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A decision support system for internal logistics operations management

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Abstract

Continuous improvement in industrial processes has made efficient internal material transportation critical. This study presents a decision support system for tracking internal transportation vehicles and providing effective inner logistics management. The proposed model includes a barcoding based transportation vehicle tracking system, a forecasting model for daily transportation demands of different buildings and presents a predictive demand-vehicle assignment mathematical model. Results show that the model reduces the operational costs due to vehicle search and vehicle transportation, and material damage costs due to vehicle-material mismatch at a great extent.

Keywords: Internal logistics, vehicle selection, multi objective selection, reorder point

1. Introduction

In today's defense industry, the importance of internal logistics cannot be underestimated, especially when transporting sensitive parts such as aircraft parts. The delicate parts must be carefully handled to avoid damage and monetary losses. Further, failure to identify suitable internal transportation vehicles for the parts results in operation time and labor time losses.

In this study, we develop a decision support system based on optimization models to improve the efficiency of the internal logistics system. The system handles vehicle tracking and selecting suitable vehicles for delivery orders. The main goals of the system are improving the use of internal resources and maintaining the integrity of a part during transport.

Decision Support Systems are vital for logistics management since they improve decision-making, as many extensive studies have emphasized[1]. Optimization problems have been proposed by the internal logistic system; some of them include the following: selecting hub locations of the vehicle under several objectives and acting under uncertainties like distance and capacity.

The Hub Location Problem is a network design optimization problem of product or service distribution from the central hubs to demand points. This problem is related to location problems, dealing with the determination of the optimum hub locations within a certain geographical area and the assignment of the respective demand points to their hub. The first known mathematical model for central hub location problems was introduced by O'Kelly[2]. It was based on the research on airline passenger networks central hub models presented in the literature follow similar principles. Problems like the p-hub median, fixed cost hub location, p-hub center, and coverage define various optimization challenges in logistics and operational research[3]. In the hub problem, allocation can be single or multiple, depending on the number of hubs involved. Campbell[4] first developed a multi-hub model. Later, Campbell[5] demonstrated that without capacity constraints, the lowest-cost hub pair would carry total demand between origins and destinations[6].

Optimization and automation models are frequently used for improving intralogistics systems[7]. In addition, support systems for logistic operations are growing with machine learning applications and crowdsourced logistics models[8,9].

When there are multiple objectives, the Pareto optimality concept offers decision-makers a set of optimal solutions rather than just one, allowing them to choose the best based on their preferences, especially in conflicting objectives like minimizing distance and maximizing capacity[10]. This method applies to a wide array of problems that require multi-objective optimization[11]. Unlike other multi-objective optimization approaches, the Pareto optimality approach derives innovative alternatives. It allows for considering previously unthinkable solutions by examining alternative strategies[12].

Triangular and trapezoidal numbers are predominantly used to convert subjective preferences to a numerical value[13]. When triangular membership functions are used, applying the geometric mean method to weigh fuzzy numbers helps minimize uncertainty[14]. Research shows that the Mamdani Inference and Weighted Average methods are effective for solving fuzzy logic problems in real-world industrial applications[15].

This study develops a decision support system that tracks vehicles and suggests vehicles to operations based on the specific order requirements, vehicle locations, and expected vehicle demands. This paper is organized as follows, Section 2 explains the existing internal logistics operations, Section 3 introduces the decision support system model, Section 4 investigates the results and finally, Section 5 concludes the study.

2. Internal Logistics Operations

The internal logistics department faced several difficulties. First, they could not track the transportation vehicles' real-time locations. Secondly, they did not have a vehicle type - part type assignment data table that showed which vehicles a part can be safely carried with. Carrying a part with an unsuitable vehicle type leads to part damage. This study includes the most frequently used vehicle types in the facility: sheet metal carts, trailers, and wooden carts. The vehicles are stored in pre-determined vehicle storage locations and the personnel periodically search for empty vehicles within the buildings and carry them to the storage locations.

