporating business and sustainability objectives. This is in line with an observed need for stochastic multiobjective models integrating both planning objectives in maritime shipping [6]. Apart from that, the importance of real-world conditions such as damaged containers or street-turns have recently been stressed in shipping network design [7], where street-turns refer to the operation of directly reusing an imported unloaded container, that is, directly moving it from the consignee's to the shippers' location without bringing the container to a depot or warehouse before.

In this paper, we present several new, inventory-based empty container management policies using emissions prices for a cost function that integrates economic and ecological objectives, on the sea and land side. These policies serve to evaluate the pollution impact of empty container transport, maintenance, and repair as well as street-turns options. We examine the proposed policies analytically and evaluate them in a simulation approach with metaheuristic parameter search, assuming the case of a Latin American shipping service operated by a major shipping company. While Markov decision processes are used to design threshold policies, simulation techniques are applied to evaluate their performance since they provide solutions for complex and realistic problems [8]. We find that the presented model may actually enable planners to master the observed potential trade-off in objectives and may be an effective way to more realistic, more sustainable empty container management.

The following sections present relevant literature, extended periodic review policies for empty container management, and a simulation optimization model with a numerical study based on real world data as well as conclusions drawn from the study. Section 2 reviews current empty container management models and emission-oriented maritime logistics. Section 3 introduces the empty container inventory management approach and analyzes the proposed policies with respect to their optimality. Section 4 describes the simulation model and the optimization approach for the evaluation, complemented by a numerical study in Section 5. Section 6 gives conclusions and an outlook on future research.

2. Literature Review

Invoked by cost saving requirements in industry, literature provides an extensive body of studies on empty container management and repositioning of empty containers between ports [9]. Some of the prominent studies in this respect adapt inventory management models already established in industrial or production management, but little work has been done to connect those models to pollution objectives and some subtle, but important real world conditions determining empty container transportation in shipping networks.

Among earliest published approaches, Crainic et al. [10] introduced a general modeling framework for various problem cases related to the allocation of empty containers between ports and port depots. Since then plenty of work has been published to address related problems with different specific constraints. Braekers et al. [11] more recently reviewed and classified those approaches with respect to multiple planning levels. Problems concerned with dispatching of empty containers and short-term leasing have been labeled as container allocation problems by the authors. In this realm, various authors focused on inventory-oriented models to define order policies for empty containers and stock levels for empty containers at ports [3–5, 10, 11]. These studies adapt classic inventory management models which can be found in standard work by Silver et al. [12], or, in a more recent review by Schmidt et al. [13].

In the domain of empty container management, Li et al. [4] introduced the idea of stock limits of empty containers at ports to support importing and exporting decisions. Li et al. [3] later enhanced this concept, formulating a heuristic container allocation algorithm that enables decision-makers to define a cost efficient allocation plan for empty containers. For a similar purpose, Dang et al. [5] presented a simulation-based optimization approach, extending earlier work by Yun et al. [14]. The authors derive optimal inventory levels and order points for empty containers for different proposed heuristic allocation policies. The successful implementation of related inventory-based empty container management has been documented by Epstein et al. [15] for the Latin American shipping company CSAV.

Apart from these studies, the relationship between empty container transport and GHG emissions has been examined by Song and Xu [2]. In an activity-based approach, the authors draw a clear picture of emissions caused in various steps of maritime container transport and on how challenges of empty container management and repositioning relate to that. In a recent review on multiobjective decision support for sustainability in maritime transport, Mansouri et al. [6] propose simulation-optimization to close the gap between theoretical insights in multiobjective planning problems and respective applicable models.

In the field of sustainable maritime transport, some topics dominate in literature. Studies with a perspective on logistics operations typically focus on Vessel emissions [16, 17], repositioning of (empty) container trucks and empty containers [2, 17, 18], hinterland transport [19–22], and terminal operations [21–23]. Psaraftis and Kontovas [16] represent a different direction in research emphasizing operational options to effectively reduce the quantitative emission impact of container shipping. Villalba and Gemechu [17], on the other hand, took the perspective of a single port and derive strategies and policies to reduce emissions in the port area caused by vessels visiting the port.

On the land side, the repositioning and capacity utilization of (empty) container trucks is an often discussed topic. Englert et al. [18] have examined the impact a potential inland port would have on pollution and congestion caused by empty truck repositioning in the Southern California region. In the same realm, Schulte et al. [24, 25] have proposed an appointment system and a corresponding mathematical planning model to reduce port-related truck emissions by means of collaboration among truckers and trucking companies for a real world case. An established approach to integrate cost and pollution objectives in an objective function has been presented by Bektaş and Laporte [26]. The authors derive costs of emissions by summing up emission-related costs such as fuel consumption. Thus, an integrated objective function may be formed as a sum of cost terms. Alternatively,

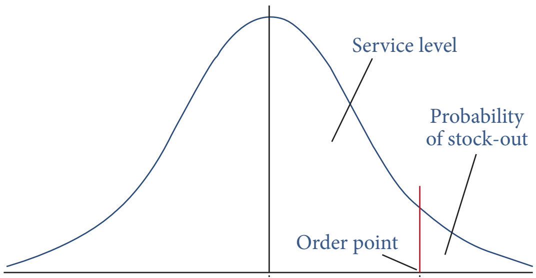

Figure 1: Order point definition with a normal demand distribution.

other authors [25, 26] have applied an emission price for the same purpose. This approach reflects the assumption that regulators may charge companies with a certain fee on their produced emissions.

Moreover, some authors recognized the need for more realistic modeling of empty container management processes. Shintani et al. [7] examined the shipping network design with respect to empty container repositioning and also considered an aggregated repair and maintenance cost. Furthermore, Jula et al. [27] developed several strategies, including street-turns, to optimize dynamic empty container reuse in a port area. Furió et al. [28] extended these ideas to optimize empty containers movements on the land side, also applying street-turns.

Overall, the economic importance of the empty repositioning process is extensively documented in literature, but there remains a lack of approaches incorporating pollution objectives as well as inventory policies considering specific requirements such as repair options or street-turns.

3. Empty Container Pollution, Repair, and Street-Turn Policies

Inventory management approaches typically use maximum and minimum (or safety) stock levels in order to define order times and quantities [12]. Furthermore, problem-specific policies are often applied to serve different kinds of objectives. Subsequently, we present these elements of inventory management adapted for the case of empty containers in maritime shipping.

