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ARTICLE

Modelling Dry Port Systems in the Framework of Inland Waterway Container Terminals

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ABSTRACT

Overcoming the global sustainability challenges of logistics requires applying solutions that minimize the negative effects of logistics activities. The most efficient way of doing so is through intermodal transportation (IT). Current IT systems rely mostly on road, rail, and sea transport, not inland waterway transport. Developing dry port (DP) terminals has been proven as a sustainable means of promoting and utilizing IT in the hinterland of seaport container terminals. Conventional DP systems consolidate container flows from/to seaports and integrate road and rail transportation modes in the hinterland which improves the sustainability of the whole logistics system. In this article, to extend literature on the sustainable development of different categories of IT terminals, especially DPs, and their varying roles, we examine the possibility of developing DP terminals within the framework of inland waterway container terminals (IWCTs). Establishing combined road–rail–inland waterway transport for observed container flows is expected to make the IT systems sustainable. As such, this article is the first to address the modelling of such DP systems. After mathematically formulating the problem of modelling DP systems, which entailed determining the number and location of DP terminals for IWCTs, their capacity, and their allocation of container flows, we solved the problem with a hybrid metaheuristic model based on the Bee Colony Optimisation (BCO) algorithm and the measurement of alternatives and ranking according to compromise solution (i.e., MARCOS) multi-criteria decision-making method. The results from our case study of the Danube region suggest that planning and developing DP terminals in the framework of IWCTs can indeed be sustainable, as well as contribute to the development of logistics networks, the regionalisation of river ports, and the geographic expansion of their hinterlands. Thus, the main contributions of this article are in proposing a novel DP concept variant, mathematically formulating the problems of its modelling, and developing an encompassing hybrid metaheuristic approach for treating the complex nature of the problem adequately.

KEYWORDS

Dry port; intermodal transport terminal; sustainability; Bee Colony Optimization; MARCOS; inland waterway transport

1 Introduction

Making logistics systems sustainable requires pivoting away from traditional approaches used to plan such systems-that is, not developing modes of transport separately [1]. Achieving sustainability is indeed possible with intensive planning and the development of intermodal transport (IT) systems [2]. Per the European Conference of Ministers of Transport [3], IT refers to the movement of goods in a particular loading unit or vehicle via two or more modes of transport without handling the goods when shifting between modes. With the application of alternative modes of transport-rail, inland waterway, and sea transport-a logistics system can save on costs and become more time-efficient while reducing negative impacts on the environment [4]. Although the apparent advantages of applying IT have motivated numerous researchers in the field to promote its use [5], IT remains neglected in practice. Aside from the multiple attempts of the European Union to promote the application of IT in different projects, its participation in overall transport remains less than satisfactory [6,7].

One of the missing links in European IT systems is the stimulation of the utilisation of inland waterways in IT chains. Achieving economies of scale in inland waterway transport is entirely possible and can not only result in cost-competitiveness when putting against road transportation [8] but also external costs that are lower than those of other modes of transport [9,10]. Although the advantages of inland waterway transport are evident, its application, aside from in north-western Europe [11], has been stagnant for decades [10,12], with inadequate connections with rail transport highlighted as the chief obstacle to integrating inland waterway transport in existing IT systems [13]. The consequences of that shortcoming are relatively narrow catchment areas for river container terminals that fail to direct larger container flow volumes to inland waterway transport.

One of the most explored categories of IT terminals in the context of developing IT systems is the dry port (DP). A DP is a subsystem of a seaport in the seaport's hinterland that encompasses an established regular rail shuttle and road connection with the seaport and offers services at the seaport's container terminals [14]. Using DPs can boost the competitiveness of seaport container terminals and their catchment areas, which consequently attracts larger container flow volumes [15,16] and facilitates integration with the IT system in the hinterland [15]. DPs are pivotal components for expanding the geographic impact of seaports and, in turn, intensifying the economic development of the regions where they are located [17]. To achieve all of those benefits, however, DP-based IT systems require appropriate network modelling, which is often a complex task. Aside from developing IT systems by applying the concept of DPs for seaport container terminals, Tadić et al. [2] have highlighted an opportunity for developing DP systems in the framework of inland waterway container terminals (IWCTs).

The purpose of this article is to investigate the concept of DPs in the framework of IWCTs. The main hypothesis is that developing DP terminals for existing IWCTs can expand their catchment areas and, by establishing regular shuttle connections between DP terminals and IWCTs, enable the efficient integration of inland waterway transport into existing IT systems. The article's principal contribution is in being the first to address the modelling of DP systems in the framework of IWCTs. The modelling of such DP system should answer the questions that refer to the number and location of DP terminals for IWCTs, their capacity, and their allocation of container flows. The second hypothesis states that it is possible to develop an encompassing and robust approach for modelling such DP concept that will adequately treat the complex nature of the problem through the lens of sustainability. In this study, we solved those problems by using a mathematical formulation that considers several different objective functions, along with a novel hybrid metaheuristic model that we developed specifically to solve the problems. The model is based on the Bee Colony Optimisation (BCO) algorithm and the measurement of alternatives and ranking according to the compromise solution (MARCOS) multi-criteria decision-making (MCDM) method. Another contribution is that we applied the model to assess the Danube region, an area that has been poorly covered in similar research. The results of this study indicate that the development of the DP concept in the framework of IWCTs could stand out as a potentially sustainable direction for developing regional IT networks. The sensitivity analysis implies that the concept is sustainable for different settings of evaluation criteria thus confirming its great potential.

In what follows, Section 2 presents a brief review of the literature on the concept of DPs, with an emphasis on research addressing the modelling of DP systems and on the methods used for problem-solving within that domain. Next, Section 3 describes the mathematical formulation for the observed problem of modelling DP systems in the framework of IWCTs, after which Section 4 explains our procedure for the combined application of BCO and MARCOS, the model set-up for solving the observed problem, and the steps of solution evaluation and modification by the model. Last, Section 5 discusses the input parameters and values of the hybrid metaheuristic model, the results of its application and conducts a sensitivity analysis, followed by Section 6, which offers our conclusions and recommends directions for future research.

2 Frame of Reference

Flows of goods have intensified due to globalisation and changes in the principles of production, particularly individualisation and personalisation. As a result, the trend of delivering small quantities of goods over greater distances has arisen and thereby increased the geographic areas for goods and transport flows [18]. To accommodate those trends, ports have been forced to develop IT networks in their hinterlands with the aim of increasing the geographic scope of door-to-door services through collaborative agreements and vertical integration [12]. Because ports thus increasingly lack space for expansion and become denser over time, a solution should be sought in developing ports' hinterlands by applying the concept of DPs [12,19].

A popular topic in the scientific community [20], the concept of DPs has been a subject of analysis in the context of regional and intercontinental sea container terminals around the world. Such research has covered areas on all populated continents: Europe [21–23], Asia [16,24,25], North America [26], South America [27], Africa [28] and Australia [29,30]. A large portion of such research has focused on modelling DP systems, and a brief literature review of recent research in the field, with highlighted characteristics and applied models, is presented in Table 1. In the context of that literature, this article is unique because it focuses on modelling DP systems in the framework of IWCTs.

Table 1: A review of recent literature regarding DP system modelling

Article	Region	Distinct feature	Criteria	Method
[31]	China	DP-seaport connection maintenance costs considered.	Transportation costs, transhipment costs, DP development costs, link maintenance costs, infrastructure maintenance costs	Genetic algorithm

(Continued)

Table 1 (continued)

Article	Region	Distinct feature	Criteria	Method
[32]	Italy	Possibility of splitting flows through several DP terminals.	Transportation costs, transhipment costs, DP development costs	Exact approach
[33]	Italy	DP service network design.	Operational costs, costs associated to value-added services, custom clearance and security inspection	Exact approach
[34]	China	Identification of appropriate potential DP locations using Fuzzy C-Means.	DP development costs, storage costs, transportation costs	Fuzzy C-Means clustering & genetic algorithm
[35]	China	Cost concession between seaports and potential DP terminals.	Logistics costs, carbon emissions	Ordered Weighted Averaging & Exact approach
[36]	North Adriatic Seaports	DP as a tool of inter-port competition.	Costs, catchment area	Exact approach & Analytic Hierarchy Process
[37]	Iran	Identification of appropriate potential DP locations using Geographic Information System and Analytic Hierarchy Process.	Transportation costs, transhipment costs, carbon emissions	Geographic Information System & Analytic Hierarchy Process & Exact approach
[38]	Hypothetical	Considering dry ports, seaports and shippers as stakeholders.	Operational costs, external costs, storage costs	Continuous approximation& Game theory approach
[39]	China	Demand and cost uncertainties considered.	Costs, environmental impact, societal impact	Exact approach
[40]	Adriatic Seaports	Regional aspect.	Transportation costs, DP development and exploitation costs	Exact approach