These problems led to personnel carrying parts with non-standard vehicles, resulting in material scrap and damage costs, and wasted labor hours during vehicle search. The company wanted to resolve these problems by optimizing the inner logistics system, reducing transport vehicle waiting times, improving vehicle usage, reducing part damage, and scrap costs, and minimizing labor time losses and production delays.

A transportation operation starts with a move order. Move order is a barcode-based document for digitally tracking the movement of a production part from one location to another. A part identification number contains details like part number, description, and material. A move order is created when a part needs to be moved, and a suitable vehicle is selected. The order includes the part's ID number, starting and ending locations, transport barcode, order creation date, personnel information, and status.

The process begins with a part transportation request. If a suitable vehicle is available, the part is loaded, and a move order is created. Otherwise, the field worker informs the chief technician, who manages the vehicles.

When a vehicle is ready, the internal logistics operator delivers it and starts the transportation. Upon part's arrival at the destination point, the order is updated as "delivered", completing the process.

The current system has several inefficiencies:

- Vehicle search time: The chief technician searches buildings for available and suitable vehicles. The system cannot reduce the distance to vehicles, due to personnel misusing vehicles. The misuse includes changing vehicle locations without informing the department and using vehicles without updating their status. This results in a daily 3.6-hour loss for the chief technician, causing delays in transportation.

- Wrong vehicle selection: An analysis of the move order database reveals an 11.52% error rate in selecting vehicles, especially in wooden carts. This problem leads to part damage and bottlenecks due to incorrect capacity usage.

Section 3 explains the model developed to overcome these inefficiencies in detail.

3. Internal Logistics Vehicle Tracking and Procurement Model

Eliminating the inefficiencies in the system requires a long-term plan with serious changes in the system and employee commitment. In this study, we propose two solutions to the firm: a short-term solution and a long-term solution.

Short-term solution: In this model, the firm continues using the pre-determined vehicle storage locations. Short term solution model includes the following parts:

1. A part-vehicle compatibility check system to ensure the correct type match. Part-Vehicle Compatibility Check uses the move order barcodes and checks the compatibility of the vehicle and the part on the order. This function ensures that each part is carried with a suitable vehicle, and reduce the possibility of damages.

2. A cart tracking system that displays the location and status of each vehicle. Transport Cart Tracking, the second step, has a barcode-based tracking system for the transportation carts within the plant, providing the real-time locations of vehicles.

3. A vehicle stock management model that determines the stock levels for each vehicle type. Whenever the number of vehicles at the vehicle storage area drops to a certain level (the reorder point), the personnel use the tracking system to determine the locations of empty vehicles and carry them to the stock area. Although the tracking system shows the vehicle locations, it can not show if the vehicle is empty (suitable) or busy. Some of the vehicles can be assumed to be suitable while others are known to be suitable. If the system cannot locate enough suitable vehicles it uses a fuzzy inference model to evaluate the buildings and selects which ones to search for suitable vehicles when it's time for stock replenishment. This enables adjusting for unpredictable demand and supply times, and ensures that the best possible level of vehicle stock is always maintained.

Long-term solution: In the long term, the firm wants to eliminate the pre-determined vehicle storage locations and use the buildings as vehicle hubs. The long-term solution uses Part 1 and 2 from the short-term solution and employs the fuzzy-based building selection model of Part 3. The long-term solution introduces the following parts:

1. A predictive day ahead (day start) vehicle assignment model. This part includes an exponential smoothing-based demand forecasting model to predict the move order demand of each building, and an integer programming model to determine where each demand should be satisfied from, given the vehicle stock of the buildings at the beginning of the day. This model assigns the predicted vehicle demand to buildings.

2. An extra demand vehicle assignment model. The demand predictions made in part 4 may not always hold. If the realized demand within the day exceeds the predicted demand, we use the pareto-based extra demand vehicle assignment model. This model uses the Pareto optimality rule to determine a vehicle for a demand,

aiming to balance distance minimization and vehicle availability maximization. The model takes the building that made the move order as the base and computes the distance between this building and other buildings. For each building, the model also computes the preference score (as explained in the Vehicle stock management model). The model evaluates the distance and preference score using the Pareto rule and determines the building from which the demand will be satisfied.

