

An Intelligent Decision Support System for the Empty Unit Load Device Repositioning Problem in Air Cargo Industry

Daniel A. Döppner
Department of Information
Systems and Information
Management,
University of Cologne
doeppner@wim.uni-koeln.de

Patrick Derckx
Department of Information
Systems and Information
Management,
University of Cologne
derckx@wim.uni-koeln.de

Detlef Schoder
Department of Information
Systems and Information
Management,
University of Cologne
schoder@wim.uni-koeln.de

Abstract

Unit load devices (ULDs) are containers and pallets used in the air cargo industry to bundle freight for efficient loading and transportation. Mainly due to imbalances in global air transportation networks, deficits and surpluses of ULDs are the result and require stock balancing through the repositioning of (empty) ULDs.

Following a design science research approach, we (1) elaborate the hitherto uninvestigated problem class of empty ULD repositioning (EUR) and (2) propose an intelligent decision support system (IDSS) that incorporates a heuristic for the given problem and combines artificial intelligence (i.e., rule-based expert system technology) with business analytics. We evaluate the IDSS with real-world data and demonstrate that the proposed solution is both effective and efficient. In addition, our results provide empirical evidence regarding the positive economic and ecological impact of leveraging the potential of ULD pooling in multi-carrier networks.

1. Introduction

Global air transportation has grown over the last decades. According to [1], air passenger traffic (measured in terms of RPK¹) increased over the last 10 years by 60%, doubles every 15 years, and grew by around 6% in 2016. World air cargo traffic—namely, the transportation of goods—grew to 223 billion RTKs² in 2015 and is estimated to increase up to 509 billion RTKs by 2035 [7]. The growth of cargo transportation is driven by numerous factors, such as rapidly growing global trade, the high demand for fast

and timely delivery, and firms' efforts to keep low inventories through frequent replenishment [32, 37]. Furthermore, increasing e-commerce and China's increasing retail sales are predicted to cause world air cargo traffic to double over the next two decades [7], which is also reflected in the increasing number of Asia-Europe and Asia-North America connections [1].

Even though air transportation is a critical area of world business and we can observe growing transportation business, airlines increasingly face the challenge of reducing costs while improving operational efficiency. One way to improve air transportation efficiency is through unit load devices (ULDs), which are used to bundle freight for faster and more efficient packaging, loading, and transportation. To ensure that the right number of ULDs is available at the proper time and location based on various economic and ecological factors [26], firms undertake ULD management, which involves the adequate allocation of serviceable ULDs within air transportation networks.

While the literature is rich in studies on the air transportation context and examines various issues [17, 19]—for example, revenue management [4, 5, 29], crew schedule planning [52], overbooking [28, 31], network configuration [40], and cargo packaging [3]—little is known about ULDs, and even less research sheds light on effective and efficient provisioning of serviceable ULDs in air transportation networks, including the movement of unutilized empty ULDs.

Following a design science research (DSR) approach [25], we elaborate the hitherto uninvestigated problem class of empty ULD repositioning (EUR) and provide two additional extensions: a multi-carrier perspective and the perspective of a ULD service provider (i.e., the central

¹ Revenue Passenger Kilometers

² Revenue Tonne Kilometers

simultaneous management of ULD stocks of several airline carriers). Furthermore, we propose an intelligent decision support systems (IDSS) that incorporates a heuristic for the stated problem and combines artificial intelligence (i.e., rule-based expert system technology) with business analytics to address the peculiarities of the stated problem class. In close cooperation with a major service provider for ULD management, we implemented and organizationally integrated the IDSS into a real ULD business context and evaluated the usefulness of the proposed solution.

Inspired by the publication schema of [21], the remainder of this paper is structured as follows. After this introduction (Section 1), we briefly summarize related work on ULDs, the problem class of empty container repositioning, and extant solution designs (Section 2). In Section 3, we briefly outline our methodology. In Section 4, we elaborate the problem class, which we call *empty ULD repositioning in the context of a multi-carrier network from the ULD service provider's perspective*. We describe our proposed solution (i.e., artifact description including demonstration) in Section 5 and provide evaluation results in Section 6. Finally, in Section 7, our conclusions, limitations, and suggestions for further research are presented.

