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OPTIMISATION OF MANAGEMENT OF MULTI-COMPONENT TRANSPORT OPERATIONS WITH APPLICATION IN MODERN LOGISTICS USING A FLEXIBLE MATHEMATICAL MODEL FOR COST MINIMISATION

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Abstract. The effective management of transport and logistics issues is a critical component of contemporary supply chain management. In the context of a globalised economy and increasing demands for speed and quality of service, the optimisation of transport processes is becoming a strategic priority for achieving economic sustainability and enhancing the competitiveness of enterprises. In view of this, the aim of this study is to develop an innovative mathematical model that will minimise the total costs of organising complex, multi-component transport operations. The proposed model framework is characterised by a high degree of realism, as it takes into account key practical constraints. These include the limited capacity of transport vehicles, the specific requirements for personnel qualifications and availability, and the detailed conditions for servicing final destinations. This approach offers flexibility and adaptability when modelling a variety of logistics scenarios, including those involving dynamic changes in consumer demand, resource availability, and infrastructure constraints. It is particularly well-suited to urban logistics and inter-platform delivery management, as well as other sectors requiring a high degree of coordination and precision in resource allocation. The mathematical formulation transforms the transport problem into an integer programming optimisation model. In this model, binary variables play a key role in representing discrete solutions for allocating tasks and resources. The model ensures compliance with operational, logistical and regulatory requirements by incorporating precisely defined constraints. Due to the problem's high combinatorial complexity, the solution is implemented using a combined approach that includes both exact (e.g., branch-and-bound) and heuristic (e.g., greedy algorithms and local search) optimisation methods. This hybrid methodological approach enables the discovery of solutions that are close to optimal within an acceptable computational time, which is critically important for real-world applications. The empirical part of the study comprises simulations and quantitative analyses demonstrating the model's ability to efficiently allocate transport tasks while reducing costs. This is achieved by making balanced use of different types of transport vehicle, engaging qualified drivers optimally, and providing an adequate service to geographically diverse destinations. This work's scientific contribution is demonstrated through the creation of a compact, applicable optimisation framework that integrates multidimensional, practically significant constraints, and through the demonstration of its effectiveness and applicability in real scenarios. The main achievements of the study can be summarised as follows: development of a detailed optimisation model for multi-component transport processes; formulation of the problem as an integer model with multiple constraints; application of a hybrid approach combining exact and heuristic methods for finding solutions; demonstration of practical applicability through simulations and quantitative evaluation of the results. All models and calculations are implemented in the MATLAB programming

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environment, which offers the computing power and flexibility required for the real-time simulation and analysis of transport scenarios.

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JEL Classification: L90, L91, L62, R48

1. Introduction

Cost optimisation plays a key role in enhancing the efficiency and sustainability of supply chains in the modern transport and logistics industry (Christopher, 2023; Azimov et al., 2024; Iliev et al., 2023). The increasing complexity of transport operations, driven by dynamic changes in demand, resource constraints and the geographical dispersion of destinations, necessitates the development of mathematical models for optimally allocating available resources (Behnke & Kirschstein, 2022; Deneva et al., 2022; Labunska et al., 2017). In this context, the effective management of vehicles, drivers, and transport routes is critical for minimising operational costs and ensuring timely deliveries.

The present study examines an optimisation problem related to the organisation of transport activities under multiple constraints. The available resources consist of a predetermined number of drivers, vehicles, and destinations, with each shipment required to be delivered in accordance with vehicle capacity and driver qualifications. The financial implications of transportation are represented by a matrix that calculates the cost of each vehicle to each destination. It is important to note that additional constraints specify that not every driver is able to operate every vehicle or serve every destination. The primary objective of the problem is to devise a feasible assignment plan that minimises the total transportation cost by determining which driver will operate which vehicle to which destination.

The problem is formulated as an integer optimization task (Furini & Ljubić, 2021; Wolsey & Nemhauser, 2022), where solutions are represented by a three-dimensional binary array. It is evident that, due to its combinatorial complexity, finding a globally optimal solution requires the application of a combination of exact and heuristic methods. The employment of such methods allows the discovery of near-optimal solutions within a reasonable time frame.