Figure 1 displays the short-term (Part 1-2-3) and long-term (Part 4-5) solution models and their relationships. The details of these functions are as follows:

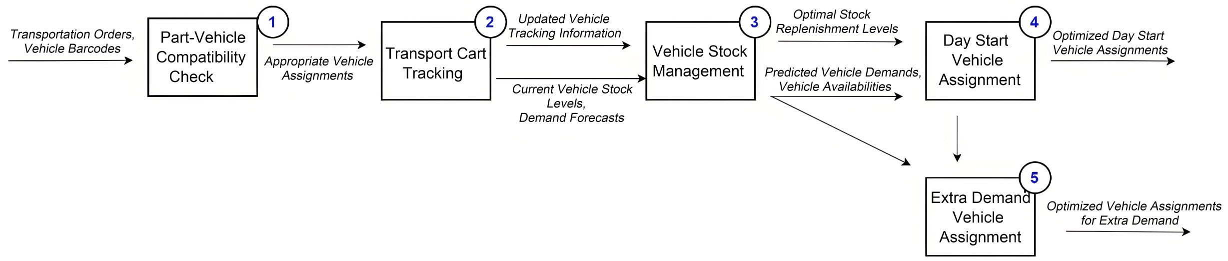

Figure 1. Internal logistics operations management model parts.

3.1 Tracking of transport vehicles

Barcode Generation and Barcoding: The number of transport vehicles was determined, and barcodes were generated for each type. After unique barcodes were generated for all vehicles within each type, they were converted into QR codes and printed on the vehicles using laser printing. The generated barcodes were mapped to vehicle types in the database.

3.2 Vehicle stock management

Calculation of Vehicle Stock Replenishment Lower Level: The company currently prefers to periodically collect available vehicles to pre-determined vehicle stock areas. This function computes a vehicle replenishment level for the stock areas. Two parameters are used for calculating the vehicle stock replenishment lower levels: the vehicle demand (d) and the time required for bringing the vehicle to the stock area (LT-lead time). The vehicle demand varies according to vehicle types and varies from day to day. As a result of this calculation, minimum quantities of vehicles that should be available in the stock area by vehicle type were determined to ensure the operational processes ran smoothly. This way, the chief technician can see when they need to go out to search for a vehicle. The targeted service rate is set at 90% after discussions with the field operators. Equations 1 to 4 compute the reorder point (ROP)-when the number of vehicles in stock drops to this level, vehicle stock should be replenished, assuming demand and lead time with normal distributions. In Eq. 3.1, dL-average demand during lead time is computed using average demand (μ_D) and average lead time (μ_{LT}). In Eq 3.2, σ_L represents the standard deviation of demand during lead time. Eq. 3.3 computes the safety stock-SS (for a 90% service level z_r = 1.285) and finally Eq. 3.4 computes the reorder point-ROP.

$$d_L = \mu_D \mu_{LT} \tag{3.1}$$

$$\sigma_L = \sqrt{\mu_{LT}\sigma_D^2 + \mu_D^2 \sigma_{LT}^2} \tag{3.2}$$

$$SS = z_r \sigma_L \tag{3.3}$$

$$ROP = SS + d_L \tag{3.4}$$

Determination of Vehicle Suitability: Stock areas are supplied with transport vehicles scattered in buildings within the facility. Although barcoding indicates the locations of transport vehicles, it does not provide definite information about their conditions. Uncertainties about the conditions of the vehicles arise from employees' ongoing use habits of resources. These usage habits include creating a demand for a vehicle before its time, stacking tendencies, and starting to use a seemingly empty vehicle without notice. To deal with the situation where a definite conclusion cannot be made about the suitability of vehicles, two uncertain concepts have been created. These concepts are Suitable Vehicle Number (SVN) and Assumed Suitable Vehicle Number (ASVN). SVN evaluates the possibility that a vehicle reported empty some time ago is still in the reported location and is empty. ASVN evaluates the possibility that a vehicle, that has not been reported as empty but has also not been updated for 24 hours, is empty and in its last known location. These concepts were used in the fuzzy set membership functions with experts. The fuzzy rules and membership functions define the number of suitable and assumed suitable vehicles as very low, low, medium, high and very high. Depending on the suitable and assumed suitable member classes of a building, the building preference changes between very bad, bad, medium, good and very good. The preference scores were obtained using Mamdani Inference and weighted average methods for buildings. The system recommends the top 5 buildings with the highest scores to the chief technician. This way, the technician can directly go to the buildings where the probability of finding the desired number of vehicles is higher.

