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Using Machine Learning for Predictive Freight Demand and Route Optimization in Road and Rail Logistics

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Abstract
About half of all line haul freight capacity in Europe is on trucks, which generate congestion, high infrastructure costs, and environmental degradation. That does not detract from the fact that transport is indispensable to economic progress, which includes the growth in welfare. The technology of machine learning is rapidly maturing. This builds on the broad availability of relevant data in the physical sphere of road and rail freight transport. The state of the art in this technology and its application in supporting better-informed decision-making in transport, with particular reference to truck and rail freight, is reviewed. The nature of prediction, the importance, and the complexities of various paradigms of pattern recognition, clustering of dependent observations, and path optimization are explained. It is discussed how these can drive growth in capacity by rendering transport more efficient and hence more cost-effective, without the need to compromise on environmental and social cohesion goals. All this requires a professional mindset, the establishment of skill sets, and the solution to ethical issues.

Keywords: Freight Capacity, Trucks, Congestion, Machine Learning, Decision-Making, Rail Transport, Pattern Recognition, Path Optimization, Environmental Impact, Ethical Considerations.

1. Introduction

The transportation industry plays a key role in regional and national development. Operations of freight transportation have been variously developed, from traditional road and rail to the most modern technologies like air cargo and smart ships. Growing freight amounts have caused problems and several challenges in urban areas, such as environmental issues, congestion, space occupation, and social impacts. Moreover, the lack of modal shifts and multimodal integration impacts environmental sustainability and traffic congestion within urban areas. Cities have an intense need for cargo transportation, and only a few urban logistics systems are in place to organize, plan, and control the flow of incoming and outgoing shipments. Smart urban logistics attempts to better plan and integrate services of goods transportation through efficient use of data and technologies, which can lead to direct benefits for logistics operators, clients, city managers, and local communities.

The works related to this study experiment with machine learning techniques and big data from transport companies to build a predictive analysis on trucks and shunting units stopping times inside intermodal terminals. These unpredictable periods are crucial for all stakeholders of the intermodal supply chain, as they are the origin of last-minute decisions about planning and organizing all operations like docking, transshipment, and the departure of units. The application of the random forest technique identifies the main input variables that can affect real-time forecast stopping times. This tool aims to support intermodal terminal managers and teams to manage all operations in more efficient and sustainable ways, reduce drivers' waiting and idling times, and improve train unit efficiency by reducing trains' block times.

1.1. Background and Significance

As we are stepping into Industry 4.0, artificial intelligence has brought benefits to various industries such as construction, healthcare, and supply chain management. The abundance of data in many different formats in supply chain logistics has affected the number of applications of AI, especially machine learning and deep learning. Furthermore, the significant revenue loss contributed to logistics delays, and high demand fluctuations affected distributors and transporters. Knowing the future is impossible, but it is essential for effective planning in the logistics domain. Thus, freight demand prediction has become the primary area of interest in logistics. Furthermore, when selecting an optimal route, the need for the best decision seems to be vital. This study aims to provide a valuable discussion on the application of machine learning in road logistics and rail logistics in predicting freight demand and facilitating route optimization.

Unsupervised learning and regression models are frequently used as opposed to a proposed deep learning model in road logistics, while time series forecasting models are more commonly utilized for rail logistics. The machine learns to predict freight demand mainly from historical data, and some utilize specific logistic attributes. Handling a variety of data formats and computational capacities can be stressful; machine learning model users selectively add heuristic selection. Hindered by data censoring, which adds an extra turn for machine learning model prediction, and including other models, for example, the Bayesian model, which is yet to be tested, the current results did not report suitable characteristics for censoring treatment parameters.

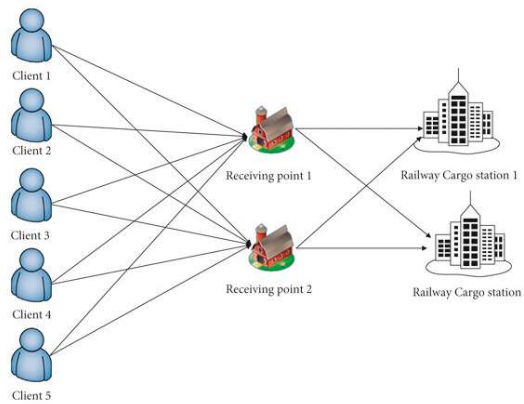

Fig 1 : A Machine Learning-Based Approach to Railway Logistics Transport Path Optimization

1.2. Research Objectives

In addition, the selection of different modes of intermodal transportation and comprehensive planning is interesting and vital in decision-making. The entire transportation network is a complex system, which is hard to solve and optimize efficiently due to various factors, including real-time traffic information and customer dynamic demand. Some machine learning models have been further developed and utilized to solve congestion problems, save energy, satisfy customer demand, reduce costs, and optimize the operation of logistics. Recent studies often apply machine learning in areas like logistics and traffic. However, those studies only focus on road or rail independently. Therefore, the present predictive freight demand based on machine learning models for further transportation schedules is realized for both Chinese roads and railways, and a comparison is carried out between those two modes.

