Applications of Artificial Intelligence in Supply Chain Management and Logistics: Focusing Onto Recognition for Supply Chain Execution

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1 Introduction

The development of new technology has always been a driver of change. Nowadays, higher computing power, more data storage and process capabilities etc. allow for new technology- and data-enabled business models, such as online retailers or mobile app service providers (Emenike, Eyk, & Hoffman, 2016).

Emerging technologies such as the Internet of Things (IoT) or big data analytics are also changing the way supply chain management (SCM) is done and have the potential to create a digital supply chain, which can be understood as a "flexibly interconnected, complex, distributed system based on a continuous and autonomous exchange of data and information between human actors and physical, technical objects" (BVL, 2017b). Apart from the already mentioned technologies, especially methods of so-called Artificial Intelligence (AI) are expected to contribute to the digitalization in SCM. In general, the application of AI techniques to not only analyze data or automate decision-making but also to optimize the whole supply chain is considered to be highly relevant and an enabler for a supply chain's digital transformation (BVL, 2017a). Nonetheless, the question on what exactly AI is and which methods do belong to the set of AI techniques remains and has not been answered by scientific literature yet. Instead, the term AI is viewed and defined from different angles focusing e.g. on "agents that receive percepts from the environment and perform actions" (Russell & Norvig, 2010) or on "computational systems that perform tasks commonly viewed as requiring intelligence" (Poole & Mackworth, 2017). It can be subsumed, that there is no common definition of what AI is. Moreover, the understanding of "intelligent" has been changing over the years, which is described

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by the AI effect. It describes the circumstance that the notion of AI changes due to advancements in the field as well as the emergence of new technologies. If something a computer can do becomes common enough that a majority of the people are used to it, it is no longer considered as AI (McCorduck, 2004). So while approaches such as genetic algorithms or expert systems are no longer considered to belong to the set of AI techniques anymore, recent progress in the fields of information processing or sensing technology as well as the shift to a data-driven paradigm have led to major advances in the field of AI such as deep learning, reinforcement learning, robotics, computer vision or natural language processing (Stone et al., 2016).

Therefore, it is necessary to answer the questions which approaches from the field of AI are applied within the SCM domain as well as which SCM problems or tasks are addressed with AI approaches.

A first answer to these two questions has already been given based on the results of a structured literature review being presented at the 9th International Scientific Symposium on Logistics (ISSL).[1] A summary of the methodology and how it has been applied are described in Sect. 2. The results are summarized in Sects. 3 and 4.

While working on these questions, an interesting point has been noticed: Despite problems of object or image recognition are rarely discussed in the investigated scientific literature, they are considered as a suitable AI application possibility especially for supply chain execution. This observation led to the idea to extend the previously mentioned results by specifically searching for literature dealing with this approach/task combination. Hence, this paper aims at answering the following question:

What are currently researched application areas for recognition approaches in supply chain execution?

This paper aims at providing an overview of which areas within supply chain execution research is most interested in, i.e. which application cases are already existent. This knowledge might then be used as a basis for further research in order to e.g. identify more promising application cases.

Section 5 describes the way the search to deepen the initial results of the already existing paper has been done and which application areas and cases could be identified. The paper is closed with a conclusion summarizing the presented work and its most important implications as well as shortly discussing limitations and future research possibilities.

2 Methodology

A structured literature review (SLR) has been utilized to identify (i) which AI approaches are applied within the SCM domain and (ii) which SCM problems or tasks are addressed with these. SLRs aim at creating rigorous research and at making the reasoning process, which has led to results presented later on, more understand-

[1] https://www.bvl.de/issl.

able and comprehensible. The SLR presented in this paper has been based on the framework by Thomé et al. (2016) who propose a step-by-step guideline on how to ensure a rigorous literature search.

Before conducting the actual SLR, a first initial literature search has been carried out in order to identify which AI approaches are used in the SCM domain, using the very general search term “artificial intelligence” AND (“supply chain management” OR logistics) within the databases of Sciencedirect, Web of Science and Scopus. After the elimination of duplicates two people evaluated the abstract of the 1366 remaining sources independently and if at least one of those regarded a paper as relevant based on this evaluation, it has been included in the following process.