(Continued)

Table 1 (continued)

Article	Region	Distinct feature	Criteria	Method
[41]	Southeastern Europe	Regional aspect. Considering terminal clusters and interconnected terminals.	Transportation costs, DP development and exploitation costs	Exact approach
This article	Danube region	DP concept in the context of inland waterway container terminals.	Transportation costs, transhipment costs, DP development costs, external costs, costs of time, goods flows volumes	BCO & MARCOS hybrid metaheuristic

Table 1 clarifies that though solutions to the problem of modelling DP systems have been diverse, the research driving those solutions has shared certain characteristics. All such research has considered some kind of cost structure while modelling DP systems, mostly operational costs and the costs of developing DP terminals. Some of it has also considered external costs (e.g., [35,37–39]). The research that tackled the DP system modelling problems in a multi-objective way failed to include a broader set of objective functions that would reflect on all three sustainability pillars (economic, environmental and social) and the complex nature of such problems. Within that literature, Kramberger et al. [36] have analysed how the degree to which DP terminals in the north Adriatic are developed affects their catchment areas and competitiveness in comparison with northern European seaport container terminals. Aside from that study, most of the research has analysed the concept of DPs in the context of a single state or country, whereas studies investigating the concept of DPs in regional contexts have been few [36,40,41]. However, developing DP systems, as well as IT systems in general, should be done in broader regional contexts, even if such a venture requires international collaboration when individual actors (e.g., countries) are incapable of developing comprehensive IT systems by themselves. This article contributes to the existing literature by approaching the modelling of a DP system through a regional perspective. While doing so, this article encompasses multiple objective functions that reflect on all three sustainability pillars and demonstrates how the complex nature of the problem should be treated.

The diversity of problems involved in implementing not only DPs but also IT in general justifies the application of different methods for solving them. The most-used methods and approaches for solving such problems are simulation models [25,42], MCDM methods [17,43], exact approaches [32,33,41], and metaheuristic algorithms [31,34,44]. Of all of those strategies, metaheuristic algorithms have proven to be efficient for solving complex combinatorial problems regarding some aspects of IT. Several popular metaheuristics in that literature have been used in IT, including genetic algorithms [31], memetic algorithms [45], simulated annealing [46,47], tabu searches [48], adaptive large neighbourhood searches [49], particle swarm optimisation [50], and greedy randomised adaptive searches [51,52].

Against that background, this article presents the first application of the BCO metaheuristic for solving an IT-related problem. This is another significant contribution of this article because it demonstrates a robust and encompassing approach to solving complex multi-objective optimization problems.

The BCO metaheuristic, inspired by the natural behaviour of bees, has proven to be a competitive metaheuristic for solving combinatorial optimisation problems, namely by providing high-quality solutions for complex problems in acceptable computational time frames [53,54]. Different classes of problems have been solved with BCO, including the *p*-centre problem [55], the anti-covering location problem [56], vehicle routing [57], transit network planning [58], airport gate assignment [59], berth allocation [60], traffic control [61], detector placement on transport networks [62], tuning of fuzzy membership functions [63], etc. To treat the complex nature of the problem appropriately, the MARCOS MCDM method is integrated into the BCO.

The MARCOS MCDM method defines the relationship of alternatives- in our case, feasible solutions- according to the ideal and anti-ideal solution [64], and that relationship is the basis for determining the degree of the utilization, or quality, of alternatives or solutions [65]. By combining the concepts of ratio and reference point sorting, the MARCOS method has proven to be stable and insensitive to the change in measurement scales [65]. A comparison with other MCDM methods, including TOPSIS, EDAS, MABAC, SAW, ARAS, and WASPAS, has revealed that the MARCOS method is relatively efficient, comprehensive and stable [65]. Aside from its independent application, the method has also been combined with other MCDM methods, including SWARA [66], FUCOM [64], Delphi and FARE [2], but never with a metaheuristic algorithm for solving multi-criteria optimization problems. The competitiveness of the MARCOS method in the domain of MCDM and its potential for uncomplicated combination with other methods were our chief reasons for integrating it with a metaheuristic algorithm in our study.

3 Mathematical Formulation of the Problem

This section describes the mathematical formulation of the problem of modelling DP systems in the framework of IWCTs. The problem entails determining the number and location of DP terminals, their capacity, and their allocation of container flows. The formulation was inspired by pre-existing formulations for modelling DP systems [32,35,41] but adapted to the problem of developing DP systems for IWCTs by considering several objective functions in order to treat the problem in the most realistic way possible.

To be clear, this article examines the possibility of developing DP terminals in the framework of IWCTs and establishing a combined road–rail–inland waterway transport for observed container flows to achieve sustainability in the IT system. The network that we observed in our study consists of flow generators and IWCTs, wherein the generators initiate the flows of goods and a certain exchange of different goods exists between them. Our initial assumption was that all of the flows are transported via road. The developed DP terminals play the role of local or regional consolidation centres and enable modal transformation from road to rail given the relationship between DPs and IWCT, after which inland waterway transport is used. Although the possibilities of combining different modes of transport are numerous, in this article the combinations are narrowed down to ones that are the most realistic and feasible to implement (Fig. 1).

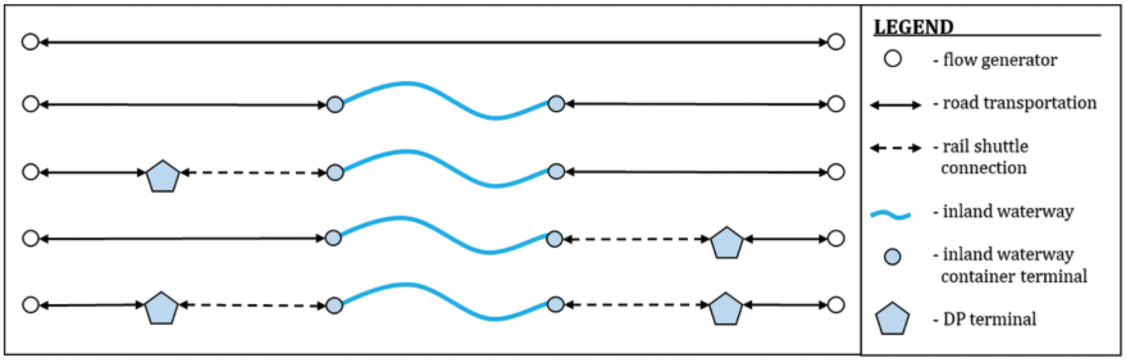

Figure 1: The considered container flow shipping variants

To adequately describe the observed problem, the following parameters are used:

- F-set of all container flows that have to be shipped. Each container flow (f) is defined by:
    - Its origin (f_o),
    - Destination (f_d),
    - Type of goods (f_c),
    - Volume of goods expressed in Twenty-foot Equivalent Units (TEUs) (q_f),
    - The average weight of one TEU for the type of goods (q_{f_c}).
- D-the set of potential locations for developing DP terminals.
- L-the set of IWCTs.
- Considering f_o and f_d of a container flow f, along with IWCTs l_1 and l_2 as well as DP terminals d_1 and d_2, there are five different variants of container flow realization: directly by road transportation (f_of_d), through IWCTs l_1 and l_2 ($f_ol_1l_2f_d$), through the DP terminal d_1 and IWCTs l_1 and l_2 ($f_od_1l_1l_2f_d$), through IWCTs l_1 and l_2 and the DP terminal d_1 ($f_ol_1l_2d_1f_d$), or through DP terminals d_1 and d_2 and IWCTs l_1 and l_2 ($f_od_1l_1l_2d_2f_d$). Each of these variants has its assigned transportation unit costs, external unit costs, and time unit costs:
    - $C^{tran}_{f_of_d}$, $C^{tran}_{f_ol_1l_2f_d}$, $C^{tran}_{f_od_1l_1l_2f_d}$, $C^{tran}_{f_ol_1l_2d_1f_d}$, $C^{tran}_{f_od_1l_1l_2d_2f_d}$-transportation unit costs of flow f for the observed realization variants.
    - $C^{ext}_{f_of_d}$, $C^{ext}_{f_ol_1l_2f_d}$, $C^{ext}_{f_od_1l_1l_2f_d}$, $C^{ext}_{f_ol_1l_2d_1f_d}$, and $C^{ext}_{f_od_1l_1l_2d_2f_d}$-external unit costs of flow f for the observed realization variants.
    - $t_{f_of_d}$, $t_{f_ol_1l_2f_d}$, $t_{f_od_1l_1l_2f_d}$, $t_{f_ol_1l_2d_1f_d}$, and $t_{f_od_1l_1l_2d_2f_d}$-time unit costs for the types of goods in flow f for the observed realization variants.
- G-the set of considered terminal size categories.
- $C^{transhipment}_{g}$-the transhipment cost for one TEU in a terminal in category g.
- $C^{category}_{g}$-the development cost of a terminal in category g.
- C^{Q}_{g}-the maximal throughput of allocated flows for such a terminal.
- $C^{transhipment}_{l}$-the transhipment cost of one TEU in IWCTl.
- $C^{transhipment}_{l-basic}$-the transhipment cost of one TEU in IWCTl if that IWCT does not have an assigned DP.