Realistic empty container management models need to consider stochastic demand during order lead-times, that is, the time from the release of an order until the arrival of the containers. Figure 1 illustrates the relation of the demand distribution during order lead time, service level, and safety stock for a normal distribution of demand.

Defining the right level of parameters such as the order point in periodic review systems allows reaching a desired service level and minimizing inventory costs. The probability for insufficient stock (stockout) increases costs, for example, for leasing operations, while overstocking is typically discouraged by holding costs. The order point is the inventory level when an order is initiated, triggered by reaching a critical, actual, or forecasted (safety) stock level of inventory.

3.1. Basic Empty Container Model. To model the multiperiod empty container management problem and to analyze inventory policies with respect to distinct objectives, we make use of dynamic programming and Markov decision processes. We apply the subsequent notation:

k: discrete decision time period index,

j: index for container sourcing option,

x_k: amount of empty containers in the beginning of period k,

u_k: decision variable indicating the amount of empty containers to be ordered in period k,

y_k: amount of empty containers after decision u_k has been applied,

w_k^i: random variable indicating the supply of import containers in each period k,

w_k^e: random variable indicating the demand of export containers in each period k,

N: time horizon or number of periods considered,

M: maximum amount of import and export containers in each period k,

Z: Number of sourcing options in the shipping network,

c^f: fixed cost for repositioning of an empty container,

c^v: variable cost for repositioning an empty container,

c^o: import cost for repositioning an empty container,

c_j^e: emission cost for repositioning an empty container for sourcing option j,

D^e: cumulative distribution function for c_j^e with $D^e(c_j^e) = \sum_{j=1}^{Z} d^e(c_j^e)$,

c^h: holding cost per container and day,

c^l: leasing cost per container and day,

c^r: repair cost per container,

α: service level $[0 \le \alpha \le 1]$,

β: random parameter for amount of damaged containers $\beta \in [0, 1, \ldots, u_k]$,

γ: random parameter for the number of possible street-turns $\gamma \in [0, 1, \ldots, w_k^i]$,

p^e: emission price in \$/ton,

s: safety stock level,

S: upper stock level.

Cost values may be indexed over specific time periods. A couple of assumptions have to be made in advance. For the basic problem, we suppose that

(1) empty containers are a single type product, for example, 20 foot-equivalent unit (TEU) containers;

(2) the entire demand of one period has to be fulfilled in the same period; that is, no backlogging is allowed;

(3) if the demand exceeds the current inventory level, empty containers may be leased from a leasing company to fulfill the demand;

(4) empty containers may be ordered in the beginning of fixed periods and involve variable ordering costs and a fixed order set-up cost;

(5) empty container holding costs occur for each period of holding a container in storage.

Subsequently, further assumptions are made to model empty container inventory policies incorporating transport pollution, repair options, street-turns, and service levels.

For the basic problem with N stages and $y_k = x_k + u_k$, the state changes from period k to period $k+1$ are given as

$$x_{k+1} = y_k - w_k^e \quad k = 0, 1, \ldots, N-1. \tag{1}$$

The export w_k^e is supposed to be bounded and independent. This implies the standard assumption [29, 30] that import decisions are supposed to lead to available containers within period k. With c_k^l and c_k^h as nonnegative parameters, expected leasing costs and expected holding costs sum to

$$\begin{aligned} H(y_k) = {} & c_k^l E \max(0, w_k^e - y_k) \\ & + c_k^h E \max(0, y_k - w_k^e). \end{aligned} \tag{2}$$

With the above definition of H, the expected minimal costs in period k are

$$\begin{aligned} J_k(x_k) = {} & \min_{u_k \geq 0} [c_k^v u_k + H(x_k + u_k) \\ & + E\{J_{k+1}(x_k + u_k - w_k^e)\}]. \end{aligned} \tag{3}$$

In order to capture the practical scenario correctly, it is important to assume $c_k^v < c_k^l$ to discourage an inventory policy that uses leasing instead of ordering. Using the just introduced problem formulation to enforce desired service levels, as illustrated in Figure 1, a chance constraint may be formulated as

$$P\{x_{k+1} < 0\} \leq 1 - \alpha \quad k = 0, 1, \ldots, N-1, \tag{4}$$

where $0 \leq \alpha \leq 1$ grants that a desired minimum probability for demand fulfilled in one period is not undercut. In addition to this basic inventory problem, we next define new extended inventory polices considering pollution caused by decisions made above as well as repair options for containers that arrive damaged and street-turns.

3.2. Pollution Policy. The amount of pollution that is generated by a decision in empty container management fundamentally depends on a couple of major aspects. First, the transportation mode needs to be taken into account. Container trucks and vessels, as the predominant means of container transportation, cause quite different amounts and types of emissions. If an empty container inventory has several distinct transportation modes to choose from for import, this should be reflected in the inventory policy. Second, the distance that an empty container needs to be transported obviously impacts the associated pollution significantly and needs to be considered in the design of appropriate pollution aware policies as well. Third, emission allocation models may be used to distinguish whether an empty container is transported in an anyways empty slot on a truck or vessel or a transport activity was initiated in order to transport empty resources. This is based on the hypothesis that empty container demand can be handled with more flexibility than full container demand. That is, empty container repositioning (or an empty container order) is preferably initiated whenever there is an empty capacity slot on a vessel or truck. Such a slot exists if for the entire repositioning operation no full container demand occurs for this slot. Consequently, the transport of an empty container in an otherwise empty slot on a vessel only adds-up marginally to the vessel emissions. From a system perspective, we now increase the capacity utilization of vessels and thus reduce overall emissions.

In order to incorporate the emissions as an objective in the inventory problem, we assume that a shipping company is charged a certain price for the emissions; and emissions may hence be formulated as an additional cost term. There are other approaches [26] to combine cost and emission objectives in transportation problems, but, considering already present emissions prices, they appear to be a realistic approach [25, 26]. Furthermore, we assume that an inventory manager will intuitively order the cheapest containers if they can choose between containers of equal type and quality. Hence, the expected variable container costs now sum up to

$$c^v = c^o + \sum_{j=1}^{Z} c_j^e d_j^e (c_j^e), \tag{5}$$

where the cost for emissions $c_j^e \in [c_1^e, c_2^e, \ldots, c_Z^e]$ depends on empty container availabilities within the shipping network considering the transportation mode, transport distance, and whether an empty slot was used or not. These availabilities together with the assumption that always the cheapest available containers are selected serve to construct an empiric distribution of emission costs that defines the variable costs of each order. For further description of such data, the reader is referred to the numerical experiment in Section 5.