After analyzing the remaining 231 publications, five major approach-groups have been identified: (1) metaheuristics, (2) machine learning, (3) multi-agent systems, (4) recognition and (5) natural language processing. The analysis showed a strong bias towards the first group, the application of metaheuristics such as evolutionary algorithms, ant or bee colony optimization or particle swarm optimization. More than 50% of the relevant sources used an approach from this group to address a SCM problem, especially from the area of transport planning. However, the question whether metaheuristics do belong to the set of AI approaches is still discussed in research and there is no definite answer. Moreover, the high number of sources, which mainly stem from the earlier of the considered years, as well as some existing reviews (e.g. Griffis, Bell, & Closs, 2012) show that the application of metaheuristics to the SCM domain is not a new and already well researched field. Therefore the decision to exclude the group of metaheuristic approaches from the further review has been made.

The remaining four approach groups have been transformed into new approach-specific search terms in order to conduct the SLR:

(“machine learning” OR “self-learning” OR “neural network” OR “support vector machine”) AND “supply chain”

“natural language processing” AND “supply chain”

(“image recognition” OR “object recognition”) AND “supply chain”

((intelligen* OR smart OR knowledge OR reasoning) AND agent) AND “supply chain”.

The search and review has been conducted in accordance again with the framework presented by Thomé et al. (2016). Out of 630 hits after removing duplicates, a final set of 153 relevant sources remained after abstract and full-text review. These have been analyzed with regard to the questions which approach they apply and which problem they address with it. A synthesis of the results is presented in the next sections.

In order to address the application of recognition approaches specifically for supply chain execution in more detail, a second literature search has been conducted. However, this has not been following a framework for a structured literature review but a more “try-and-error”-focused approach has been used.

3 Applied AI Approaches

In scientific literature numerous different AI approaches are used. The number is even increased, since many researchers adapt known algorithms to their needs and publish this variation with a new name. To provide a better overview the classification scheme based on Poole and Mackworth (2017) and Russell and Norvig (2010) has been used. Table 1 provides an explanation and examples for each class as well as an indication of how many of the sources identified as relevant in the literature search do belong to this problem class. The percentages are not only based on the sources identified in the SLR but also include the ones from the literature search focusing on recognition problems in supply chain execution (for more detail on this search cf. Sect. 5). Hence, the percentages differ from the ones presented in the ISSL paper and a higher proportion of the sources can now be attributed to the recognition problem class.

In general, independent from the problem class, variants of neural networks are with 58% the by far most applied AI approach. Such networks consist of one input layer, one output layer and at least one hidden layer between them. The majority of identified sources utilizes so called *deep learning* for their neural networks, i.e. the networks possess many hidden layers which allows them to process greater amounts of and more complex data in shorter time. This composition of many layers allows neural networks to learn very complex functions (LeCun, Bengio, & Hinton, 2015; Poole & Mackworth, 2017). Moreover, many authors show that neural networks outperform other approaches with regard to e.g. solution quality or convergence speed towards a good solution (e.g. Aengchuan & Phruksaphanrat, 2018; Ma, Wang, & Wang, 2018). Neural networks are mostly used to solve prediction, classification/clustering, optimization, recognition or NLP problems. The second-most used approach, multi-agent systems (MAS), is applied for knowledge representation and reasoning problems. In a MAS, different agents follow their individual goals and strategies. Based on these they perform actions and propose different solution alternatives, which are often presented to a human decision maker who is responsible for the final decision.

Considering the different problem classes, it becomes obvious that the majority of sources uses AI approaches to predict something, e.g. customer demand (Watanabe et al., 2016) or supplier performance (Mirkouei & Haapala, 2014). Therefore, a strong suitability of AI approaches to solve prediction tasks can be concluded. The same holds true for classification/clustering as well as knowledge representation and reasoning problems. The amount of sources considering these problem classes is lower than the ones for prediction problems but still a considerable number of sources deals with these categories. An example from the classification class is presented by Ye, Xiao, and Zhu (2015) who classify companies according to which supply chain disruptions they can expect. Knowledge representation and reasoning problems dealt with by scientific literature are e.g. the analysis of the effects that information sharing has on supply chain performance (Ponte, Pino, & La Fuente, 2014).