Decision variables used in the formulation are:

- X^f (binary variable) equals 1 if the container flow f is shipped only by road; 0 if otherwise.
- $X^f_{l_1 l_2}$ (binary variable) equals 1 if the container flow f is being shipped via road–inland waterway transport through IWCTs l_1 and l_2; 0 if otherwise.
- $X^f_{d_1 l_1 l_2}$ (binary variable) equals 1 if the container flow f is shipped through DP terminal d_1 and subsequently through IWCTs l_1 and l_2; 0 if otherwise.
- $X^f_{l_1 l_2 d_1}$ (binary variable) equals 1 if the container flow f is first shipped through IWCTs l_1 and l_2 and subsequently through DP terminal d_1; 0 if otherwise.
- $X^f_{d_1 l_1 l_2 d_2}$ (binary variable) equals 1 if the container flow f is shipped through DP terminal d_1, next through IWCTs l_1 and l_2, and later through DP terminal d_2; 0 if otherwise.
- L_{ld} (integer variable) denotes how many DP terminals IWCT l has an established connection with.
- Y_d (binary variable) equals 1 if a DP terminal is located in d; 0 if otherwise.
- W_{dg} (binary variable) equals 1 if DP terminal d is, by capacity, in category g; 0 if otherwise.
- Q_d (integer variable) refers to the number of TEUs that flow through DP terminal d.
- Q_l (integer variable) refers to the amount of containers in TEUs that pass through IWCT l.

With such parameters and definitions of variables, the problem can be mathematically formulated as follows:

$$min: \sum_{f}^{F} q_f \cdot f_c \cdot \left(X^f \cdot C^{tran}_{f_o f_d} + \sum_{l_1}^{L}\sum_{l_2}^{L} X^f_{l_1 l_2} \cdot C^{tran}_{f_o l_1 l_2 f_d} + \sum_{d_1}^{D}\sum_{l_1}^{L}\sum_{l_2}^{L} \left(X^f_{d_1 l_1 l_2} \cdot C^{tran}_{f_o d_1 l_1 l_2 f_d} + X^f_{l_1 l_2 d_1} \cdot C^{tran}_{f_o l_1 l_2 d_1 f_d} \right) \right.$$
$$\left. + \sum_{d_1}^{D}\sum_{d_2}^{D}\sum_{l_1}^{L}\sum_{l_2}^{L} X^f_{d_1 l_1 l_2 d_2} \cdot C^{tran}_{f_o d_1 l_1 l_2 d_2 f_d} \right) + \sum_{d}^{D}\sum_{g}^{G} W_{dg} \cdot Q_d \cdot C^{transhipment}_{g} + \sum_{l}^{L} \cdot Q_l \cdot C^{transhipment}_{l} \tag{1}$$

$$min: \sum_{f}^{F} q_f \cdot f_c \cdot \left(X^f \cdot C^{ext}_{f_o f_d} + \sum_{l_1}^{L}\sum_{l_2}^{L} X^f_{l_1 l_2} \cdot C^{ext}_{f_o l_1 l_2 f_d} + \sum_{d_1}^{D}\sum_{l_1}^{L}\sum_{l_2}^{L} \left(X^f_{d_1 l_1 l_2} \cdot C^{ext}_{f_o d_1 l_1 l_2 f_d} + X^f_{l_1 l_2 d_1} \cdot C^{ext}_{f_o l_1 l_2 d_1 f_d} \right) \right.$$
$$\left. + \sum_{d_1}^{D}\sum_{d_2}^{D}\sum_{l_1}^{L}\sum_{l_2}^{L} X^f_{d_1 l_1 l_2 d_2} \cdot C^{ext}_{f_o d_1 l_1 l_2 d_2 f_d} \right) \tag{2}$$

$$min: \sum_{f}^{F} q_f \cdot C^{time}_{f} \left(X^f \cdot t_{f_o f_d} + \sum_{l_1}^{L}\sum_{l_2}^{L} X^f_{l_1 l_2} \cdot t_{f_o l_1 l_2 f_d} + \sum_{d_1}^{D}\sum_{l_1}^{L}\sum_{l_2}^{L} \left(X^f_{d_1 l_1 l_2} \cdot t_{f_o d_1 l_1 l_2 f_d} + X^f_{l_1 l_2 d_1} \cdot t_{f_o l_1 l_2 d_1 f_d} \right) \right.$$
$$\left. + \sum_{d_1}^{D}\sum_{d_2}^{D}\sum_{l_1}^{L}\sum_{l_2}^{L} X^f_{d_1 l_1 l_2 d_2} \cdot t_{f_o d_1 l_1 l_2 d_2 f_d} \right) \tag{3}$$

$$min: \sum_{d}^{D}\sum_{g}^{G} W_{dg} \cdot C^{category}_{g} \tag{4}$$

$$max: \sum_{f}^{F} q_f \cdot \left(\sum_{d_1}^{D} \sum_{l_1}^{L} \sum_{l_2}^{L} \left(X^f_{d_1 l_1 l_2} + X^f_{l_1 l_2 d_1} \right) + \sum_{d_1}^{D} \sum_{d_2}^{D} \sum_{l_1}^{L} \sum_{l_2}^{L} X^f_{d_1 l_1 l_2 d_2} \right) \tag{5}$$

with the following constraints:

$$X^f + \sum_{l_1}^{L} \sum_{l_2}^{L} X^f_{l_1 l_2} + \sum_{d_1}^{D} \sum_{l_1}^{L} \sum_{l_2}^{L} X^f_{d_1 l_1 l_2} + \sum_{d_2}^{D} \sum_{l_1}^{L} \sum_{l_2}^{L} X^f_{l_1 l_2 d_2} + \sum_{d_1}^{D} \sum_{d_2}^{D} \sum_{l_1}^{L} \sum_{l_2}^{L} X^f_{d_1 l_1 l_2 d_2} = 1 \qquad \forall f \in F \tag{6}$$

$$Y_d \geq X^f_{d l_1 l_2} + X^f_{l_1 l_2 d} + X^f_{d l_1 l_2 d_2} + X^f_{d_2 l_1 l_2 d} \qquad \begin{array}{l} \forall d, d_2 \in D; \\ d \neq d_2; \\ f \in F; l_1, l_2 \in L; \\ l_1 \neq l_2 \end{array} \tag{7}$$

$$L_{ld} \geq X^f_{d l l_2} + X^f_{d l_2 l} + X^f_{d l l_2 d_2} + X^f_{d l_2 l d_2} \qquad \begin{array}{l} \forall d, d_2 \in D; \\ d \neq d_2; \\ f \in F; \\ l, l_2 \in L; l \neq l_2 \end{array} \tag{8}$$

$$\sum_{d \in D} L_{ld} \leq 1; \quad \forall l \in L \tag{9}$$

$$Q_d \geq \sum_{f}^{F} \left(q_f \cdot \left(\sum_{l_1}^{L} \sum_{l_2}^{L} \left(X^f_{d l_1 l_2} + X^f_{l_1 l_2 d} \right) + \sum_{d_2}^{D} \sum_{l_1}^{L} \sum_{l_2}^{L} \left(X^f_{d l_1 l_2 d_2} + X^f_{d_2 l_1 l_2 d} \right) \right) \right) \qquad \forall d \in D \tag{10}$$

$$Q_l \geq \sum_{f}^{F} \left(q_f \cdot \left(\sum_{l_2}^{L} \left(X^f_{l l_2} + X^f_{l l_2} \right) + \sum_{d_1}^{D} \sum_{l_2}^{L} \left(X^f_{d_1 l l_2} + X^f_{l l_2 d_1} \right) + \sum_{d_1}^{D} \sum_{d_2}^{D} \sum_{l_2}^{L} \left(X^f_{d_1 l l_2 d_2} + X^f_{d_2 l l_2 d_1} \right) \right) \right) \qquad \forall l \in L \tag{11}$$

$$Q_d \leq \sum_{g}^{G} W_{dg} \cdot C^Q_g \qquad \forall d \in D \tag{12}$$

$$\sum_{g \in G} W_{dg} = 1 \qquad \forall d \in D \tag{13}$$

$$C_l^{transhipment} \geq C_{l-basic}^{transhipment} + \sum_{d_1}^{D} \sum_{g}^{G} \left(W_{dg} \cdot C_g^{transhipment} \cdot L_{ld_1} - C_{l-basic}^{transhipment} \right) \qquad \forall l \in L \tag{14}$$

