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The Logistics of Volkswagen Development Center Applies Operations Research to Optimize Transshipments

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Abstract: Volkswagen Technical Development (TE) is responsible for all prototype development and prototype production for the Volkswagen brand and has its own logistics department (TE-Logistics). In the logistics of prototype parts in the automotive industry, new versions of prototype parts (henceforth referred to as updating parts) are repeatedly assembled in finished prototype vehicles. These updating parts are stored in warehouses and provided to an assembly site to ensure a timely assembly of the associated prototype vehicles. As the internal warehouse on the company site is not large enough for the high variety of parts, an additional external warehouse in the logistics network is needed. However, since prototype parts are unique, the allocation of the parts in suitable warehouses is particularly important. Currently, the various warehouses and the short-term demands repeatedly lead to reactive transshipments between the warehouses. To this end, we developed an approach for proactive transshipments based on a machine learning forecast and a mixed-integer linear programming model for planning proactive transshipments of parts between the warehouses to minimize transport costs. The model is based on a probability estimation of future demands to anticipate the expected optimal warehouse. After the model had revealed high improvement potential through a case study with real-world data in terms of costs and availability time compared to the current reactive process, we derived decision rules and developed a rule-based heuristic algorithm that leads to the optimal solution for the industrial use case. We implemented the heuristic with a spreadsheet-based decision support system (DSS) for daily transshipment planning. After successful test implementation, TE-Logistics estimated the annual cost savings for transport to be approximately 10%.

Keywords: lateral transshipments; multi-location inventory; proactive transshipments; pooling; automotive; prototype; logistics; decision support system; neural network; probability

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1. Introduction

The Volkswagen brand deploys more than 10,000 employees to pursue innovation in the Research and Technical Development departments (TE) at its site in Wolfsburg, Germany. The Pre-Production Center is responsible for the coordination and manufacturing of prototype vehicles of the Volkswagen brand [1]. These prototype vehicles are frequently presented to the public at automotive exhibitions or internally as concept or design models to the management board. The most considerable number of prototypes, however, is dedicated to technical tests before the pilot-run series of the specific car models. The Vehicle Development Department tests the finished prototype vehicles from the Pre-Production Center (for homologation, etc.) [2]. It often happens that parts in a finished prototype vehicle have to be replaced by other parts with a newer development status. These parts are henceforth referred to as updating parts.

TE-Logistics as part of the Technical Development is responsible for coordinating all logistics activities in the TE and is therefore responsible for the logistics of the updating parts. The updating parts were initially stored in an internal warehouse next to the assembly site. In recent times, the internal warehouse has been confronted with an increasing number of updating parts, which has led to considerably exceeding the internal warehouse capacity. This tremendous increase is mainly due to an increasing product variety worldwide, along with more extensive tests of mechanical functionality and an increase in electric vehicle components [3]. To ensure that all updating parts can be stored, the internal warehouse had to be expanded. However, there were no free warehouses on the plant site in Wolfsburg. For this reason, an external warehouse had to be rented. By renting an external warehouse, the decision arises regarding which parts should be stored in which warehouse. This task is further complicated as prototype parts are unique, i.e., they can only be available in one of the warehouses at a time. If one part from an external warehouse is demanded, it must be delivered immediately to the internal warehouse next to the assembly site where the part can be picked up by the employees of the Vehicle Development Department.

In TE-Logistics, the operational logistics planner is responsible for deciding on the allocation of parts and the transshipment. These decisions are determined by the available internal and external warehouse capacity as well as daily short-term orders from customers. Currently, the planning task is performed manually. To reduce transportation costs, the management is aiming for improved transshipment and parts allocation concepts.

In the literature on transshipment models, the transshipment of parts between warehouses, before a demand occurs, is known as a proactive lateral transshipment [4]. However, only Weckenborg et al. [5] consider the characteristics of unique prototype parts and conduct a numerical study. An estimation of the parts' future customers of each part was used to determine the best possible warehouse and decide on proactive transshipments. The demand probabilities for calculating the approximated future transshipment costs were assumed as given. In contrast to the numerical study, only two demand options are possible in the industrial use case. Either the parts are demanded by the Vehicle Development Department in the future, or they will be scrapped. Scrapping occurs when parts are not assembled due to other parts being used for the updating instead. However, the manual estimation of demand probabilities is associated with a high workload due to the large number of different parts. That is why we use neural networks that we trained with labeled historical data for the estimation of demand probabilities and combine it with an optimization model [6].

The main contribution of this paper is to adapt the mixed-integer linear programming model by Weckenborg et al. [5] to the industrial use case and to compare the current reactive approach in TE-Logistics with a proactive approach. We want to investigate whether proactive transshipments are advantageous for the industrial use case. The expected goals of the approach are diverse:

- Reduction in transport costs by dynamically allocating the individual parts to the various warehouses through proactive transshipments;
- Reduction in waiting times until customers can pick up the parts after the demand occurs, thus increasing the availability of updating parts for customers by avoiding reactive transshipments;
- Simplifying work for the operational planners.

In a case study with real-world data over a time period of 135 days, we showed that proactive transshipments in combination with a neural network for estimating demand probabilities can lead to a minimization of the transport costs of prototype parts. Based on the requirements and implementation conditions of the Volkswagen brand, we derive decision rules from the industrial case study and develop a rule-based heuristic algorithm that leads to the optimal solution in the specific case. Towards the end, we described the implementation of the heuristic and developed a decision support system (DSS) to support the planner in deciding on transshipments. The DSS should lead to a considerable advantage over a reactive approach for the logistics of prototype parts in the future.

The remainder of this article is structured as follows: Section 2 provides an overview of the related literature. A detailed description of the problem setting is given in Section 3.

The mixed-integer linear programming model is developed in Section 4. In Section 5, the introduction of a neural network is given to estimate demand probabilities. A case study based on historical real-world data as well as the development of the rule-based heuristic algorithm is conducted in Section 6. In Section 7 the DSS is introduced. The article concludes in Section 8.

2. Related Work

Our work is related to the stream of lateral transshipment. Paterson et al. [4] give an overview of the literature on lateral transshipments within an echelon and categorize them into reactive and proactive transshipments. Reactive transshipments are a reaction to situations in which a shortage has already occurred. Transshipments are aimed to satisfy demand from other locations. These types of problems are well-observed in the literature [7–22]. Proactive transshipments, on the other hand, take place before a demand for parts occurs and should therefore prevent future bottlenecks [8,23–34].

The review [4,35] identifies various distinguishing features of models and categorizes the existing literature. In addition to the distinction between reactive and proactive transshipment, a distinction is made between the number of echelons, parts, and locations, as well as the cost structure and the backorder option. Another distinguishing feature of transshipment models is the partial or complete pooling in the model. Our model is a proactive transshipment model with one echelon, any number of parts, and two different locations in which no backorders are allowed. It is a complete pooling and a model in which the costs are dependent on the transshipments.

Transshipment models are applied in various industries, such as the fashion industry [36–38], retail industry [39–41], and medical industry [42–47]. However, the focus of the studies can also be on the transportation mode. While most studies investigate vehicle transport, some authors specialize in container transshipment in shipping [48–50] or rail transport [51]. The use of transshipments is also analyzed in the special case of logistics service providers [52].

Our approach is close to the spare parts industry [53–57], as spare parts, just like prototype parts, are generally only available in small quantities and their absence causes high costs. In both cases, the parts are slow-moving. Paul and Yenipazarli [53] find that a proactive transshipment approach is particularly suitable for slow-moving parts.