2. Related work

In this section, we provide a brief overview of related work on the problem class and existing solution approaches in the literature.

While there is a large body of literature related to air cargo operations [17], only a few studies have investigated ULDs and their management from a decision-support perspective. In general, ULD management comprises various activities, including (among others) the purchasing, maintenance, and tracking of ULDs. The goal of ULD management is to provide sufficient stocks of serviceable ULDs at airports in response to airline carriers' needs. Such ULD resource management can be divided into two problems: (1) the composition and sizing of ULD inventories at airports [33, 34, 38] and (2) the continuous reallocation of (empty) ULDs to compensate for imbalances in ULD flows [15]. However, even though the issue of serviceable ULD provisioning has received a great deal of attention in practice, scientific research has not yet provided a precise formulation of the problem in the domain of air transportation.

Nevertheless, since the problem occurs in other modes of transportation, there is related research from other domains, such as the empty container

repositioning (ECR) problem. The ECR problem is defined as "arranging the storage and movement of empty containers in the shipping networks in order to better position the moveable resource to better satisfy customers demands" [44, p. 5]. It "aims to reposition empty containers efficiently and effectively in order to minimize the relevant costs" [44, p. 10].

Since the first research studies on ECR in the 1990s [12, 13], diverse aspects of ECR have been examined in the literature [44]. Because, on an abstract level, all the different modes of transportation share a set of assumptions and characteristics, the ECR problem class might be transferable to air transportation (as examined in this study).

From a solution perspective, different approaches have been proposed in the literature to deal with the ECR problem. These include, for example, simulations, heuristics, and linear programming [44].

However, despite the latest advancements in artificial intelligence (AI) and in business intelligence and business analytics (BI&BA) [9] and even though there is an increasing call for applying modern AI and BI&BA approaches to optimization problems [24, 49], ECR literature on these approaches is hitherto limited to a few examples (e.g., genetic algorithms [2, 14, 36] and tabu search [8, 45, 53]).

All in all, we have a few overall observations about previous work in this area. Although ECR is already well researched in transportation science, previous work has mainly focused on sea, rail, or road transportation modes and has neglected the context of air transportation. Thus, a solid problem class discussion has not yet been conducted. Furthermore, we identified only a few studies that explore AI's suitability as a solution for the ECR problem. Our study aims to address both shortcomings.

3. Methodology

Our research approach follows the DSR paradigm, which aims to build and evaluate novel and innovative IT artifacts for relevant real-world problems [25].

In this study, we focus on the problem structuring and solution design [23] outcomes of a multi-year DSR project with a large ULD management service provider for the air transportation industry.

As suggested by [48], problem classes should be grounded in prior knowledge (kernel theories). Therefore, we apply a multi-grounded approach [20] by (1) drawing on the literature on ECR for other modes of transport, such as sea, rail, and road, and by (2) reflecting on our experiences from our field work [41]. By providing examples from a concrete case, we describe the problem (and later the proposed solution)

on two levels: the concrete/situated level and on the abstract/more general level [20, 23, 51].

The resulting artifacts are (1) a heuristic to generate movement alternatives and support the repositioning of empty ULDs and (2) an IDSS that incorporates the heuristic and provides movement recommendations to ULD dispatchers. Working closely together with practitioners, we designed, implemented, and organizationally introduced an instantiation of the proposed IDSS for the given decision-support problem, which has been used in daily operations since then. In this study, we focus on the final problem formulation and solution design (see Section 4 and Section 5) and an ex-post evaluation [47] (see Section 6). A detailed narrative of the iterative artifact-development process is presented in [15].

4. Problem Class: Empty ULD Repositioning

Repositioning empty containers has been an issue since the idea of containerization was formed [44]. However, it has become more prominent with the growth in freight transportation and regional differences in economic development. In this section, we discuss the problem of repositioning empty ULDs and the associated characteristics from an air transportation perspective.