Objective Function 1 minimises the overall operational costs of the system, which consist of transportation costs, transhipment costs in DP terminals and transhipment costs in IWCTs. Objective Function 2 minimises the external costs of the system, while Objective Function 3 minimises the time costs (i.e., losses) of goods; the time costs of goods are treated as a separate objective function in order to highlight the different compatibilities of particular types of goods with inland waterway transport and IT in general. Next, Objective Function 4 minimises the development costs of DP terminals, while Objective Function 5 maximises the volume of container flows in the catchment area of the DP system. To reiterate, our goal was to develop a system with the largest possible catchment area, which is a prerequisite for achieving regional sustainability.

As for the constraints, Constraint 6 ensures that every flow can be shipped in only one way, while Constraint 7 keeps track of the locations where the DP terminals are developed. Constraint 8 keeps track of the DP terminal connections for the IWCTs, where the number of connections of one IWCT is limited to 1 by virtue of Constraint 9. Constraint 10 keeps track of the container flows that pass through DP terminals, while Constraint 11 keeps track of the same parameter for IWCTs. Constraint 12 ensures that the volumes of container flows that pass through DP terminals do not exceed their capacities. The capacity constraints for IWCTs were intentionally excluded because our goal was to develop a new system able to attract more intermodal flows, which is not constrained by the existing capacity limitations of IWCTs. The existing capacities are mostly small and, even as such, mostly unutilized, which confirms that the current system is inadequately used. Constraint 13 ensures that the DP terminals as located have only one assigned category of terminal capacity. Last, Constraint 14 for transhipment costs in the IWCTs establishes the transhipment costs of its assigned DP terminal. In the case that an IWCT lacks an assigned DP terminal, the basic transhipment cost ($C_{l-basic}^{transshipment}$) is assigned.

4 A Hybrid BCO-MARCOS Metaheuristic Model

For this article, we developed a novel hybrid BCO–MARCOS metaheuristic model to solve the mathematical problem described in Section 3–the problem of modelling DP systems for IWCTs, for the case of the Danube region. To address the combinatorial complexity of the problem, a metaheuristic approach was selected, while the presence of several objective functions justified the integration of a MCDM method into the process of evaluating solutions. The role of the BCO algorithm was to search the solution space for feasible solutions, while the MARCOS method was used in their evaluation. The generalized algorithmic steps of the developed BCO–MARCOS model are presented in Fig. A1 (Appendix), while the following subsections provide detailed explanations of the BCO metaheuristic and MARCOS MCDM method.

4.1 The BCO Metaheuristic

The initial variant of the BCO algorithm defined a constructive approach to problem-solving [53], but a later variant based on solution improvement was developed [54] and is used in this article as well. The algorithmic steps of the BCO metaheuristic based on solution improvement are as follows [53,54]:

Input parameters-number of bees (m), number of forward passes (i.e., flights) per iteration (N_f), and termination criteria-are initialized, and the initial solution is defined.

In every iteration, every bee executes N_f forward passes. At the beginning of every iteration, the best-known solution (*BKS*) is assigned to all bees. During each forward pass, a bee modifies its solution based on the defined modification operators, and every solution modification is followed by a backward pass.

During a backward pass, every bee evaluates the quality of its solution in relation to the solutions of other bees. For maximization problems, the i^{th} bee's normalized solution value (O_i) is determined by the following equation:

$$O_i = \frac{\Phi_i - \Phi_{min}}{\Phi_{max} - \Phi_{min}} \tag{15}$$

in which Φ_i is the aggregated value of the quality of the solution of the i^{th} bee according to all objective functions, and Φ_{max} and Φ_{min} respectively represent the best- and worst-aggregated values of the quality of the solution for all bees in the observed flight. From another angle, Φ_i is in fact the output value of the MARCOS–MCDM method, whose algorithmic steps are explained in the next subsection.

Based on the quality of the solution, for every bee i the probability that it remains loyal to its solution $\left(p_i^{loyal}\right)$ is determined by using the following equation:

$$p_i^{loyal} = e^{-\frac{O_{max}-O_i}{n}} \tag{16}$$

in which O_{max} represents the largest normalized value of the solutions' quality for all bees in the observed flight n. For every bee i, a random number within the interval between 0 and 1 is generated, and if the number is less than the value of p_i^{loyal}, then the bee remains loyal to its solution.

After returning to the hive, bees that remained loyal to their solutions recruit non-loyal bees. The probability that the loyal bee k is followed $\left(p_k^{following}\right)$ is determined according to the following equation:

$$p_k^{following} = \frac{O_k}{\sum_{q \in L_k} O_q} \tag{17}$$

in which O_k represents the normalized value of the quality of the solution for bee k, and L_k represents the set of all loyal bees.

Based on the roulette wheel method, every non-loyal bee determines which loyal bee to follow in the next forward pass.

The iterations are repeated until the criterion for termination is met. In the case that a better solution than the *BKS* is found at any moment, the *BKS* is updated.

4.2 The MARCOS MCDM Method

The input parameters for the MARCOS method are the set of alternatives (R)-in our case, the set of bees' solutions in the observed flight-along with the set of criteria (C)-in our case, the objective functions described in Section 3-weight coefficients of the objective functions (w_j), and the decision matrix Δ. The decision matrix Δ is composed of the bees' solution values for all objective functions in the observed flight, in which x_{ij} represents the i^{th} bee's solution value according to the objective function j for the observed flight, m is the number of bees, and n is the number of objective functions. In the framework of our hybrid metaheuristic model, the MARCOS method is executed in the third step of the BCO metaheuristic (i.e., Eq. (15)). To analyse whether the solutions of bees are better than the current *BKS*, the current *BKS* is also considered in their evaluation.

The algorithmic steps of the MARCOS method were adapted from [64] for the context of its integration with the BCO method:

To evaluate the solutions of bees in the observed flight, the *BKS* is included in the decision matrix, which can be expanded by defining the ideal (R_{id}) and anti-ideal (R_{ai}) solution:

$$\Delta = \begin{array}{c} \\ R_{ai} \\ R_1 \\ R_2 \\ \vdots \\ R_m \\ BKS \\ R_{id} \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{ai1} & x_{ai2} & \cdots & x_{ain} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ x_{BKS1} & x_{BKS2} & \cdots & x_{BKSn} \\ x_{id1} & x_{id2} & \cdots & x_{idn} \end{bmatrix} \end{array} \tag{18}$$

Thus, C^{max} is the set of all maximization objective functions, and C^{min} is the set of all minimization objective functions. R_{id} and R_{ai} are defined according to the following equations:

$$R_{ai} = \min_{1 \le i \le m+1} x_{ij},\ \ j \in C^{max}\ \ and\ \ \max_{1 \le i \le m+1} x_{ij},\ \ j \in C^{min} \tag{19}$$

$$R_{id} = \max_{1 \le i \le m+1} x_{ij},\ \ j \in C^{max}\ \ and\ \ \min_{1 \le i \le m+1} x_{ij},\ \ j \in C^{min} \tag{20}$$

The normalised decision matrix $U = \left[u_{ij}\right]_{m+1 \times n}$ is formed according to the following equation:

$$u_{ij} = \frac{x_{id}}{x_{ij}},\ \ j \in C^{min} \tag{21}$$

$$u_{ij} = \frac{x_{ij}}{x_{id}},\ \ j \in C^{max} \tag{22}$$

The weighted matrix $V = \left[v_{ij}\right]_{m+1 \times n}$ is formed by multiplying the elements of matrix U with the corresponding objective function weight coefficients according to the following equation:

$$v_{ij} = u_{ij} \cdot w_j \tag{23}$$

The degree of the utility of bee's solutions K_i is calculated in relation to S_{ai} and S_{id}:

$$K_i^- = \frac{S_i}{S_{ai}} \tag{24}$$

$$K_i^+ = \frac{S_i}{S_{id}} \tag{25}$$

in which S_i represents the sum of all elements of the weighted matrix V for the i^{th} bee's solution:

$$S_i = \sum_{j=1}^{n} v_{ij} \tag{26}$$

while S_{ai} and S_{id} represent the S_i parameter value for R_{ai} and R_{id} solution.

