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Utilizing machine learning on freight transportation and logistics applications: A review

Kalliopi Tsolaki, Thanasis Vafeiadis*, Alexandros Nizamis, Dimosthenis Ioannidis, Dimitrios Tzovaras

Centre for Research and Technology Hellas, Information Technologies Institute, 57001 Thessaloniki, Greece

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Abstract

This review article explores and locates the current state-of-the-art related to application areas from freight transportation, supply chain and logistics that focuses on arrival time, demand forecasting, industrial processes optimization, traffic flow and location prediction, the vehicle routing problem and anomaly detection on transportation data. This review categorizes the related works according to machine learning methodologies so as to present the methods' evolution through time, their combinations and their connection with the various applications in the specified fields. Thus, a reader would effortlessly get insights about the current state-of-the-art related to machine learning in freight transportation and related application areas.

Keywords: Machine learning; Data mining; Intermodal freight transportation; Logistics 4.0; Supply chain; Literature review

Contents

1. Introduction

Continuous globalization has increasingly interconnected the world. Thus, it is nowadays more evident and profound the importance of international freight transportation, which creates the need for effective and efficient management, of the corresponding services and providers. At the same time, the emergence of new technologies highlights the related research that integrates the concepts of *Big Data Analytics*, *Data Mining*, *Machine Learning*, *Supply Chain Analytics* and *Logistics 4.0*. The proliferation of big data analytics for freight transportation and the advancements in machine learning have renewed the data-driven research. In the recent years, many

* Corresponding author.
E-mail addresses: ktsolaki@iti.gr (K. Tsolaki), thanvaf@iti.gr (T. Vafeiadis), alnizami@iti.gr (A. Nizamis), djoannid@iti.gr (D. Ioannidis), dimitrios.tzovaras@iti.gr (D. Tzovaras).
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data mining and machine learning based studies have been conducted, that investigate a range of issues associated with international freight transportation, supply chain and logistics management.

Recent literature reviews in these areas are provided below. In [1], the authors provide the results of their research methodology for big data analytics in supply chain management without reference to machine learning and in [2], the author classifies data mining articles also in supply chain management. In [3], authors provide an extensive review for sub-cases (demand forecast and operation and asset maintenance) of freight transportation and the use of machine learning techniques. In [4], authors record multiple machine learning algorithms applied for various supply chain processes, while emphasizing on artificial neural networks' applications. Finally, in [5] authors investigate and analyze relevant articles dealing with logistics service quality without referring to the advances of machine learning techniques in the specified area.

The motivation behind this survey is to present recent scientific articles that utilize machine learning techniques in the optimization of different operations related to freight transportation, supply chain and logistics. The articles are selected and categorized according to their application areas, which are: (a) arrival time forecasting, (b) demand forecasting, (c) industrial processes optimization, (d) traffic flow and location prediction, (e) vehicle routing problem and (f) anomaly detection on transportation data. Having in mind that most transportation companies face long term forecasting of time and location of future orders and deliveries problem, authors researched for the relevant literature, that utilizes machine learning and data mining techniques to solve these kind of industry problems.

To the best of our knowledge, there are many studies conducted that overall concern supply chain management. Also, many articles concern issues related to optimization, knowledge discovery and solutions developed for freight transportation, supply chain and logistics processes, utilizing capabilities of machine learning and data mining. For the purposes of this work, recent and related studies along with advancements in the area of supply chain management have been surveyed and selected to be presented.

The remainder of this paper is organized as follows. Section 2 provides a brief description of the steps followed for the collection of information and articles related to the topic of our research. Section 3 presents in detail several scientific articles related to application areas mentioned above. In Section 4 we draw our conclusions highlighting the key points of this review and some directions for future research.

2. Manuscript preparation

This section presents in detail the research methodology followed in order to make the literature review according to the domain and research areas mentioned above. Besides our research interests, the lack of a review for the latest existing works that address the specific application areas has been identified and led us to the creation of this brief guide concerning issues of freight transportation, supply chain and logistics applications utilizing machine learning and data mining techniques. Furthermore, we identified a lack of grouping of various works related to freight transportation, in some root categories of machine learning. This grouping and mapping between machine learning methods and application areas would enable readers to recognize quickly the type of algorithms that they can use in order to solve a specific problem in an application area. Moreover, we defined the lack of an analysis that presents the combination of different machine learning methods and how it is connected with application areas.

This study has followed a methodology to determine how other researchers have approached the domain application areas, what kind of machine learning and data mining techniques have used, what related problems they have solved, the relevant data sources that have leveraged, as well as the frameworks that have developed. Our research approach involved several phases such as the research planning, the published articles collection including articles of the last decade (2012 to 2021) published within journals and conferences proceedings, the study assessment, filtering and selection, the category division and the papers' evaluation and analysis. The research planning phase included the identification of the crucial research questions, in order to have a clear formulation of our work: (a) Which are the approaches and methods that lately are used for building machine learning and data mining-based solutions regarding freight transportation, supply chain and logistics management?, (b) Which are the most common domain applications approached?, (c) What kind of frameworks have been developed and how they were built?, (d) Do the related works evaluate their methods using transportation and logistics data sources? (e) Which is machine learning methodologies usage trends through time? and (f) Are there relations and combination in machine learning categories' usage?