Drawing on the literature on decision-making theory [42] and ECR in other modes of transport and reflecting on our learnings from intensive case work in practice, we conceptualize the problem of EUR as a three-phase decision-making process and identify the problem's peculiarities.

4.1 EUR Decision-Making Process

The literature on ECR outlines two broad types of ECR problems [30]: quantity decisions and cost estimation. *Quantity decisions* seek to answer the questions of how many empty containers should be kept at a station and when and how many containers should be moved from one station to another. *Cost estimation* aims to quantify the costs associated with repositioning empty containers. Our proposed decision-making process comprises elements of both types: Step 1 addresses the quantity decision and Step 3 considers the costs of repositioning decisions, which are the results of Step 2.

We conceptualize the three-step decision-making process as follows:

1. **Determine the need for action.** The initial step is the assessment of whether stations have or will

have a deficit or surplus of ULDs and whether this deficit/surplus requires action. The result should be a set of stations.

2. **Identify repositioning alternatives.** Air transportation networks offer a variety of options to reposition (empty) ULDs. In this step, these options are identified. The result should be a set of movement alternatives with the number of ULDs that should be transported.
3. **Assess repositioning alternatives.** In this step, the identified options to move (empty) ULDs within the air transportation network are assessed. The result should be a set of movement alternatives that are valued and can be compared with each other.

4.2 ULD Demands

The main drivers for the need of EUR are imbalances at airports or on routes (i.e., ULD flows in one direction are greater than in the other direction). Imbalances can be differentiated between (1) systematic imbalances, which, for example, can be the result of holidays (systematic and temporary imbalance) or as the result of trade imbalances (systematic non-temporary imbalance), and (2) ad-hoc imbalances, for example, due to unforeseen additional business. The literature on ECR in the domain of maritime documents this phenomenon as well. For instance, European ports and American ports have a high surplus of empty containers, whereas Asian ports are facing severe shortages [44].

A common way to quantify the demand for empty ULDs is to calculate and monitor safety stock levels [34] and continuously compare them with actual stock levels. We identify four different perspectives on ULD stocks: (1) single carrier/single station (SC/SS), (2) multi-carrier/single station (MC/SS), (3) single carrier/multi-stations (SC/MS), and (4) multi-carrier/multi-stations (MC/MS). Figure 1 demonstrates these perspectives.

Another approach is to consider future outgoing ULD demands (measured in terms of laden ULDs) and compare them with actual stock levels.

Since the reallocation of empty ULDs is a continuous task, instructed movements and ULDs that are already en route to a demanding destination should be considered in the calculation of ULD demands.

4.3 ULD Types and Vehicle Types

Another challenge in EUR is the diversity of ULD types. Due to differences in the freight that needs to be shipped and in the transporting aircrafts (narrow-body

versus wide-body aircrafts), the air cargo industry utilizes different types of ULDs. ULD types are divided into containers (mainly for baggage and mail) and pallets (mainly for freight). While pallets can be stacked, containers cannot. For example, our case company manages the stock levels of around 120 different ULD types worldwide. This results in the challenge that, on the one hand, decision makers have to consider diverse ULD types, often depending on the carrier and its aircraft fleet, and on the other hand, they have to consider that ULDs can be used interchangeably (which we refer as to the substitutability of ULD types).

To reposition the ULDs within air transportation networks, depending on the local position of the aircrafts, several options are available (e.g., flights, trucks, or the exchange of ULDs between different carriers onsite) (see Section 4.4).

In our experience, in most cases, flights are used to reallocate empty ULDs. These flights are operated by airline carriers and transport both laden and empty ULDs. The number of empty positions for the reallocation of ULDs depends on flight utilization. Problems occur if no free capacity is available, for example, because the aircrafts are fully loaded.