3.3. Repair and Maintenance Policy. When empty containers return to the inventory, a certain percentage is typically damaged but may be used for further service after repair. This leads to another extension of the basic problem above. First (1) takes a different form

$$\begin{aligned} x_{k+1} &= x_k + u_k E\left(1 - \frac{\beta}{u_k}\right) - w_k^e + w_k^i + u_k E \frac{\beta}{u_k} \\ &= y_k - w_k^e + w_k^i + u_k E \frac{\beta}{u_k} \quad k = 0, 1, \ldots, N-1, \end{aligned} \tag{6}$$

with $\beta \in [0, 1, \ldots, u_k]$ as a random parameter indicating a certain amount of damaged containers among arriving ordered containers. As stated above, ordered containers are expected to be available immediately in the same period. In contrast, full import containers w_k^i are expected to require one period for unloading, maintenance, and repair. Ordered containers that arrive damaged are obviously not available in the same period k. Hence, they are subtracted from y_k and added to the import containers w_k^i that become available in x_{k+1}. Furthermore, the costs need to be updated to

$$c^v = c^o + \sum_{j=1}^{Z} c_j^e d_j^e \left(c_j^e\right) + E\frac{\beta}{u_k} c^r, \tag{7}$$

where the order costs c^o, the emission costs c_j^e, and the repair costs c^r are assumed to be constant over time.

3.4. Street-Turn Policy. Street-turns provide an opportunity in empty container management to fulfill an empty container demand with an import container without having to return the container to inventory. This enables shipping companies to save holding costs as well as ordering costs when a street-turn is applied. To incorporate this opportunity into the problem formulation, we assume that street-turns are conducted whenever an import container arrives early enough, without any damage, and hence ready to be reused immediately at the site of a client. This extends (1) to

$$\begin{aligned} x_{k+1} &= x_k + u_k - w_k^e + w_k^i E\left(1 - \frac{\gamma}{w_k^i}\right) + w_k^i E\frac{\gamma}{w_k^i} \\ &= y_k - w_k^e + w_k^i E\left(1 - \frac{\gamma}{w_k^i}\right) \\ &\qquad k = 0, 1, \ldots, N-1, \end{aligned} \tag{8}$$

with $\gamma \in [0, 1, \ldots, w_k^i]$ as a random parameter indicating a certain amount of containers for street-turns. Hence, w_k^i is reduced by a certain amount of containers defined by the expected value of γ and this amount is added to the amount of available containers y_k. Furthermore, street-turns indirectly reduce holding costs since fewer containers must be held in inventory to satisfy customer demand.

3.5. Optimal Empty Container Control Strategies. Having defined the objective function and its properties considering various policies, we next aim to derive an appropriate (optimal) inventory control strategy that implements these policies under the given assumptions. With $y_k = x_k + u_k$ (3) may be written as follows to find the optimal system state after decision u_k since x_k only appears as part of the sum $x_k + u_k$ in (3):

$$J_k\left(y_k\right) = \min_{y_k \geq x_k} \left[c_k^v u_k + H\left(y_k\right) + E\left\{J_{k+1}\left(y_k - w_k^e\right)\right\}\right]. \tag{9}$$

Assuming that this function has a minimum for $y_k = s_k$ and bearing in mind $y_k \geq x_k$, an optimal strategy is given as

$$u_k^* = \begin{cases} s_k - x_k & \text{if } x_k < s_k \\ 0 & \text{if } x_k \geq s_k. \end{cases} \tag{10}$$

The optimality of this strategy is proved since J_k is convex and $\lim_{|y|\to\infty} J_k(y) = \infty$ [29]. In cases of a fixed order cost $K > 0$, it can be shown that the following strategy is optimal when J_k has the K-convexity property [30] and is continuous, and $\lim_{|y|\to\infty} J_k(y) = \infty$

$$u_k^* = \begin{cases} S_k - x_k & \text{if } x_k < s_k \\ 0 & \text{if } x_k \geq s_k, \end{cases} \tag{11}$$

where s_k indicates when to order containers and S_k determines the amount that is ordered.

Now we have to show that these strategies are still optimal when policies (in Sections 3.2–3.4) are introduced; that is, the optimality conditions for (10) and (11) are preserved. First, the *pollution strategy* will be analyzed: Since the policy does not require fixed order costs, the optimality conditions for (10) may suffice. By adding (5) to (9) we receive

$$\begin{aligned} &J_k\left(x_k\right) \\ &= \begin{cases} Ec_k^v u_k + H\left(s_k\right) + E\left\{J_{k+1}\left(x_k + u_k - w_k^e\right)\right\} & \text{if } x_k < s_k \\ H\left(s_k\right) + E\left\{J_{k+1}\left(x_k + u_k - w_k^e\right)\right\} & \text{if } x_k \geq s_k, \end{cases} \end{aligned} \tag{12}$$

where taking the expectation over c_k^v preserves the convexity and limits behavior of the function. That is, the strategy considering distributed emissions is an optimal strategy of type (10).

Second, the *repair and maintenance policy* should be considered. In this case, we need to analyze several changes, similarly without fixed order costs. The damaged containers, modeled by the expectation value of β, reduce the available containers y by a distributed integer value depending on u_k. As in (12), this operation maintains optimality conditions for a strategy of type (10). Furthermore, imports w_k^i are added. The imports, as the exports, are bound by a maximum amount and also preserve the convexity and infinity behavior of the function. Finally, $(\beta/u_k)c^r$ transforms c_k^v into a weighted sum, an operation that is also known to preserve convexity. With $\lim_{|y|\to\infty} J_k(y) = \infty$ the strategy may be formulated as

$$\begin{aligned} &J_k\left(x_k\right) \\ &= \begin{cases} Ec_k^v u_k + H\left(s_k\right) + E\left\{J_{k+1}\left(x_k + u_k - w_k^e + w_k^i\right)\right\} & \text{if } x_k < s_k \\ H\left(s_k\right) + E\left\{J_{k+1}\left(x_k + u_k - w_k^e + w_k^i\right)\right\} & \text{if } x_k \geq s_k. \end{cases} \end{aligned} \tag{13}$$

Hence, this policy may also be modeled as an optimal strategy of type (10).