Therefore, for the study assessment and selection phases, the goal was to select articles that their analysis and synthesis were answering the research questions given above. For category division phase, descriptive categories were created according to the selected articles' subjects and continued with the synthesis of brief presentations of the analyzed works according to research questions. Finally, for articles' evaluation and analysis phase, brief presentations for each paper were synthesized. Relevant tables and graphs were also extracted and presented. Following the research approach described above step by step, research goals initially set were attained and resulted in the present literature review.

3. Machine learning and data mining for freight transportation, supply chain and logistics management applications

The present section reviews machine learning and data mining research on applications concerning freight transportation, supply chain and logistics management and it is organized based on application areas.

Hence, in Sections 3.1 and 3.2, are reviewed studies focusing on forecasting of arrival time and demand, respectively.

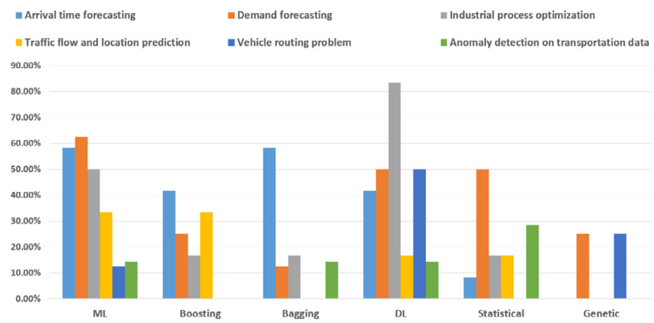

Fig. 1. Grouped bar chart of percentages of machine learning categories usage per application areas.

Section 3.3 is dedicated to data mining approaches applied for resolving problems related to industrial processes. Subsections, 3.4, 3.5, include applications that generally refer to the freight transportation procedure and more specifically the traffic flow and location prediction and the vehicle routing problem. Finally, Section 3.6, refers to recent studies conducted regarding the anomaly detection problem, that constitutes one of the biggest challenges in data mining.

During this research, all articles were categorized according to machine learning methodology(ies) utilized in each application area in order to find the usage trends in decade time horizon. Fig. 1 provides the percentages of machine learning categories per application area. The percentages were exported by observing the two categorizations in Tables 1 and 3 explained below. Fig. 2 describes how the use of machine learning categories is evolving through time and Fig. 3 provides a Venn-diagram of machine learning categories usage. Table 1 provides a list of machine learning techniques utilized by researches to address each application area and their categorization based on these areas. Table 2 provides a brief description of related key concepts addressed in this work, such as intermodal freight transportation, logistics 4.0, data mining and machine learning and Table 3 provides a categorization of articles per method category. Findings from figures and tables are described in Section 4.

3.1. Arrival time forecasting applications

An important issue for transportation operators is to have fairly reliable and affordable predictions about modes of transportation arrivals. Administration and operators need to estimate the actual time of arrival in warehouses/terminals/ports, in order to determine the daily demand in resources required (human resources, equipment, spatial resources etc.) and then to allocate them more efficiently. In [6], authors are proposing a Classification and Regression Trees (CART) model to reduce the range of uncertainty of ship arrivals in port, applying it on data registered at the Transhipment Container Terminal (TCT) of Cagliari in Italy. CART is a landmark among DT algorithms [7]. As researchers' goal was to forecast container ship delays, their data collection process led to a database containing information about mother and feeder vessels arriving at the container terminal in 2010.

Another work that utilizes classification techniques concerning the logistics optimization is an application for predicting on-time delivery in the trucking segment of transportation industry [8]. In the transportation industry, third-party logistic firms (3PLs) have a stake in making accurate predictions. A key metric by which 3PLs are measured on is on-time-delivery. If on-time-delivery could be predicted with some degree of certainty, then efforts could be focused on those loads that require resources. After identifying from the input variables which combination would allow the predictions of on-time delivery, exploring approaches that can alleviate multi-collinearity and reviewing widely used models to predict categorical response using continuous and categorical predictors, authors resulted in using Logistic Regression (LR) models. The selected model was then validated by neural networks and bootstrap forest models.

In [9], authors conducted a case study to examine and validate the factors that influence arrival time. The study includes a survey of 230 truckers, a data analysis and a data mining experiment, using real traffic and weather data. This research concerns a European Distribution Center and attempts to find ways to predict a truck's arrival time, as this will enable a Distribution Center (DC) to respond sufficiently and effectively to exceptions.

Several data mining techniques were used to see if it was possible to predict arrival times, even though the independent variables have a negligible correlation with the dependent variable: tardiness or difference between planned and actual arrival time [9]. The five data mining techniques used in the study are: DT, a variation on Breiman et al.'s Clustering and Regression Trees [7], k-NNs [10], SVM [11] and its ensemble classifiers Adaboost.M1 [12,13] and RF [14].