Trucks are another option to move ULDs and can be separated into scheduled trucks, which operate on a regular basis, and chartered trucks, which have to be booked. Booking trucks often leads to extra costs and is generally only used if no other options are available, for example, because a station became an offline station (i.e., the station is no longer operated by an airline carrier temporarily or permanently).

Because diverse vehicle types are used in the air transportation business, decision makers have to consider restrictions regarding the loadability of ULD types on specific vehicles and the capacity constraints of the vehicles.

4.4 Pooling

In addition to flights and trucks, for the allocation of empty ULDs, decision makers can consider the stock levels and demands of various carriers in the network and identify complementary stock situations. For example, managing the ULD stocks of more than one airline carrier (see MC/SS or MC/MS perspective in Section 4.2) allows ULDs to be pooled, which refers to the sharing of empty containers across carriers (see the station perspective in Figure 1) or coordinating empty ULDs among routes [43]. This option becomes even more attractive if both carriers have complementary ULD demand patterns.

4.5 Uncertainties

In the supply chain context, transparency cannot be assumed [50]. Nevertheless, effective EUR and the identification of movement alternatives highly depends on having access to information that provides insights into planned laden ULDs on a flight and free capacity. In an ideal world, all information would be known. However, in most cases, this not given in reality. We observe that for EUR, three types of uncertainties are prevalent: (1) uncertainties in demand, (2) uncertainties in capacity, and (3) uncertainties surrounding the implementation of instructed repositioning.

First, the calculation of ULD demands highly depends on accurate data on current and future ULD flows and expected changes in stock levels. For example, we learned that for external ULD management service providers (in comparison to in-house ULD management), if such data access is not granted, decision makers have to deal with immense uncertainty as little or nothing is known about the current state of the network.

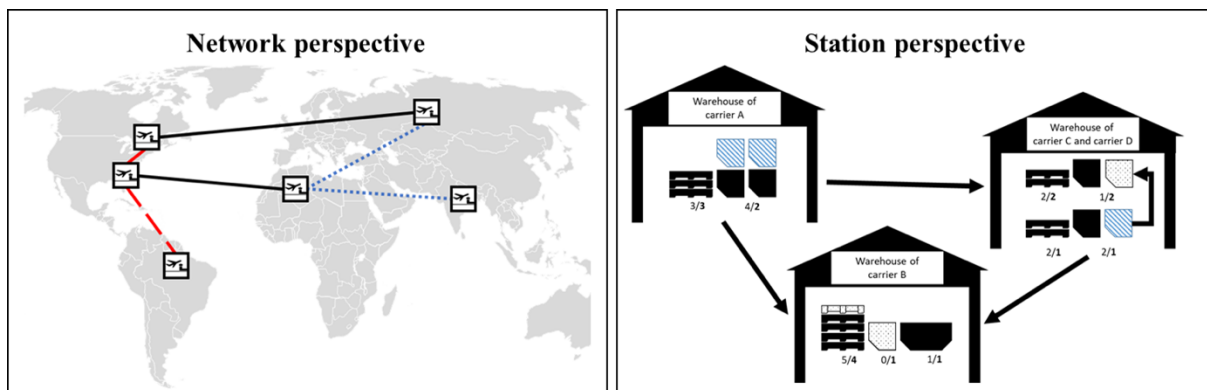


Figure 1. Comparison of the network perspective and the station perspective on ULD stock levels and repositioning alternatives.

Secondly, knowledge about free vehicle capacity is often missing. When determining the number of ULDs that should be moved with a repositioning alternative (e.g., a concrete flight), decision makers should consider the expected free capacity of the vehicle to get a sense of what extent the alternative will solve the problem.

Third, depending on the division of labor, movement is usually requested by one party, and execution is performed by other parties, such as ground handling agents onsite. Decision makers seldom have certainty that the movement request will be fulfilled.

While airline carriers that handle ULD management themselves possess these information resources, external service providers need to request access if possible. A major challenge in repositioning empty ULDs as a service provider is gaining access to accurate and timely data about ULD demands and finding a solution to deal with the mentioned uncertainties.