Equation 1 : Route Optimization Model

To optimize routes based on travel time, distance, and cost:

$$\min R = \sum_{i=1}^{N} (C(i) + T(i) \cdot r)$$

Where: R = total routing cost

N = number of routes

$C(i)$ = fixed cost of route i

$T(i)$ = travel time for route i

r = cost per time unit

2. Literature Review

In recent years, organizations across the world have significantly invested in big data, machine learning models, and intelligent applications such as AI and ML to gain an in-depth understanding to make decisions for running operations, maintaining business priorities, and understanding their customers' requirements proactively. It is easier to capture the data using sensors and digital devices. Though it is easier to capture data, it is not that easy to transform data into information and generate knowledge to predict the future. The significance of the intersection between big data analytics and machine learning is due to the value that companies can extract from information already available and captured to optimize their operations and improve asset performance. In the big data space of approximately 15 years, machine learning is the recent affinity of enterprises because of the democratization of computing power due to elastic computing infrastructure, the trusted platform for training machine learning models, and simpler programming languages and libraries to implement sophisticated machine learning models. We propose ML models to predict freight demand and determine the optimal routes for road and rail logistics operations, which are the primary processes in freight companies.

Optimization of routes in freight logistics plays a critical role in revenue as well as the business competitiveness of logistics companies. However, with the modern advances in technology and techniques, it is a little unwise to describe the route planning problem in everyday logistics operations with the model usually utilized. Traditional route planning methods have encountered significant challenges in satisfying the demands of future smart logistics networks. While optimally solving the present route planning problem, those methods are typically computationally expensive or lack flexibility. Some of the most commonly used path algorithms only consider backtracking or do not implement it in railway delivery. Although complex statistical models and optimization techniques have been employed to study decision-making and form an enormous specialty, such as dynamic route optimization and lane-level trajectory, challenges associated with data, agility, and future use keep the research focus limited. As the core of the logistics process, an accurate prediction of future freight demand would certainly be beneficial for them concerning the adjustment of different strategies, decisions, and even business plans. It is also important for policymakers concerning the formulation of a reasonable transportation policy and reasonable spatial arrangements. Against this backdrop, it is not difficult to explain why freight-demand prediction has become a critical hotspot.

2.1. Machine Learning in Logistics

The use of machine learning has seen a rapid rise in different fields as it provides a precise, consistent, and efficient tool for the prediction, classification, and generation of various intrinsic data patterns. Numerous researchers have previously applied diverse methodologies on road and rail transportation to model and predict future freight demand, passenger demand, accidents, travel behavior, network usage, route choice, and several other applications within the broader field of logistic network design, management, and policy-making. These studies have confirmed the utility of these models and methodologies in accurately predicting future transportation-related indices. In employing machine learning tools, which are part of a broader set of computational intelligence techniques in transportation modeling, these researchers have attributed the usefulness of the computing technology to its efficiency in helping to model non-linear transportation systems without resorting to assumptions and simplifications that could add error to the predictions. Like the earlier studies, we also believe that the use of machine learning for freight demand management, route selection, fleet size estimation, dwell time prediction, and positioning and dispatching can greatly enhance the efficiency of either the road or rail off-peak delivery system. Moreover, as the ability exists to employ machine learning to switch demand from road transport to rail, particularly for a mixed transport network, the potential exists to more effectively exploit the co-modal nature of private urban and overhead rail networks. We believe a mixed transport network technical solution can benefit from machine learning in two significant ways. Firstly, spatial logistics links and nodes, which are connections or hubs of national freight road and rail networks, can be optimally leveraged in the service of freight customer needs regardless of the delivery medium, and the control-driven policy market for transporting freight between these service providers can be coordinated using specific routes and frequencies. Secondarily, routing customer freight along the fastest, cheapest, or least policed routes and special purpose vehicles for the transport of two or more goods can provide a source of additional rental revenue and reduce the number of vehicles and total road and rail transport expenses in a co-modal network.