The value of the utility function Φ_i is determined for every bee's solution in the observed flight by using the following equation:

$$\Phi_i = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f\left(K_i^+\right)}{f\left(K_i^+\right)} + \frac{1 - f\left(K_i^-\right)}{f\left(K_i^-\right)}} \tag{27}$$

in which $f(K_i^+)$ represents the utility function in relation to R_{id}, and $f(K_i^-)$ represents the utility function in relation to R_{ai}, both of which are determined according to the following equations:

$$f\left(K_i^+\right) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{28}$$

$$f\left(K_i^-\right) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{29}$$

The solutions of the bees are ranked according to the parameter Φ_i. Solutions with a greater value of Φ_i are considered to be better. If a solution exists that, according to the parameter Φ_i is better than the current *BKS*, then that solution is updated to be the new *BKS*. The values Φ_i represent the basis upon which the quality of the bee's solution is determined in the third step of the BCO.

4.3 Solution Evaluation and Modification by the Bees

The most time-consuming part of solving IT network modelling problems is evaluating the objective function of the solutions because it requires allocating observed flows within the given network structure. Allocating flows in IT networks is a problem in itself that various studies have examined (e.g., [67,68]). In our work, allocating flows is only one component of a more complex problem that entails determining the number of DP terminals and their location, connecting the terminals with appropriate IWCTs, and determining their capacity. In our model, after a solution is modified by a bee, it is necessary to again allocate the container flows for the new system structure in order to evaluate the solution according to all of the objective functions. Thus, the allocation of container flows is executed every time that a solution is modified by a bee and according to the same rules for all bees.

Flows for a given IT network structure can be allocated by applying a heuristic approach inspired by Sörensen et al. [51]. The idea of the heuristic is to determine the priority of allocation based on the costs and benefits of the allocation. Its application thus allows prioritizing the allocation of flows that contribute to improving the observed objective functions. The priority of allocating the observed container flow f ($f \in F$) to the DP terminal d ($Priority_f^d$), in which $d \in D$, is determined according to the following equation:

$$Priority_f^d = Q_f \cdot \frac{w_{op} \cdot S_{op}^{f,d} + w_e \cdot S_e^{f,d} - w_t \cdot S_t^{f,d}}{max\left\{w_{op}, w_e, w_t\right\}} \tag{30}$$

in which Q_f represents the intensity of the flow f in TEUs, while $S_{op}^{f,d}$, $S_e^{f,d}$, and $S_t^{f,d}$ respectively refer to the operational savings, external costs savings, and time costs when flow f passes through the terminal d. Beyond that, w_{op}, w_e, and w_t are the weighted coefficients of those objective functions, respectively.

For every evaluated IT network structure, we formed a list consisting of the $Priority_f^d$ values for all flows and all possible flow shipping variants. The list is sorted in descending order, and the flows are allocated according to the sorted list and their $Priority_f^d$ value while considering the existing capacities of DP terminals as located. That approach affords the advantage of allocating flows that most contribute to improving the objective functions.

We defined three types of bees that differ in how they modify the solution. For each type of bee, a certain level of uncertainty (i.e., randomized search) exists during the modification of a solution in order to ensure diversity when exploring the space of feasible solutions.

Type 1 bees modify a solution by opening new DP terminals or closing an existing DP terminal. The decision to open a new DP terminal d ($d \in D$) for a randomly selected IWCT l ($l \in L$) is based on the parameter $Potential_d^L$, which represents the maximum possible benefits of opening the terminal according to the sum of the elements $Priority_f^d$ in relation to $d - l$:

$$Potential_d^l = \sum_{f=1}^{F} Priority_f^{d-l} \tag{31}$$

When opening a DP terminal for IWCT l, the bee considers z closest locations for the observed IWCT ($z \in D$). The probability that a DP terminal is located at location d is calculated according to the following equation:

$$p_d^{locating} = \frac{Potential_d^l}{\sum_{q=1}^{z} Potential_q^l} \tag{32}$$

According to probabilities $p_d^{locating}$, the new location of a DP terminal is determined by the roulette wheel method, while terminal capacity is determined by choosing a random capacity category.

In the case of closing a DP terminal, the selection of the terminal is determined according to the capacity utilization of the existing DP terminals. The probability that the DP terminal d ($d \in \{\forall d \in D | Y_d = 1\}$) is selected to be closed is determined according to the following equation:

$$p_d^{closing} = \frac{\left(1 - \frac{Q_d}{Q_d^{max}}\right)}{\sum_{q=1}^{n_d} \left(1 - \frac{Q_q}{Q_q^{max}}\right)} \tag{33}$$

in which Q_d represents the volume of container flows that pass through terminal d, Q_d^{max} the capacity of terminal d, and n_d the number of DP terminals as located. In that approach, priority for closing is given to DP terminals with less capacity utilization. Following the roulette wheel method according to probabilities $p_d^{closing}$, a DP terminal to be closed is chosen. In the case that all terminals fully utilize their capacities, the DP terminal to be closed is selected at random. Because opening new and closing existing DP terminals are acts performed with one type of bee, it is predetermined in the model that in 70% of cases the bee will decide to open a new DP terminal.

Type 2 bees, by contrast, modify the solution by changing the category of terminal capacity for an existing DP terminal. Such bees choose one of the located terminals at random and, based on its TEU throughput, determine the two neighbouring (i.e., larger and smaller) categories of capacity. Next, the category of capacity is randomly selected between the two neighbouring categories.

Last, Type 3 bees modify the solution by changing the location of existing DP terminals. The probability that terminal d ($d \in \{\forall d \in D | Y_d = 1\}$) is relocated is determined according to the following equation:

$$p_d^{relocating} = 1 - \frac{Potential_d^{l_d}}{\sum_{q=1}^{n_t} Potential_q^{l_q}} \tag{34}$$

in which l_d represents the IWCT to which the DP terminal d is assigned. After choosing the terminal to relocate by using the roulette wheel method, z nearest locations to the DP terminals are determined, and a new location is subsequently chosen according to the probabilities from Eq. (32), also by using the roulette wheel method.

In a series of experiments, we determined that the best solutions could be obtained with the configuration of five bees: one type 1 bee, one type 2 bee and three types 3 bees. The number of forward passes per iteration was set to be 5. The criterion for terminating the model was 10 successive iterations without any improvement in BKS greater than 0.005 according to the parameter Φ_i. The experiment was conducted on a personal computer with an Intel Core i7-8750H central processing unit with 2.20 GHz and 8 GM of RAM memory.

5 Application of the Model for Solving the Observed Problem

In our model, flow generators are represented as regional nodes, defined according to the official Nomenclature Of Territorial Units and Statistics at the second level (i.e., NUTS 2) and the region's spatial-geographic characteristics. In our analysis, the primary categories of goods according to the Standard International Trade Classification [69] were taken into account. Every category of goods was divided into logical subcategories, for each of which a typical representative, its characteristics, the average amount of goods per container, and average market value were determined (Table 2). The value of time for different goods was determined with reference to [70], which, though dated, is the only work known to us that considers the matter in an appropriate way.