4.6 Conflicting Objectives

Within the course of the project, we compared movement alternatives with each other to sort them. Similar to ECR in maritime shipping [39], as different options to move ULDs within air transportation networks come with different economical, ecological, and operational consequences, we started to collect data on useful criteria for comparison. We found that EUR is embedded in a multi-stakeholder environment, which means that different, partly conflicting, objectives are pursued with EUR.

For example, while the overarching goal is to satisfy ULD demands while minimizing the number of empty ULD movements, which has a positive impact on fuel consumption (carrier perspective) and CO₂ emissions (environmental perspective), from an operational perspective, reducing the complexity of decisions seems to be the goal.

For example, recalling empty ULDs back to hub stations and subsequently replenishing stocks from hubs might have lower operational complexity compared to sending ULDs directly between spoke stations, but this approach leads to higher fuel consumption and CO₂ emissions (assuming that the distance of the spoke-spoke connection is shorter than the spoke-hub-spoke-connection), and the ULD needs to be handled and loaded twice (extra handling costs).

4.7 Contractual Relationships

Since the air transportation industry is under high cost pressure, most non-core operations are outsourced (e.g., ground handling and ULD management), and there are numerous relationships between providers. For example, we witnessed that outsourced ULD management is responsible for the instruction of repositioning empty ULDs, but decision implementation is done by ground handling agents onsite.

A peculiarity in the given context is that ULD providers have no way to reliably determine whether an ordered movement will be performed by acting ground handling agents onsite (see uncertainties of implementation in Section 4.5).

4.8 Dynamic Environment

Embedded in a complex and vivid environment, EUR is highly influenced by external factors. An example is the impact of weather conditions on the delivery of empty ULDs because high wind strengths prohibit the positioning of empty ULDs on the runway. Weather can also cause delays in transportation or flight cancellations. Decision makers have to consider external factors when identifying and assessing repositioning alternatives.

5. Proposed Solution Design

To cope with the problem of EUR, we had to identify a technology that primarily augments (not replaces) human decision makers and is adaptable as the requirements and understanding of the problem at hand will evolve over time.

An IDSS is a decision support system that utilizes AI and aims to enhance human cognitive capacities [10, 27]. Expert systems (ESs) are one type of IDSS. ESs are computational systems that emulate human experts' decision capabilities for specific topics [18]. The advantage of an ES approach is that the knowledge base can be changed or adapted to incorporate new knowledge as it emerges without the need to change the rest of the system. In this project, we opted for a rule-based knowledge base in which information is coded as IF-THEN rules. The advantage of this form of knowledge representation is