Fig 2 : Benefits of Machine Learning in Logistics Industry

2.2. Freight Demand Prediction

Freight demand prediction is important not only for the management of freight traffic but also for policy-making concerning the development of large-scale commercial goods transportation infrastructure. However, freight demand modeling has received less attention compared to passenger demand modeling in the last decades. The focus of freight demand modeling was limited to specific industries or regions, such as agricultural commodity groups, tourism freight, or regional freight demand in different counties. Traditional modeling methods used in transportation demand prediction, such as regression analysis, gravity models, and econometric models, have been popularly used for freight demand prediction but have limitations in dealing with the real-world dynamics of freight demand. Different freight transportation modes have different prediction modeling problems due to the particular demands and characteristics associated with commerce, economics, location, and political boundaries. To overcome these problems, decision-makers need to be informed by accurate and actionable data that uses current advances in data acquisition, pre-processing, and processing.

Machine learning techniques, which have advantages such as automatic learning from data patterns, nonlinearity, and modeling without loss of generality, are emerging as a promising method for different transportation applications, such as demand prediction, safety analysis, mode detection, and transit occupancy estimation. However, machine learning applications for freight demand prediction have been less focused. Commercial goods transportation over a long distance with a complex pathway via road and rail transportation is core freight logistics. In addition to freight demand prediction, freight route optimization is another important research topic. Efficient freight route planning and logistics have become increasingly important in the era of e-commerce. Many methods attempt to solve the freight route problem, but the results fail to meet the real-world transportation conditions of freight. These are dynamic during transportation times and emerge from route changes among road and rail transportation modes. Furthermore, static data-driven approaches do not provide managerial or political insights that address time-sensitive transportation planning and the possible impacts of demographic change. We present the application of machine learning for predicting freight demand and reconfiguring real-time feasible routes during large-scale commercial goods transportation over long distances on the spatial domain via road and rail transportation.

2.3. Route Optimization in Logistics

In logistics, transport route optimization refers to finding the best routes for different delivery tasks such that the operational costs, typically the distance, time, or toll fees, and constraints are minimized while meeting certain requirements or restrictions. One such requirement is the arrival times at certain delivery locations to satisfy the service level agreements among delivery companies and their customers. Examples of such hard constraints are those signaling the maximum allowable trip durations for drivers. Central to route optimization are the tasks of path or route finding. Both are essentially the same, with an exception being that the latter is more representative when applied to moving transportation where traffic conditions change with time. That is to say, finding the shortest path from one location to another using road networks or finding the least costly movement over a spatial network. Since the 1960s, transport route optimization has been extensively studied in engineering. The methodologies that have been developed can be classified into three categories based on the route optimization approach itself and how the problem is modeled.

3. Methodology

The predictive freight demand models are based on a sort of regression model for logistic capabilities, which is estimated utilizing a large number of input variables, such as the number of jobs, employment type, distance to destinations, and destination region. The objective of logistic capabilities is to provide novel insights into the requirements concerning logistics transparency, integrated and automated logistic chains, and the use of a larger modal share for rail cargo. Moreover, logistic capabilities could be of interest for the investigation of potential passengers of passenger trains and hence may support authorities and railway operators in improving tailor-made public transport systems. However, since the model relies on a large number of input variables, it might be occasionally hard to interpret the results concerning the estimation of coefficients for specific input variables and to provide a comprehensive overview of relevant variables. For route optimization, popular routing algorithms have been tested with a sample dataset, and a range of supporting infrastructure has then been introduced in the GIS system to obtain an optimized route for predicting a spectrum of logistical costs. Subsequently, a machine learning approach has been tested using a similar dataset to handle the optimization of logistical processes, thereby optimizing possible routes, like the classic logistic regression model for demand forecasting. However, it may predict results differently and require less effort due to its versatile data-handling capabilities. The machine learning approach can model such figures in a precise and fast way to achieve a competitive edge in road haulage logistics over traditional historical demand forecasting models. More advanced recent machine learning algorithms can be used for route optimization using advances in deep learning. Some questions arise on whether the use of such complex algorithms can further increase the precision of the optimized route, or possibly here overfitting can negatively impact their performance.