In [15], researchers utilized regression as a data mining technique, that demonstrates the use of machine learning algorithms, as more suitable to solve non-linear and complex relationships in tracking data, for travel time prediction in multimodal transports. Researchers have selected Extremely Randomized Trees (ExtraTrees), Adaptive Boosting (AdaBoost) and Support Vector Regression (SVR) as representative algorithms for modeling their use case. All three algorithms are capable of adapting to complex systems and are robust in dealing with complex and small data sets. They have shown superior performance in previous research with low processing time.

Authors in [16], proposed the use of well-studied machine learning algorithms to generate estimated times of arrival (ETAs) in real time for freight trains. The algorithms trained on railroad operational historical data including also physical train characteristics and train crew information. Their work presents the comparison of predictive performance of linear and non-linear SVR, Random Forest Regression (RFR) and deep neural network models.

For this study, the proposed framework was based on KDD in [17] and includes eight steps. Data acquisition and preprocessing, train/test splitting of data, clustering for identifying stops and trans-loading points, feature selection, grid search and cross validation with five train and validation sets for

Table 1
Machine learning techniques utilized per application area.

Application area	References	Machine learning/Data mining techniques
Arrival time forecasting	C. Pani et al. (2014)	Classification and Regression Tree
	S. Van der Spoel et al. (2016)	Decision Trees, k-Nearest Neighbors, Support Vector Machines, Ensemble classifiers: Adaboost.M1 and Random Forest
	N. Servos et al. (2020)	Support Vector Regression, Extremely Randomized Trees, Adaptive Boosting
	J. Yu et al. (2018)	Back-propagation Neural Networks, Classification and Regression Tree, Random Forest
	N. H. M. Salleh et al. (2017)	Fuzzy Rule-Based Bayesian Network
	R. D. Alcoba and K. Ohlund (2017)	Logistic Regression
	T. Antamis *et at.* (2021)	Random Forest, Gradient Boosting, WaveNet, Bagging
	P. Valatsos *et at.* (2021)	Bagging, Random Forest, Gradient Boosting, Natural Gradient Boosting, Extreme Gradient Boosting
	A. Balster *et at.* (2020)	Linear Regression Trees, Random Forest and Gradient Boosting
	W. Barbour*et at.* (2018)	Linear and Non-Linear Support Vector Regression, Random Forest Regression and Deep Neural Network
	A. Derrow-Pinion et al. (2021)	Graph Neural Networks
	F. Li et al. (2021)	Dynamic Graph Convolutional Recurrent Network
Demand forecasting	M.Niu et al. (2018)	Hybrid decomposition of the Variational Mode Decomposition algorithm, Autoregressive Integrated Moving Average models, Support Vector Regression models and the Hybridizing Grey Wolf Optimization
	L. Mo et al. (2018)	Group method of Data Handling Neural Network, combining the Seasonal Autoregressive Integrated Moving Average, Support Vector Regression, Back-Propagation Neural Network and Genetic Programming
	J. Moscoso López et al. (2016)	Ensemble framework of the best Bayesian Regularization Neural Network models
	D. Knoll et al. (2016)	Integration of generalized Machine Learning modelling processes and business knowledge of logistics planning into a predictive framework
	C.K.H. Lee (2017)	Genetic Algorithm-based optimization model
	V. Plakandaras et al. (2019)	SVR with linear, radial bases, sigmoid and polynomial kernel functions along with Least Absolute Shrinkage and Selection Operator and Ordinary Least Square Regression
	S. Bakhtyar and L. Henesey (2014)	Averaged One-Dependence Estimators, Sequential Minimal Optimization, k-Nearest Neighbors, LogitBoost, Repeated Incremental Pruning to Produce Error Reduction, Logistic Model Trees and HyperPipes
	S. Jaipuria and S.S. Mahapatra (2013)	Discrete wavelet transforms, Artificial Neural Networks and Auroregressive Integrated Moving Average
Industrial processes optimization	O. Matei et al. (2016)	Neural Networks, Naive Bayes, Support Vector Machine, Fast Large Margin, k-Nearest Neighbour, Logistic Regression, Random Forest, Rule Induction
	A. Avram et al. (2020)	Context-Aware Data Mining and Collaborative Data Mining integrating k-Nearest Neighbor, Neural Networks, Gradient Boosted Trees, Decision Trees
	N. Stefanovic (2015)	Clustering Algorithm, Decision Trees and Neural Networks
	A. Metzger et al. (2015)	Artificial Neural Networks
	I. Kourounioti et al. (2016)	Artificial Neural Networks
	R. Piendl et al. (2019)	Bayesian Classifier
Traffic flow and location prediction	A. Bhattacharya et al. (2014)	Support Vector Regression, combined with Mixed Integer Programming
	Y. Liu et al. (2021)	Decision Trees, Support Vector Machines, Gaussian process regression, Artificial Neural Networks, Particle Swarm Optimization
	R. Wu et al. (2018)	Spatio-temporal data mining utilizing Content, Distribution, Pattern, Preference, Social relation and Representation
	X. Li and R. Bai (2016)	Gradient Boosting Regression Tree models
	Y. Song et al. (2019)	Segment-based regression kriging and Segment-based ordinary kriging
	X. Li and R. Bai et al. (2016)	Gradient Boosting Regression Tree

(*continued on next page*)

Table 1 (*continued*).