Third, the *street-turn* policy is examined. This policy is modeled similarly as the two above policies. Here, a distributed amount of import containers w_k^i is expected to be available in period k and is hence added to y_k. These operations transform w_k^i and y_k into weighted sums, which preserves the optimality conditions as well as taking the expectation value

$$J_k(x_k) = \begin{cases} Ec_k^v u_k + H(s_k) + E\left\{J_{k+1}\left(x_k + u_k - w_k^e + Ew_k^i\right)\right\} & \text{if } x_k < s_k \\ H(s_k) + E\left\{J_{k+1}\left(x_k + u_k - w_k^e + Ew_k^i\right)\right\} & \text{if } x_k \geq s_k. \end{cases} \tag{14}$$

Therefore, all introduced policies may be controlled by a strategy of type (10). If we assume a positive value for c^f, this analysis needs to be slightly extended using the concept of K-convexity [30].

4. Simulation Model with Metaheuristic Search

Considering their complexity, threshold-based stochastic dynamic models for inventory control and related problems are appropriately addressed by numerical search methods or simulation-based meta-heuristics methods [8]. We develop a discrete-event simulation (DES) model to evaluate the proposed policies in various scenarios and use a genetic algorithm (GA) metaheuristic to find improved parameter settings for the empty container inventory control. The DES approach only updates the system state when events occur and naturally models activities of random duration [8], for example, ordering or maintenance. Furthermore, simulation models with metaheuristic search have been successfully applied for complex problems, while dynamic programming approaches for Markov decision models lack efficiency for related complex systems or rely on approximation strategies to solve an optimization [31].

Figure 2 illustrates the procedure using the nomenclature introduced in Section 3. The procedure starts with the generation of initial parameters that enter the evaluation process of the simulation model marked by the dashed rectangle. Within the simulation model, demand and supply of empty containers are modeled as stochastic events. When these events occur, holding or leasing costs are triggered and alter the inventory costs H. Both values are considered by their contribution to the time-average (per month), and the inventory levels are updated, respectively, after that. As long as the simulation time t is within the determined time horizon of the experiment N, supply and demand events may continuously occur.

Whenever a discrete time period k has passed, an inventory review is triggered. If the inventory falls below the safety stock level, an order amount and a stochastic amount of damaged containers are determined. After that, the inventory costs are updated again, taking into account fixed and variable order costs as well as emission costs depending on the order options available in the network. Furthermore, repair costs are considered. As already defined, repaired containers are expected to be available one period later than unimpaired containers. When the experiment is terminated, an objective function value is returned to the GA. Until the algorithm is terminated by a stopping criterion, the metaheuristic will proceed with the genetics-inspired intensification and diversification steps referred to as selection, crossover, and mutation. These define the parameters for the next period evaluation.

The general idea behind this procedure is a frequent review of inventory and ordering strategies and to find near-optimal plans reflecting both objectives by applying the proposed replenishment strategies and inventory constraints derived by defining (s, S). This means, whenever an order is placed, emissions are calculated for the available empty container sourcing options of the shipping network. These emissions are weighted by an emission price and thus added up to H. The simulation optimization model entails three fundamental components: the model formulation with the objective function and constraints, a DES model, and a metaheuristic. Subsequently, we introduce these elements and demonstrate how they are related. That is, the objective is to minimize the sum of all costs determined by the proposed policies, that is, the sum of fixed and variable ordering costs, leasing, holding, and emission costs.

With $c^v = c^o + \sum_{j=1}^{Z} c_j^e p_j^e(c_j^e) + E(\beta/u_k)c^r$ the objective function becomes

$$\begin{aligned} J_k(y_k) = \min_{y_k \geq x_k} & \left[c_k^v u_k + H(y_k)\right. \\ & \left. + E\left\{J_{k+1}\left(Ey_k - w_k^e + Ew_k^i\right)\right\}\right]. \end{aligned} \tag{15}$$

The major constraint for the optimization is s, the safety stock, which represents the order point and the desired service level as described in Section 3. For s and S, a range of possible values may be defined before starting the optimization. Furthermore, probability distributions determining the expected values in (15) are defined in the simulation model.

To guide the search for near optimal replenishment strategies and inventory parameters, the GA is applied. For a detailed description of simulation-based GA implementations with respective inventory models, the reader may be referred to [32] or [5]. Here, the main steps for the GA configuration will be discussed: a problem specific chromosome representation, the evaluation using the simulation model, the selection step determining the selection for parent and offspring, and the crossover and mutation procedure. In this case, the chromosome or gene representation for the GA is built by integer values (s, S, the safety stock, and upper stock level). Within a certain constraining range, valid chromosomes can be formed and evaluated by the GA. That is, the safety stock related service level may not fall below the predefined value and the upper stock level S must always be a larger value than s. Based on the chromosomes, the GA can be initialized using predefined chromosomes or a random configuration and creates generations in this way. Next, these solutions of the first generation are given to the simulation model and evaluated with respect to the costs and emissions. Based on this, the so-called parent selection is performed, considering an acceptance probability that can be adapted to an individual data sample. After that, the offspring,