The special characteristic of the model of Glazebrook et al. [58] from the automotive industry is the hybrid approach between reactive and proactive transshipments. If reactive transshipments are necessary to satisfy demand, a decision is made on additional proactive transshipments. In this case, proactive transshipments are parts that are transshipped regardless of demand in order to avoid future bottlenecks. Weckenborg et al. [5] have adapted this approach to the logistics of prototype parts. The unique parts, which cannot be stored in different inventory levels at different warehouses at the same time and cannot be reordered, differentiate the model from the existing literature. The focus is therefore on allocating the individual part to the best possible warehouse. The numerical study by Weckenborg et al. [5] showed that transport costs of 5–19% can be saved compared to a strictly reactive approach. However, the use of such an approach faces certain challenges in practice, such as the availability of all data. For this reason, we transfer the approach with assumptions to the industrial use case and then derive decision rules. Certain decision rules have already been established in the literature [59–63]. However, specific decision rules for unique parts are required for the industrial use case.

To conclude this section, no existing approach has yet been applied to an industrial use case in prototype parts logistics. Therefore, in the next section, we present the problem setting of prototype part logistics in the automotive industry and adapt the proactive transshipment model [5] to the industrial use case.

3. Problem Setting

The problem we are considering comprises various elements. To this end, this section describes in detail the characteristics of the assembly process of updating parts, the logistics network, the transports, and the prototype parts.

In the life cycle of prototype vehicles, updating parts have to be assembled in a vehicle. The time when updating parts are assembled in the vehicle is decided at short notice and is therefore unknown. In addition, the responsible engineers can pick up individual parts from the internal warehouse for investigations without them being installed in a vehicle. The time of demand from the engineers is also unknown. As soon as a demand for an investigation or for assembly has been received, the parts must be provided as quickly as possible so that the development process is not affected. The aim is to minimize the costs and time for the supply of parts through an optimized allocation concept.

Regarding the logistics network, TE-Logistics operates a central hub where all prototype parts for Technical Development are being delivered. The central hub only operates as a receiving point and has no storage capacity for updating parts. The updating parts are ordered by the engineers and delivered by the suppliers. Each part is unique and cannot be reordered. After delivery to the hub, the parts are transshipped to the warehouses. Due to the increasing number of parts, an external warehouse had to be rented on a long-term basis in addition to the internal warehouse, i.e., the network structure cannot be adapted at short notice. Both warehouses have limited capacity and are used exclusively for the storage of updating parts. All incoming parts in the hub are preferably transshipped to the internal warehouse. If the internal warehouse is fully utilized, the parts are transshipped directly to the external warehouse. As the parts are unique, they cannot be stored in both warehouses at the same time. As a result, it is not possible to store all parts in the internal warehouse in the immediate surroundings of the assembly site. If parts from an external warehouse are demanded, they have to be transshipped to the internal warehouse to be picked up by the customer. These transshipments cause high costs and waiting times until customers can pick up the parts.

Due to the short-term nature of demands and the necessary quick provision of parts, the transshipments in the prototype logistics cannot be planned in advance, as it can only take place if demands occur. For this reason, it is not possible to consolidate several orders over a longer period of time. The demand for parts from the external warehouse is consolidated for one day before the parts are transshipped. The consolidation of demands for parts from the external warehouse results in waiting times for the assembly or investigation of updating parts, which must be avoided. The task of the logistics planner is to plan the transshipment between the warehouses at short notice in order to provide the demanded parts.

All transshipments are carried out by an external logistics service provider (LSP) and are available unlimited at short notice. For each transshipment, fixed transport costs are incurred, depending on the connection between the two warehouses. The transport costs are independent of the utilization of the vehicles. A vehicle with low capacity utilization incurs the same costs as a fully utilized vehicle. All internal transports (hub to internal warehouse) are integrated into a shuttle transport and all transshipments between the internal and external warehouse are carried out pairwise with integrated return transport.

If prototype parts are not used for updating prototype vehicles or are no longer required for investigations, they will be scrapped. This can occur if parts have already been further developed with newer versions available with an updated development status and the parts with the older development status have not yet been assembled. However, there are no fixed rules regarding the point at which a part can be scrapped. The decision on scrapping cannot be made by the logistics planner, but only by the engineer. The scrapping of parts can be carried out in the internal and external warehouse, while the provision of parts for assembly or investigation is only possible in the internal warehouse.

As soon as a part from the external warehouse is requested for assembly or investigations, the part is transshipped from the external warehouse to the internal warehouse.

However, it remains unknown when the part will be requested, and the final customer of the part will only be known when the order is placed. This process represents a reactive transshipment approach. The logistics network of the assembly site for updating parts is summarized in Figure 1.

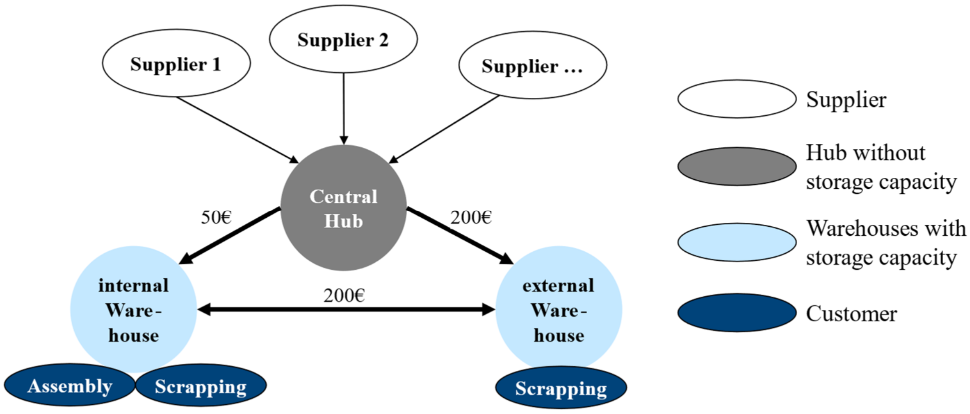

Figure 1. Logistics network of the assembly site of updating parts.

In the following section, we provide the modifications in the mixed-integer linear programming model in more detail and describe the calculation of the approximated future transshipment costs. In Section 5, we introduce how the demand probabilities for the model can be generated in practice by a neural network.

4. Operations Research Model

This section presents the proactive transshipment model. It is based on the model of Weckenborg et al. [5] and was adapted to the industrial use case of the Volkswagen brand. To this end, further assumptions of the approach are justified in Section 4.1. In Section 4.2, the proactive approach is introduced. The mathematical problem formulation is given in Section 4.3.

4.1. Assumptions

Our modeling approach is based on further assumptions regarding the parts, the transshipments, and the warehouses:

- Parts are all the same size. This assumption is necessary because the measurements of the different parts are not included in the IT systems. For this reason, all parts have an unspecified standard size. The capacities of the vehicles and warehouses can therefore only be indicated by the number of parts. Due to the simplification, the capacities and utilization of the vehicles and warehouses cannot be determined exactly, as the measurements of the parts are unknown to the model. However, the number of parts for the capacity restrictions was determined on the basis of averaged part measurements;
- Transportation times of transshipments are neglected. Due to the transshipment of the demanded parts on the same day and the related provision at the customer, the transportation time has no influence on the planning problem;
- Warehouses maintain limited staff capacity, i.e., storing and picking parts is limited to a prespecified amount per period. Each storing and picking operation is assumed to consume the identic proportion of capacity;
- Costs of transshipments are deterministic and known in advance. The LSPs are assumed to operate vehicles of homogeneous capacity.