Application area	References	Machine learning/Data mining techniques
Vehicle routing problem	P. C. Pop et al. (2013)	A hybrid heuristic algorithm, combining a Genetic Algorithm with a local-global search procedure
	Y. Zhao et al. (2016)	A hybrid heuristic algorithm, combining Monte-Carlo, Artificial Neural Networks and a Genetic Algorithm
	L. Qi and Z. Zheng (2016)	Spatial Clustering algorithm, Support Vector Machine algorithm
	J. J. Q. Yu et al. (2019)	Neural combinatorial optimization strategy based on Reinforcement Learning
	T. Becker et al. (2016)	Routing Agent-based Neural Network computational model
	R. S. Kumar et al. (2016)	Hybrid Self-Learning Particle Swarm Optimization
	M. Nazari et al. (2018)	Reinforcement Learning
	V. Oriol et al. (2017)	Pointers Network
Anomaly detection on transportation data	A. Kiersztyn et al. (2020)	Granular Computing
	M. H. Hassan et al. (2019)	Multi-channel Singular Spectrum Analysis
	P. Karczmarek et al. (2020)	k-Means-Based Isolation Forest
	P.-R. Lei (2016)	A framework for maritime trajectory modeling and anomaly detection
	A. Kiersztyn et al. (2020)	Fuzzy set – based techniques, the crisp filling and fuzzy filling of time series missing data
	C. Liu et al. (2016)	An improved grey neural network model
	C. Di Ciccio et al. (2016)	One-class Support Vector Machines

Table 2
Related key concepts description.

Key concept	Description
Intermodal freight transportation	A branch term of international freight transportation is the *Intermodal Freight Transportation* which is defined as the transportation of cargo from an origin location to a destination, through a sequence of at least two transportation modes, the transfer between the modes is being performed at an intermodal terminal.
Logistics 4.0	Logistics 4.0 concern the various aspects of logistics and supply chain management that are addressed with solutions from AI and from the fields of Industry 4.0, Internet of Things, emerging technologies, advanced data analytics and autonomous or semi-autonomous decisions systems.
Data mining	*Data mining* is a process used by companies in an effort to transform raw data from machines and IoT devices, stored in large datasets, into useful information and discover patterns, behaviors and hidden insights, that would lead them to more effective decision making.
Machine learning	*Machine Learning* involves the study of computational algorithms that automatically learn to perform complex, advanced and challenging computational tasks so as to extract valuable information through extensive training, using data called features. There are three main types of learning problems in machine learning: the supervised learning, the unsupervised learning and the reinforcement learning, which are widely used to solve problems related to freight transportation field.

parameter tuning, model testing and evaluation and finally, machine learning models (SVR, ExtraTrees and AdaBoost) comparison with commonly used average-based approaches (Root Mean Square Error).

In [18], researches employed data mining approaches to address the issue of ship port arrival uncertainty. They applied back-propagation neural networks, CART and RF, to predict the arrival time of ships in a container terminal in China. Authors' experiments showed that the most significant predictors that affect the ETA are the ETA day/shift/month, ship length and route type. Additionally, the RF model outperformed the other two models for estimating ship arrival time. A similar study in [19], proposes a model that utilizes a hybrid decision-making technique, the Fuzzy Rule-Based Bayesian Network (FRBBN), a technique that combines a Fuzzy Rule-Based

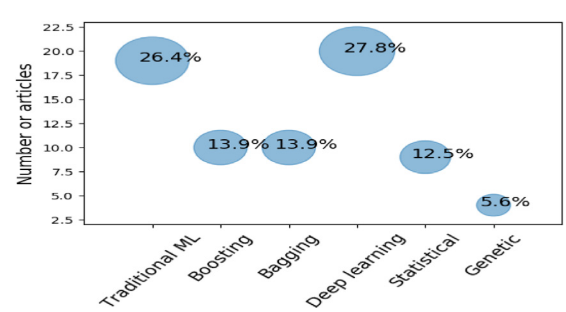

Fig. 2. Use of machine learning categories at 2012–2021.

Table 3
Articles per method categories.