3.3 Predictive day ahead vehicle assignment model

Replenishing the vehicle stock areas serves as an intermediate solution for the firm. The main goal of the firm is to use a real-time tracking-enabled optimal vehicle recommendation system. This recommendation system should track the vehicles daily, predict the next day's demand, and recommend vehicles to buildings to minimize the total vehicle carrying distance. For this goal, we offer a demand forecasting model and provide the outputs of this model as input to the mathematical model that assigns vehicles to building demands.

Building-Based Vehicle Demand Forecasting: The exponential smoothing method was used to forecast daily vehicle demands from buildings. Eq. 3.5 shows the exponential smoothing model, using the forecast (*Ft*) and Actual (*At*) values at time period-t, to forecast the demand at the next period t+1, where represents the smoothing factor. There are 62 active buildings in the facility. The α value was optimized (through iterative heuristic search methods) for each building using a 30 periods long training dataset. The mean absolute percentage deviation (MAPE-Eq. 3.6) averaged over all buildings was 9.7% on the test data set (n = 10 periods). As the demand profiles of the buildings change within time according to the projects they handle, their values are periodically recalculated and updated.

$$F_{t+1} = \alpha A_t + (1 - \alpha) F_t \tag{3.5}$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{(A_i - F_i)}{A_i} * 100 \tag{3.6}$$

Determination of Vehicle Hubs: The developed integer programming model is inspired by the "Location Hub" problem. This challenge revolves around pinpointing buildings that require a sufficient fleet of vehicles to fulfill the transportation requirements of neighboring structures. Hubs are defined as buildings with vehicle quantities exceeding a set threshold, serving their internal needs and supplying vehicles to other buildings. The primary goal of this model is to meet all demands efficiently by reducing the overall distance covered by the allocated vehicles. At the beginning of each day, the model produces a demand schedule for the hubs and assigns each predicted demand to a building such that the total distance traveled is minimized. In this case, the model does not determine the hubs-it determines the number of vehicles that can be transferred from one building to another.

Day ahead vehicle assignment mathematical model:

Sets

Buildings = {1, ..., N}, the set of locations of the buildings

Parameters

t_j: Total car demand at building j.

a_i: The number of suitable cars at the beginning of the day in building i.

d_{ij}: The distance between buildings i and j.

Variables

$$x_i = \begin{cases} 1, \text{ if the number of suitable vehicles at building i at the beginning of the day is} > \text{minVeh} \\ 0, \text{ Otherwise} \end{cases}$$

P_{ij} : The number of cars allocated for the demand at building j in building i.

Objective Function

$$\text{Min} \sum_{i=1}^{N} \sum_{j=1}^{N} P_{ij} * d_{ij}$$

$$(\text{minVeh} - a_i) * x_i \leq 0 \ \forall i \in \text{Building} \tag{3.7}$$

$$\sum_{j=1}^{\text{Building}} P_{ij} - a_i * x_i \leq 0 \ \forall i \in \text{ Building} \tag{3.8}$$

$$\sum_{i=1}^{\text{Building}} P_{ij} \geq t_j \ \forall j \in \text{ Building} \tag{3.9}$$

$$x_i \in \{0, 1\}, \ \forall i \in \text{ Building} \tag{3.10}$$

$$P_{ij} \geq 0, \text{ integer } \ \forall (i, j) \in \text{ Building} \tag{3.11}$$

The objective is to minimize the total distance traveled by vehicles to satisfy the demand.

Eq. 3.7 prevents the assignment of vehicles from a building if the number of vehicles in that building is less than minVeh (minimum vehicles). The value of minVeh=20 has been determined by experts in the field. Eq. 3.8 ensures that the number of assignments from building i cannot exceed the available number of vehicles in that building. Eq. 3.9 ensures that all buildings' demands are satisfied. Eq. 3.10 is the binary value constraint for vehicle availability in a building.