4.2. Proactive Approach

In the proactive approach, demand probabilities Q_{xi} is included in the transshipment decision, which indicates how likely it is that a part will be demanded by the respective customers $N^{\text{Customers}}$ in the future. The generation of the demand probabilities is described in detail in Section 5. The demand probability Q_{xi} and the transshipment costs rate r_{ij}^{T} between the warehouses and customers is used to precompute the approximated future transshipment costs r_{xi}^{F} for each part x and each warehouse i in Constraints (1).

$$r_{xi}^{\text{F}} = \sum_{j \in N^{\text{Customers}}} Q_{xi} \cdot r_{ij}^{\text{T}} \ \forall x \in P;\ i \in N^{\text{Warehouses}} \tag{1}$$

Approximated future transshipment costs can serve as an indicator for the best possible warehouse and be included in the transshipment decision. However, the approximated future transshipment costs are not necessarily incurred and only serve as an indicator. When a transshipment is carried out between two warehouses, the full transshipment cost rate is charged for the transport vehicle, regardless of its utilization. Therefore, if the transport vehicle is not fully utilized, several parts may be transshipped between the warehouses using remaining capacities without incurring the cost rate multiple times.

4.3. Mathematical Model

In this section, the sets and indices, parameters, and decision variables for the proactive model are defined in Table 1. In addition, the objective function and constraints are presented. The model is based on the model by Weckenborg et al. [5]. Adjustments to the model were made based on the industrial use case and the resulting requirements. In the industrial use case, a distinction must be made in the connections between the warehouses. The newly introduced Set L contains all possible connections. However, some connections force an integrated return transport. A Set G has been introduced for these connections. The model formulation had to be adapted due to the introduction of the sets. In addition, Constraints (8) are introduced.

Table 1. Definitions of sets and indices, parameters, and decision variables for the proactive model.

Sets and indices	
$i, j, k \in N$	Set of all locations
$N^{\text{Warehouses}}$	Set of all warehouses, with $N^{\text{Warehouses}} \subseteq N$
$N^{\text{Customers}}$	Set of all customers, with $N^{\text{Customers}} \subseteq N$
L	Set of all tuples of warehouses and customers that are subject to a direct precedence relationship $(k, j) \in L$
G	Set of all tuples of warehouses that are subject to a direct precedence relationship for transports with obligatory return transport $(k, j) \in G \subseteq L$
$x \in P$	Set of parts
Parameters	
B_{xk}	Stock of part x in warehouse k, parameterized in $\mathbb{B}$
D_{xk}	Demand of part x by customer k, parameterized in $\mathbb{B}$
c_k^{Storing}	Capacity of warehouse k for storing parts, parameterized in $\mathbb{N}_0$
c_k^{Handling}	Capacity of warehouse k for handling parts, parameterized in $\mathbb{N}_0$
c^{Vehicles}	Capacity of vehicles for transporting parts, parameterized in $\mathbb{N}_0$
r_{kj}^{T}	Cost rate for traveling locations (k, j), parameterized in $\mathbb{R}_0^+$
r_{xi}^{F}	Approximated future transshipment costs for delivery of part x if stored in warehouse i, parameterized in $\mathbb{R}_0^+$
ε	A sufficiently small number, parameterized in (0, 1]
Decision variables	
$z_{xkj} \in \mathbb{B}$	$\begin{cases} 1, & \text{if part } x \text{ is transshipped between locations } (k,j) \\ 0, & \text{otherwise} \end{cases}$
$w_{kj} \in \mathbb{N}_0$	Number of vehicles traveling (k, j)
$R^{\text{T}} \in \mathbb{R}_0^+$	Sum of realized transshipment costs
$R^{\text{F}} \in \mathbb{R}_0^+$	Sum of approximated future transshipment costs

The objective function and the constraints are given below:

$$\min R^{\mathrm{T}} + \varepsilon \cdot R^{\mathrm{F}} \tag{2}$$

$$\sum_{(k,\, j)\, \in\, L\ |\ k=i} z_{xkj} \leq B_{xi} + \sum_{(j,\, k)\, \in\, L\ |\ k=i} z_{xjk} \quad \forall x \in P;\ i \in N^{\mathrm{Warehouses}} \tag{3}$$

$$D_{xi} = \sum_{(j,\, k)\, \in\, L\ |\ k=i} z_{xjk} \quad \forall x \in P;\ i \in N^{\mathrm{Customers}} \tag{4}$$

$$c_i^{\mathrm{Storing}} \geq \sum_{x\, \in\, P} B_{xi} + \sum_{x\, \in\, P} \sum_{(j,\, k)\, \in\, L\ |\ k=i} z_{xjk} - \sum_{x\, \in\, P} \sum_{(k,\, j)\, \in\, L\ |\ k=i} z_{xkj} \quad \forall i \in N^{\mathrm{Warehouses}} \tag{5}$$

$$c_i^{\mathrm{Handling}} \geq \sum_{x\, \in\, P} \sum_{(j,\, k)\, \in\, L\ |\ k=i} z_{xjk} + \sum_{x\, \in\, P} \sum_{(j,\, k)\, \in\, L\ |\ k=i} z_{xkj} \quad \forall i \in N^{\mathrm{Warehouses}} \tag{6}$$

$$c^{\mathrm{Vehicles}} \geq \frac{1}{w_{kj}} \sum_{x\, \in\, P} z_{xkj} \quad \forall (k,\ j) \in L \tag{7}$$

$$w_{kj} = w_{jk} \quad \forall (k, j) \in G \tag{8}$$

The objective function (2) minimizes the realized costs for transshipments and the approximated future transshipment costs. The parameter ε is chosen to be sufficiently small in order not to influence the primary objective of minimizing transport costs. By minimizing the approximated future shipping costs, further parts are proactively transshipped in addition to the reactive transshipments in the already commissioned transports.

Constraints (3) ensure that parts can be transshipped to another warehouse or can be picked up from a warehouse only if they are already in the warehouse or are transshipped there. Constraints (4) ensure that every order is satisfied. If demanded parts are stored in the external warehouse, they have to be transshipped in the same period. Constraints (5) ensure that the capacities of the warehouses are not exceeded. Constraints (6) ensure that the handling capacity is not exceeded by the number of incoming and outgoing parts within a warehouse. Constraints (7) ensure that enough vehicles are used for transshipments so that the capacities of the individual vehicles are not exceeded. Constraints (8) ensure that there is also a return transport for each transport from the internal to the external warehouse.

$$R^{\mathrm{T}} = \sum_{(k,\, j)\, \in\, L} w_{kj} \cdot r_{kj}^{\mathrm{T}} \tag{9}$$

$$R^{\mathrm{F}} = \sum_{x\, \in\, P} \sum_{i\, \in\, N^{\mathrm{Warehouses}}} r_{xi}^{\mathrm{F}} \cdot \left(B_{xi} + \sum_{(j,\, k)\, \in\, L\ |\ k=i} z_{xjk} - \sum_{(k,\, j)\, \in\, L\ |\ k=i} z_{xkj} \right) \tag{10}$$

To this end, Constraint (9) calculates the realized costs R^{T}. Constraint (10) calculates the approximated future transshipping costs R^{F} considering the approximated cost rate for future transshipments. This constraint incentivizes proactive transshipments of parts to the warehouse with a lower approximated cost rate for future customer delivery.

$$w_{kj} \in \mathbb{N}_0 \quad \forall (k,\ j) \in L \tag{11}$$

$$z_{xkj} \in \mathbb{B} \ \ \forall x \in P; (k,\ j) \in L \tag{12}$$

$$R^{\mathrm{T}} \in \mathbb{R}_0^{+} \tag{13}$$

$$R^{\mathrm{F}} \in \mathbb{R}_0^{+} \tag{14}$$

Constraints (11)–(14) define the range of decision variables.