Method category	Articles
Machine learning	C. Pani et al. (2014), S. Van der Spoel et al. (2016), N. Servos et al. (2020), R. D. Alcoba and K. Ohlund (2017), A. Balster et at. (2020), W. Barbouret at. (2018), M.Niu et al. (2018), L. Mo et al. (2018), D. Knoll et al. (2016), V. Plakandaras et al. (2019), S. Bakhtyar and L. Henesey (2014), O. Matei et al. (2016), A. Avram et al. (2020), N. Stefanovic (2015), A. Bhattacharya et al. (2014), Y. Liu et al. (2021), L. Qi and Z. Zheng (2016), C. Di Ciccio et al. (2016), J. Yu et al. (2018)
Boosting	S. Van der Spoel et al. (2016), N. Servos et al. (2020), A. Balster et at. (2020), D. Knoll et al. (2016), S. Bakhtyar and L. Henesey (2014), A. Avram et al. (2020), T. Antamis et at. (2021), P. Valatsos et at. (2021), X. Li and R. Bai (2016), X. Li and R. Bai et al. (2016)
Bagging	Van der Spoel et al. (2016), N. Servos et al. (2020), A. Balster et at. (2020), W. Barbouret at. (2018), D. Knoll et al. (2016), O. Matei et al. (2016), T. Antamis et at. (2021), P. Valatsos et at. (2021), P. Karczmarek et al. (2020), J. Yu et al. (2018)
Deep learning	W. Barbouret at. (2018), L. Mo et al. (2018), D. Knoll et al. (2016), O. Matei et al. (2016), A. Avram et al. (2020), N. Stefanovic (2015), Y. Liu et al. (2021), J. Yu et al. (2018), T. Antamis et at. (2021), A. Derrow-Pinionet at. (2021), F. Liet at. (2021), J. Moscoso Lòpez et al. (2016), S. Jaipuria and S.S. Mahapatra (2013), A. Metzger et al. (2015), I. Kourounioti et al. (2016), J. J. Q. Yu et al. (2019), T. Becker et al. (2016), M. Nazari et al. (2018), V. Oriol et al. (2017), C. Liu et al. (2016)
Statistical	M.Niu et al. (2018), L. Mo et al. (2018), S. Bakhtyar and L. Henesey (2014), S. Jaipuria and S.S. Mahapatra (2013), N. H. M. Salleh et al. (2017), R. Piendl et al. (2019), Y. Song et al. (2019), M. H. Hassan et al. (2019), A. Kiersztyn et al. (2020)
Genetic	L. Mo et al. (2018), C.K.H. Lee (2017), P. C. Pop et al. (2013), Y. Zhao et al. (2016)

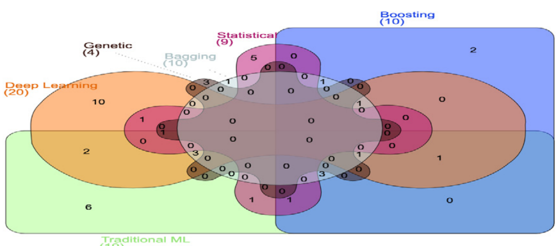

Fig. 3. Venn diagram of machine learning categories usage.

(FRB) approach and a BN. Researchers use their model to analyze and predict vessel arrival punctuality, a feature that depends on many factors, such as environment conditions, agencies' management efficiency, etc. It evolves in six steps, starting from the identification of the influential factors and through node state definition, conditional and unconditional probabilities determination, generic model development and ends up to validation of final predictions using sensitivity analysis.

In [20,21], the authors presented a comparison of machine learning and ensemble learning techniques in order to decide about the method with the best predictive performance on forecasting the delivery time and intermodal freight transportation warehouse problem.

In [22], the authors presented a computational study of an ETA prediction model for intermodal freight transport networks, which combines schedule-based and non-schedule-based transports and utilizes machine learning techniques. More specifically, the prediction model that estimates the transport time on road between the shipper and the inland terminal uses linear regression trees. The lead-time regression in the inland terminal is based on RF, with which the connecting train is then determined. RF and GB are used to predict the transport time for all rail sections between the individual operating points along the transport route from the inland terminal to the sea terminal. To predict the connecting train in the marshaling yard ordinal forests are used.

In [23], researchers presented a Graph Neural Network (GNN) estimator for ETA which has deployed in production at Google Maps. They use MetaGradients training schedule method in order to make the model robust and production-ready. The proposed GNN proved powerful, significantly reducing negative ETA outcomes in several regions compared to the previous production baseline. In [24], researchers propose a novel traffic prediction framework, named Dynamic Graph Convolutional Recurrent Network (DGCRN) in order to address dynamic characteristics of correlations among locations on road networks of an urban environment and to overcome the fact that most Recurrent Neural Networks (RNNs) are not efficient enough due to their recurrent operations.

3.2. Demand forecasting applications

For port container throughput forecast in [25], authors built a hybrid decomposition ensemble model. The proposed model consists of a combination of the Variational Mode Decomposition (VMD) algorithm, Autoregressive Integrated Moving Average (ARIMA) models, SVR models and the Hybridizing Gray Wolf Optimization (HGWO). The proposed hybrid model yielded high accuracy in the related experiments, indicating its future use in practical use cases.

A similar study in [26], also proposes a hybrid model which is based on Group Method of Data Handling (GMDH) neural network. The introduced model decomposes the original series data into linear and non-linear components. The linear components are predicted by the Seasonal Autoregressive Integrated Moving Average (SARIMA) approach and the non-linear subseries by three single models, SVR, back-propagation (BP) neural network and Genetic Programming (GP). These predictions are selectively combined by the GMDH neural network to obtain the non-linear forecasting results. The two-part predictions are then integrated to get the final forecasting results. Its performance exceed the single SARIMA model, as well as other SARIMA hybrid models that have been compared to.

