Preface

Artificial Intelligence and Machine Learning currently get constant attention in the media, where the latest and most impressive new and potential applications of this technology are presented to the public. While these articles describe developments that are mainly amazing to the general public, in the background, implementations of Machine Learning, in particular, are taking place in numerous companies and different application areas. Recent surveys, e.g. by Bitkom, Germany's leading digital association, show that two-thirds of companies consider Machine Learning to be the most important technology of the future. About 50% of the companies surveyed are either already applying technologies from Machine Learning or intend to do so in the near future.

As this technology is highly generic, one finds applications in almost every industry, from health services to manufacturing. There are also numerous potential applications for Artificial Intelligence in Supply Chain Management. These range from improved demand forecasts to warehouse automation and risk management. Especially the application of Machine Learning plays a prominent role in Supply Chain Management, being assessed as the technology providing the most benefits compared to other applications by recent studies. Research shows that such applications of Machine Learning can be found in the whole spectrum of tasks related to Supply Chain Management, covering strategic aspects of Supply Chain Design, supporting the tactical Supply Chain Planning and guiding the operations of Supply Chain Execution. If one examines these application areas more closely, one finds a focus on the tasks related to execution. There is a good reason for this: these tasks are characterized by the availability of large amounts of data, a high uncertainty through the influence of various environmental factors, and the need for fast decision-making. Exactly these characteristics speak for the use of machine learning. However, these characteristics differ for different tasks; not all benefit significantly from using Machine Learning. Therefore, it is a great challenge for anyone intending to use Machine Learning to select the right ones. A look at current research also shows no approach to solving this question in a structured way.

Further challenges can be found in the design of the Machine Learning solution, its integration into the company and the necessary continuous maintenance and further development. The design of a Machine Learning solution requires a solid understanding of the different learning models, their parametrization and optimization. As with every Information System, a Machine Learning solution also changes the organization, business processes, and application landscape. Therefore, an exclusively technical view is insufficient to integrate an application based on Machine Learning. Finally, a Machine Learning system has to be continuously monitored and adapted to changing data sources and requirements. These systems are also subject to a life cycle, i.e., the right time must be found to replace such a system. These aspects all call for a guideline to support practitioners and researchers in developing, deploying and maintaining Machine Learning systems. A look into current research shows that although guidelines for Data Analytics implementations are available, these do not cover the specifics of Machine Learning and miss important aspects like application task selection or solution revision.

These challenges are addressed by the thesis of Ms. Lechtenberg. She developed and evaluated such a guideline for identifying use cases, assessing the suitability of Machine Learning for these use cases and implementing as well as maintaining a Machine Learning solution. Her work focuses on the area of operational transport planning.

Out of the areas of Supply Chain execution warehousing, manufacturing, and transportation, the last one is specifically suited to consider the application of Machine Learning techniques. This is based on the one hand on the extensive data sources available in today's digitalized transport systems and on the other hand on the numerous influencing factors that affect the execution of transports and thus often require short-term decisions. Considering the dominance of road transport in relation to other transportation modes, an investigation of this domain is economically most interesting.

Moreover, since the selection and evaluation of tasks for which the use of Machine Learning is considered strongly depends on the task context, the restriction to a subset of Supply Chain Execution is necessary to achieve effective results. A further consideration is that 90% of the companies operating in the road transport domain are small and medium-sized enterprises. This of course limits their capabilities to gain and contain the capabilities to identify viable application cases for Machine Learning, develop a Machine Learning solution, and operate this continuously. Especially these companies need support in the implementation of Machine Learning solutions. Thus, the selection of operational transport planning for road freight transports by Ms. Lechtenberg as the application domain to be researched is thus a very good choice.

The artifacts developed by Ms. Lechtenberg represent a valuable contribution to the problem domain of how to apply Machine Learning methods to operational and real-time planning of road freight transport, especially from the practical but also from the scientific perspective.

The process reference model she developed for operational and real-time planning of road freight transport addresses the problem of methodologically identifying all decision tasks taking place in the planning process. Furthermore, the reference model is the first work to give a consistent and detailed view of the processes of road freight transport in light of digitalization.

With the Machine Learning suitability assessment approach, she developed an operationalizable method to support practitioners in deciding whether a decision task can be addressed by Machine Learning. As the assessment approach mainly uses generic task characteristics, it is easily transferable to other application domains than operational and real-time planning of road freight transport. Scientifically taking a problem-centric perspective adds a new view to the identification of application potentials of Machine Learning.