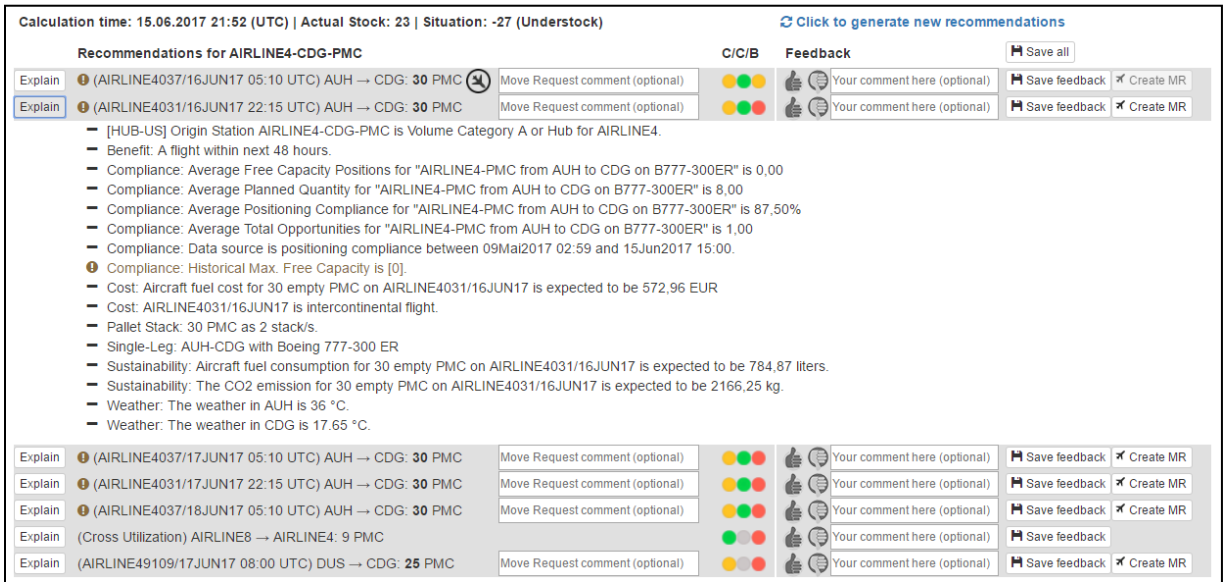


Figure 2. Screenshot of the latest prototype system's user interface.

that the rules are easy to formulate and to understand for humans. A second advantage and the reason we selected the ES approach is its explanation facility, which makes the system's reasoning behind recommendations and its assessment more transparent and comprehensible to end users (e.g., which data were considered for a specific recommendation and why a specific ULD quantity is suggested).

Following a typical ES development approach [35], we began with knowledge elicitation by conducting interviews and participant observations, and we started to model human decision making for EUR. We continuously fed the IDSS' rule base as new knowledge emerged. One integral part of the derived solution knowledge is a heuristic to determine the need for ULD repositioning for a given air transportation network and to generate a set of assessed repositioning alternatives to balance ULD stocks (see Figure 3). The heuristic is implemented as a rule flow model in the IDSS' knowledge base using the JBoss Drools rule engine. The heuristic and its concrete instantiation is described in the following.

In the first step, the heuristic aims to assess situations at stations. The IDSS uses safety stock levels, actual stock levels, and ULDs en route (generated by the case company's asset-tracking system) to calculate ULD surpluses and deficits (Heuristic Step 1).

In Heuristic Step 2, the IDSS uses airline carriers' flight schedules and truck options, and since our practice partner operates in an MC/MS environment (see section 4.2), pooling alternatives are also considered. In addition, the load restriction (i.e., if a specific ULD type can be loaded onto a specific

vehicle) is checked. The result is a set of possible repositioning alternatives.

In Heuristic Step 3, the IDSS has to deal with uncertainties surrounding vehicle capacity. We choose a BI&BA approach as it provides reasonable approximations in the given context and builds statistical models that calculate the estimated utilization of a vehicle based on historical ULD movement data. The IDSS uses this data in the heuristic to adjust the quantity of a movement alternative according to the expected vehicle's free capacity. The IDSS also considers that pallets can be stacked and thus only require one ULD position per stack. The models consider ULD types, vehicle types, and routes. The IDSS' rule base and system architecture are designed to easily select more accurate data instead of estimation models if they become available in the future (see [16] for further information on architecture design). The underlying vehicle capacities are explained to the user via the web interface (see Figure 2). The user is also notified if the system estimates no free capacity (see exclamation marks in Figure 2).

In Heuristic Step 4, conflicting objectives are addressed. In the concrete case, IDSS incorporates a multi-criteria decision-making model (i.e., simple additive weighting [SAW] also known as the weighted sum method [WSM]), which seeks to obtain a weighted sum of the performance rating of each alternative considering all attributes [11, 46]. Resulting from design workshops, we conceptualize three case-specific criteria: costs, compliance (the probability that an instructed movement will be executed), and benefit. The implemented prototype

system applies the following formula to calculate the value of each movement alternative m :

$$R_i^{WSM-Score} = \sum_{c=1}^C w_c r_{cj}, \text{ for } i = 1, 2, 3, \dots, m. \quad (1)$$

For the sake of simplicity, for each decision criterion c , we define four identical values mapping the visual representation through traffic lights in the user interface: green (1000), yellow (100), red (10), and grey (1). In the given case, we set the relative weight w_c of each criterion c to the same value. Recommendations with same calculated scores (see R_1 and R_5 in Table 1) are ordered by their scheduled time of departure.