Table 2: The observed goods categories (defined by authors and other experts in the field)

Goods category	Subcategory	Typical representative	Amount of goods in one 20ft EITU container (kg)	Average market value (€/kg)	Average value of goods in one EITU (€/TEU)	Value of time of goods (€/TEU ∗ h)
Food & Live animals	Spices, coffee, tea, etc.	Coffee	~16250	3.00	48750	1.11
	Fresh fruits, vegetables, meat, fish, etc.	Apples	~11000	5.00	55000	0.32
Beverages & Tobacco	Tobacco products	Cigarettes	~2000	11.00	22000	0.73
	Beverages	Beer	~8670	0.76	6589	0.23
Crude materials	Timber, rubber, paper, textile etc.	Timber	~25000	0.19	4750	0.16
	Metal	Raw metal materials	~25000	0.27	6750	0.24
Mineral fuels & Lubricants	Solid fossil fuels	Coal	~25000	0.20	5000	0.17
	Liquid fossil fuels	Petrol	~16800	0.41	6888	0.24
	Gas	Propane	~10353	0.18	1864	0.06
	Electric energy	–	–	–	–	–
Animal and vegetable oils	–	Oils	~19000	0.91	17289	0.59
Chemicals	Chemical products	Fertilizers	~21500	2.57	55255	1.89
	Organic and inorganic chemicals	Liquid and gas chemicals	~15750	0.67	10552.5	0.36
Manufactured goods	–	Cement	~24500	1.50	36750	1.25
Machinery & Transport equipment	Office machinery and electric devices	PC	~5500	20.00	110000	3.85
	Industrial machines and vehicles	–	–	–	–	–
Miscellaneous manufactured articles	Other products	Furniture	~12500	9.70	121250	4.15
	Industrial plants and prefabricated buildings	–	–	–	–	–

According to the official statistics of Eurostat and the national governments of countries in the Danube region, the volume of goods traded between pairs of countries is determined for all subcategories of goods. The quantity of goods between generator pairs is proportionally distributed according to the population of the regions where those generators are located. Our analysis included generators from 14 countries or regions: southern Germany, Austria, Czech Republic, Slovakia, Hungary, Romania, Moldova, Ukraine, Slovenia, Croatia, Bosnia and Herzegovina, Serbia, Montenegro, and Bulgaria. Eight potential IWCTs in strategically important locations were also considered: Deggendorf, Linz, Vienna, Budapest, Baja, Belgrade, Ruse, and Giurgiulesti.

Other input parameters, presented in Table 3, were the per-unit transport and emission costs of different modes of transport, their average speed, basic transhipment costs in IWCTs, and the average length of container stays at the terminals. According to [2,17,71], our own experience in the field, and the characteristics of the problem, the weighted coefficients for the objective functions were 0.25 for operational costs, 0.22 for external costs, 0.16 for time costs, 0.13 for terminal development costs, and 0.24 for the amount of container flows attracted. Following Wiegmans et al. [72], nine different capacity categories of DP terminals were considered (Table 4). Terminals with greater capacity generally had greater development costs but lower transhipment costs per unit.

Table 3: Remaining input parameters for the model

Parameter	Value	Measurement unit	Source
Road transportation unit costs	0.110	€/t ∗ km	[73]
Rail transportation unit costs	0.050	€/t ∗ km	[73]
Inland waterway transportation unit costs	0.015	€/t ∗ km	[73]
Road transportation external unit costs	1.65	€/t ∗ km	[9]
Rail transportation external unit costs	1.10	€/t ∗ km	[9]
Inland waterway transportation external unit costs	0.26	€/t ∗ km	[9]
Base transhipment costs at inland waterway container terminals	50	€/TEU	Approximated
Average road transportation speed	60	km/h	Empirical value
Average rail transportation speed	40	km/h	Empirical value
Average inland waterway transportation speed	13	km/h	[74]
Average time of container stay at terminals	12	h	Approximated

Table 4: Considered DP terminal categories

Terminal category by throughput (TEU)	Development costs (mln. €)	Transhipment costs (€/TEU)
10000	3.5	70
30000	9.5	65
50000	15	60
100000	47	55

(Continued)

Table 4 (continued)

Terminal category by throughput (TEU)	Development costs (mln. €)	Transhipment costs (€/TEU)
150000	60	52.5
250000	90	50
500000	138	45
1000000	210	43
1500000	260	41.5

5.1 Results

Using the input parameters from Section 5.1 and Tables 2–4, the optimization problem, defined by Objective Functions 1–5 and Constraints 6–14, was solved. The BCO metaheuristic was applied according to the steps described in Section 4.1, Eqs. (15)–(17), and the solution modification described in Section 4.3 and Eqs. (30)–(34). During every evaluation of solutions following the third step of executing BCO, the MARCOS method was applied according to Eqs. (18)–(29). The observed optimization problem was solved in 15 executed instances in order to determine the stability of the developed BCO–MARCOS model. For the initial solution in every execution, a solution was generated with one DP terminal located according to the modification of type 1 bees for a randomly selected IWCT. The objective functions values for best-found solutions for every model execution are presented in Table 5.

Table 5: Model results for all instances of its execution

Execution instance	Operational savings (bln. €)	External cost savings (bln. €)	Time losses (mln. €)	Development costs (bln. €)	Attracted TEU volumes (mln.TEU)	Φ_i	Computational time (s)	Number of iterations
1	5.896	88.326	572	1.758	6.059	0.674	2636	33
2	5.480	81.762	532	1.372	5.630	0.665	3353	50
3	5.729	85.557	567	1.442	6.082	0.681	3501	46
4	5.597	83.684	551	1.636	5.918	0.662	3024	38
5	5.746	86.184	533	1.708	5.632	0.662	1535	20
6	5.860	87.357	567	1.586	5.994	0.678	2210	28
7	5.448	81.786	554	1.564	5.833	0.655	1939	26
8	5.591	83.936	565	1.758	6.020	0.657	4121	62
9	5.513	82.437	538	1.492	5.816	0.664	3869	55
10	5.847	87.228	564	1.686	5.922	0.671	2431	32
11	5.542	82.682	538	1.558	5.811	0.661	1618	23
12	5.332	80.199	521	1.595	5.540	0.644	1594	23
13	5427	81.569	525	1.536	5.540	0.652	2095	26
14	5.598	83.684	551	1.564	5.918	0.665	2997	40
15	5.782	86.176	553	1.564	5.925	0.675	3007	34
Average	5.626	84.171	549	1.588	5.843	0.664	2662	36
Average deviation	2.62%	2.50%	2.59%	5.15%	2.50%	1.17%	26.24%	28.58%

In all instances of the model's execution, the result consisted of eight DP terminals. However, in some cases, variations existed in terminal location and terminal capacity as a consequence of the simultaneous optimisation of five objective functions. According to the results presented in Table 5, the average deviation of solution values for each of the five objective functions was small (2.62%, 2.50%, 2.59%, 5.15%, and 2.50%, respectively), which indicates that the model had good convergence, as confirmed by the average deviation of the parameter Φ_i of only 1.17% when comparing the best-found solution in all instances. The average computational time of the model was 2662 s, and the average number of iterations was 36, both of which can be considered to be low given the extreme complexity and size of the problem.

The best-found solution (i.e., Execution 3) involves developing one DP terminal for every analyzed IWCT (Fig. 2). Three of the DP terminals (i.e., at Munich for the IWCT in Deggendorf, at Graz for the IWCT in Vienna, and at Miskolc for the IWCT in Budapest) have a capacity of at least 1 million (e.g., 1.5 million TEUs for the Miskolc DP terminal), the DP terminal for the IWCT in Linz (Ceske Budejovice) has a throughput of 625,000 TEU, while the remaining terminals (i.e., Szeged for the IWCT in Baja, Kragujevac for the IWCT in Belgrade, Bucharest for the IWCT in Ruse, and Comrat for the IWCT in Giurgiulesti) have a capacity of 500,000 TEUs.