5. Neural Network for Estimating the Demand Probability

In the numerical study by Weckenborg et al. [5], the demand probability of each part was assumed to be given as a planner's expert estimate. However, the manual estimation of demand probabilities is associated with a high workload due to the large number of different parts. For this reason, a neural network is used to estimate the demand probability of each part for every customer. In the industrial use case of the updating parts, both the assembly and the scrapping of a part can occur at a certain percentage rate. This demand probability should be estimated by the neural network. In Figure 2, various features were set up for the neural network, which are assumed to influence the decision regarding assembly or scrapping.

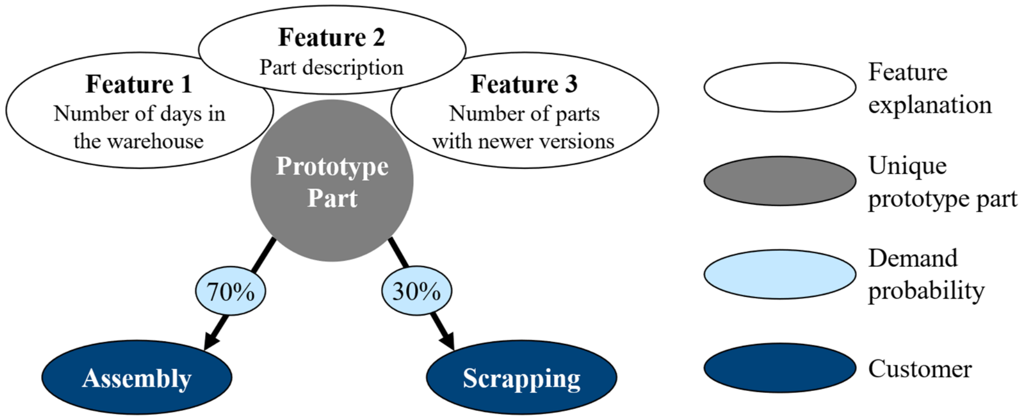

Figure 2. Overview of generating demand probabilities based on all relevant features.

The demands of the last 5 years were used to train the neural network. For each demand, the attributes of the features from Figure 2 were determined at the time of the demand. The attributes of the features were either taken from the Enterprise Resource Planning System (ERP) or have been generated retrospectively. This generated approx. 200,000 labeled data records with the purpose of assembly or scrapping. Table 2 shows two exemplary prepared and labeled data records.

Table 2. Exemplary prepared and labeled data records from the ERP system.

	Feature			Label
	1	**2**	**3**	
Examples	6	Control unit	0	Assembly
	350	Steering wheel	2	Scrapping

In the first example in Table 2, a control unit was demanded for assembly. At the time of the demand, the part had been in the warehouse for 6 days and there were no parts with newer versions in any of the warehouses. In the second example, a steering wheel was scrapped. At the time of the scrapping decision, the part had been in the warehouse for 350 days and there were two parts with newer versions in the logistics network.

The data sets were divided into a training set (80%) and a test set (20%) [64,65]. The neural network was programmed in Python with the sklearn library. The programming of the neural network model is illustrated in the Equation (15).

$$\begin{gathered} MLPClassifier(hidden\_layer\_sizes = (64,\ 32),\ \max_{iter} = 1000,\ random_{state} \\ = 1,\ early\_stopping = True,\ n\_iter\_no\_change = 10) \end{gathered} \tag{15}$$

After training the neural network, the trained neural network was applied to the test set. The estimation is evaluated according to the classification report [64]. The result is shown in Table 3.

Table 3. Classification report of the neural network.

	Precision	Recall	F1-Score	Support
Assembly	0.88	0.84	0.86	11,215
Scrapping	0.94	0.95	0.95	28,205
Accuracy			0.92	39,420
Macro avg.	0.91	0.90	0.90	39,420
Weighted avg.	0.92	0.92	0.92	39,420

The classification report shows that 94% (precision for scrapping) of all records labeled as scrapping were correctly identified as scrapping by the neural network. At total of 6% of the records were incorrectly estimated as assembly. On the other hand, 95% of all records where the model estimated scrapping matched the records labeled as scrapping (recall for scrapping). This means that 5% were identified as scrap, although they were still required for assembly. An overall accuracy of 92% was achieved. Various neural networks were trained with different combinations of the features and their accuracy was validated in the test set. A combination of all three features from Figure 2 resulted in the highest accuracy.

6. Case Study

In this section, a case study is conducted using real-world data from TE-Logistics to evaluate the effectiveness of the proposed approach. Section 6.1 presents the study's design regarding warehouse structure, transport and handling capacities, and costs as well as the introduction of the reactive model serving as a benchmark and the computational setup. The results of the case study are presented in Section 6.2. In Section 6.3, a rule-based heuristic algorithm is developed and compared with the mixed-integer linear programming model.

6.1. Study Design, Data, and Computational Setup

This section presents the design of the study and the used data. Furthermore, the sequential planning approach is described. The study is based on historical data to evaluate the proactive transshipment approach with the introduction of demand probabilities.

The network for the case study is based on the industrial use case of updating parts of the Volkswagen brand (see Figure 1). The customers $N^{\text{Customers}}$ are the assembly and scrapping. All parts are delivered to the central hub by the suppliers. However, the hub has no storage capacity. The parts can be transshipped from the hub to either the internal or external warehouse. Both warehouses have a limited storage capacity c_i^{L} and handling capacity c_i^{Handling} (see Table 4). All transports are carried out by an external service provider and have unlimited availability. Fixed transshipment costs are incurred for each transport R_{ji}^{fix} (see Figure 1). All internal transports (hub to internal warehouse) are integrated into a shuttle transport with further destinations in the Technical Development. All transports between the internal and external warehouse are carried out directly with integrated return transport. The return transport is integrated in the transport costs of Figure 1. A fixed capacity c^V of 1000 parts for all vehicles is assumed. Table 4 shows the storage and handling capacities as well as the allocation of the 38,379 parts that were initially in the logistics network to the warehouses.

Table 4. Characterization of the logistics network in the case study.

Warehouse	Capacity [Parts]	Initial Available Inventory [Parts]	Handling Capacity [Parts]
1 (Hub)	0	0	Unlimited
2 (Internal warehouse)	40,000	30,000	5000
3 (External warehouse)	Unlimited	8379	5000

For the case study, the orders of a time period of 135 working days from the ERP system are used. Each working day is equal to one period in the model. We depicted the stock at the beginning of the time period and extracted the daily incoming and demanded parts from the ERP system. As this is daily operational planning process and the demands are only available to the planner in the respective period, the periods are solved sequentially. The incoming parts of the respective period are added to the stock B_{ix} of the hub prior to each new period. We report the total number of demands and incoming parts over all periods and the average and standard deviation (Ø (σ)) per period in Table 5.

Table 5. Overview of demands and incoming parts in the case study.

		Over All Periods	Average per Period Ø (σ)
Demand	Assembly	21,806	161.5 (77.1)
	Scrapping	10,685	79.1 (107.4)
	Total	32,491	240.7 (140.7)
Incoming parts		41,567	309.9 (188.0)

To determine the demand probabilities for calculating the approximated future transshipment costs, the neural network from Section 5 is used sequentially. In each period, the features are generated according to the stock of the current period and are provided to the trained neural network. This generates a demand probability for each part in stock.

The proactive approach is compared with the reactive approach. The costs of the reactive approach are also modeled according to the currently implemented transshipment rules. For this purpose, we adapt the previously presented model formulation. The reactive model consists of the objective function (16), the constraints (3)–(9), and (11)–(13), as no demand probabilities are taken into account. In the objective function (16), both the transport costs and the number of parts to be transshipped are minimized. The minimization of the transshipped parts is required in order to map the current transshipment behavior in the model. Parts are only transshipped if there is not enough storage capacity in the warehouse or if parts are requested from another warehouse.

$$\min R^{\mathrm{T}} + \varepsilon \cdot \sum_{x \in P} \sum_{(j,\, i) \in L} z_{xji} \tag{16}$$

One period of the model for both the reactive and the proactive approach is shown in Figure 3 and is repeated sequentially for all periods. Both models are implemented in Python 3.10.9 and are solved using Gurobi 11.0.1 on machines with 64 GB RAM and eight threads of an Intel Xenon Platinum 8180 CPU at 2.5 GHz.