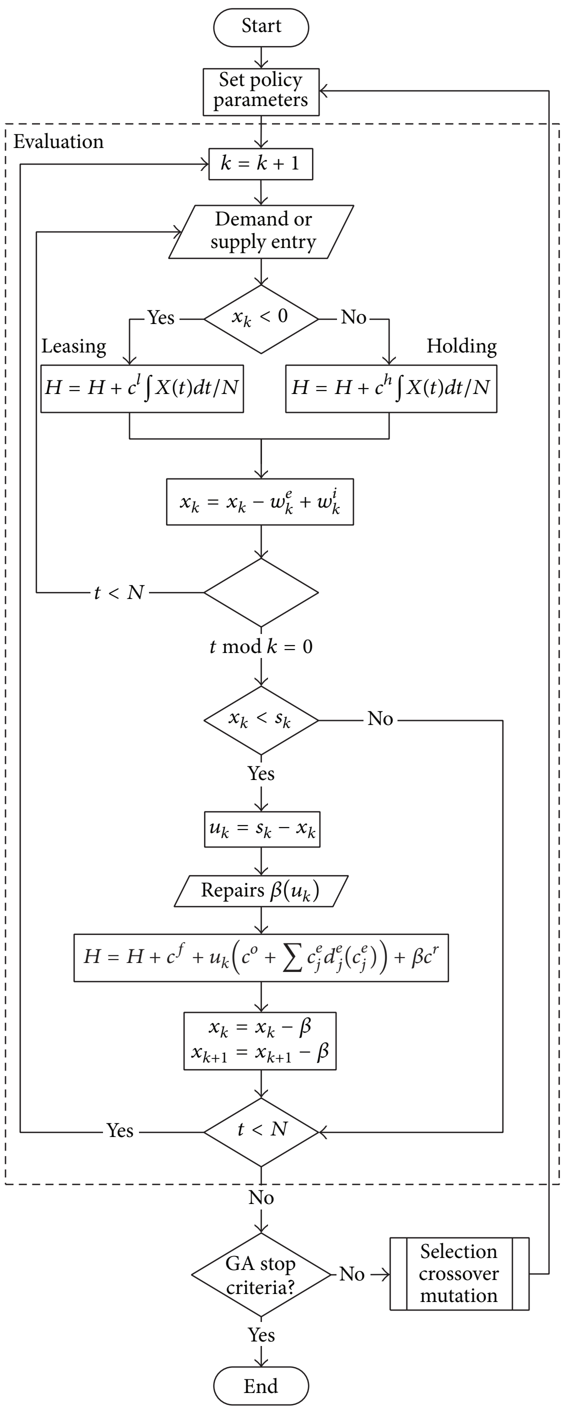

Figure 2: Simulation model with combined metaheuristic parameter search.

or children, are generated and evaluated likewise applying crossover and mutation strategies. Applying the well-known general idea of a GA, the crossover rate defines how many chromosomes the offspring copies from their parents, and the mutation rate defines how much is changed afterwards This routine continues until a defined stopping criterion, for example, a low percentage of improvements over several generations, holds. Let, for example, $P_1 = \{1, 0, 0, 1, 1, 0, 0, 0, 1\}$ and $P_2 = \{0, 1, 0, 1, 1, 0, 1, 0, 1\}$ be binary encoded parameter combinations of (s, S), deterministically selected from a population as superior chromosomes with respect to the fitness function. With l as the length of P_1 and P_2 a random integer value from a range $[1, \dots, l]$ is then selected to identify a crossover point after which the binary values of parents are exchanged to generate the children $C_1 = \{1, 0, 0, 1, 1, 0, 1, 0, 1\}$ and $C_2 = \{0, 1, 0, 1, 1, 0, 0, 0, 1\}$ (for 6 as a crossover point). A low mutation probability (0.01) finally defines the likelihood of a single bit to change its state.

5. Numerical Study

For the numerical evaluation of the approach we have analyzed more than 30.000 import and export container movements from, respectively to, Chile in the year 2012. The data corresponds to global to intra- and intercontinental services provided by a major international shipping company. Hence, the enterprise is challenged by different requirements to reposition empty containers that are imbalanced within their network. The additional data for this case has been collected in industry interviews, market inquiries, and public databases such as Ecotransit.org [33]. In this section, we present the data used for the numerical experiment, the experiment itself including quantitative results for various experimental setups, and a discussion on implications.

5.1. Empirical Data. All data used for this numerical study refers to the underlying data set on container movements from or to Chilean ports. Table 1 gives an overview on empirical data used and how it was modeled. Subsequently, we discuss each input data type and explain how it was derived and integrated into the model.

Demand and Supply. To derive the appropriate demand of empty containers in the considered case, we have analyzed extensive turnover data from the year 2012. We have used this data to approximate negative exponential and Poisson distributions of demand and supply, assuming exponentially distributed interarrival times (β = 20 min./25 min.) and Poisson distributed container amounts (λ = 8.5/8.1), where the latter refers to TEUs.

Costs. Besides demand and supply, all costs related to the empty container management approach are an important data input in order to create a realistic model. Table 1 lists these costs for the considered case. Whether a land side repositioning or sea side repositioning strategy is applied, holding costs at a depot of a port remain equal and depend on the location and various local costs. Order and leasing costs, on the other hand, can be retrieved by market research or inquiries. Order costs are typically split into a fixed and a variable part, where the fixed part represents operations at the ports of origin and destination, while the variable part is more closely related to the distance travelled in between the ports.

Pollution. In order to incorporate emissions as a planning objective, we need to implement a clear polluter pay principle in emissions allocation [34]. In this case, we have to distinguish between sea and land side repositioning. Furthermore,

Table 1: Overview on empirical data that was used for the numerical experiments.

Data type	Empirical source	Modeling approach
Demand/supply	30.000 container movements in 2012	Exponential and Poisson distribution
Leasing costs	Market analysis	Range [$5–20] daily
Ordering costs	Industry interviews	Range [$1–10] per TEU
Holding costs	Industry interviews	Range [$1–5] per TEU/day
Emissions	Ecotransit.org/EN 16258	Weighted average of ordering options
Emission price	Market analysis	Range [$0–20] per ton
Repair distribution	Industry interviews	Poisson distribution
Repair price	Market analysis	Range [$50–300] per TEU
Street-turns	Industry interviews	Range [0–20%] of import TEU

we need to consider whether the repositioning is performed in an empty slot of a container vessel or as part of the regular tonnage of the vessel. GHG emissions for regular sea side repositioning and land side repositioning using trucks can easily be calculated according to the norm European EN 16258, which is, for example, applied by the public database Ecotransit.org [33]. With this approach, various types of GHG emissions are calculated and consolidated as carbon dioxide equivalents (CDEs) which represent the global warming potential the same amount of carbon dioxide (CO_2) would have. This helps to compare different transport modes emitting different proportions of GHG types.

We generally assume that emissions from all vessel engines are considered and allocated entirely to the freight. Individual emission factors are derived for bulk vessels as E_V^B in g/ton and for container vessels as E_V^C in g/TEU. If an otherwise idle capacity, an empty slot, is used to transport an empty container, we need to account for the GHG emissions E_e according to what these containers add up to the partly loaded vessel. On the other hand, ordered empty containers OC, transported in a regular slot, are associated with emissions E_r according to their share of the overall transported containers TC. This rationale is reflected in (16) and (17), where

$$E_r = E_V^C \frac{\mathrm{OC}}{\mathrm{TC}} \tag{16}$$

considers regular slot orders and

$$E_e = E_V^C * \mathrm{TC} \frac{\mathrm{ECW}}{\mathrm{NTD} * T} \tag{17}$$

empty slot orders with NTD as the normal ton displacement or empty weight of the vessel, T as the loaded tonnage, and ECW as the weight of the ordered empty containers, all in tons. Table 2 lists the GHG emissions and resulting CDEs for these four types of repositioning options. All values are given in tons for the respective repositioning distance considering the transport option and assume global trade vessels with a capacity between 4700 TEU, 65% load factor, and weight of goods as 10 tons per TEU as well as an empty weight of 2 tons per TEU. Furthermore, we assume an NTD of 25000 tons.