4. Results

The proposed decision support system is currently in the test and implementation phase in Turkish Aerospace.

Parts 1 & 2-Part-Vehicle Compatibility Check: **Figure 2** displays one of the user interfaces. The user can read the barcode of the part that will be carried and identify the location of a suitable vehicle. The database first checks the suitable vehicle type for this part and then identifies the locations of the available vehicles of that type. This database and user interface prevent vehicle-part mismatch related part damage and time loss because of vehicle search.

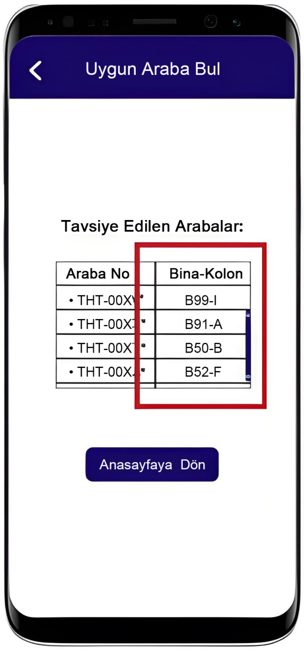

Figure 2. Vehicle suitability check and tracking user interface.

Part 3-Vehicle Stock Management: The model computes different stock replenishment levels (ROP) for each vehicle. The maximum number of vehicles that can be brought to the stock with a single replenishment tour differs for each vehicle type: Sheet-metal cart and wooden cart limit equals 10, and trailer limit is 5. Using the type dependent demand rates and lead times, the ROP levels are computed as: Sheet-metal cart and wooden cart reorder point is 6 carts, whereas the reorder point for trailers is 3. Using the reorder point model will enable the chief technician to satisfy the demand on time at 90% of the time (target service rate).

Part 4-Predictive day ahead vehicle assignment: To measure the performance of this model, we compared it with a heuristic-non predictive dynamic vehicle assignment model. The dynamic vehicle assignment model takes the demands one by one as they arrive and recommends the closest vehicle to the building the demand originated. Historical move orders in the current database are used for these analyses. The test cases are based on building-based daily transport requests and required vehicle types of historical orders.

The integer programming based predictive day ahead vehicle assignment model was executed separately for sheet metal, trailers, and wooden vehicles. There were a total of $N = 62$ actively vehicle demanding buildings in the facility. The total execution time for all vehicle types was approximately 10 minutes with IBM ILOG CPLEX Optimization Studio with a i7, 16 GB RAM computer. The configuration of input, model execution, and transferring of outputs to a database takes approximately three minutes.

Figure 3 compares the daily mean distances traveled to satisfy a vehicle demand during a 30 day long simulation. Results show that the 95% confidence intervals for the average vehicle to demand point distances are [67.17 115.84] meters with the predictive model and [98,41 180.25] meters with the dynamic assignment model.