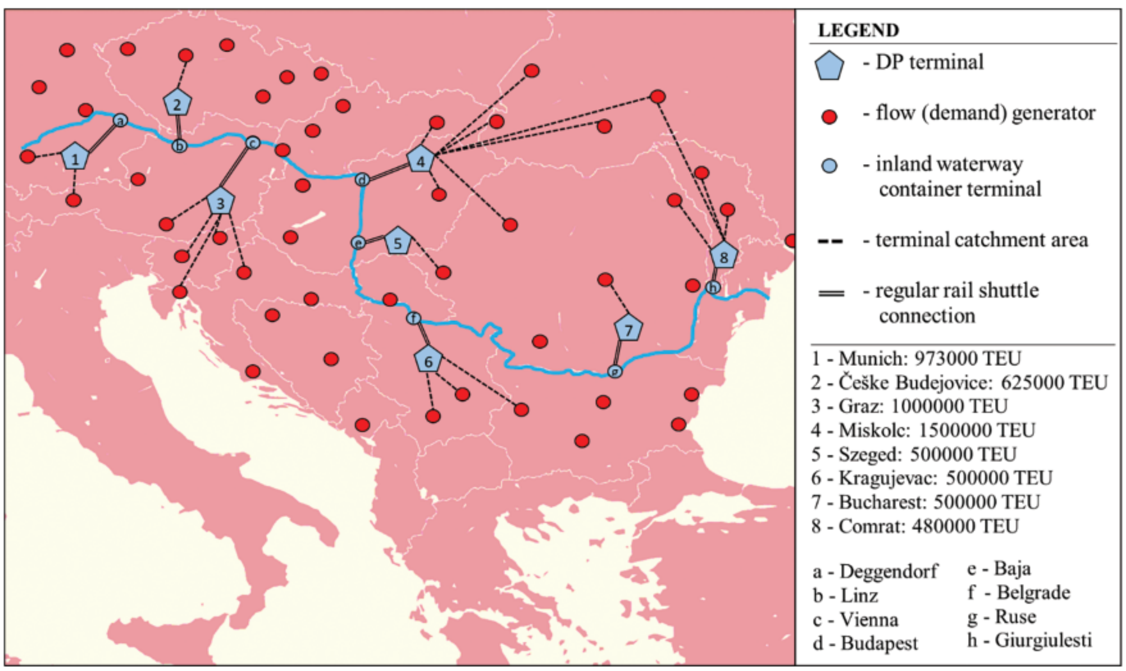

Figure 2: Output results–the best-found solution

The results are especially interesting considering that a relatively narrow region was analyzed. According to the model, developing eight DP terminals is justified. Such a result justifies implementing the concept of DPs for IWCTs, and it can be expected that with the analysis of a broader geographical area that the justification only becomes greater. To better examine the behaviour of the DP concept in the framework of IWCTs, a sensitivity analysis is conducted and presented in the next subsection.

5.2 Sensitivity Analysis & Discussion

Output results of every multi-objective optimization problem are influenced. By the way, the objective functions' importance is perceived and treated. To better understand the nature of the problem/solution, it is necessary to perform appropriate sensitivity analyses. To inspect the behaviour of the DP concept in the framework of IWCTs, the sensitivity analysis is conducted through 11 different scenarios. Scenarios differ in the configuration of weight coefficients for the objective functions (Table 6). In the first scenario (Sc. 1), all objective functions are treated equally (their weight coefficients are set to 0.2). In scenarios Sc. 2–Sc. 6, for every individual objective function, 0.350 is adopted as its weight coefficient while other weight coefficients were set to 0.165. This was done to see how the dominance of one objective function over others influences the final solution. In the remaining scenarios (Sc. 7–Sc. 11), one of the objective functions is excluded (its weight coefficient is set to 0), while the other objective functions were treated equally important (with weight coefficients set to 0.250).

Table 6: Scenarios used for the sensitivity analysis

Scenarios	Objective functions weight coefficients				
	w1	w2	w3	w4	w5
Sc. 1	0.200	0.200	0.200	0.200	0.200
Sc. 2	0.350	0.165	0.165	0.165	0.165
Sc. 3	0.165	0.350	0.165	0.165	0.165
Sc. 4	0.165	0.165	0.350	0.165	0.165
Sc. 5	0.165	0.165	0.165	0.350	0.163
Sc. 6	0.165	0.165	0.165	0.165	0.350
Sc. 7	0.000	0.250	0.250	0.250	0.250
Sc. 8	0.250	0.000	0.250	0.250	0.250
Sc. 9	0.250	0.250	0.000	0.250	0.250
Sc. 10	0.250	0.250	0.250	0.000	0.250
Sc. 11	0.250	0.250	0.250	0.250	0.000

The application of the developed model over the defined scenarios showed that different solutions are obtained in different weight coefficient settings (Table 7). In scenarios Sc. 1, Sc. 2, Sc. 3, Sc. 6, Sc. 9, and Sc. 10, the results still imply that the development of DPs for every IWCT is justified. In scenarios Sc. 7 and Sc. 8, seven DPs emerged in the final solution. In the remaining scenarios (Sc. 4, Sc. 5 and Sc. 11), according to the results, the development of six DPs is justified. Depending on the scenario, the locations and capacities of DP terminals differ as well (Tables A1 and A2 in the Appendix).

Table 7: Sensitivity analysis output results

Scenario	DP terminals	Operational savings (mln. €)	External costs savings (bln. €)	Time losses (mln. €)	Flow volume (mln. TEU)	Average DP capacity (TEU)
Sc. 1	8	5774	86.112	503	5.834	812500
Sc. 2	8	4833	72.135	436	5.042	700000

(Continued)

Table 7 (continued)

Scenario	DP terminals	Operational savings (mln. €)	External costs savings (bln. €)	Time losses (mln. €)	Flow volume (mln. TEU)	Average DP capacity (TEU)
Sc. 3	8	5852	87.231	540	6.219	1000000
Sc. 4	6	2831	41.811	145	2.950	491667
Sc. 5	6	2513	37.244	191	2.300	383333
Sc. 6	8	4617	68.859	440	5.152	718750
Sc. 7	7	3485	52.179	271	3.440	491429
Sc. 8	7	4575	68.703	246	4.275	675714
Sc. 9	8	5334	79.617	508	5.671	831250
Sc. 10	8	5945	88.733	539	6.255	1312500
Sc. 11	6	2505	37.159	147	2.130	355000

The sensitivity analysis indicates that the development of DP terminals in the framework of IWCTs is justified, but its configuration depends on the initial settings (objective function prioritization). This is natural since different objective functions tend to shape the solution in specific ways–some contribute to a specific concept while others are against it. Of course, the analysis in this article is limited to the five defined objective functions. More research should be done in different settings and configurations in order to better understand the advantages and weaknesses of the DP concept in the framework of IWCTs.

The purpose of this article has been to draw attention to the implementation of the concept of DPs for IWCTs, which can enable the efficient integration of inland waterway transport into IT systems. Developing such ports can significantly affect sustainability by reducing operational and external logistics costs. Although the results show that DPs in the framework of IWCTs can be sustainable, it is necessary to conduct more in-depth analyses of the possibilities and effects of their implementation.

The main limitation of this work is in considering a narrow geographical area around the Danube river. The article has proven that this is sufficient to illustrate the idea behind the concept and to demonstrate its potential sustainability. Another limitation is in not considering the stochastic nature of container flow characteristics. This would be a good direction for future research that will continue the examination of such DP concept variant. The container flows are narrowed down to the main goods categories, but further research could focus on some specific goods types and do more detailed analyses.

Several managerial insights could be drawn from the results. Firstly, policy creators in the field of IT are presented with another potentially sustainable development direction of IT systems–DP in the framework of IWCT. The developed model can help decision-makers to select locations for DP terminals and to narrow down future analyses to specific case studies of individual DPs. Stakeholders in the field of IT could conclude what specific locations/regions are potent for developing DP that will serve IWCTs in their region. The developed model, although developed for this specific problem, is universal in its nature and could be used, with minor tweaks and reconfigurations, to solve any multi-objective optimization problem in the domain of IT and other fields.

6 Conclusion

This article has examined the concept of DPs in the framework of IWCTs. Its chief contribution and the basis of its novelty is that it addresses modelling DP systems in the context of IWCTs.

The article enriches an already versatile literature body regarding different configurations of DP-based IT systems but stands out as the only one that provides integration of inland waterways into existing IT systems. The article also contributes by treating the modelling of DP systems by virtue of the comprehensiveness of the problem's formulation. The problem was mathematically formulated considering several objective functions. The selected objective functions are inherited from the existing literature and included simultaneously during the modelling of the observed DP concept, which has not been done in any previous research. Ultimately, its other contributions are the development of a novel hybrid BCO–MARCOS metaheuristic model for solving the problem and the demonstration of its application in the Danube region.

The results of the model's application indicate the sustainability of the concept of DPs in the framework of IWCTs, even for narrow areas around inland waterways. According to the results, developing eight DP terminals in different categories in and for the Danube region is justified.

In the future, researchers should consider conducting more detailed analyses of the concept in a stochastic–dynamic environment, developing adequate evaluation models, and defining different IT development scenarios based on the concept of DPs for IWCTs. It would be especially interesting to analyse scenarios in which DP terminals have established regular shuttle connections between themselves to cover a broader set of container flows and to include rail transport to a greater extent. A detailed analysis of the DP concept in different settings of objective functions' weights should be conducted. This should be done to see how the justification of such a concept behaves with different angles of approach towards its modelling.

Special attention should also be given to the BCO metaheuristic, which has again proven to be an efficient way to solve combinatorial problems. The developed hybrid metaheuristic model, which combines the BCO metaheuristic and MARCOS MCDM method, is unique, and future research could therefore focus on its application for other multi-criteria optimization problems in IT as well as in other fields. A final direction for future research is to analyze a broader set of metaheuristic algorithms for solving combinatorial problems in IT and compare their performance.