The study in [27], presents a GA-based optimization approach that tackles anticipatory shipping issues, meaning the prediction of customers' behavior. Researchers applied predictive analytics, in order to propose an optimization model that will determine the distribution and allocation of products to different distribution centers, considering transportation cost and time, as well as the confidence of the prediction results. The proposed model consists of three core modules: (a) a big data management module, (b) a consumer analytics module and (c) a shipping optimization module. Authors reported experiments that prove the reliability of their methodology, while examining the trade-off between different factors of anticipatory shipping.

In [28], researches examined the short-term forecasting problem of fresh freight weight on Ro-Ro transport for a period of 7 and 14 days ahead. Authors' approach is based on a two-stage procedure that predicts freight flow at the Port of Algeciras Bay. The first stage, utilizes Bayesian Regularization Neural Networks (BRNN) to predict the flow of 7 and 14 days ahead and at the second stage the forecasts of the best BRNN models are optimized through an ensemble framework consisting of multiple processes. The experiments results were very promising approach on the forecasting of Ro-Ro freight time series. The authors in [29], present a machine learning approach for future inbound logistics processes prediction. Thus, the authors' had combined machine learning modeling processes with business knowledge on logistics planning.

In [30], researchers have used a combination of SVR with all types of kernel functions (linear, radial bases, sigmoid and polynomial) from machine learning field along with Least Absolute Shrinkage and Selection Operator (LASSO) and Ordinary Least Square (OLS) Regression from econometrics in order to forecast train transportation demand for the U.S. domestic market in various forecasting horizons up to 18 months ahead.

In [31], an integrated approach of Discrete Wavelet Transform (DWT) and ANNs is proposed to improve the demand forecasting accuracy. The proposed DWT–ANN model is tested and validated by conducting a comparative study with Autoregressive Integrated Moving Average (ARIMA) using a data set from open literature. Further, the DWT–ANN model is tested with demand data collected from three different manufacturing firms. The proposed model invariably produces less forecasting error and leads to reduction in bullwhip effect and net stock amplification in supply chains.

Researchers in [32], examined the utilization of waybills, i.e. the documents that accompany the transported freight, in predicting the type of transported freight between a given origin and destination, using the following machine learning algorithms: Averaged One-Dependence Estimators (AODE), Sequential Minimal Optimization (SMO), k-NNs, the boosting algorithm LogitBoost, an implementation of the popular RIPPER algorithm (Repeated Incremental Pruning to Produce Error Reduction) (JRIP), Logistic Model Trees (LMT) and HyperPipes.

3.3. Industrial processes optimization applications

In supply chain management, supply and demand decisions are one of many great challenges the involved stakeholders need to face. The authors in [33], examined supply chain inventory management by applying data mining. The unified business intelligence semantic model is presented for providing better predictive inventory management and more particularly, by giving predictions of the out of stock spare parts in the automotive industry. Their collaborative business intelligence semantic model integrates data from several data sources, uses analytical queries to incorporate business logic, provides scalability, enables cooperative decision making and process improvement, as well as it supports various analytics scenarios. The proposed method is designed to make predictions at a location/product level of out of stock products. Researchers evaluated their methodology by utilizing sales data, product inventory data and relevant information for the products, the stores and the dates for the experiments. For the predictive modeling, a clustering algorithm for grouping the different stores was used and the forecasting models utilize DT and neural networks. Due to the temporal nature of the data, a sliding window strategy was incorporated. Finally, a web portal was designed and built in order to be presented and delivered the derived knowledge of the BI semantic model and its forecasts.

In [34], various machine learning techniques have been used combined with a voting system. Specifically, if the prediction concerns a classification, the voting results in the outcome with the highest probability, according to all algorithms' output. If the prediction concerns a regression, then the overall result is the average of each algorithm's output. Authors concluded to eight algorithms that presented significant results, neural networks, Naive Bayes (NB), SVM, Fast Large Margin (FLM), k-NN, LR, RF and rule induction. The results reported did not show neither very high, nor very low accuracy, due to very limited data.

The authors in [35], proposed an efficient platform for designing prediction models, called Scenarios Platform-Collaborative & Context-Aware Data Mining (SP-CCADM). Their platform combines two techniques of data mining, Context-Aware Data Mining (CADM) and Collaborative Data Mining (CDM), with high flexibility. It enables to set and test different data mining scenarios with the desirable configuration, concurrently. The method's superiority over the two individual techniques (CADM and CDM) has been validated on real life scenarios, utilizing various machine learning algorithms, such as k-NNs, Neural Networks, Gradient Boosted Trees (GBT) and DT .

In [36], the authors performed an empirical comparison of three main classes of predictive monitoring techniques such as machine learning, constraint satisfaction and Quality-of-Service (QoS) aggregation. They analyze their applicability and prediction accuracy in an industrial case study in the area of transport and logistics. The case study covers a global supply chain involving actual transport and logistics services managed by a large, international forwarding company.

Researchers in [37], introduced a Bayesian classifier as machine learning techniques to freight transport modeling regarding large-scale operationalization of latent segments. This approach, link segments obtained from a sample to data of commodity flows being available on a national level. In an exemplary scenario, the impact of information and communication technologies on shipment size distributions is calculated, revealing moderate elasticities and a predominant substitution of less than truck loads by full truck loads.