Table 1. Example score calculations for recommendations.

	Criteria			Score
	Cost	Compliance	Benefit	
Rec.	$w_{cost} = 1/3$	$w_{compliance} = 1/3$	$w_{benefit} = 1/3$	
R_1	Green	Yellow	Yellow	400
R_2	Green	Grey	Green	667
R_3	Yellow	Yellow	Yellow	100
R_4	Yellow	Grey	Red	37
R_5	Yellow	Yellow	Green	400

The modular architecture of the implemented prototype system enables the modification or replacement of the evaluation component as new criteria requirements emerge (e.g., through a realignment of the business strategy, objectives, or values). Further, the IDSS explains the reasoning behind each assessment in the web interface.

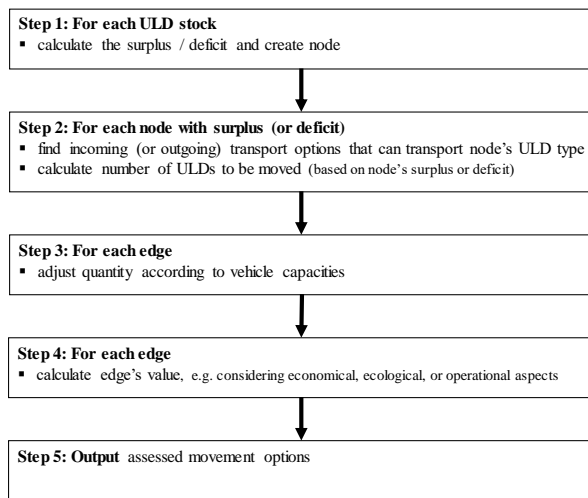


Figure 3. Flow chart of the proposed heuristic to generate repositioning alternatives for EUR.

Finally, in Heuristic Step 5, the set of valued repositioning alternatives is returned. Because the heuristic is implemented in a web-based IDSS, the repositioning alternatives can be requested via a web interface. Additionally, the user can click the “Create MR” button to create movement instructions directly from the recommendations.

The IDSS also provides functionalities to submit feedback. The responses reveal gaps in the rule base and refine solutions (see the development of the knowledge base in Figure 4 in Section 6).

6. Evaluation

Consistent with DSR guidelines [6, 25, 47], we evaluated the effectiveness and efficiency of the implemented prototype system, which serves as an expository instantiation of the proposed solution [22].

For this purpose, we conducted a two-sided evaluation design. First, we validated the developed solution’s capability to represent the human decision-making process. Second, we calculated the potential of the system’s recommendation in terms of reduced CO₂ emissions. Since the artifact has already been introduced and is used by ULD dispatchers in their daily routines, we were able to conduct the evaluation in a natural field setting.

Expert systems are typically evaluated by their ability to match human decision makers’ knowledge and inference skills. Thus, to demonstrate the usefulness of the IDSS in supporting ULD resource allocation, we calculated the share of instructed movements (by ULD dispatchers) that are also recommended by the IDSS. Figure 4 shows the development of this indicator for a large globally operating airline during a 31-month period (August 2014–February 2017) as an example. In addition, we began to collect data about the usage of the system and recorded which decisions were informed by the system. This data provides interesting insights regarding which decision situations benefit from the IDSS and which situations may require more human decision making.

For the second evaluation part, we calculated and compared CO₂ emissions from real instructed movements with CO₂ emissions from the recommendations generated by the IDSS. Figure 5 shows the real average CO₂ emission per unit in May 2017 by ULD dispatcher decision (red dotted line) and the potential average CO₂ emissions per unit for the IDSS recommendations (blue dashed line) in the same period.