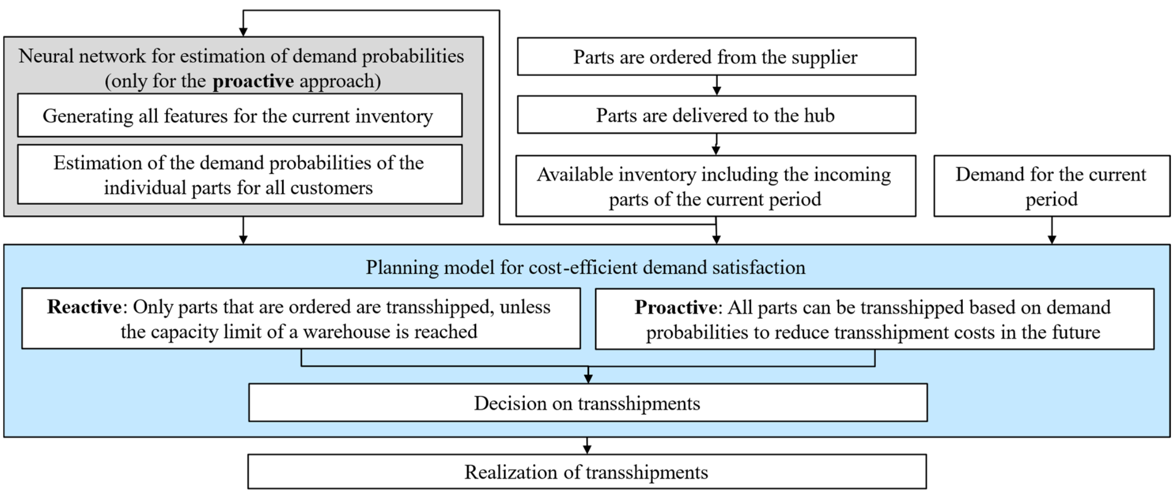

Figure 3. Schematic overview of the sequential process. The planning model is highlighted in blue and the neural network in grey.

6.2. Results of Reactive and Proactive Approach

In this section, the results of the proactive approach are presented and compared to the reactive approach. We report the costs, transshipment decisions, and the implications of the sequential planning approach. All periods are solved to optimality in terms of costs. Repeating the case study leads to the same optimal solution.

The results of the cost of the case study are summarized in Table 6. We report the overall cost of all 135 periods and the average and standard deviation (Ø (σ)) of the cost per period for the reactive and the proactive approach. Further, we report on the percentage deviation between the reactive and proactive approach.

Table 6. Comparison of the cost and the percentage saving in different approaches.

	Transshipment Cost [€]		Deviation between the Reactive and Proactive Approach [%]
	Reactive Approach	Proactive Approach	
Over all periods	33,400	29,900	−10.5
Average per period Ø (σ)	247.41 (24.7)	221.48 (60.3)	

The results from Table 6 show that the proactive approach is more cost-efficient than the reactive approach. An average of 10.5% of costs are saved per period compared to the reactive approach. The representation of the cumulative cost distribution over time is shown in Figure 4.

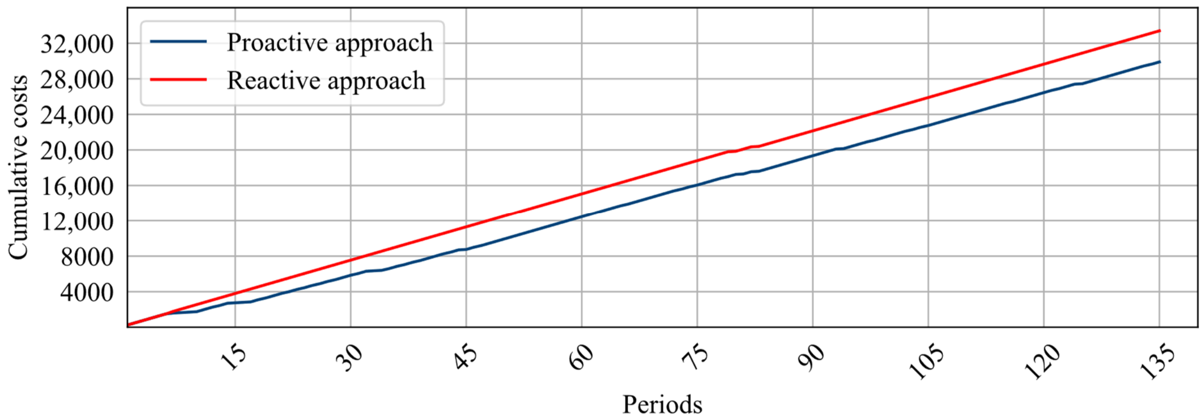

Figure 4. Cumulative cost per period.

The costs in the first periods are the same for the reactive and the proactive approach, as both approaches start with the same initial situation. After a few periods, however, costs are saved in the proactive approach compared to the reactive approach, as the parts are allocated to warehouses with lower approximated future transshipment costs. This leads to lower transshipment costs over all periods. In general, each part has the lowest approximated future transshipment costs in the internal warehouse, as delivery and scrapping are carried out there without transshipment costs. For this reason, the approximated future transshipment costs for each part in the internal warehouse are 0. Therefore, each part should be stored in the internal warehouse if possible. Figure 5 shows the utilization of the internal warehouse over time. It can be seen that the utilization of the internal warehouse increases to almost 100% within a few periods.

However, parts with a high probability of being scrapped have lower approximated future transshipment costs in the external warehouse than parts with a high probability of being assembled. For this reason, the model with the proactive approach stores the parts with the highest probability of scrapping in the external warehouse if the capacities of the internal warehouse are fully utilized. Only in the proactive approach, the approximated future transshipment costs are taken into account in the transshipment decision, so that the parts can be transshipped to the optimum warehouse in the first periods.

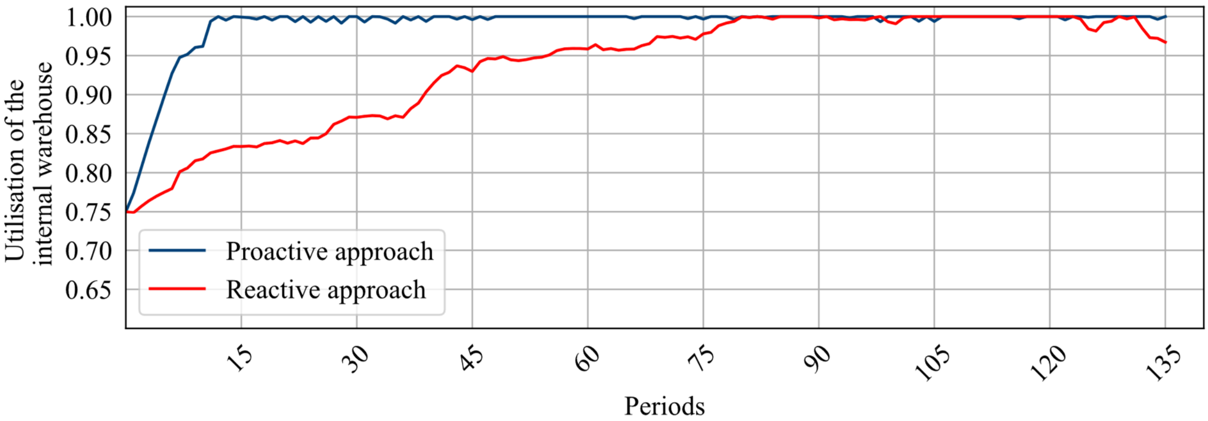

Figure 5. Warehouse utilization of the internal warehouse per period.