The study presents a novel model that integrates various constraints into a unified optimization framework, with a focus on the practical applicability of the method. The proposed optimisation strategy has been demonstrated to be applicable to a variety of logistics scenarios, including urban transportation, goods distribution, and inter-platform delivery management. Moreover, the findings from simulations and quantitative analyses corroborate the efficacy of the proposed solution in reducing costs and enhancing resource allocation.

In the contemporary context of modern logistics and transport systems, the evaluation of optimal and near-optimal solutions to transportation problems is becoming increasingly significant. This evaluation not only serves as an indicator of the solution's quality, but can also form the basis for addressing significantly more complex problems. Such problems may include vehicle routing tasks involving multiple time periods (multi-period problems) or decision-making in real-time environments, which are typical of online settings.

One of the key metrics used to characterise routing solutions is the total distance travelled by vehicles in order to serve a given set of customers. The capacity to precisely predict or estimate this value, without resorting to the explicit resolution of the underlying combinatorial problem, engenders novel prospects for enhancing planning efficiency and decision-making processes. This study explores the applicability of simple regression models for this purpose, based on a limited but carefully selected set of features that describe the spatial configuration of customers, capacity constraints, and other structural aspects of the specific problem.

In addition to the commonly utilised features documented in the extant literature, such as the number of customers, the average and maximum distance to the depot, and the spatial dispersion of customers, this study introduces new classes of spatial indicators. These are designed to capture more subtle aspects of the geometric structure of customer distributions. The factors under consideration are local density, degree of symmetry, the presence of clusters, and deviation from isotropic structure. The incorporation of these new characteristics into the input space of the regression models has been demonstrated to engender a substantial enhancement in the precision of the approximated estimates.

The increasing scale and complexity of real-world logistics systems generate a growing need for methods capable of providing solutions or estimates within short time frames – sometimes within seconds (Nykyforov et al., 2021; Petrova, Tairov, 2022; Ramazanov, Petrova, 2020). This is of particular pertinence in the context of multi-period problems, wherein customer assignments must be distributed across multiple days while observing capacity constraints, or in the case of online problem variants, where customer information arrives incrementally and decisions must be made dynamically. In such cases, it is often practically impossible to solve the full combinatorial problem for each new input, necessitating the use of approximation methods.

One of the primary applications of the developed models for approximating solution values is the decomposition of complex multi-period problems into a sequence of simpler single-period subproblems. For instance, in instances where it is not feasible to accommodate all customers within a stipulated timeframe, the estimation of solution value for various customer subsets can facilitate the selection of the most optimal or near-optimal subgroup for service. This facilitates the establishment of effective customer selection strategies that minimise total logistics costs while ensuring an acceptable level of service.

Furthermore, within the paradigm of online or adaptive planning, where prompt responses to emergent customer requests are imperative, the capacity to furnish a swift and dependable estimate of a solution's worth assumes paramount importance. The regression models that have been developed and trained on a substantial corpus of simulated or real-world data can be embedded into decision support systems. This provides a reliable basis for selecting actions in real time without the need for computationally expensive optimisation of the full problem.

The figure presents a sample two-dimensional configuration of customers (in blue) and a single depot (in red). The grey lines illustrate the Euclidean distances from each customer to the depot, which are utilised to compute spatial features that serve as inputs to the regression model.

The provision of a high-quality service is of pivotal importance to the development of any company, irrespective of the economic sector in which it operates. The quality of service is directly linked to its demand; many clients consider it a leading factor, sometimes even more important than price. However, the most sought-after products and services on the market typically combine high quality with a competitive (low) price. This phenomenon is also evident in the context of maintenance services offered by automotive repair shops.

The pricing of services in a transport company can influence the number of completed deliveries, and this effect depends on a variety of factors, including:

– Price competitiveness. Transport services with excessively high prices risk losing clients to more affordable alternatives, unless they offer added value that justifies the cost.