Looking at Table 2, one can clearly understand that an empty slot policy is almost always superior to regular slot policies in terms of emissions. Even ordering an empty container from Buenaventura to Valparaíso in an empty slot causes significantly less emissions than sending a truck to Santiago de Chile for the same purpose, though this is as little as 115 kilometers away from the port. The emission price is reflected as a range based on the current market figures to model possible future regulator decisions as well.

Table 2: Sample excerpt of emission values for different empty container sourcing options in the shipping network (for the port of Valparaiso, Chile, and a service to Middle America and Asia).

Port of origin	Emissions regular slot [t/TEU]	Emissions empty slot [t/TEU]
Santiago de Chile	0,081	0,048
Buenaventura	0,492	0,054
Manzanillo	0,748	0,082
Shanghai	2,210	0,243

5.2. Simulation Study. For the numerical experiments, we have implemented the simulation model and the optimizing GA in the discrete-event simulation software Plant Simulation. We have simulated 3600 days and built several observations for each individual created by the GA in order. We have evaluated all strategies proposed in Section 3 for a range of (s, S). In a basic experiment, we evaluated 36 scenarios for different combinations of (s, S) as shown in Table 3. The further columns provide insights on the development of monthly averages for various cost types, depending on these parameter combinations. Repair costs are not considered in the presentation of Table 3.

Some general observations can be made. First, in regard of the total costs slopes, the convexity of the function becomes visible when observing a fixed s value for rising values of S. This practically means that the amount of containers in the system is increased, reducing leasing cost, but increasing holding costs.

Within the discrete analysis of the generated scenarios, an S value of 1000 is associated with the lowest total costs. Second, a clear correlation between order costs and CDE costs is shown. Since the experiment assumes emission costs to be defined by availability of ordering options within the shipping network, the emission costs add up to the variable ordering costs.

TABLE 3: Numerical results for a 3600-day period with costs for leasing, holding, ordering, and emissions (CDE costs) for (s, S) strategies in empty container management.

s	S	Total costs	Lease costs	Hold costs	Order costs	CDE costs
0	0	31915.1	1404.0	0.0	8985.2	3282.3
	1000	30946.7	184.2	134.8	8998.9	3300.7
	2000	31672.6	97.9	740.2	9069.3	3330.2
	3000	32325.5	77.1	1401.0	9081.1	3335.4
	4000	33108.1	67.0	2247.2	9061.5	3329.2
	5000	34456.7	50.1	3152.2	9194.6	3378.0
500	0	32051.3	1408.9	0.0	8987.9	3282.1
	1000	30959.9	6.4	258.4	9029.0	3306.4
	2000	31757.1	0.3	940.3	9069.7	3328.8
	3000	32553.4	0.3	1746.5	9070.8	3331.2
	4000	33369.2	0.0	2625.9	9044.0	3322.1
	5000	34238.7	0.1	3604.3	9010.6	3310.3
1000	0	32051.3	1408.9	0.0	8987.9	3282.1
	1000	31080.1	5.9	386.6	9029.0	3297.5
	2000	32043.4	0.0	1279.9	9042.0	3316.8
	3000	33198.4	0.0	2214.6	9112.7	3345.2
	4000	33889.8	0.0	3063.0	9074.5	3333.0
	5000	35271.2	0.0	3984.4	9197.7	3378.7
1500	0	32051.3	1408.9	0.0	8987.9	3282.1
	1000	31088.2	5.9	385.6	9029.5	3297.3
	2000	32620.5	0.0	1737.9	9073.5	3322.4
	3000	33600.9	0.0	2621.3	9113.4	3344.7
	4000	34465.3	0.0	3495.3	9114.8	3347.1
	5000	35331.7	0.0	4440.9	9088.5	3338.4
2000	0	32051.3	1408.9	0.0	8987.9	3282.1
	1000	31088.2	5.9	385.6	9029.5	3297.3
	2000	32841.9	0.0	1987.5	9074.2	3314.5
	3000	33967.0	0.0	3073.8	9085.7	3332.2
	4000	35189.7	0.0	4069.4	9156.5	3361.8
	5000	35954.2	0.0	4958.8	9118.6	3349.3
2500	0	32051.3	1408.9	0.0	8987.9	3282.1
	1000	31088.2	5.9	385.6	9029.5	3297.3
	2000	32826.7	0.0	1986.3	9073.8	3313.9
	3000	34563.1	0.0	3597.0	9116.2	3338.8
	4000	35676.5	0.0	4518.9	9158.2	3361.1
	5000	36754.1	0.0	5473.7	9199.2	3378.2

5.3. Pollution-Integrated Analysis. The pollution-integrated policy has been analyzed with respect to different levels of emission prices p^e and safety stock s. Figure 3 comprises the results for the total inventory costs, considering leasing, holding, order, CDE, and maintenance cost. The emission price simulates market and regulatory scenarios assuming \$0, \$15, and \$30 per ton of CDE emissions, while safety stock levels from 200 to 2000 TEUs are assumed and simulated with a step-size of 200. It is obvious to recognize the important impact of emission prices on total costs. While different levels only lead to slight cost changes, each increase of emission

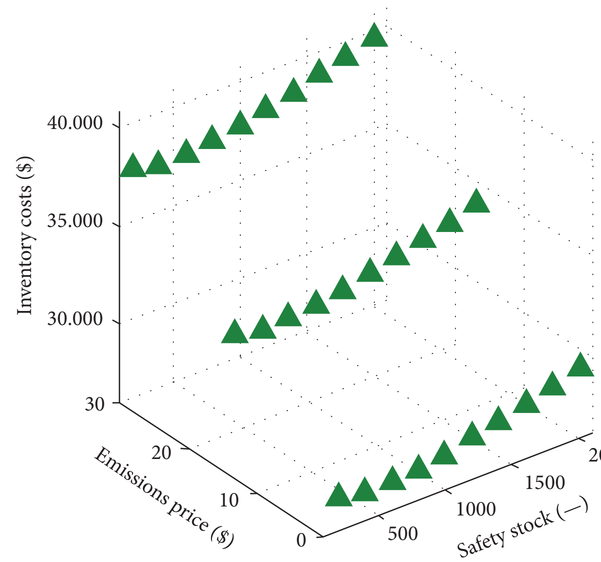

FIGURE 3: Three-dimensional analysis of total inventory costs for different levels of emission prices and safety stock.

prices causes a sharp rise of costs as long as the emission price is defined on a sufficient level.