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Appendix

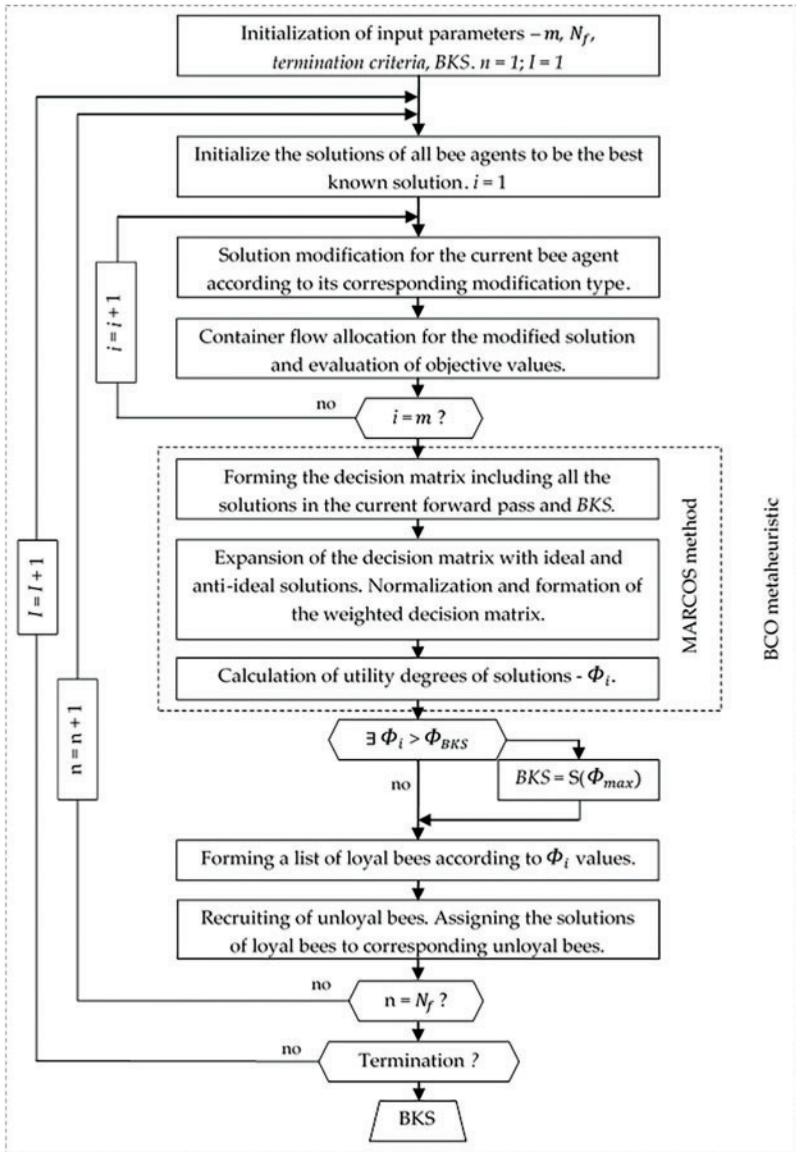

Figure A1: Algorithmic steps of the BCO-MARCOS metaheuristic model

Table A1: Sensitivity analysis output results (Sc. 1–Sc. 6)

Scenario	DP terminals	Capacity (TEU)	Throughput (TEU)	IWCT	Operational savings (mln. €)	External costs savings (mln. €)	Time losses (mln. €)	Flow volume (TEU)	Average DP capacity
Sc. 1	Bucharest	500000	500000	Ruse	5774	86112	503	5833668	812500
	Comrat	500000	498934	Giurgiulesti					
	Kragujevac	500000	488042	Belgrade					
	Munich	1000000	979570	Deggendorf					
	Klagenfurt	500000	500000	Linz					

(Continued)

Table A1 (continued)

Scenario	DP terminals	Capacity (TEU)	Throughput (TEU)	IWCT	Operational savings (mln. €)	External costs savings (mln. €)	Time losses (mln. €)	Flow volume (TEU)	Average DP capacity
	Osijek	1000000	637184	Baja					
	Graz	1000000	729938	Vienna					
	Miskolc	1500000	1500000	Budapest					
Sc. 2	Comrat	1000000	598247	Giurgiulesti	4833	72135	436	5041976	700000
	České Budejovice	1000000	897212	Linz					
	Nagykanizsa	1000000	946517	Baja					
	Bucharest	500000	500000	Ruse					
	Kragujevac	500000	500000	Belgrade					
	Gyor	100000	100000	Budapest					
	Munich	1000000	1000000	Deggendorf					
	Bratislava	500000	500000	Vienna					
Sc. 3	Miskolc	1500000	1500000	Budapest	5852	87231	540	6218759	1000000
	Bucharest	500000	500000	Ruse					
	Munich	1000000	971746	Deggendorf					
	Osijek	1000000	632299	Baja					
	Comrat	500000	500000	Giurgiulesti					
	Kragujevac	1000000	483870	Belgrade					
	Graz	1000000	1000000	Vienna					
	České Budejovice	1500000	630844	Linz					
Sc. 4	Miskolc	1000000	1000000	Budapest	2831	41811	145	2950000	491667
	Graz	1000000	1000000	Vienna					
	Munich	250000	250000	Linz					
	Comrat	500000	500000	Giurgiulesti					
	Ansbach	150000	150000	Deggendorf					
	Timisoara	50000	50000	Baja					
Sc. 5	Munich	1000000	1000000	Deggendorf	2513	37244	191	2300000	383333
	Comrat	250000	250000	Giurgiulesti					
	České Budejovice	30000	30000	Linz					
	Bucharest	10000	10000	Ruse					
	Graz	1000000	1000000	Vienna					
	Zagreb	10000	10000	Baja					
Sc. 6	Munich	1000000	1000000	Deggendorf	4617	68859	440	5151698	718750
	Gyor	500000	365561	Budapest					
	Bucharest	500000	489289	Ruse					
	Sarajevo	250000	250000	Belgrade					
	Nagykanizsa	1000000	950689	Baja					
	České Budejovice	1000000	888568	Linz					
	Comrat	500000	441159	Giurgiulesti					
	Brno	1000000	766432	Vienna					

Table A2: Sensitivity analysis output results (Sc. 7–Sc. 11)

Scenario	DP terminals	Capacity (TEU)	Throughput (TEU)	IWCT	Operational savings (mln. €)	External costs savings (mln. €)	Time losses (mln. €)	Flow volume (TEU)	Average DP capacity
Sc. 7	Miskolc	1500000	1500000	Budapest	3485	52179	271	3440000	491429
	Bucharest	250000	250000	Ruse					
	Munich	1000000	1000000	Deggendorf					
	Graz	500000	500000	Vienna					
	Chisinau	150000	150000	Giurgiulesti					
	Sofia	30000	30000	Belgrade					
	Česke Budejovice	10000	10000	Linz					
Sc. 8	Munich	1000000	870626	Deggendorf	4575	68703	246	4275630	675714
	Miskolc	1500000	1500000	Budapest					
	Maribor	1000000	1000000	Linz, Vienna					
	Comrat	1000000	675004	Giurgiulesti					
	Bucharest	150000	150000	Ruse					
	Priština	50000	50000	Belgrade					
	Osijek	30000	30000	Baja					
Sc. 9	Nagykanizsa	1000000	806730	Baja	5334	79617	508	5671328	831250
	Bucharest	500000	500000	Ruse					
	Comrat	500000	500000	Giurgiulesti					
	Miskolc	1500000	1500000	Budapest					
	Salzburg	150000	150000	Linz					
	Munich	1000000	1000000	Deggendorf					
	Kragujevac	500000	500000	Belgrade					
	Bratislava	1500000	714598	Vienna					
Sc. 10	Miskolc	1500000	1500000	Budapest	5945	88733	539	6255092	1312500
	Kragujevac	1000000	488111	Belgrade					
	Munich	1500000	969926	Deggendorf					
	Bucharest	1500000	543157	Ruse					
	Graz	1500000	1011918	Vienna					
	Osijek	1500000	632114	Baja					
	Česke Budejovice	1500000	629656	Linz					
	Comrat	500000	480210	Giurgiulesti					
Sc. 11	Munich	500000	500000	Deggendorf	2505	37159	147	2130000	355000
	Salzburg	50000	50000	Linz					
	Comrat	500000	500000	Giurgiulesti					
	Graz	1000000	1000000	Vienna					
	Trencin	30000	30000	Budapest					
	Timisoara	50000	50000	Baja					