– Service quality. Clients satisfied with the level of service are willing to pay more and are likely to recommend the company to others.

– Marketing strategies. Promotions, loyalty programs, and bundled offers can successfully attract customers, even when prices are higher.

– Target audience. A clear understanding of customer needs and expectations enables better pricing and service positioning.

In the majority of cases, the most effective strategy is one that balances reasonable prices with high quality. This principle is applicable not only in the transport sector but also in financial services, biological systems, artificial intelligence, and others.

Efficient Transport Management

Effective management of transport operations is a key element in maintaining the balance between cost and quality. Some of the core strategies include:

– Needs analysis and forecasting. Using statistical data to identify the most commonly used parts and forecast future requirements.

– Determining optimal inventory levels. Maintaining adequate stock to avoid delays while limiting unnecessary storage costs.

– Supplier partnerships. Long-term contracts with reliable suppliers can ensure better prices and shorter delivery times.

– Use of specialized software. Management systems facilitate tracking, forecasting, and order optimisation.

Application of Mathematical Models

Mathematical modeling provides a powerful tool for optimising operations management. Among the most popular approaches are:

– EOQ model (Economic Order Quantity). Determines the optimal order quantity to minimise total ordering and holding costs.

– JIT model (Just-in-Time). Aims for minimal inventory by delivering parts exactly when needed, requiring excellent coordination with suppliers.

– Demand forecasting. Based on historical data and statistical methods to estimate future demand.

– Simulation models. Use computer simulations to analyse various management scenarios.

These models can be combined and adapted to the specific characteristics of a company. The quality of input data and the precise definition of the parameters affecting transportation are critical to achieving effective results.

To estimate the value of the optimal solution (e.g., the total minimum distance) in a vehicle routing problem, a regression model of the following type can be used:

$$z = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \varepsilon$$

where:

z is the predicted value of the optimal solution (e.g., the total distance),

x_i are the input features (e.g., number of customers, average distance to the depot, customer dispersion),

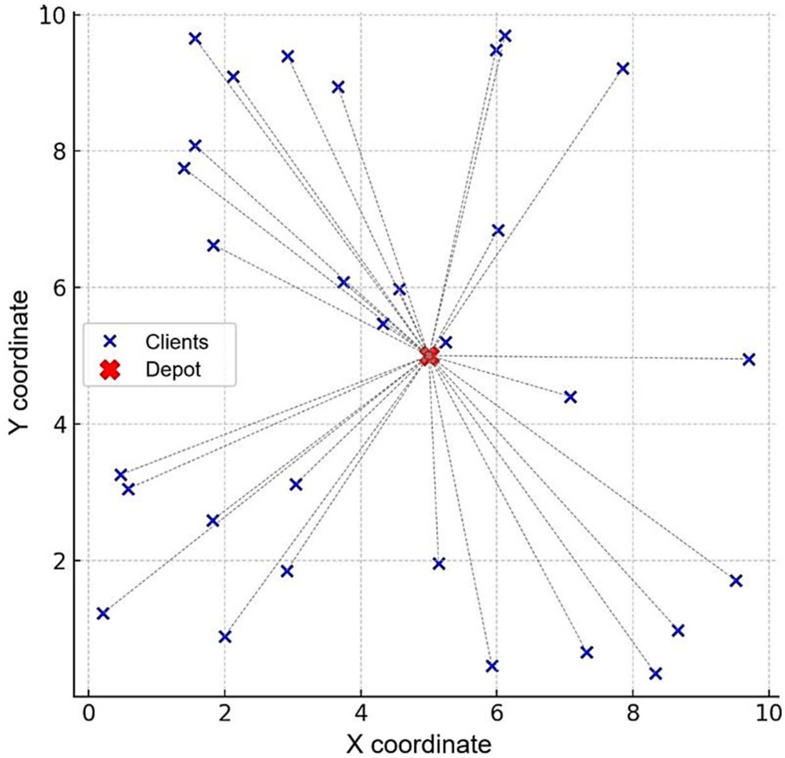

Figure 1. Two-dimensional configuration of customers and a single depot

β_i are the model parameters,

ε is the random error term.