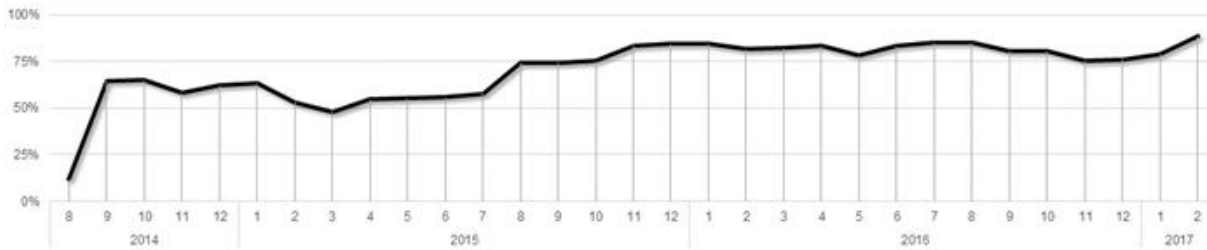


Figure 4. Share of recommended and instructed movements by all instructed movements.

The results show that the recommended repositioning alternatives can decrease (1) CO₂ emission per unit and (2) increases the availability of ULDs (i.e., reduce the average time that an empty ULD resides on an aircraft and is not serviceable). Further, we demonstrate that the pooling effect can be enhanced by comparing the average CO₂ emission per unit in relation to the number of airline carriers in the network. The gap is remarkable even if only two airline carriers are involved. When more carriers are included, the gap increases because the carriers can benefit from pooling opportunities as the network’s overlap grows (network effects). Saturation is also apparent in the given data sample as after integrating a certain number of airline carriers, no further improvements in average CO₂ savings per unit can be seen.

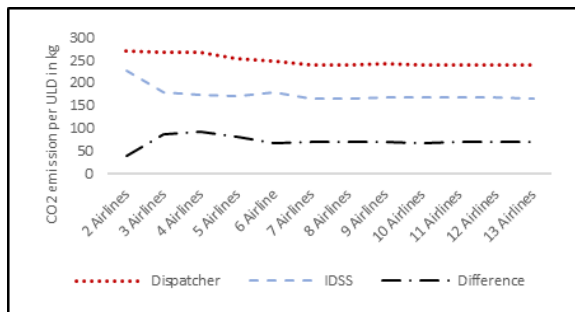


Figure 5. Comparison of CO₂ emission per ULD.

7. Conclusion

In this study, we elaborated the hitherto uninvestigated problem class of EUR. Furthermore, we proposed an IDSS that incorporates a heuristic for the given problem and combines artificial intelligence (i.e., rule-based expert system technology) with business analytics to address the peculiarities of the stated problem class. The proposed IDSS was developed to assist ULD dispatchers for ULD resource-allocation decisions. We evaluated the IDSS with real-world data and demonstrated that the proposed solution is both effective and efficient. In addition, our results also provide empirical evidence

regarding the positive economic and ecological impact of leveraging the potential of ULD pooling in multi-carrier networks.

This study makes three contributions. First, to the best of our knowledge, this is the first article describing the EUR problem in the air transportation industry. Second, we proposed a solution for the EUR problem, demonstrated an expository instantiation, and provided empirical evidence about its usefulness. Third, we revealed interesting insights about the pooling of ULD resources in the air cargo industry. As such, this study further clarifies the potential of ULD pooling in multi-carrier air cargo networks.

As with all research, our study has its limitations. First, we do not claim to provide a complete description of the stated problem class of EUR; rather, we want to encourage discussion. Because only a single case company was analyzed in detail in this study, our first suggestion for future research is to expand the number of companies examined.

Second, and in line with the increasing call for ECR approaches that incorporate pollution objectives [39], we analyzed CO₂ emissions and potential pollution reduction through increased leverage of pooling effects across airline carriers. Because we considered a rather short time frame, which nevertheless provided rich insights into this potential, further research should scrutinize this phenomenon over an extended period to gain deeper understanding of the dynamics involved.

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