Table 4 presents a clear quantitative picture of this relation, where total costs increase by 10–20% in reaction to a scenario with a raised emission price. On the other hand, altered safety stock levels predominantly cause changes within a 1-2% range. Hence, this policy will encourage planners to consider low-emission ordering options within their shipping network in order to decrease overall costs, as long as the emission price is defined on a sufficient level. Figure 4 illustrates this effect showing the cost slopes for all considered simulation experiments. This depiction reveals the dominating impact of the emission price on total inventory costs. While most of the other cost types only show a slight impact on total inventory costs, the oscillating slope of emission costs is clearly visible in the inventory cost slope as well. Comparing leasing and holding cost slopes, the convexity of inventory costs over s may also be recognized.

5.4. Maintenance and Repair Analysis. The maintenance and repair policy has been analyzed for different levels of safety stock s and a rate β_λ as the share of damaged containers of an order, modeled as a Poisson distribution with a minimum value of 0 and expectation value $\lambda_k = \beta_\lambda u_k$. Table 5 outlines the impact of repair, leasing, holding, and total costs in reaction to altered levels of β_λ, while keeping all remaining parameters fixed. Since repair costs per TEU are significantly higher than all other variable costs, a level $\beta_\lambda = 0.05$ already leads to an almost threefold total cost level in comparison to a scenario without corrupted containers. Moreover, leasing and holding costs also clearly depend on the amount of damaged containers. This happens because these containers are not available in the current period. Hence, more containers need to be leased to satisfy the demand, and, on the other hand, fewer containers contribute to holding costs. As Table 5

TABLE 4: Emissions and CDE costs for different combinations of safety stock s and emissions price p^e.

s	p^e	Total costs	CDE costs	Emissions
	0	27686.3	0.0	328.5
200	15	32644.8	4927.4	328.5
	30	37605.5	9854.7	328.5
	0	27376.5	0.0	328.8
400	15	32339.7	4932.4	328.8
	30	37304.9	9864.7	328.8
	0	27417.9	0.0	329.2
600	15	32386.1	4938.1	329.2
	30	37356.3	9876.2	329.2
	0	27545.2	0.0	329.6
800	15	32518.1	4943.4	
	30	37493.0	9886.7	329.6
	0	27757.5	0.0	329.8
1000	15	32734.9	4947.6	329.8
	30	37714.4	9895.2	329.8
	0	28130.5	0.0	330.3
1200	15	33114.2	4954.0	330.3
	30	38100.0	9908.0	330.3
	0	28437.6	0.0	330.6
1400	15	33425.9	4958.6	330.6
	30	38416.4	9917.2	330.6
	0	28775.3	0.0	330.9
1600	15	33768.2	4963.7	330.9
	30	38763.3	9927.5	330.9
	0	29126.6	0.0	331.2
1800	15	34124.1	4968.5	331.2
	30	39123.8	9937.0	331.2
	0	29549.8	0.0	331.6
2000	15	34552.4	4974.3	331.6
	30	39557.2	9948.6	331.6

reveals, this effect diminishes if higher levels of safety stock are applied.

5.5. Street-Turn Analysis. Similar to the above experiments, the street-turn policy has been analyzed for distinct factorial combinations. Three scenarios for street-turns are assumed: 5%, 10%, and 15% of all imports are expected to allow street-turn operations, reflected by γ_λ as the share of import containers suitable for street-turns. Table 6 presents the results for the total costs and major cost components for different levels of γ_λ and safety stock s. It is obvious to see that a higher number of street-turns reduce the total inventory costs, independent from the safety stock level. This effect goes back to the reduced leasing costs. These are lower in cases of street-turns, since the demand is immediately fulfilled and leasing need not be considered. However, due to street-turns, some additional containers remain in the depots and cause a slight increase in holding costs. In general, an increased amount of street-turns may allow lower safety stock levels.

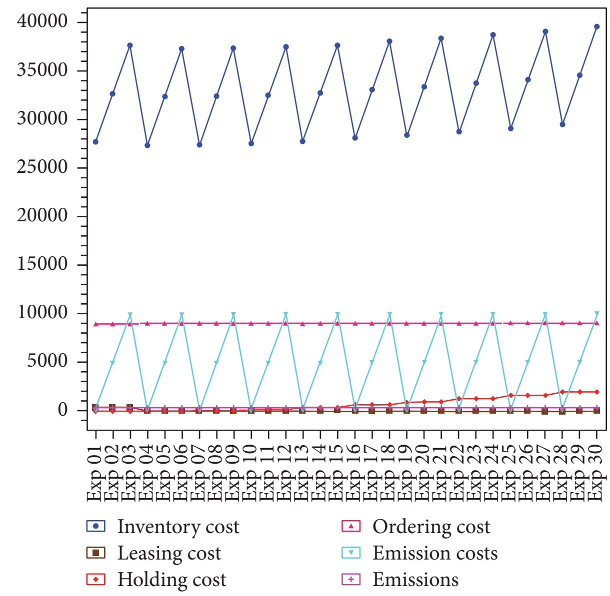

FIGURE 4: Slopes of cost types for simulation experiments with different safety stock and emission levels.

