Predicting Estimated Arrival Times in Logistics Using Machine Learning

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INTRODUCTION

ML techniques offer great potentials to support decision-making processes in companies by allowing the prediction of unknown information. The ability to extract and approximate system relationships from training data without explicit a priori knowledge makes them highly suitable for modeling highly complex and dynamic real-world systems. Due to the learning capability of ML-based systems, problems can be solved more flexibly, with less effort and with higher accuracy, and there is the potential to automate decisions (Wahlster, 2017). Against this background, ML-based applications are of particular importance, especially in the field of logistics. However, while the majority of logistics companies already use technologies for real-time visibility like Track & Trace, ML-based decision support systems have so far rarely been applied in logistics (Straube, 2019). The goal of the chapter is to demonstrate the application of ML methods on a significant use case in logistics practice: the prediction of ETA in intermodal transport networks as a basis for the detection of process disruptions.

The maritime transport chain serves as the practical use case considered in the chapter. International container transports by ship are handled via complex transport networks involving a large number of logistics actors. The implementation requires the interaction of numerous, closely timed and interdependent sub-processes. At the same time, the execution of the processes is influenced by a variety of impact factors such as resource availability, weather and the human factor. In addition, there is often no complete transparency between the actors, as information on process planning, status and disruptions has so far only been exchanged insufficiently and often manually between the involved logistics companies. Many of the decisions are therefore made under high uncertainty and rather reactively. As a result, according to Poschmann et al. (2019) decisions are often not optimal in regard to the entire chain and lead to high economic and ecological disadvantages in the form of unpunctual deliveries, resources not optimally utilized, cost-intensive special processes and unnecessary risk buffers.

Against this background, early prediction of arrival times and possible delays is highly important. Thus, ETA information enables logistics actors to identify and deal with possible process disruptions at an early stage by initiating appropriate measures. Furthermore, information on arrival times is an important basis to ensure a demand-oriented capacity planning with regard to material stocks, personnel and infrastructure (Walter, 2015). ML-based ETA predictions can thus make an important contribution to

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improving today's logistics networks, which are affected by increasing customer requirements in terms of reliability, transparency and sustainability and cost efficiency (Handfield et al., 2013).

The chapter aims to demonstrate the application of ML for ETA prediction in logistics. A detailed insight is given into the results of a research project whose objective was to develop an ETA prediction for combined road-rail traffic in the port hinterland. The chapter is organized as follows: In the first step, a general methodology is presented, which contains all essential subphases of the development, starting from the requirements analysis and data collection up to the IT integration. Subsequently, the conception of an approach for the above-mentioned use case is presented and ML approaches for three selected sub-processes are prototypically implemented and evaluated.

BACKGROUND

The following is a brief description of the fundamentals relevant to this chapter. First, a definition of ML is given, followed by an overview of the state of the art in ETA prediction research.

Machine Learning

ML is a sub-domain of Artificial Intelligence (AI) and comprises various methods that enable computer systems to independently extract patterns from extensive data (Murphy, 2012). ML thus enables computer systems to learn inductively. (Nilsson, 2010) This means that inference takes place on the basis of hypothetical correlations that a learning algorithm has acquired in the course of a training process by adapting to observations and generalizing patterns contained therein. (Awad & Khanna, 2015) This automatic extraction of patterns from data enables the recognition of complex relationships that are not recognizable to humans, or only with great effort, and an industrial use, for example, for segmenting and predicting information, deriving rules and solving optimization problems. (Alpaydın, 2010; Döbel, et al., 2018). Approaches to ML can be roughly divided into the three main types supervised, unsupervised and reinforcement learning. (Russell & Norvig, 2010). For ETA prediction, supervised and unsupervised learning are of particular importance, as learning is mainly based on historical transport data.

Prediction of Estimated Times of Arrival

With regard to the existing approaches to ETA prediction in the literature, a basic distinction can be made between model-based approaches, which are based on simulations or analytical models, and data-based approaches, according to Wen et al. (2017). The application of ML for ETA prediction can be regarded as a sub-group of the data-based approaches. Model-based approaches have been widely used in the literature for delay prediction in rail networks. They can be found in Berger et al. (2011) as well as Büker and Seybold (2012), for example. However, their disadvantage lies in the complex modeling and the low adaptability to changing operational conditions. Despite the great potential of ML for ETA prediction, its application has been explored only selectively and with a strong focus on passenger transport. Existing approaches to logistics are usually only related to isolated sub-processes and specific modes of transport.

Initial approaches already exist for maritime transport, which represents the main leg in international maritime transport chains. Parolas et al. (2016) predict the arrival time of ocean vessels at the port of Rotterdam started about 120 hours before arrival using Artificial Neural Networks (ANN) and Support Vector Machines (SVM). Bodunov et al. (2018) and Lechtenberg et al. (2019) developed models for the

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