In Figure 6, we have graphically illustrated the proportion of optimally allocated parts per period. We have determined the evaluation of the optimal allocation in a period using a separate optimization model. The sequential approach and the minimization of the approximated future transshipment costs with proactive transshipments have almost achieved the optimal warehouse allocation within the first 10 periods. As no approximated future transshipment costs are used in the reactive approach, the proportion of optimally allocated parts stagnates between 70% and 80%.

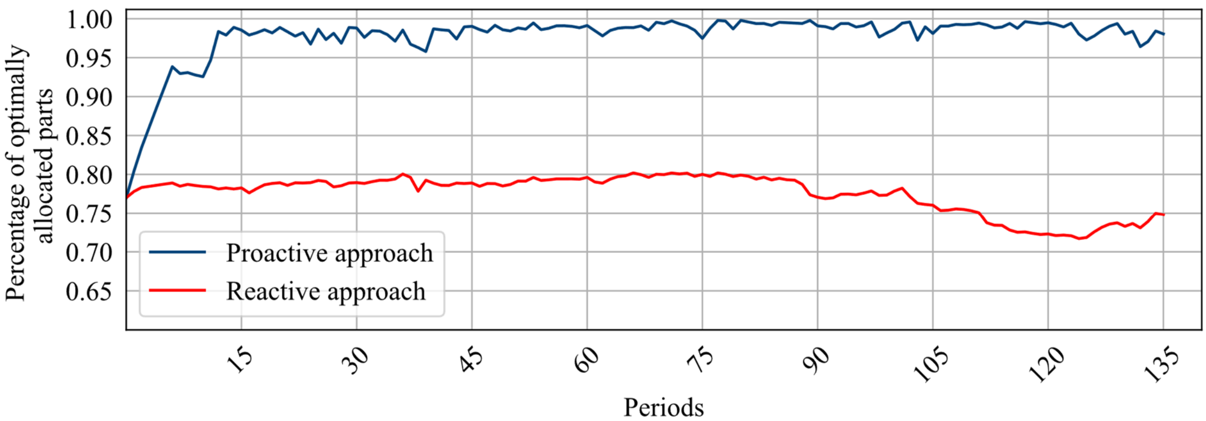

Figure 6. Percentage of optimally allocated parts per period.

Figures 5 and 6 thus explain the reduced costs in Figure 4 as soon as the utilization of the internal warehouse increased together with the proportion of optimally allocated parts. Figure 7 shows the number of parts that had to be transshipped to satisfy demand. In the reactive approach, parts had to be transshipped from the external to the internal warehouse in each period. In the proactive approach, however, parts only had to be transshipped in 100 out of 135 periods.

The number of transshipped parts that are independent of demand is shown in Figure 8.

In the first periods of the proactive approach, a large number of parts were transshipped proactively. Whenever no transshipment was necessary to satisfy demand and the internal warehouse was fully utilized, the incoming parts were transshipped to the external warehouse. As soon as a demand for assembly with parts from the external warehouse occurred, additional parts with a high assembly demand probability were transshipped from the incoming parts of the previous periods to the internal warehouse. Parts from the internal warehouse with a higher probability of being scrapped were transshipped from the internal to the external warehouse. For this reason, peaks of transshipped parts repeatedly occur in Figure 8 after periods in which transshipments were avoided. In the reactive approach, parts are only transshipped regardless of demand if the minimum cost solution of the period cannot be realized due to capacity bottlenecks in a warehouse, as is the case from period 80 onwards (see Figure 8).

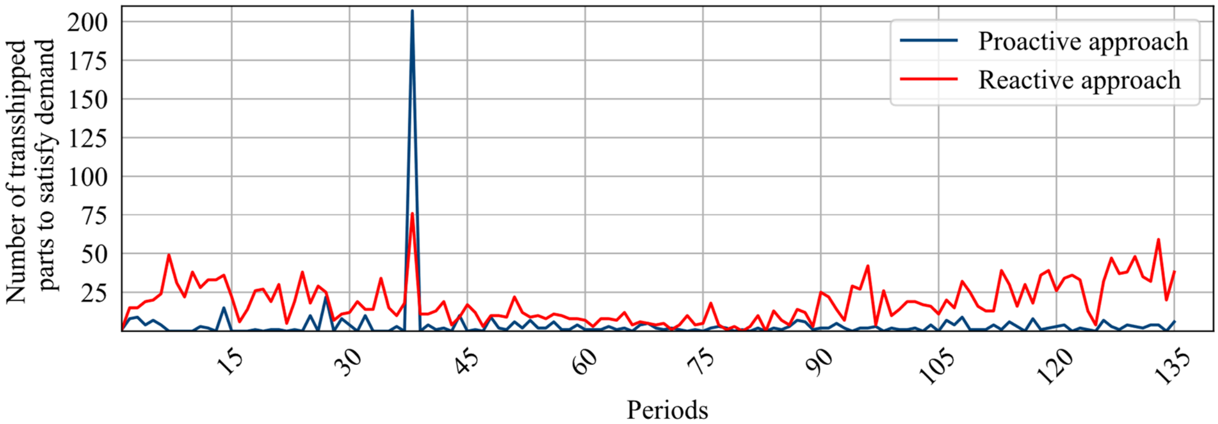

Figure 7. Number of transshipped parts to satisfy demand per period.

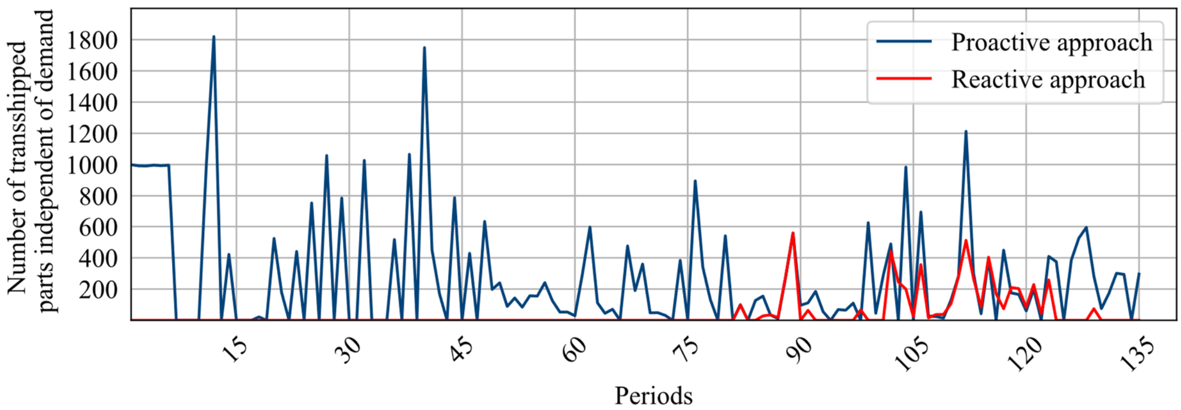

Figure 8. Number of transshipped parts independent of demand per period.

Table 7 reports further key figures with average values per period for both approaches. The deviation between the reactive and proactive approach is also reported.

Table 7. Key figures with average values per period.