The Machine Learning implementation guideline developed by Ms. Lechtenberg integrates the aforementioned artifacts and extends current existing guidelines through the distinction between exploratory, experiment, and operation cycles. Furthermore, the specifics of Machine Learning are considered in the steps underlying the different cycles. Adding supporting function descriptions to the guideline, like project management and team roles, makes this result again highly relevant for practitioners. As the guideline is mainly agnostic to the application domain, it will apply to other domains with little effort. A significant scientific contribution lies in extending the current research by considering the identification and assessment of potential use cases and the operation of a Machine learning solution explicitly.

Reading the thesis of Ms. Lechtenberg is therefore of great interest to researchers and practitioners alike and I would highly recommend it.

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1 Introduction

1.1 Motivation and Problem Statement

The logistics industry is viewed as "a trillion-Euro industry" (Schwemmer and Klaus 2021, p. 2). Indeed, the logistics volume, which includes all spending on internal logistics activities and on buying services from external logistics service providers, within the EU30 (European Union, Norway, Switzerland, and the UK) has steadily grown over the last few years (Schwemmer and Klaus 2021, p. 10). Even though the COVID-19 pandemic has stopped the constantly increasing trend of logistics expenditures, the logistics sector did not suffer as much as other sectors. While the logistics volume in € dropped by 3.5% in 2020, this is low compared to the 5.8% decrease in the aggregated European GDP. In addition, more than a third of logistics companies have already reached a pre-pandemic state after the third quarter of 2021, emphasizing the importance of logistics activities (Schwemmer and Klaus 2021, p. 7). Freight transport, i.e., moving goods from the location" of origin to their destination, is a majorly relevant logistics activity and accounts for roughly 50% of the logistics volume (Schwemmer and Klaus 2021, p. 11). In 2019, almost 2 trillion tonne-kilometers within the European union were covered via road, which is more than 75% of the overall intra-EU freight transport volume (statista 2019; eurostat 2022). Indeed, the relevance of road as a transport mode is still increasing. While the overall transport volume is constantly growing, in particular less-than-truckload road transports, i.e., the transport of goods via road not filling a complete truck, are becoming more relevant. Despite various discussions and efforts regarding shifting transports to other modes to save costs and emissions, the dominating role of road freight transport is not expected to decrease (Ridouane et al. 2020, pp. 1 f.; Aifadopoulou et al. 2019, p. 653). In absolute terms, it is expected to grow more than any other transport mode (Engström 2016, p. 1444). A major reason is its flexibility regarding locations' accessibility, delivery time, and adjustments to special service requirements. Moreover, road freight is favored for short to medium distances because for those, the costs of changing transport modes or reloading are proportionally high and can be avoided by using road freight transport (DHL 2022; Engström 2016, pp. 1444–1446; Inkinen and Hämäläinen 2020, p. 1).

Like almost the whole manufacturing and logistics industry, road freight transport companies are affected by world-wide trends such as globalization, demographic development, higher customer demands, and shorter product lifecycles. Those trends result in a constantly increasing demand for road freight transport. Meeting the demand while still remaining economically profitable and also operating as sustainable as possible is a major challenge to the road freight transport sector (Aifadopoulou et al. 2019, p. 653; Engström 2016, p. 1444). Profitability is challenging to achieve as transport costs rise, and the current dependency on oil exported from outside the EU is expected to aggravate this situation in the future (Liachovicius and Skrickij 2019, pp. 455 f.; Schwemmer and Klaus 2021, pp. 8 f.). Furthermore, the road freight sector faces high competition, as the market entry barriers are shallow. Only low capital investment is needed to start operating as a freight forwarder or carrier. Hence, the sector mainly comprises companies with less than ten employees, leading to a highly scattered, competitive market with low margins (Engström 2016, p. 1445; Liachovicius and Skrickij 2019, pp. 461 f.). At the same time, increasing freight demand is endangered of not being met due to a lack of truck drivers –more than 45 thousand positions were vacant only within Germany in 2020 (DHL 2022; Holcomb et al. 2014, p. 520). Next to economic challenges, the road freight transport sector has to become more sustainable as trucks significantly add to worldwide emissions (Inkinen and Hämäläinen 2020, p. 1). Apart from innovations such as e-vehicles, automotive driving, or using e-fuels, which have not become prevalent yet, efficient traffic flow and transport management can severely contribute to reducing emissions and becoming more sustainable (Engström 2016, p. 1444; Inkinen and Hämäläinen 2020, pp. 2–4).