The corresponding example spatial features used in the model include:

1. Average distance to the depot:

$$\bar{d} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}$$

where

(x_i, y_i) are the coordinates of customer *r*, and (x_0, y_0) are the coordinates of the depot.

2. Customer dispersion based on coordinates:

$$\sigma_x^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$$

$$\sigma_y^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2$$

Clustering and local density. The number of customers within a radius *r* around each customer is used to assess local concentration.

Exhibition

Cost optimisation is essential for the efficient functioning of transport and logistics systems and the supply chain. Against this backdrop, the present study addresses the issue of optimally allocating resources –drivers, vehicles and routes – under various constraints.

The goal of the optimisation model is to minimise total transportation costs while ensuring that:

– Each shipment is delivered to its designated destination;

– drivers operate only suitable vehicles and are assigned to permitted routes;

– vehicle capacity is efficiently utilised.

This problem is formulated as a nonlinear integer optimisation model [5, 6], which is solved using exact or approximate methods due to its high combinatorial complexity.

To formulate the problem, the following known parameters are introduced:

- m – number of drivers;
- n – number of vehicles;
- p – number of destinations.

The specific characteristics of the transportation system are defined by the following matrices and vectors:

– Cost matrix: c_{jk} denotes the cost of transporting cargo with vehicle j to destination k.

– Destination eligibility matrix D: d_{ik} equals 1 if driver i is authorised to travel to destination k, and 0 otherwise.

– Vehicle eligibility matrix B: b_{ij} equals 1 if driver i is authorised to operate vehicle j, and 0 otherwise.

– Demand vector Q: q_k is the amount of cargo to be delivered to the k^{th} destination.

Vehicle capacity vector $R: r_j$ indicates the maximum cargo load that vehicle j can transport.

To solve the problem, a binary variable x_{ijk} is introduced:

$$x_{ijk} = \begin{cases} 1, if\ driver\ i\ operates\ vehicle\ j\ to\ destination\ k \\ 0, otherwise \end{cases}$$

In the optimisation problem under consideration, a set of constraints is defined in order to ensure that the solutions are realistic and comply with specific requirements. These constraints are formulated mathematically and reflect real-world conditions relating to driver assignments, vehicle utilisation and deliveries to destinations. Each constraint is examined in more detail to clarify its meaning and the real-world condition it represents.

$$\sum_{j=1}^{n}\sum_{k=1}^{p} x_{ijk} \le 1, \forall i = \overline{1,m} \quad (1)$$

Constraint (1) reflects the fact that a driver can be assigned to at most one trip with a single vehicle. The constraint ≤ 1 ensures that driver i can be assigned to no more than one combination of vehicle and destination.

$$\sum_{i=1}^{m}\sum_{j=1}^{n} r_j x_{ijk} \ge q_{k,} \forall k = \overline{1,p} \quad (2)$$

Constraint (2) conveys that the total cargo capacity of all vehicles assigned to destination k must be at least equal to the required quantity of goods q_k for that destination.

$$\sum_{i=1}^{m}\sum_{k=1}^{p} x_{ijk} \le 1, \forall j = \overline{1,n} \quad (3)$$

Constraint (3) corresponds to the fact that a vehicle cannot be used simultaneously for more than one destination.

$$\sum_{j=1}^{n} x_{ijk} \le d_{ik}, \ \forall i = \overline{1,m}, \forall k = \overline{1,p} \quad (4)$$

Constraint (4) reflects that driver i may be assigned to destination *k* only if no legal or regulatory restrictions prevent it. These may include:

- Customs-related criminal offenses.
- Entry bans for specific countries.
- Lack of a valid passport for non-European destinations.
- Personal refusal to travel to the destination.