The authors of [38], proposed a methodological framework that integrates ANNs in the process of identifying the factors that affect dwell time of containers in container terminals. Their experiments were conducted on aggregate data collected from the Terminal Operating System of a container terminal.

3.4. Applications of traffic flow and location prediction for intermodal freight transportation

Transportation agencies often need to perform microscopic traffic simulations in order to gain knowledge on the impact that traffic changes and their consequences have on transportation performance. The authors in [39], proposed a combination of machine learning and Particle Swarm Optimization (PSO) that leads to more efficient calibration of microscopic traffic simulations parameters. According to authors, the simulated predictive process utilized four different machine learning algorithms: DT, SVM, Gaussian process regression and ANNs. Experiments concluded that ANNs with PSO outperform the other combinations and is more efficient and accurate.

In [40], researchers proposed a strategic model for transport planning, involving a network wide intermodal transport system, in order to determine the spatio-temporal states of road-based freight networks and future traffic flow in definite time intervals. The traffic flow estimation is achieved by utilizing SVR, combined with Mixed Integer Programming (MIP), which optimizes schedules for intermodal transport network by considering costs, requirements and constraints. Consequently, this model has been applied for a Fast Moving Consumer Goods (FMCG) distribution network in India.

The review study in [41], explores location prediction by using trajectory data that have proven really useful in contrast to traditional data [42]. Authors discuss about algorithms and applications that concern the location prediction field. Some practical applications pointed out are urban planning, relieving traffic congestion and effective location recommendation systems, location-aware advertisements and early warning of potential public emergencies. Many new challenges and opportunities for knowledge mining have been brought by trajectory data. They also have recorded some representative location prediction algorithms, categorizing them by their prediction models. The categories are: (a) Content-based, (b) Distribution-based, (c) Pattern-based, (d) Preference-based, (e) Social relation-based, (f) Time-dependent, (g) Representation-based and (h) Semantic-based methods.

In [43], researchers employed Segment-based Ordinary Kriging (SOK) and Segment-based Regression Kriging (SRK), which are developed from point-based Ordinary Kriging (OK) and Regression Kriging (RK), for the traffic data with variable road segment support in the Wheatbelt region of Western Australia. This approach is proposed for traffic volume prediction with differentiation between heavy and light vehicles.

The study in [44], addresses the freight vehicle travel time prediction by utilizing Gradient Boosting Regression Tree (GBRT) models to predict travel time for freight vehicles. Authors extracted the data used for the experiments from temporally sparse trajectory data of vehicles.

3.5. Vehicle routing problem applications

One of the most important task that modern transportation service providers need to process is the online vehicle routing. In [45], authors introduced a novel improvement on a hybrid algorithm that solves the Generalized Vehicle Routing Problem (GVRP), originally studied by Ghiani and Improta [46]. In their work, an efficient hybrid heuristic algorithm is presented that combines a GA with a local–global approach to the problem and a local search procedure.

In [47], in order to define vehicle routes with minimized timing, researchers developed a novel neural combinatorial optimization strategy based on reinforcement learning. Experimenting with a real-world transportation network, the proposed method proved to significantly outperform conventional methods.

In [48], researchers are dealing with the Intermodal Container Routing Problem (ICRP) and present a chance constrained methodology, based on a hybrid heuristic algorithm, combining Monte-Carlo, ANNs and a GA, which utilizes predefined chance constraints, in order to choose the best routes for each container transported between two points of interest, by rail and sea and to minimizing the total transportation costs.

The study in [49], introduces an intelligent model that solves the issue of vessel trajectory prediction. The proposed model was based on data mining (spatial clustering algorithm was utilized to group the recorded vessel trajectories) and machine learning technique (SVM was used to predict the pattern that a new vessel trajectory follows).

In [50], researchers developed a two-issue vehicle routing problem that considers the production and pollution routing problems with time window (PPRP-TW). A hybrid Self-Learning Particle Swarm Optimization (SLPSO) algorithm is proposed to solve the multi-objective multi-vehicle PPRP-TW problem.

Authors in [51], are conducting a study to determine if a neural-network computational model is able to make more efficiently routing decisions, compared to five routing heuristics algorithms from the literature. The relevant experiments were performed using a real-world logistics simulation scenario, based on a highly demanding logistics site, the Hamburg Harbor Car Terminal.

In [52], researchers used a reinforcement learning model that finds near-optimal solutions for a broad range of problem instances of similar size, only by observing the reward signals and following feasibility rules. In [53], researchers develop a neural architecture called Pointer Net to learn the conditional probability of an output sequence with elements that are discrete tokens corresponding to positions in an input sequence and to solve the problem of variable size output.

3.6. Applications of anomaly detection on transportation data

In recent years, Intelligent Transportation Systems (ITS) face the problem of detecting anomalies in vehicles movement. These anomalies point to either wrong direction, traffic or accident(s). The accurate and instant detection of these anomalies, especially in real time, will lead to risk reduction for drivers and their vehicles and of course to immediate route adjustment.