Table 1 Problem class of relevant sources (classes based on Poole and Mackworth 2017 and Russell and Norvig 2010)

Problem class	Examples	Percentage of sources (%)
Prediction Based on training with examples, approaches predict an output for given input values	Demand prediction Supplier performance prediction Production completion time prediction	48
Classification/Clustering Approaches that identify classes in datasets either based on known labels (classification) or without additional information (clustering)	Classification of disturbances in a supply chain Identification of customer groups	17
Knowledge representation and reasoning Approaches used to not only find a solution but rather to present different alternatives and the reasoning that has led to them	Analysis of the effects of information sharing on supply chain performance	14
Recognition Approaches which are able to detect something on images or recognize objects in a 3D space	Food quality recognition based on images Automatic container unloading	11
Optimization Identifying an optimal (or at least very good) solution to a given problem	Vehicle routing problem Inventory level optimization	6
Natural language processing Approaches for understanding and processing human language (text or voice)	Extraction of sentiment from social media comments Analysis of reports to predict failures	3

Rather rarely approached problem classes are optimization, recognition and natural language processing (NLP). However, especially the two latter ones should not be considered as unsuitable since recent sources show high potential for applications in the SCM domain e.g. for food quality recognition (Cavallo, Cefola, Pace, Logrieco, & Attolico, 2018), or the analysis of documents to automatically derive information such as failure predictions (Aqlan & Saha, 2015). Also the area of warehouse automation is considered as highly relevant for AI applications. For example, Thamer et al. (2018) examine application possibilities of deep learning in this field and present a way to increase the intelligence of a forklift within a dynamic warehouse environment to make it able to recognize people.

Overall, it can be subsumed that variants of neural networks are clearly the most utilized AI approach in the SCM domain. These are used to not only solve regression and classification but also optimization, recognition and NLP problems. The second-most used technology, MAS, is mostly applied to reasoning problems to better understand a system or estimate the effects of certain strategies or actions. While SVMs are also more or less frequently applied, other methods such as decision trees, fuzzy reinforcement learning or named entity recognition are only considered by a minority of the sources.

4 Addressed SCM Task

It is also possible to classify the different sources according to which SCM problem or task they are applying AI approaches to. Fleischmann et al. (2005) provide a good overview of SCM planning tasks in their Supply Chain Planning Matrix and depict them along two dimensions: the planning horizon (long-term, mid-term, short-term) and the type of supply chain process (procurement, production, distribution, sales) (cf. Fig. 1).

However, the matrix solely focuses on planning tasks and hence had to be extended to also depict tasks from supply chain execution as well as ones providing support along the supply chain, e.g. performance evaluation. The tasks mentioned in Fig. 1 as examples for each class are quite general and their configuration depends on the specific situation at hand. However, they give a good overview of the various kinds of tasks which are part of SCM.

Table 2 gives an overview of the percentage of relevant sources dealing with the tasks of the extended supply chain planning matrix. Again, the sources from the

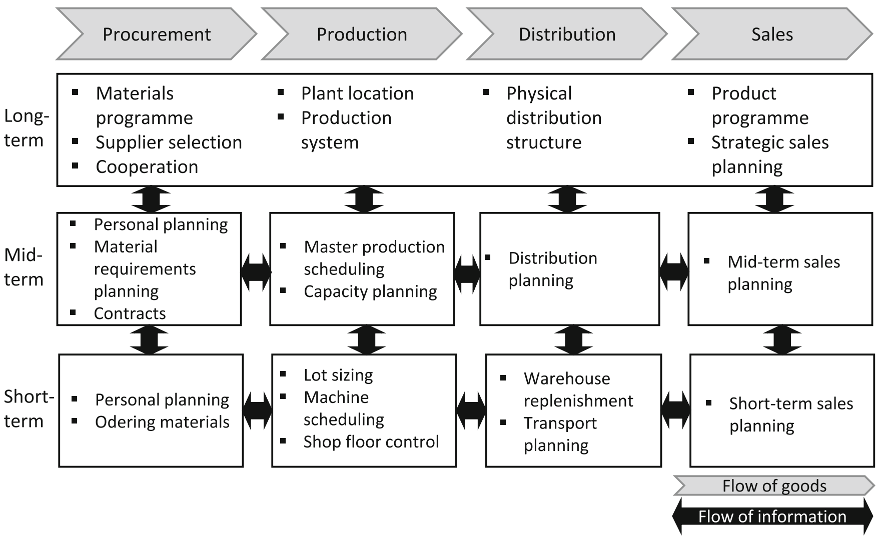

Fig. 1 Supply chain planning matrix (Fleischmann et al., 2005)