$$\sum_{k=1}^{p} \boldsymbol{x_{ijk}} \le \boldsymbol{b_{ij}}, \forall \boldsymbol{i} = \overline{1,\boldsymbol{m}}, \forall \boldsymbol{j} = \overline{1,\boldsymbol{n}} \quad (5)$$

Constraint (5) represents that driver $\mathbf{i}$ may operate vehicle $\mathbf{j}$ only if they possess the required license or qualification. The condition ≤ $\mathbf{b_{ij}}$ ensures that the driver will not be assigned to a vehicle for which they are not certified.

$$x_{ijk} \in \{0,1\}, \forall i = \overline{1,m}, \forall j = \overline{1,n}, \forall k = \overline{1,p} \quad (6)$$

Constraint (6) requires the decision variables x_{ijk} to be binary, meaning they can take only the values 0 or 1.

The main objective of the model is to deter mine a feasible assignment plan that minimises the total transportation costs. This is formalised by the following objective function:

$$\min \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{p} c_{jk} x_{ijk} \quad (7)$$

The final version of the mathematical model takes the following form:

$$\min Z = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{p} C_{jk} x_{ijk}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{p} x_{ijk} \le 1, \forall i = \overline{1,m}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n} r_j x_{ijk} \ge q_k, \ \forall k = \overline{1,p}$$

$$\sum_{j=1}^{n} x_{ijk} \le d_{ik}, \ \forall i = \overline{1,m}, \forall k = \overline{1,p}$$

$$\sum_{k=1}^{p} x_{ijk} \le b_{ij}, \ \forall i = \overline{1,m}, \forall j = \overline{1,n}$$

$$x_{ijk} \in \{0,1\}, \forall i = \overline{1,m}, \forall j = \overline{1,n}, \forall k = \overline{1,p}$$

Numerical example:

The transportation company in question operates with a total of twelve drivers, ten vehicles, and five regularly served destinations. Consequently, the objective is to enhance the efficacy of transportation planning to achieve optimal economic efficiency.

Table 1 presents the potential transportation costs (in arbitrary units) to each destination using a specific vehicle. Table 2 provides information about the load capacity of each vehicle. Table 3 shows the quantity of goods that need to be transported to the respective destination. Table 4 provides information on whether a specific driver is allowed to travel to a given destination. Table 5 shows whether a given driver is qualified to operate a specific vehicle.

Solution:

As illustrated in Table 6, a proposed plan is presented in which all destinations are to be served by designated drivers operating specific vehicles. This approach is intended to ensure that all requirements and constraints are satisfied, thereby achieving minimal transportation costs. The solution shows that Destination No. 1 should be served by Driver No. 11 operating Vehicle No. 6. Destination No. 2 will be served by two drivers – No. 4 and No. 10 – operating Vehicles No. 2 and No. 8, respectively. The next destination, No. 3, is served by Vehicle No. 7 and Driver No. 7. For Destination No. 4, two drivers are again needed: No. 3 and No. 12, along with two vehicles: No. 4 and No. 9. The last destination, No. 5, is served by Vehicle No. 10 and Driver No. 9. With this schedule,

Table 1
Transportation costs for each vehicle to the respective destinations

n/p(Matrix C)	1(300km)	2(600km)	3(1000km)	4(2000km)	5(3000km)
1(N1)	0.60*300=180	0.6*600=360	0.55*1000=550	0.5*2000=1000	0.45*3000=1350
2(N1)	0.60*300=180	0.6*600=360	0.55*1000=550	0.5*2000=1000	0.45*3000=1350
3(N2)	0.96*300=288	0.96*600=576	0.91*1000=910	0.86*2000=1720	0.81*3000=2430
4(N2)	0.96*300=288	0.96*600=576	0.91*1000=910	0.86*2000=1720	0.81*3000=2430
5(N2)	0.96*300=288	0.96*600=576	0.91*1000=910	0.86*2000=1720	0.81*3000=2430
6(N3)	1.60*300=480	1.60*600=960	1.55*1000=1550	1.50*2000=3000	1.45*3000=4350
7(N3)	1.60*300=480	1.60*600=960	1.55*1000=1550	1.50*2000=3000	1.45*3000=4350
8(N3)	1.60*300=480	1.60*600=960	1.55*1000=1550	1.50*2000=3000	1.45*3000=4350
9(N3)	1.60*300=480	1.60*600=960	1.55*1000=1550	1.50*2000=3000	1.45*3000=4350
10(N3)	1.60*300=480	1.60*600=960	1.55*1000=1550	1.50*2000=3000	1.45*3000=4350