Meeting the above-described challenges while still maintaining the advantage of flexible deliveries requires effective and efficient road freight transport planning. Establishing high-quality transport plans ensures fulfilling more transport demand at the lowest costs and emissions possible (Engström 2016, p. 1448; Holcomb et al. 2014, p. 520). At the same time, planning has to meet laws and regulations, which are numerous since the road freight transport sector is heavily regulated. Domain-specific restrictions regard, among others, drivers' working and rest hours or speed limits and driving bans (Liachovicius and Skrickij 2019, p. 459). Strategic planning mainly includes infrastructure design decisions and defines the transport network. While strategic decisions are made considering costs and emissions and trying to increase future flexibility, the time horizon only allows working with assumed or stochastic values (Roy 2001, p. 5; Stank and Goldsby 2000, p. 76). Tactical planning tasks are more targeted towards fleet composition and design of offered services. Within a time horizon of months, tactical planning defines which transport services are provided, which routes are generally served, or which capacities are used. The defined services and capacities further stipulate the frame in which operational planning has to operate (Crainic and Semet 2013, p. 123; Roy 2001, p. 5; Stank and Goldsby 2000, p. 76). Operational decisions usually relate to planning the current and next-day activities, such as driver and equipment assignment, route planning, or scheduling. It is essential to adequately respond to changes in daily demand and availability of drivers and equipment, which are very common in the road freight industry, by planning or adjusting plans daily instead of weekly. Planning needs to be in accordance with earlier defined service levels and adhere to capacity restrictions (Crainic and Semet 2013, p. 131; Roy 2001, p. 5; Stank and Goldsby 2000, p. 76). Those day-to-day decisions are particularly relevant to meet the abovementioned challenges. Strategic and tactical planning decisions aim to reduce costs and emissions and provide flexible and reliable transport networks and equipment. However, operational planning is then responsible for creating effective and efficient transport plans that fulfill the actual freight demand while considering all restrictions and meeting the prevalent challenges to the best extent possible (Sigakova et al. 2015, pp. 1 f.). Decisions with a short lead time can significantly enhance competitiveness and lead to additional profit. Therefore, efficient and effective operational planning offers the opportunity to meet the challenges faced by the road freight transport industry (Chen et al. 2021, pp. 1–3; Holcomb et al. 2020, p. 4).

Next to the potential of operational planning for achieving competitive advantages and increasing margins, making short-time decisions is a challenge in itself. Strategic and tactical decisions, e.g., regarding the position of distribution centers or composition of vehicle fleets, limit the set of possible decision alternatives for operational planning. Nonetheless, the number of decisions to be made on a short-term level, as well as the number of available solution options for each decision, is still huge. Every day, many of transport orders have to be processed, routes to be planned. Furthermore drivers and trucks must be assigned to them. Daily demand is prone to increasing fluctuations requiring daily planning instead of replicating earlier established plans. Additionally, external influences, such as the current traffic situation or weather, and uncertainty, e.g., regarding spontaneous shifts in the traffic situation because of accidents, can change the setting and result in another decision alternative to becoming more favorable (Stank and Goldsby 2000, p. 76; Sigakova et al. 2015, pp. 1 f.). Uncertainty in transport planning stems from five sources: suppliers, customers, carriers, control systems, and external uncertainties. Each of these groups contains several aspects that may lead to situations causing the need for adaptation. While strategic and tactical planning typically uses assumptions or stochasticity to abstract from those uncertainties, operational planning decisions have to consider their often unanticipated consequences. Examples of uncertainties to be incorporated into operational transport plans are changes in the delivery amount due to problems at a supplier, inefficient unloading processes at the customer or traffic congestion leading to increased travel times, or wrong information in ICT systems leading to uncertainty regarding the correct route to take (Sanchez-Rodrigues 2010, p. 49). The sudden and unforeseeable manifestation of those uncertainties can cause complex consequences, not only for one route but for various links of the transport chain. (Chen et al. 2021, p. 1; Holcomb and Manrodt 2018, p. 32; Ridouane et al. 2020, pp. 1 f.).