Table 2 Addressed SCM task

<table>
<tr><th></th><th>Procurement</th><th>Production</th><th>Distribution</th><th>Sales</th><th>Support</th></tr>
<tr><td>Long-term</td><td colspan="4">23%</td><td rowspan="3">12%</td></tr>
<tr><td>Mid- and short-term</td><td>3%</td><td>7%</td><td>12%</td><td>19%</td></tr>
<tr><td>Execution</td><td colspan="4">24%</td></tr>
</table>

literature search focused on recognition problems in supply chain execution have been considered when calculating the percentages. Therefore, the number of papers dealing with execution has increased when compared to the first investigation.

The top three application areas within SCM are—at least according to scientific literature—long-term planning, mid-and short-term sales planning as well as execution. Sources of the category long-term planning typically deal with supply chain or network configurations. Usually variations of neural networks are applied to e.g. predict the capability of a supply chain to fulfill all customer orders (Silva, Ferreira, Silva, Magalhães, & Neto, 2017) or multi-agent systems are used to e.g. examine the influence of different communication and collaboration strategies on SC performance (Medini & Rabénasolo, 2014). Another area is focusing on supplier selection and evaluation, for example in agricultural supply chains (Guo & Lu, 2013) or to estimate a supplier's resilience capability (Hosseini & Khaled, 2016).

Mid- and short-term planning is dealt with by 41% and among the different functions, mid- and short-term sales planning is the most prominent one. All sources from this task category aim at forecasting demand for hard to forecast products such as blood transfusions (Khaldi, El Afia, Chiheb, & Faizi, 2017) or at improving demand forecasts by incorporating external information such as weather data (Watanabe et al., 2016) or social media information (Cui, Gallino, Moreno, & Zhang, 2017).

The third task category having received lots of attention from research is supply chain execution. Here, two different tasks show a high occurrence among the identified sources: First, supply chain monitoring e.g. for cold chain transports (Emenike et al. 2016) and second, automated warehousing and production encompassing tasks such as the development of an automated ordering management system (Mortazavi, Arshadi Khamseh, & Azimi, 2015).

5 Recognition Approaches for Supply Chain Execution

As mentioned before, the number of sources applying AI approaches to recognition problems has been surprisingly low in the SLR presented in Sect. 3. Especially after looking at the tasks AI approaches are applied to both in research and industry the impression of a high suitability for applications in supply chain execution has been strengthened. Many sources apply neural networks and support vector machines to address recognition problems from the area of supply chain execution and report realizable benefits such as high accuracy in recognition (Schlüter, Niebuhr, Lehr,

& Krüger, 2018) or the possibility to deal with external factors such as lightning or weather conditions when recognizing objects from camera images (Huang, Li, Chen, Zhang, & Lang, 2017).