	Average per Period Ø (σ)		Deviation between the Reactive and Proactive Approach
	Reactive Approach	Proactive Approach	
Number of transshipments between the internal and external warehouse	0.99 (0.12)	0.74 (0.45)	−24.3%
Number of transshipped parts to satisfy demand	18.2 (13.3)	4.1 (17.9)	−77.5%
Number of transshipped parts independent of demand	40.7 (104.3)	282.9 (367.9)	695.1%
Utilization of the internal warehouse [%]	0.94 (0.07)	0.99 (0.03)	5.3%

Of particular interest is the reduction of the number of transshipped parts to satisfy demand. From the reduction in parts by an average of 77.5%, it can be interpreted that significantly more parts were already stored in the internal warehouse at the time of demand for assembly. At the same time, this means that in the proactive model, the waiting times until customers can pick up the parts have decreased for a large number of parts. The engineers and the assemblers have to wait for transshipments from the external to the internal warehouse in fewer cases and can therefore pick up the ordered parts more quickly than in the reactive approach.

The average computational time per period for the reactive and proactive approach is shown in Table 8. The result shows that solving the reactive approach takes less time than solving the proactive approach. However, the solution time for the proactive approach is also appropriate for operational use.

Table 8. Overview of the average computation time per period and standard deviation.

Reactive Approach Ø (σ) Computation Time [s]	**Proactive Approach Ø (σ) Computation Time [s]**
1.3 (0.2)	1.6 (0.2)

6.3. Development of a Rule-Based Heuristic Algorithm

From this case study, certain decision rules can be derived for the storage of incoming parts and for the transshipment of parts between the internal and external warehouse for the specific industrial use case. An overview of the derived decision rules can be found in Figure 9.

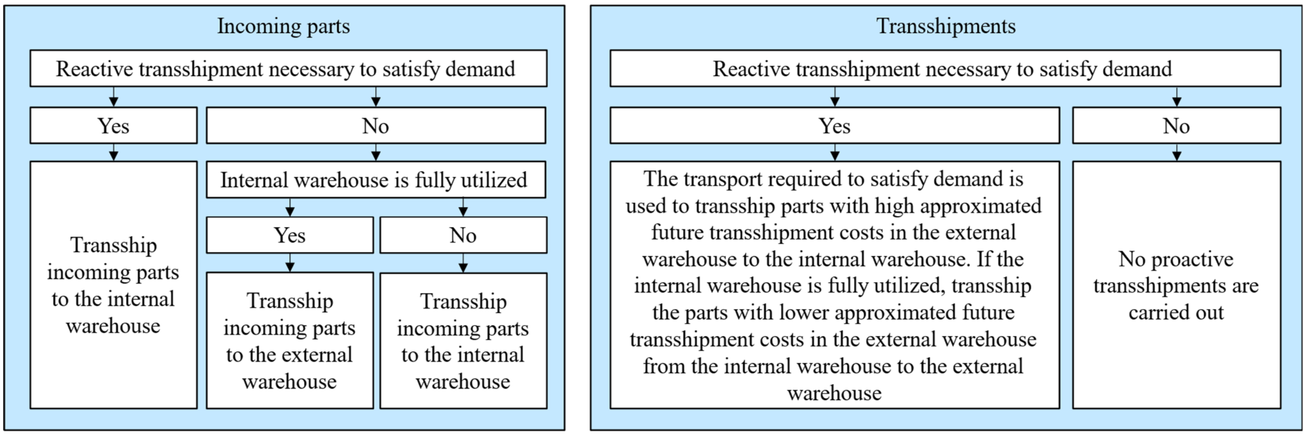

Figure 9. Identification of decision rules from the case study.

Figure 9 shows that the decision on proactive transshipments depends on the situation if parts have to be transshipped reactively in the period to satisfy demand. If parts have to be transshipped reactively and the internal warehouse has free capacity at the same time, the parts with the highest approximated future transshipment costs in the external warehouse are also transshipped from the external to the internal warehouse. If the internal warehouse is fully utilized, parts can be exchanged. Parts in the internal warehouse with lower approximated future transshipment costs in the external warehouse are exchanged with parts in the external warehouse with higher approximated future transshipment costs in the external warehouse through transshipments. These decision rules based on the decision tree in Figure 9 were programmed in Python as a rule-based heuristic algorithm and applied to the case study data. The pseudocode is provided in Appendix A. Table 9 compares the result of the mixed-integer linear programming model with the result of the rule-based heuristic algorithm.

Table 9. Comparison of the total cost in different proactive approaches.

Transshipment Cost of the Proactive Approaches [€]	
Mixed Integer Linear Programming Model	**Rule-Based Heuristic Algorithm**
29,900	29,900

It is interesting to see that the costs with the rule-based heuristic algorithm are equal to the optimal solution of the mixed integer linear programming model. However, when analyzing the results, it was noticed that different decisions were made and therefore different costs resulted in 4 out of 135 periods. This result can be explained by the partially equal demand probabilities of different parts. If the remaining capacity from reactive transports is used for further proactive transshipments, it is possible that not all parts with the same demand probability can be transshipped. Consequently, in both models, it is random which parts with the same demand probability are transshipped. As a result, a part was demanded in a period of the MILP that was not transshipped in the previous period due to the described problem. In contrast to the heuristic, this made another reactive transshipment necessary. On the other hand, reactive transshipments were also avoided in the MILP compared to the heuristic in other periods.

Basically, the comparison of the mixed-integer linear programming model with the rule-based heuristic algorithm has shown that the derived decision rules implemented in the heuristic match the optimal solution of the mixed-integer linear programming model.

7. The Decision Support System

After presenting the results to the managers of TE-Logistics, the aim of using the potential of the model-based planning approach to support operational planners in their transshipment decisions was expressed. The next step was to develop and provide a decision support system (DSS). To design the future process and tool, we organized various workshops to collect the requirements and ideas of the planners and management. The DSS should be implemented in Python, depending on the internal approval processes for IT systems. Information is provided to the planners via Microsoft Excel, as the planners are familiar with its functionality.

In addition, requirements were identified by TE-Logistics that a comprehensive DSS should fulfill. Compared to the MILP and rule-based heuristic algorithm, these requirements represent additional restrictions for the resulting DSS.

Requirement (R.1). An estimate of the capacity utilization or the free storage locations in the network should be made daily by the planner, as the dimensions of the prototype parts and the storage areas in the system are not known. Only the planner has an overview of free storage spaces in the internal and external warehouse and knows the dimensions of the prototype parts.

Requirement (R.2). Decisions made by the DSS do not have to be adopted by the planner. If the planner decides against implementing the recommendation, this decision should be taken into account for future decision support. A distinction must be made as to whether a transshipment was rejected due to short-term restrictions such as limited warehouse, employee, or vehicle capacities or due to strategic company policy decisions, such as ensuring a minimum waiting time for pick up special parts when ordering. Accordingly, planners should not be repeatedly confronted with transshipment proposals that have been determined by strategic decisions. For this reason, long-term decisions should be adopted and retained by the system for decision support.

Requirement (R.3). The data from ERP should be forwarded to the DSS without manual effort. We therefore have stored the required data in the form of stock levels in a data warehouse, from where it can be imported into the DSS. The data are updated every night in order to process the latest information. In addition, the planner has the option of manually updating the ERP data in order to make it available to the DSS.

Requirement (R.4). A user-friendly interface for the decision support is required. A clear interface should improve user acceptance of the system. Based on R.2, the planner is provided with various filter options for decision support. Accordingly, it should be possible to hide parts that should not be transshipped due to previous strategic decisions.

Requirement (R.5). Various key figures should provide planners and management with an overview of the distribution of parts across the warehouses.

Based on the results of the rule-based heuristic algorithm, which led to the optimum solution, the decision rules from Section 6.3 are introduced for the future transshipment decision process. A suitable DSS for the planner was developed according to the decision rules. The transshipment decision process is shown in Figure 10.