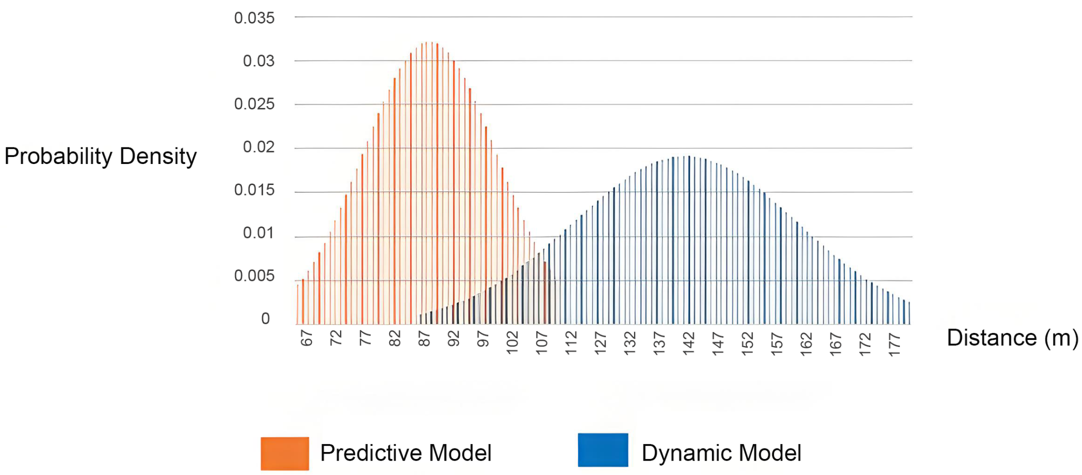

Figure 3. Dynamic and predictive model comparison-average distance to fulfill demand.

This comparison shows the effectiveness of the predictive model against the dynamic assignment model. The dynamic model takes each demand as they come and assigns the closest vehicle to that demand. This type of greedy approach does not take the future demand probabilities into consideration. In some cases, right after the dynamic model allocates a vehicle to a demand, another demand that is much closer to that vehicle can come to the system. The predictive model takes the complete predicted daily demand as an input, and it acts to minimize the total distance covered during all daily operations. This predictive approach enables the model to achieve a significantly lower total distance traveled.

The overall projected improvements enabled by this smart internal logistics system are summarized as follows:

Annual Cost Savings on Part Damage: Part damage costs due to vehicle-part mismatch are expected to reduce by 60%.

Annual Labor Cost Savings: Labor costs due to vehicle search time will be reduced to a great extent. A saving of nearly $4,000, which roughly translates to about 97.5 workdays is estimated.

Improvement in Demand Fulfillment Cycle: The time to meet a vehicle demand reduced by approximately 35%.

Total Cost Savings: The overall cost reduction amount, related to part damage, labor, and demand fulfillment improvement is estimated as $60,000.

5. Conclusion

This study developed a decision support system for internal logistics and showed that operational efficiency can be enhanced through sophisticated models that manage process optimization along with vehicle tracking and inventory.

The proposed model introduced several benefits in the short term and will bring additional benefits in the long term. In the short term, the part-vehicle compatibility check model eliminated the mismatch related accidents and operational losses. The vehicle tracking system eliminated the labor hour losses during vehicle search. The vehicle stock management model limited the number of trips the field workers make to stock empty vehicles to the vehicle storage area. In the long term, the vehicle storage locations will be eliminated, and the field operators will directly carry the vehicles from the assigned buildings to the destination buildings. Results show that this model will significantly reduce the total distance and therefore total time required to satisfy a demand.

The most important limitation of the current model is that the system cannot determine if the vehicles are empty or busy at a given moment. The model takes the last usage dates of the vehicles to determine whether the vehicle is empty or not. The assumed-suitable-vehicle approach tries to solve this problem but implementing a load sensor to the vehicles would be the best approach to overcome this limitation. Another limitation is the potential errors in the demand predictions. In this case, the Pareto based extra demand allocation model improves the robustness of the system.

This model is developed for tracking transportation vehicles of a manufacturer, but it is applicable to other places which share mobile equipment. A good example of this type of system is hospitals where the nurses carry mobile healthcare equipment between hospital departments[16,17].

Future developments would further improve system capabilities through the integration of IoT sensors for real-time monitoring of the vehicle condition, machine-learning techniques to enhance demand forecasting, and more advanced vehicle routing algorithms to improve the delivery route. Future systems can include sustainability metrics with the aim of reducing environmental impact and using blockchain technology to ensure greater transparency and reliability in transportation records.

Declarations

Authors contribution

Akbiyik D, Ulusoy T: Conceptualization, investigation, data curation, formal analysis.

Özen S, Dagsuyu E: Conceptualization, investigation, data curation, formal analysis, writing-original draft.

Akpinar E: Conceptualization, investigation, data curation, formal analysis.

Fescioglu-Unver N: Writing-review & editing, supervision.

Burak Ucak Y, Uyduran S, Demir D: Supervision.

Conflicts of interest

The authors declare that there are no conflicts of interest.

Ethical approval

Not applicable.

Consent to participate

Not applicable.

Consent to publication

Not applicable.

Availability of data and materials

Not applicable.

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