In [54], researchers presented some initial results of their proposed Granular Computing approach for data imputation and missing data analysis. They are utilizing the concept of information granules to propose solutions for searching and classifying anomalies, based on data granular representations. Researchers conducted their experimental analysis on a dataset describing the movement of New York taxis.

In [55], researchers proposed an innovative approach on Isolation Forest (IF), which brings a solution to the anomaly or outlier detection problem. Authors propose the k-Means-based Isolation Forest (k-MIF) method which builds a search tree based on multiple branches and the estimated times each DT, spatio-temporal data, as well as its advantageous fitting of the data during the DT building stage.

The imputation of missing data in the study of mutual links between the analyzed time series is examined in [56]. Researchers proposed and tested the level of suitability of various fuzzy set methods concerning filling the missing values on datasets with ecological interest and transportation. Authors describe two methods to fill in the missing data of time series, the crisp filling and the fuzzy filling.

In [57], utilizing data from the sensors suitable for transportation systems, authors proposed an anomaly detection method applied on road traffic data, which at the same time captures the spatial and temporal characteristics of the intelligent transportation systems. The defined learning scheme is based on Multi-channel Singular Spectrum Analysis (MSSA), which enables the quick and accurate adaptation to changes in the data, as well as the detection of unusual patterns in the data streams, in real-time and without manual parameterization.

Researchers in [58], proposed a framework that models maritime trajectory data and anomaly detection. Their model considers the spatial aspect of unusual location points and sub-trajectories, as well as the patterns they present.

In [59], researchers introduce a prediction model that just requires information on an airplane's position, velocity and intended destination, in order to distinguish between regular and anomalous behavior. They utilize an one-class SVMs so as to be trained on behavior observed in regular flights.

In [60], authors design and propose an improved model of gray neural networks to address the problem of market demand abnormalities, that occur after transportation disruption. In particular, this integrated approach suggests that gray neural networks can provide better market demand predictions, than the traditional gray model GM(1,1).

4. Conclusions & future research

By this survey, it is shown that all machine learning techniques and hybrid approaches mentioned here as tools for further comprehend the functionality and extend the capabilities of freight transportation, supply chain and logistics systems, enable better predictions of evolution and future states of these systems and offer robust support for knowledge discovery, planning and decision making.

The proposed categorization of the presented articles in this survey was divided into categories concerning different issues occurring while analyzing, modeling and managing problems regarding freight transportation, supply chain and logistics systems' functionalities and was conducted with respect to machine learning techniques and their hybrid approaches utilized to deal with each problem.

A fact that is strongly emphasized in this work is that machine learning techniques were used for value (i.e. number of containers to be loaded on container vessels) or state (i.e on-time and delayed) predictions in many variables regarding transportation and planning and also to enhance optimization procedures so as to be part of a large scale data analytics framework. Machine learning is evolving into a very important and collaborative ally of operation research by significantly supporting its models on transportation in operations management by providing the optimization algorithm with valuable information to help solve the problem. This work shows also a significant usage of deep learning methodologies in recent years, along with a rise on ensemble techniques and statistical algorithms, a trend that it is believed to continue due to increasing interest and production of scientific research.

Furthermore, findings from Fig. 1, illustrate that traditional machine learning and ensemble bagging methods are highly used for solving arrival forecasting problems. Traditional machine learning is also detected in over 60% of demand forecasting applications. Besides this, deep learning and statistics are also presented in over 50% for this type of application area. Another significant observation is the highly usage (over 80%) of deep learning methods in industrial processes optimization. Moreover, it is perceived that ensemble methods, boosting and bagging, are not used for vehicle routing problems. The genetic algorithms are reported only in demand forecasting and vehicle routing problems. Fig. 2 shows that for the period of 2012–2021, research articles use mostly either traditional machine learning or deep learning techniques, but at the end of this period (2018–2021), statistical analysis showed that deep learning usage is dominant while bagging and statistical approaches show a significant increase.

Examining Tables 1 and 3 categorization and looking at Venn diagram of Fig. 3, we can see that there are not significant patterns of machine learning categories' combination. The only case that can be considered as an interesting combination is the one including boosting, bagging and traditional machine learning. This combination is detected three times and in all these cases the application area is the arrival time forecasting. Therefore, it seems that the combination of these methods could be beneficial for solving this type of issues.

Future research and efforts should continue focusing on the use of machine learning techniques and other hybrid approaches on applications regarding freight transportation, supply chain and logistics. Especially, researchers could examine giving more attention to ANNs and ensemble learning techniques, which have been proven to present superior performance over less sophisticated machine learning techniques, such as SVM or LR. Moreover, due to the fact that transportation and management scenarios become more and more complex and the amount of data collected from all these cases increase exponentially, more attention could be given on reinforcement learning techniques, that are able to deal with lots of different scenarios and make decent choices.

This review contributes to the utilization of machine learning techniques and hybrid approaches on problems regarding freight transportation, supply chain and logistics operations' management body of knowledge and also, contributes significantly and practically to researchers for what has been done on these fields the last 10 years, where machine learning is evolving.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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