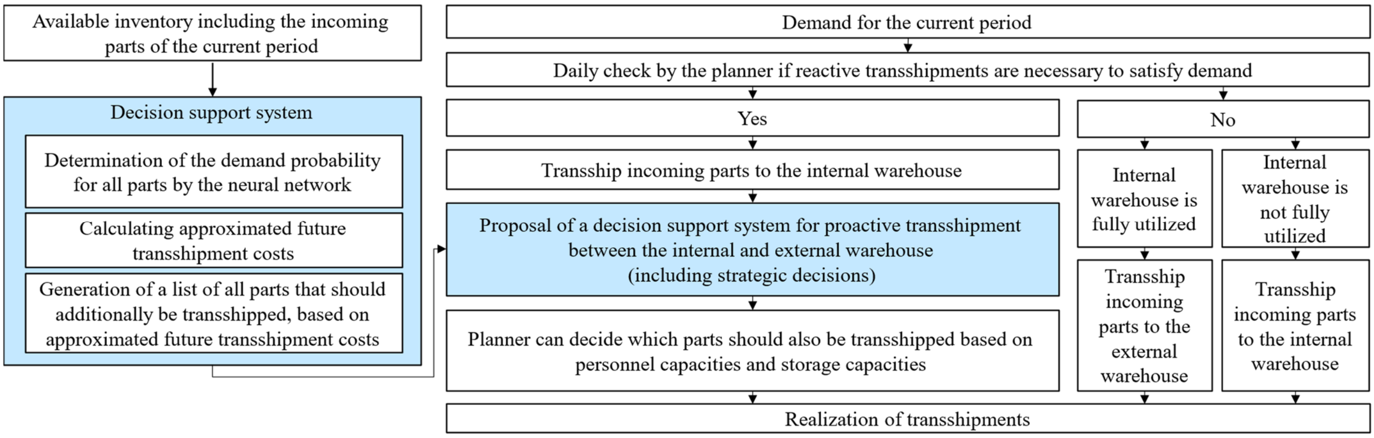

Figure 10. Transshipment decision process based on the rule-based heuristic algorithm in combination with the DSS. The DSS is highlighted in blue.

Figure 10 shows that the planner receives the information on demand on a daily basis. The planner then checks whether reactive transshipments are necessary to satisfy the demand. If the demanded parts for assembly are in the external warehouse, the planner must react to this and order transport from the LSP. The process of transshipment of incoming parts in the hub has been adopted identically to the decision rules from Figure 9.

According to the decision rules, proactive transshipments only occur if some parts have to be transshipped reactively. To support the decision on proactive transshipments, the planner receives a list of parts for which a transshipment leads to a reduction in the total sum of approximated future transshipment costs (see Section 4.3 Formula (4)). As the utilization of the warehouse cannot be tracked by the system, the planner is requested to estimate the utilization of the internal warehouse. If the warehouse is fully utilized, the planner is informed that parts must be transshipped to the external warehouse if other parts are transshipped to the internal warehouse. The provided list shows the transshipment recommendations based on the approximated future transshipment costs. At the same time, it is marked which parts should not be relocated for strategic reasons, based on previous decisions. The planner can hide these transshipment recommendations. If further parts should not be transshipped for strategic reasons, the planner can mark these parts and the decision is saved for future transshipment recommendations. As soon as the planner selects parts that lead to a deterioration in the total sum of approximated future transshipment costs, the DSS provides a notification.

Due to the reduction in transport and waiting time before parts are assembled, cost savings are expected to be in the EUR five-digit range per year. Another positive effect is the estimation of demand probabilities by the neural network. This estimation can not only be used in the proactive transshipment model but can also support decision-making regarding possible scrapping. Every part that has been identified and approved for scrapping can help to avoid expensive external storage space and save costs. In the future, the data from the ERP system will be connected with additional data from other IT systems in order to generate further features for the neural network. In this way, the neural network will also be constantly improved in order to estimate the demand probabilities even more accurately.

8. Conclusions

The investigation has shown how a numerical study by Weckenborg et al. [5] can be applied to an industrial use case. The potential shown by the numerical study of proactive transshipments in an automotive prototype assembly demonstrated the potential savings. In order to estimate the full cost–saving potential in practice, a case study was carried out based on real world data over a period of 135 days. For this case study, a neural network was used to estimate the demand probabilities for the parts. The case study showed that the proactive approach can lead to cost savings of up to 10.5% compared to a reactive approach.

Due to the insufficient data quality of the measurements of the parts and warehouses and other requirements of the Volkswagen brand, the MILP model cannot be adopted in practice and cannot replace the planner for the decisions. Instead, the rule-based heuristic algorithm from Section 6.3 can be used, which also leads to the optimal solution.

For the decision support of proactive transshipment, a proposal of parts to be transshipped is generated for the planner using Python, and the output is in the form of Microsoft Excel. This proposal is based on the approximated future transshipment costs generated with the demand probabilities of the neural network. The decision rules and the DSS can be integrated into existing systems and are easy to use.

The model can also be used in other areas in addition to automotive prototype parts logistics. The results of the research can be applied to all cases in which unique parts are stored in a logistics network with several warehouses or cases in which batches with the same parts should not be split and allocated to several warehouses at the same time. The number of warehouses, customers, and parts, as well as the capacities, can be flexibly adjusted. The approach of the neural network to predict the demand probability in combination with the approximated future transshipment costs proved to be a good indicator for predicting the best possible warehouse. This method can be used in many ways as an indicator for decisions.

In future research, further logistics networks can be investigated. One example is the logistics network of the Pre-Production Center, where parts are stored for the initial prototype assembly in different internal and external warehouses. After the assembly of a prototype vehicle has been scheduled at short notice, the parts of a vehicle must be sent to one out of many assembly locations. However, the parts of a vehicle can be stored in different warehouses. This results in either parallel shipments to the assembly site or reactive transshipments before one shipment to the assembly site. Both cases could be reduced by proactive transshipments. In addition, the influence of different measurements of the parts and storage locations can be included in the model and investigated. This would allow the model to integrate a storage location assignment that takes into account the free capacities of the warehouses with the measurements of the transshipped parts. It is also interesting to examine how advantageous proactive transshipments are if no remaining capacities of vehicles or employees are assumed when handling the parts. This can be investigated by adjusting the technical parameter ε. Furthermore, the influence of additional costs such as different storage costs can be analyzed. In summary, a wide variety of investigations can be carried out on proactive transshipment of unique parts.

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Appendix A

Algorithm A1: Pseudocode of the rule-based heuristic algorithm.

```
if demanded parts are not in int. warehouse then
    order a reactive transshipment
    transship incoming parts from hub to int. warehouse
    transship demanded parts from ext. to int. warehouse
    if int. warehouse has free capacities after subtraction of demanded parts then
        transship parts with highest approximated future transshipment costs in
        ext. warehouse to int. warehouse
    else
        transship parts with lowest approximated future transshipment costs in ext.
        warehouse to ext. warehouse
    if there are parts in ext. warehouse with a high approximated future
    transshipment costs in ext. warehouse (low probability of scrapping) than other
    parts in the int. warehouse then
        parts in int. warehouse with a low approximated future transshipment
        costs in ext. warehouse (high probability of scrapping) are transshipped to
        ext. warehouse and parts with a high approximated future transshipment
        costs in ext. warehouse (low probability of scrapping) are transshipped to
        the int. warehouse
else
    if internal warehouse is fully utilized then
        transship incoming parts from the hub to the ext. warehouse
    else
        transship incoming parts from the hub to the internal warehouse
realization of the planned transshipments
```

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