In order to identify more sources dealing with this apparently promising area, the literature review presented before has been complemented by a further search process. Instead of following another structured approach, publications specifically dealing with the topic of interest have been searched with a few different methods. First, further databases, namely IEEE Xplore and Google Scholar have been queried with the search term ("image recognition" OR "object recognition") AND "supply chain" which has already been used in the SLR presented before. Having talked to experts from the field of robotics it became imminent that the conducted search focuses on SCM-domain-oriented databases and e.g. neglects ones indexing more technology-focused journals and conferences. Therefore an extension of the set of databases has led to a few more relevant results. Additionally, the set of utilized keywords for the search term has been adapted several times. For example, the term "logistics", which was dropped as a search term in the first literature review due to it causing many false positive results, has been re-introduced since the overall number of results for this very specific search has been low enough for a manual identification of false positives. Furthermore, once a promising application area such as warehouse automation has been identified this keyword has been utilized to detect more sources from this area and give an indication on whether the perceived relevance can be supported. It has to be noted that the search process has not been extensive and has not been capable to detect all relevant sources. Instead, once an area has been identified as suitable for the application of AI approaches, i.e. a few sources doing so have been found, no further publications have been looked for. Since the purpose of this focus-section is to give an overview on possible and promising application fields and not to identify all possible applications, it has been regarded as sufficient to provide a set of examples for each of the fields. However, due to the non-structured search process this section cannot and does not want to claim to be comprehensible. Since the search was conducted more or less on a "try-and-error" basis and further results were retrieved based on initial ones, it of course is possible that important application areas have been missed. Nonetheless, this way it is possible to get a first impression on where many applications are already existing. And since the search process has mainly been based on sources initially identified in the SLR presented before it is considered as unlikely that major areas have been missed.

In the following the identified areas, where applications of AI approaches to address recognition problems in supply chain execution are already existent, are presented and examples for such applications are given. The information as well as the example cases are taken both from research and industry.

5.1 Warehouse Automation

Warehouse automation is one of the highly researched fields for the application of AI recognition approaches. Not only research but especially industry is interested in using advances in AI as well as robotics to automate typical warehouse operations such as bin picking. Amazon even has organized a "bin picking challenge" to encourage teams from different universities etc. to let their solutions for picking robots compete against each other (for a summary of the first Amazon Picking Challenge and lessons learned from it, compare Correll et al. 2018).

The design of picking robots seems to be a highly interesting topic and numerous researchers deal with different aspects of these robots. One of the most important ones is enabling the robot to recognize the objects it is supposed to pick. Usually this is realized by applying a machine learning algorithm trained with and learning from example images. Typical setups of a bin picking robot are stationary and include a robot arm with a gripper that detects objects based on a 3D sensor and plans its motions accordingly (Nieuwenhuisen et al. 2013). To extend this scenario and make the robot more flexible with regard to its operation space Holz et al. (2014) and Nieuwenhuisen et al. (2013) propose a complete system with a mobile robot capable of active object recognition and also grasp planning. Previous to the operation, the robot learns object models that represent objects in graphs depicting compounds of primitive shapes and contours such as cylinders. Having been trained, the robot is able to recognize objects by detecting parts of the graph to be looked for in the captured scene, e.g. detecting a single screw in a transport box filled with several screws or even other objects. The presented approach shows a robust behavior "even in the presence of noise, occlusions, erroneous measurements and missing information" (Holz et al., 2014).

Laskey et al. (2016) also propose a picking robot which is capable of picking objects even when access to it is blocked by other object, i.e. grasping in clutter. They iteratively train the robot based on humans demonstrating the picking actions and giving direct feedback to the robot on its current policy. Moreover, a hierarchy of supervisors is used in order to decrease the amount of human demonstrations needed for the robot to learn to pick objects amid clutter. On the first stage, the robot learns from a simple motion planner that ignores the obstacles, i.e. other objects, when grasping the desired object. Then crowd-sourced human workers are used as supervisors on the second stage and finally, an expert from the field of robotics is supervising the robot. With this approach it is possible to achieve a reliability of 90% (Laskey et al., 2016). Another example for the utilization of AI approaches to address recognition problems in a warehouse setting, resp. in the context of picking, is provided by Mo and Lorchirachoonkul (2016) who present a way how to automatically detect which item has been picked and what has been done with it by capturing the worker's physical interaction and gestures within the picking environment with an array of 3D cameras.

However, not only bin packing is addressed with AI approaches. Similar robots resp. approaches to enable them to recognize objects can also be applied to the problem of automatic container unloading (Uriarte, Thamer, Freitag, & Thoben, 2016). For example, Stoyanov et al. (2016) propose a robot to automatically unload coffee sacks. Uriarte et al. (2016) additionally propose the so-called "celluveyor", a modular conveying system which can be utilized to automate the flow of material in a warehouse.

The provided examples show, that especially when combined with advances in robotics and other technologies, AI approaches to solve recognition problems are capable of automating many warehouse processes. This indicates a high potential for the application of AI. However, DHL for example states that only 5% of today's warehouses are automated (DHL, 2016). This number shows that the available potential still has to be realized.