Equation 2 : Cost Function for Freight Transportation

To evaluate the total cost of freight transportation including variable and fixed costs:

$$C_{total} = C_{fixed} + \sum_{j=1}^{M} (C_{variable}(j) \cdot Q(j))$$

Where: *Ctotal* = total transportation cost

Cfixed = fixed costs (e.g., administrative expenses)

M = number of freight items

Cvariable(j) = variable cost per unit for freight item *j*

Q(j) = quantity of freight item *j*

3.1. Data Collection and Preprocessing

The information for the system is based on two data sources: the transportation network is based on spatial data available to build the graph. Also, on the European network available from various organizations. The demand is a real field dataset from a mobile network provider. This data includes traffic distribution through the territory, and it is only classified by active SIM cards in their different packages. The client has a huge number of clients across Europe. From the database, we restrict it to the customers who have installed and are using their application to monitor the traffic or have their SIMs with a mobile phone while driving. This last selection tries to capture the effect of the penetration of SIM cards among the population, i.e., if most of the traffic is from tourists or the local population.

The process in this case has three fundamental steps. The first one is the collection of data, where we make sure we take out the traffic that is not related to freight transport. This is done by removing the traffic of two types: the one which has hours that coincide with lunchtime, and the other that lowers the edge density below a certain value. After that, we settle the data by selecting the spatial location of those mobile phone frequencies and finding the first demand candidate selection. These methods are all common for data analysis. Although the data we used to generate the demand at this stage may raise questions and criticisms, we believe this will be one of the main strengths of our method, since this data and the techniques extend to other areas, offering a reliable, fast, and freely available manner of gathering data while guaranteeing the privacy of the data gathered under a safe privacy policy.

3.2. Machine Learning Models for Freight Demand Prediction

Setting up a model for freight demand prediction requires historical records of freight volumes, freight carried, and destinations. In addition, variables that affect freight demand should be taken into consideration, including changes in channel value and business cycle, freight rates, external constraints, market competition, and company strategy. The simplest approach, such as regression analysis, might not be useful to understand the necessity of the alteration or to observe the application of those changes. Thus, advanced techniques, such as neural network modeling, should be used to address the identification of some unusual complex patterns in the general working function whenever needed. Due to such superior acquisition of knowledge about the model's characteristics, neural networks have various advantages when compared to other statistical methods. Indeed, a neural network can model a larger number of complex statistical interdependencies through its incredibly flexible functional form, and this capability can produce improved fitting specifications that outperform other approaches. Frequent applications of neural network models in freight demand include recurrent pattern recognition, forecasting, classification, and route assignment to determine future utilization of transport resources and capacity.

A neural network tool has been used to predict the sophisticated freight demand on nine rail lines. Mixing outputs of multiple networks would be the best approach in this case. Initially, independent networks predict the origins and destinations, respectively, and then transfer these results into another network that considers general trip characteristics to predict a named advanced demand segment. The neural network methodology, therefore, predicts a person's origin-destination demand pair by considering the unique trip characteristics along the way. Furthermore, the support vector tool is capable of predicting continuous and discrete outcomes for binary and multi-class problems. Moreover, the support vector machine tool primarily addresses various forecasting problems and mainly applies binary classification and regression analysis techniques.

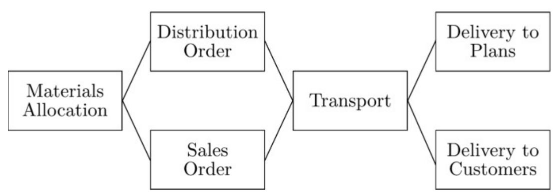

Fig 3 : Demand Forecasting for Freight Transport Applying Machine Learning into the Logistic

3.3. Machine Learning Models for Route Optimization

While some studies have applied machine learning for the estimation or prediction of final performance levels, there is not much research on the application of machine learning for route optimization. Thus, more research is needed. The main idea of the route optimization model is to diminish overall route distance while considering truck weight limitations, freight demand distribution along the routes, and road conditions such as traffic jams. The routes for a truck's delivery may have completely different lengths, roads, and places. Moreover, some places to be visited may need more time as they take longer and require detours through ferry routes, which should be the fewest and fastest. More recently, some studies have focused on just considering a fixed terminal to a city without considering routing within the city and urban constraints from the terminal to the delivery location.

When developing such models, we have categorically chosen from three possible approaches. Route-based optimization methods may range from primitive distance matrices and heuristics, classic exact optimization methods through integer linear programming, dynamic programming, and branch-and-bound algorithms to approximate solutions with metaheuristics such as genetic algorithms, simulated annealing, and ant colony optimization, which are not based on learning algorithms. In the machine learning approach, we interpret route optimization as a classification or regression problem and apply machine learning methods that are commonly used for such tasks simultaneously. The strengths and weaknesses of both approaches are significant.