Different tools and methods have been used to support decision-making in operational transport planning and increase efficiency. Operations research methods, such as combinatorial optimization or (meta-) heuristics, have a long history of targeting problems from transport planning. Models and corresponding solution approaches can support load design, routing, scheduling, empty container re-positioning, or driver assignment. Next to deterministic models, dynamic ones also try to partly address planning uncertainty regarding the transport volume or time (Crainic and Semet 2013, p. 112; Gorman et al. 2014, pp. 544–546; Garza-Reyes et al. 2017, p. 1901). In addition to operations research approaches, information systems have been designed to support operational transport planning tasks. They collect and process relevant information to support transport planners with their daily tasks, such as driver assignment and scheduling or vehicle selection and routing, by incorporating operations research, simulation, or visualization methods (Ocalir-Akunal 2016, pp. 1120–1125; Bäumler and Kotzab 2020, pp. 185–187). Over the last decades, the capabilities of such information systems have increased significantly. The amount of manageable data rose while the time needed to process them decreased. This development led to the emergence of so-called "intelligent transport systems" (ITS). ITS support operational transport planning by providing relevant information on transport plans, drivers, and traffic, proposing options to transform transport orders into transport plans or monitoring transport executions. For the future, ITS are expected to become data-intensive systems that extract and process huge amounts of information relevant for transports and thereby provide faster and more efficient support to operational transport planning (Bäumler and Kotzab 2017, pp. 280 f.; Kadłubek et al. 2022, pp. 5–7; Khan et al. 2017, pp. 2 f.). However, in order to transform ITS into truly data-intensive systems, it is necessary to incorporate more advanced technologies and algorithms. One of the biggest issues of currently used approaches is that they typically abstract from reality. Thereby they are only capable of depicting and considering the uncertainty and fluctuations to a certan extent, which is not sufficient for completely coping with today's dynamic and complex environment of operational road freight transport planning (Crainic and Semet 2013, pp. 159 f.; Ocalir-Akunal 2016, pp. 1119 f.). Common approaches that support the creation of driver schedules and pre-planned routes with little or no flexibility can only manage this fast-changing decision environment to a limited extent. While these established solutions might work, the use of more advanced technology and more powerful approaches to incorporate more information and create more responsive transport systems can lead to the provision of better transport services and thereby increasing performance (Chen et al. 2021, p. 1; Holcomb and Manrodt 2018, p. 32; Kadłubek et al. 2022, p. 2). Since transport planners only have a very short time to react to environment changes, e.g. there is only a very limited time frame to reroute a vehicle before it gets stuck in a traffic jam, information on those changes has to be collected and processed as fast as possible. The ideal speed would be in (near) real-time, i.e., the information should be available and analyzed without (noticeable) time delays. Such a fast analysis would allow transport planners to react quickly and re-arrange transport plans to act efficiently and fulfill existing constraints while considering the change in the environment. This idea of (near) real-time planning cannot be supported by currently established approaches, as they neither provide the necessary speed, flexibility, nor data processing capabilities. Hence, new approaches are needed to allow for faster and more efficient decision-making regarding operational planning and its real-time adjustments (Chen et al. 2021, p. 1; Crainic and Semet 2013, p. 131; Holcomb and Manrodt 2018, p. 32; Ridouane et al. 2020, pp. 1 f.; Zumbé and Bornfleth 2016, p. 4)