TABLE 5: Costs for maintenance and repair for different levels of damaged containers β_λ and safety stock s.

s	β_λ	Total costs	Repair costs	Lease costs	Hold costs
	0	11745.3	0.0	22.5	29.8
500	0.05	30709.7	18341.7	26.5	24.05
	0.1	50982.7	37943.3	33.4	18.85
	0	12139.9	0.00	5.4	413.1
1000	0.05	31080.1	18341.7	5.9	386.6
	0.1	51463.8	38078.3	6.5	359.63
	0	12904.2	0.00	1.2	1153.0
1500	0.05	31836.9	18343.3	1.7	1117.5
	0.1	52251.6	38121.7	2.2	1078.3
	0	13805.3	0	0	2026.9
2000	0.05	32841.9	18446.7	0.0	1987.5
	0.1	53261.7	38235	0.9	1944.9

5.6. Improved Strategies. To derive improved parameter settings for the proposed strategies, a metaheuristic search is applied as described in Section 4. Figure 5 visualizes the procedure of the GA that was used for this purpose. The fitness function value corresponds to the total inventory costs and the vertical red lines distinguish different generations of offspring created by the algorithm, while the blue dots mark fitness values of the offspring solutions. Table 7 presents the results for different combinations of emission prices, damaged containers, and possible street-turns. In order to increase the solution quality and reduce the simulation time, insights from Sections 3 and 5.2 were used to define the GA procedure. Since the functions are convex, the experiments in Section 5.3 let us assume a bounded range for the location of the optimum. Initial values s were hence sampled from a uniform distribution between 0 and 1500; these values also

TABLE 6: Total inventory, leasing, holding, and CDE costs for various combinations of street-turns rate γ_λ and safety stock s.

γ_λ	s	Total costs	Lease costs	Hold costs	CDE costs
0.05	500	30739.2	30.9	23.6	3295.9
	1000	31109.3	9.2	386.9	3303.7
	1500	32015.2	3.9	1117.4	3312.1
	2000	32911.6	0.8	1988.4	3319.2
0.1	500	30721.7	29.1	24.0	3293.2
	1000	31147.7	7.5	387.3	3300.9
	1500	31995.6	2.7	1118.2	3310.8
	2000	32890.2	0.3	1986.8	3317.9
0.15	500	30709.7	26.5	24.1	3290.5
	1000	31080.1	5.9	386.5	3297.5
	1500	31836.9	1.7	1117.4	3305.8
	2000	32841.9	0.0	1987.5	3314.5

TABLE 7: Improved total inventory costs and corresponding safety stock levels s for various combinations of emission prices p^e, corrupted containers rate β_λ, and street-turns rate γ_λ.

p^e	γ_λ	β_λ	s	Total costs
0	0.2	0	540	8791.2
		0.05	540	27666.6
		0.1	540	48496.5
	0.3	0	464	8772.1
		0.05	517	27643.9
		0.1	517	48411.7
15	0.2	0	540	13603.6
		0.05	540	32732.4
		0.1	540	53842.2
	0.3	0	464	13577.5
		0.05	517	32703.9
		0.1	517	53750.7
30	0.2	0	540	18418.2
		0.05	540	37800.4
		0.1	540	59190.0
	0.3	0	464	18385.1
		0.05	517	37766.1
		0.1	517	59091.9

served as bounds during the experiments. Five generations with a size of 10 and 10 observations for each individual were conducted. Despite the limited scope of evaluations, the observations confirm the effectiveness of the procedure. An increased amount of damaged containers, indicated by β_λ, leads to an increased or equal safety stock level. This is in line with the intuitive policy to cope with the increased stock-out risk by adding additional stock. Similarly, safety stocks are decreased for scenarios with more street-turns. Like a just-in-time delivery, street-turns lower container holding. As observed in the previous experiments, street-turns decrease costs and repair increases costs.

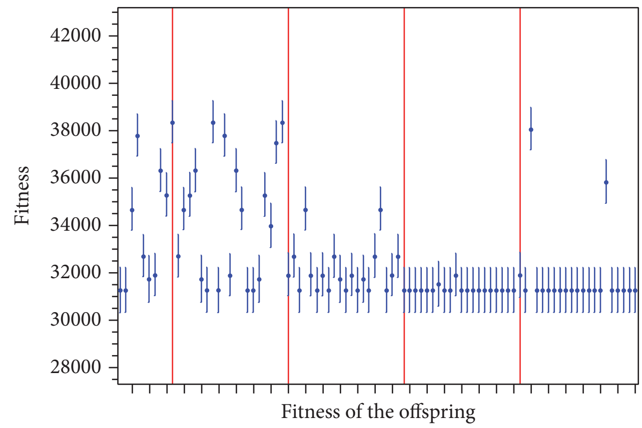

FIGURE 5: Exemplified solution process based on intensification and diversification within the GA.

6. Conclusion

Prior research has demonstrated the importance of empty container repositioning for economic and ecological objectives in maritime shipping and global trade [2]. Further studies have successfully shown that periodic review strategies for empty container depots at sea ports can be an effective tool to reduce costs in the repositioning process [3, 28]. Nevertheless, these studies focused on a pure cost objective without considering pollution or practical conditions such as corrupted containers or street-turn opportunities.

In this study, we have developed new periodic review polices that reflect emissions for various sourcing options of empty containers within a shipping network, repair options for damaged containers, and street-turns. Using the concept of emission prices, all resulting costs and emissions are considered in the objective function. Moreover, we have analyzed the optimality of the introduced policies and evaluated them in a simulation study based on extensive real world data. In order to capture emissions appropriately, a new way of calculating emissions for empty container transport was developed. Thus, emissions differ based on where and how transport operations are conducted.

A metaheuristic approach was used to find near-optimal parameters for the proposed strategies. The results demonstrate that periodic review systems for empty container management may become more realistic when the proposed extensions are considered. Evaluating different scenarios, the impact of emissions, repair options, and street-turns on various costs become traceable. In this way, this study extends work form Song and Xu [2] as well as different research by Li et al. [3, 35]. In empty container management, the approach provides decision support instead of pure analytics for the problem of GHG emissions, repair options, and street-turns.

The potential trade-off of conflicting costs and emissions objective may be mastered when applying a planning approach with integrated operational strategies as proposed. Moreover, this is the first study to the knowledge of the authors to develop effective strategies for reduction of emissions raised by empty container transport and thus paths the way to leveraging the flexibility in empty container demand requirements. The results are furthermore meaningful because they are based on industry data, making the approach more realistic and more likely to be adopted in practice. Nevertheless, there are a few limitations worth noting. Although the simulation experiments clearly demonstrate the cost and emission impact of the proposed policies, further evaluation may be needed for a general understanding on how repair options and street-turns impact periodic review polices. To encourage further emission savings, multiproduct inventory strategies may be adapted to better distinguish empty container sourcing options by their emission impact and to find optimal parameters reflecting the distinct emission values. Aside from that, modeling collaboration within the network would be an interesting extension.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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