Table 2
Vehicle load capacities

t/n	1	2	3	4	5	6	7	8	9	10
	4.5	4.5	8	8	8	20	20	20	20	20

Table 3
Quantity of goods (t) to be delivered

t/k	1	2	3	4	5
	13	23	17	25	20

Table 4
Driver eligibility to travel to specific destinations (1 – allowed, 0 – not allowed)

Driver\Destination	1	2	3	4	5
1	1	1	1	1	1
2	0	1	1	1	1
3	1	1	1	1	0
4	1	1	1	1	1
5	1	0	1	1	0
6	1	1	1	1	1
7	1	1	1	1	1
8	1	0	1	1	1
9	1	1	1	0	1
10	1	1	1	1	1

Table 5
Driver qualifications to operate specific vehicles (1 – qualified, 0 – not qualified)

Driver\Vehicle	1	2	3	4	5	6	7	8	9	10
1	1	1	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0
3	1	1	1	1	1	0	0	0	0	0
4	1	1	1	1	1	0	0	0	0	0
5	1	1	1	1	1	0	0	0	0	0
6	1	1	1	1	1	0	0	0	0	0
7	1	1	1	1	1	1	1	1	1	1
8	1	1	1	1	1	1	1	1	1	1
9	1	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	1	1	1
12	1	1	1	1	1	1	1	1	1	1

Table 6
Allocation of destinations served by a given driver and vehicle

Destination	Driver No.	Vehicle No.
1	11	6
2	4	2
2	10	8
3	7	7
4	3	4
4	12	9
5	9	10

the total transportation costs are minimised to 12,420 monetary units.

Findings

The article hereby presented is an exposition of a mathematical model that provides a solution to a class of transport-logistics problems. The model yields an optimal (in terms of transportation costs) allocation of drivers servicing destinations with specific vehicles, taking into account all legal and physical constraints (Ray, Li & Song, 2005). A case study is considered in which 12 drivers must service 5 destinations using 10 vehicles, accounting for the specific legal and physical limitations. It is demonstrated that the most cost-effective plan is one in which seven drivers, operating the respective vehicles, service all destinations. The total cost of this plan is 12,420 monetary units.

Conclusions

The study presented a mathematical model for the optimal allocation of transportation resources with the aim of minimising costs in logistics operations. The considered optimisation problem incorporates numerous constraints pertaining to vehicle capacity, driver qualifications, and service requirements for destinations. The formulated model uses binary variables (Pellinen, 2003) to describe the connections between drivers, vehicles and routes. This creates a complex, combinatorial structure.

The resolution of such issues poses a considerable challenge, primarily due to the exponentially expanding solution space. In this context, the application of hybrid methods combining exact approaches (linear and integer programming) and heuristic algorithms (genetic algorithms, particle swarm optimisation, etc.) (Eiben & Smith, 2023) is crucial for finding efficient solutions within a reasonable timeframe. As demonstrated by Law & Kelton (2023), simulation experiments based on the proposed optimization framework have shown that the model has the capacity to reduce transportation costs, improve resource utilisation, and ensure reliable task allocation. The main contributions of the study can be summarised as follows:

1. Development of an optimisation model integrating real-world constraints in transport-logistics processes.
2. Formulation of an integer optimisation problem encompassing driver qualifications, vehicle capacity, and mandatory coverage of transportation demands for each destination.
3. Application of hybrid methods enabling effective search for near-optimal solutions in complex combinatorial environments.
4. Practical applicability, as the model can be adapted to various industrial scenarios – urban logistics, international transport, and distribution networks.

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