In order for more advanced support of operational planning and real-time planning to become possible, the availability of data on transports' status and the current traffic situation has to be ensured. Due to the increased use of sensors, specifically in the road freight transport industry, and cheaper data storage capabilities, this requirement can be regarded as fulfilled. GPS technology and sensors in trucks and on freight are available to track their location, movement, status, and further specific information such as driving speed, temperature, or signals possibly indicating the need for maintenance. Moreover, external information on current traffic or weather, and more collaboration and information exchange between parties can be used to integrate additional information decision making. This information can be stored as more storage space is available at cheaper rates (Bäumler and Kotzab 2017, p. 281; Bhavsar et al. 2017, pp. 283 f.; Khan et al. 2017, pp. 1 f.). Consequently, it has become possible to collect and store data on all factors relevant to operational and real-time planning and, based on their information, encounter the dynamic and complex decision environment better. Decision makers can track transports, learn about drivers' behavior and stay informed about the most current traffic situation (Bhavsar et al. 2017, p. 283; Chen et al. 2021, pp. 1 f.; Dong et al. 2021, p. 387; Holcomb et al. 2020, p. 4). However, data need to be pre-processed and analyzed to provide value to transport planning. Therefore, data analytics approaches capable of processing a large amount of data are necessary to use all available information for decision-making. Methods of operations research and currently established information systems to support operational transport planning tasks cannot manage the volume and variety of available data to a satisfactory extent (Ni et al. 2020, p. 1476; Santoso et al. 2021, p. 3). In contrast, algorithms referred to as machine learning (ML) are a class of data analytics techniques specifically suited to analyze big data sets, i.e., data sets of high volume, variety, and velocity. In the context of road freight transport, ML algorithms can detect hidden traffic flow patterns, analyze large numbers of transport orders, or incorporate weather data into routing decisions (Athmaja et al. 2017, pp. 1 f.; Bhavsar et al. 2017, pp. 283–285; Khan et al. 2017, pp. 1 f.). For application in operational and real-time transport planning, ML algorithms show three strengths over more traditional data analytics approaches usually used for transport planning (mainly statistics and operations research): (1) no reliance on prior assumptions and hence no biased description of the transport system, (2) robustness to multi-collinearity and hence the capability to deal with data of high volume and variety about factors influencing transport planning decisions, and (3) small amount of solution time (once algorithms are trained) while yielding high-quality solutions which allows to apply them in the short amount of time available for operational and real-time decisions (Barua et al. 2020, pp. 1 f.). Overall, using ML algorithms can enable more efficient and faster decision-making, improving operational planning by incorporating more information and enabling real-time planning by significantly reducing decision times (Liachovicius and Skrickij 2019, p. 460; Nowakowska-Grunt and Strzelczyk 2019, p. 350). Hence, ML algorithms are regarded as an opportunity to "comprehend the functionality and extend capabilities of freight transportation [...] and offer robust support for knowledge discovery, planning, and decision making" (Tsolaki et al. 2022, p. 9). Significant opportunities are expected once the available data is leveraged with ML (Barua et al. 2020, pp. 1 f.; Holcomb and Manrodt 2018, pp. 28–31; Ni et al. 2020, pp. 1463 f.)

Currently, there are some lighthouse applications of ML algorithms to operational and real-time transport planning, such as dynamic routing, arrival time predictions, congestion mitigation, or travel flow estimation (Dong et al. 2021, p. 398; Ni et al. 2020, p. 1476; Tsolaki et al. 2022, p. 9). However, while the capability to apply ML is often considered a requirement to pertain competitive advantage, companies struggle to identify suitable applications and implement use cases (Holcomb and Manrodt 2018, p. 32). The little real-life use of ML is often accounted to a lack of understanding of where and how to apply it. Indeed, scientific literature lacks to address issues of how to identify suitable use cases and what to consider for a successful ML implementation project, both in general as well as specifically for road freight transport (Akkiraju et al. 2020, p. 17; Ni et al. 2020, p. 1464). There are some sources regarding the application of ML methods, e.g., to the vehicle routing problem or route optimization, which can be used as initial guidance or insight on where and how to apply ML to problems of operational road freight transport planning. However, more extensive support is needed to identify generally suitable use cases. Moreover, implementing ML is not solely a technical endeavor and requires adapting business processes and organizational structures (Holcomb et al. 2020; Dong et al. 2021, p. 398). While the technology and data are available, it is necessary also to tackle non-technical challenges. Otherwise, issues such as a lack of knowledge about ML, a limited understanding of how it can affect business processes and organizational structures, and a general aversion to the changes associated with its implementation, e.g., loss of jobs, will hinder a project's success. Competitive advantages can only be achieved when considering the characteristics of road freight transport and operational planning processes, incorporating impacted employees, e.g., truck drivers or dispatchers, their worries, knowledge, and needs into the project, and addressing organizational and structural questions. First, considering those aspects leads to an implementation that actually provides benefits and fits the targeted context. Second, only by also regarding structural and organizational change the ML algorithm can be integrated into existing processes and IT landscapes. Lastly, re-distributing responsibilities and possibly assigning new tasks to employees is vital to ensure the continued