4. Case Studies

The methods proposed in this paper are used to forecast, for a logistics company, the freight demand assigned to its road and rail transportation services. Annual freight demand data for 177 individual origin-destination pairs from German customers in the automotive industry are analyzed. Publicly available statistical and operational data are given as input features to a machine learning model that is used to make, 12 months in advance, route-level and service-level forecasts of the number of transportation requests from customers. The uncertainty and accuracy of these predictions are measured, and conditional boxplots are used to split OD pairs into deciles indicating where the largest errors can occur as a function of input features.
Another machine learning model is employed to predict, 15 months in advance, customer orders for automobile parts and, 18 months in advance, customer orders for whole vehicles. The statistical similarity between the time series of customer orders helps to strengthen these predictions by imposing the autocorrelation, as well as the cross-correlation, of the predicted time series. Both the route-level and service-level predictions of the transportation demand and the time series of orders are concatenated and utilized in an optimization routine that solves a multi-objective problem addressed in rail standard 1.9.3.3.

4.1. Road Logistics Case Study

In this case study, we applied our previously developed model on the U.S. Import Shipments dataset to predict U.S. truck tonnage demand on a specific route. Two different scenarios have been designed. We first predict truck tonnage demand (scenario 1) on a hypothetical route for 2019 based on the actual demand in the real world. This route links the distribution warehouses on the West Coast to the consumption markets on the East Coast. All the prediction work is based on real demand in the years 2013-2018, and the estimation includes both short-term periodic and long-term changes in truck demand on the same route. We further compare these two demand patterns to justify the prediction accuracy using the actual tonnage statistics from the 2019 data. We then predict total truck tonnage demand (scenario 2) in the U.S. for 2019 to validate the generalization of our model. Please note that both the time and location factors have been taken into account in the model, while the actual orders for the truck are not included. The performance of our model should be considered in solving a specific truck distribution problem based on the estimated truck demand on a particular route.
Data and Data Preprocessing The system we consider is the just-in-time (JIT) truck delivery from the West Coast port to the East Coast distribution warehouses. We set the regional demand prediction model for the oracles; we combine a comprehensive weekly U.S. Import Shipments dataset that consists of shipment details in terms of carriers, distribution origins, destination airports, periods, distributions, and corresponding truck demands. The yearly data contains both air and truck demand in the period 2013-2018 for most of the 323 distribution airports in the U.S.A. After loading all the data into a database and aggregating them year by year, we have two main tables: the Shipments Table, which provides a list of the weekly shipments with the shipment details like carriers, truck drivers, origin and destination airports, shipment timestamps, etc., and the Flights Table, which provides information on the parameters of the air freight services. As an example of important data columns, the top records of the 2018 shipments table are shown under a hypothetical origin called "SEA" in Washington state, and the top records of its flights table are shown. Through this dataset, we can analyze the JIT truck delivery from the U.S.A. distribution airports by air cargo direct delivery. Different dates of orders' export are regulated by the manufacturer because of different lead times. The observations of data were demonstrated using the overall growth in air freight. Subject to the characteristics of this case study, we only consider the truck tonnage in two stages. In stage 1, we investigate the aggregated average weekly truck tonnage release day by using pattern exploration, estimation, and validation of just-in-time truck delivery from the West Coast to the East Coast. We further obtain the cyclic trend of freight demand in a fixed period. Built on the weekly or four-week average weekday truck tonnages from the available data, we predict the truck tonnage per day through the cross-temperature ratio to deliver the conservative tonnages of critical value that need to be supported (preparation tonnages) to meet the just-in-time truck delivery to enhance cargo security. The cross-temperature ratio is the turning point for truck tonnages released across the distributions during the West Coast port drayage request process. Furthermore, the preparation tonnages are sorted day by day, then marked in the plane with tonnage and referred time or written down based on the driver's equipment.

4.2. Rail Logistics Case Study

This section will discuss the application of machine learning in rail logistics. We will address the key challenges of the case study, including classifying different customer queries and optimizing the customer onboarding process and customer fulfillment process.

The company was initially founded with the vision of utilizing big data analytics in the process of modernizing railroads and improving their economics and finances. In this vision, machine learning is one of the most contrasting enablers of the transformation of traditional freight railways. The company needed to solve three key challenges that the data could help immensely: classifying different customer queries and directing them to the relevant company representative, optimizing the customer onboarding process through the use of decision trees for predicting equipment availability, and optimizing the customer fulfillment process by utilizing predictive models for weight and transit time of train service.