5.2 Operation Support

This category subsumes applications supporting people in their every-day operations for example in manufacturing or transport. For example, Sharma et al. (2018) utilize a neural network to automatically parse geographical addresses. This supports the delivery process of mails and parcels which is of high relevance especially due to the increasing amount ordered due to e-commerce etc. The special challenge with regard to addresses is that they exist in various formats and an approach to recognize important parts such as the street name therefore has to be able to deal with this high variety. A neural network is proposed that is capable of extracting individual fields from an address in raw text format and provide a standardized representation (Sharma et al., 2018).

Support can also be provided in manufacturing. Longo et al. (2016) develop a system that is equipped with a neural network to process human voice and is able to recognize what the user is currently doing, e.g. which parts are currently handled. Based on this information the system is able to answer questions and give information relevant and suited for the situation and problem at hand. Other applications to support manufacturing operations are e.g. the automatic detection of counterfeited electronic parts to avoid their assembly and possible resulting issues (Frazier, Gilmore, Collins, & Chouika, 2016) or the automatic detection of parts to remanufacture, i.e. to recognize parts which can and which cannot be used further (Schlüter et al., 2018).

Another example for how to support actions happening on an everyday basis is provided by Tuszynski et al. (2013). They apply a deep learning neural network to analyze so-called container manifest, documents stating which goods are in a container, and the corresponding container. Radiography images are taken of the container and based on that containers with loads inconsistent from their manifest can be detected.

As said before, these are the areas which have been identified as promising application fields of AI recognition approaches in supply chain execution. While the list of classes or examples is certainly not comprehensive, it still is able to give an impression on what has already been developed in this field and provide ideas on where possibly to look at for further applications.

Overall, it also needs to be noted that major advances concerning approaches such as deep learning, robotics and computer vision—as already mentioned in the introduction—have just been made and are a requirement for successful applications. Therefore, much more can be expected for these problem classes in the future.

6 Conclusion

In summary, the paper aimed at giving a short overview on the most interesting AI approaches and the SCM tasks most often addressed in research. Furthermore, a focus on the application of recognition approaches for tasks from supply chain execution has been set.

Looking at results from scientific literature, the main implication that can be derived is that there is a high variety of AI approaches and there are many problems in SCM and logistics to be tackled with AI successfully. Regarding the applied approaches it is obvious, that—while research shows a high variety of them—machine learning in general and neural networks specifically are the by far most applied method. Interestingly, the number of sources dealing with recognition problems is still rather small, but by specifically looking for more examples from this area, it became obvious that there is a great suitability for applying AI to solve issues regarding recognition, especially in supply chain execution.

However, research still mainly deals with developing or improving algorithms and not with actually applying them in a real-world setting. There is only a limited set of pilots or specific real application scenarios. Most publications test their approach on a dataset based on e.g. simulations or bench-mark data. Moreover, organizational, process- and human-related issues are rarely discussed. This connects to a more general issue. The identified sources mainly do not report on the process on how to identify good and promising application cases nor on how to choose a suitable approach and implement it. Publications show a focus on applying an AI approach to a given problem but in order to receive a successful solution, it is first necessary to estimate how suitable an application case is. Only this way, the chance of success can at least be increased and the possibility to fail with applying AI can be lowered. Since this aspect has so far not been considered by any of the identified sources, it is a good opportunity for future research.

While the paper aimed at basing the results on a structured and understandable way, it cannot claim to be comprehensive. Especially, the chapter focusing on recognition and supply chain execution only can provide an introduction to possible applications. Nonetheless, the goal to give a first idea on suitable application cases and raise awareness on how SCM has so far benefited from is considered to be achieved successfully. Therefore the presented applications classes (warehouse automation and operations support) can be regarded as a starting point for more research on utilizing recognition approaches for supply chain execution. In the future it could be possible to identify more application cases within these classes or examine more supply chain execution problems regarding their suitability for applying AI. Since the technologies enabling the utilization of new and more enhanced AI approaches are developed further, the set of application cases can be expected to also increase and broaden in the future.

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