The company has shown the steps followed by rail logistics to solve the customer onboarding process using machine learning. By utilizing machine learning for classifying different customer queries, they managed to transform the company from a passive participant to an active proponent and provide insights through data into how the business operates rather than assuming it is happening. In terms of the technology used in the approach, the company utilized decision trees, logistic regression, and K-means algorithms. At the end of the day, using automated machine learning, automated feature engineering, and model evaluation were created. However, the final models suffer from low R-squared and a lot of multicollinearity, so the stakeholders dropped the idea of using these models for production.

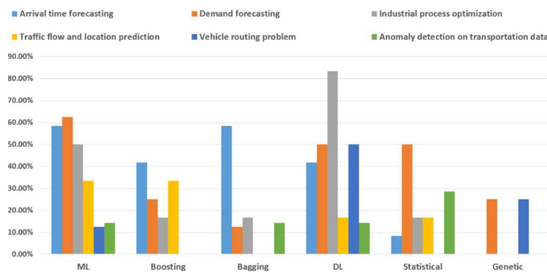

Fig 4: Utilizing machine learning on freight transportation and logistics

5. Conclusion

urrently, the impacts of the Fourth Industrial Revolution on the transformation in logistics and supply chain management are the trend of supply chain cooperation optimization. The application of machine learning solutions to the management of logistics and supply chains based on the establishment of a predictive freight network model can support and improve decision-making in logistics, express, and warehousing. This paper has presented an outline framework to determine and analyze the relationship feature importance in the freight demand estimation considering interurban freight transportation, as well as the possible gap in location planning. Additionally, a predictive express terminal demand network is generated and can point out similar terminals with obstacles and constraints that plan new international stations in the same network. The novel contribution of the paper is a practical tool that can predict a time-consuming route for transport modal shift. The experiments showed the quality of the proposed methodology and the potential of predictive freight demand integration in logistics facility location and route optimization problems. To confirm the acceptability of the results, they need to be corroborated in future studies. This approach bears promise because it has the potential to significantly improve the expressed shifts toward more efficient, resilient, and environmentally friendly transport. The method of identifying highly important terminals may give a better policy formulation, in the planning process as well as providing an assortment of services. It should also be noted that there are alternative ways that might be used to further improve the development of the demand model with more available data. Information about other facilities near terminals would have helped to improve the load and determine the proportion of sub-operating income points for customers. In addition, according to the actual traffic status, data from drivers operated on radiated express trains may be used to further improve the model, as well as the potential allocation of point-of-interest data in urban indicator systems and urban sub-regionalization.

Equation 3 : Machine Learning Model Loss Function

For training machine learning models predicting demand and optimizing routes, the loss function can be defined as:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}(D_{pred}(i) - D_{true}(i))^2 + \lambda R_{route}$$

Where: $D_{pred}(i)$ = predicted demand for observation i

$D_{true}(i)$ = actual demand for observation i

λ = regularization factor for route optimization

R_{route} = routing efficiency score (e.g., based on distance or time)

5.1. Future Trends

1) More global research incorporating explicable ML models and simulation tools in the areas of logistics and supply chains could be expected. Environments with business constraints for the ML model training process or the scenario comparison could increase the combination of arithmetic modeling, physics, and domain knowledge in the training and validation of the applied models, allowing optimization and helping for a better understanding of the developed tools by users and the public. Related possible future trends could be business-focused model training and model learnability exceeding other models. Ensembles of economic indices and machine learning and optimizing models could be designed to cover and aggregate market influences. For close-to-business applications, hybrid models combining statistical techniques, traditional optimization algorithms, or simulation models to forecast or optimize commercial transport development might have priority.
2) Development of ML that highlights its product usage safety issues for the reduction of potential concealed diversity-based bias in outputs. Instead of a universal solution of multiple business targets with optimal performance in a real dynamic environment, where a model algorithm satisfying the business conditions can exhibit adverse side effects, such as customer blocking, performance degradation, and a technology digital divide, could be achieved. Combining conversational worst-case and best-practice scenarios to help the business practitioner in decision-making, monitoring business guidelines, realizing consequences, and searching for solutions on the way to operational and resource management stages. What-if calculations built on an adaptable ontology could be published with the model software. The integrated published design of simulation and optimization technology should continuously provide solution reports, suggesting rules that can support problem solvers in business multitarget management with explanations, which could be considered in the iterative design process.

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