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IFAC PapersOnLine 58-19 (2024) 37–42

Towards a Framework for AI Applications in Intralogistics ⋆

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Abstract: The field of intralogistics is ideal for applying artificial intelligence (AI). However, there is currently no comprehensive framework for AI-enabled intralogistics that considers decision making layers. This paper aims to fill that gap by providing context, reviewing recent publications, and identifying key elements for framework development. It explores how AI can be used in intralogistics system design, planning and operations, at both physical and virtual levels. Our focus is on engineering pragmatic systems within the intralogistics domain, with a framework comprising human interaction, intelligent agents, and devices. The paper also addresses training data for AI-enabled intralogistics.

Keywords: Intralogistics, Artificial Intelligence, Logistics, Machine Learning, Simulation, Digital Twinning, Warehouse 5.0, Framework

1. INTRODUCTION

It is difficult to overstate the impact of artificial intelligence (AI) on culture, society, and industry. In fact, AI is already accepted as an important ingredient of Industry 4.0, an "Effective combination of IoT, cloud computing, artificial intelligence, and big data and their integration into business and automation processes will conceivably improve the industry not only on operational but also on economic and environmental scales." (Suleiman et al., 2022).

The proliferation of AI driven technologies is rapidly changing the logistics industry, the area of focus in this paper. In particular, we focus on intralogistics, loosely defined as the logistics (movement of goods) within a facility. Fottner et al. (2021) for example, define it as the "complex interplay of different logistics functions – covers the organization control, execution and optimization of internal material and information flows," while specifically including functions within facilities such as factories, warehouses, distribution centers, freight terminals, inland ports, seaports and airports. On the other hand, the definition in other papers seems to exclude ports. Regardless, AI is rapidly permeating the logistics industry at several levels from the physical to the informational and cognitive domains.

We will not attempt to present a formal definition of AI here; from our perspective, we view it as a set of methods, concepts or even a philosophy that fluidly works through these levels and includes but is not limited to learning, autonomy, goal setting and achievement, expert knowledge, self-awareness and cognition. On one hand, AI will eventually help humans become more like machines through virtual reality and assistive technologies, chip implants in the brain, bio implants for locomotion, etc. (Brunetti et al., 2022), while on the other, machines are already becoming humanoid as was even the case in the early days of robotics (Rosheim, 1994).

While there has been an explosion of academic journal papers, white papers, industry use cases, there is no formal framework for AI in intralogistics that considers the decision making entities involved. The objective of this paper is to provide directions for such a framework. In doing so, we will keep in mind that training, a complementary aspect of learning, is a key enabler of AI in intralogistics systems. While an intralogistic system with training and learning is naturally more "autonomous", as opposed to simply "automated", we will also bear in mind that humans will be part of the system, as captured in Industry 5.0 (Adel, 2022; Grosse et al., 2023). In fact, Grosse et al. (2023) explicitly refer to the dark side of Industry 4.0.

2. WHY INTRALOGISTICS IS A GREAT AREA OF APPLICATION OF AI

A modern intralogistics facility is a system in which humans, automated or autonomous handling devices, information systems, sensors, networks, RF emitters, and transmitters engage with each other in real time. Such a system is complex, dynamic, stochastic, and increasingly autonomous, all areas of strength for AI. Some examples are noted below (they will be further developed through the paper) motivated by AI methodologies:

- Supervised Learning (SL), a sub-field of methods from Machine Learning (ML), is great for mapping

⋆ Author Venkatadri would like to acknowledge the support by the National Science and Engineering Research Council (NSERC) of Canada for their support through a Discovery Grant awarded to the proposal "Optimization Models for Contemporary and Sustainable Production-Distribution Systems."

10.1016/j.ifacol.2024.09.084

input-output relationships (Gambella et al., 2021). In fact, the authors of this paper present machine learning problems as optimization problems, as it would be of interest to logistics engineers who often have an optimization background. An intralogistics facility has many such: ensuring responsive delivery, mapping fill rate or pricing decisions with demand, measuring the asymptotic relationship between throughput and resource allocation, e.g. congestion increases with autonomous mobile robot (AMR) fleet size, etc.

- Reinforcement Learning (RL), also a sub-field of methods from ML, is a newer paradigm in the AI age for classical operations research (OR) problems which may be seen as sequential decision-making problems where decisions are made based on an observation of a state and result in new states (Powell, 2022b,a). While RL is useful in the operational or planning contexts, it is also used in device mobility and task planning.
- Natural Language Processing (NLP) creates an interface for humans to interact with systems (Khurana et al., 2023). In the intralogistics context, this might involve voice activated instructions for a manual piece picker in an e-commerce fulfillment center.
- Computer Vision (CV) is used for object recognition and classification, identification, and detection (Davies, 2018). Such systems are necessary as autonomous robots guide themselves through the aisles of a warehouse (Fuentes-Pacheco et al., 2015).

The AI methodologies mentioned above are not mutually exclusive, as will be elaborated upon later in this paper. For example, both NLP and CV algorithms are trained using artificial neural networks (ANNs) (Zou et al., 2009).

3. CONCEPT DEVELOPMENT BASED ON THE LITERATURE

This section presents a brief literature review of articles relevant to AI and the application of AI in intralogistics. Due to the vastness of the literature and limitations the scope of this section is limited to a few key survey articles and those with information on contextual technologies and tools in both the physical and virtual domains. We begin by looking at two articles on autonomous intralogistics systems, then review the main methodologies of AI relevant to intralogistics, and finally shift gears to look at how AI is being adopted in allied and broader domains such as supply chain management.

3.1 Autonmous Intralogistics systems

Fottner et al. (2021) propose a two-dimensional framework for different intralogistics tasks based on task levels and the stage of automation. The authors describe how there is a shift from centralization towards autonomy and apply the framework to use cases to bring out the issues in implementations of such autonomous systems. Fragapane et al. (2021) also explore the themes of decentralization and autonomy in intralogistics for AMRs through the development of a planning and control framework for decision-making process.

3.2 Context-based simulation and Digital twinning for AI in intralogistics

In the context of increasing autonomy in intralogistics, context-based simulation and digital twinning for AI gain in importance. There are two use cases for context-based simulation in an AI enabled intralogistics environment: performance analysis, as in traditional intralogistics, and for training purposes. The simulation environments either serve as synthetic data providers, be it to generate data for supervised or unsupervised learning, or as training environments for RL algorithms that provide feedback on chosen actions, or integrate distributions that have been determined through ML from real-world data.

Context-based simulation and digital twinning are indispensable tools for training and learning in intralogistics (Murrenhoff, 2023). This paper discusses the Digital Continuum, where logistics entities have both a physical and a data (digital twin) reality. The digital reality includes a training and testing environment in a simulation environment. The paper also presents requirements for an automated generation of learning environments for intralogistics spanning the physical and digital domains.

While distribution fitting for simulation data generation is a classic challenge, an AI based approach for this task is the use of Generative Adversarial Nets (GANS) which employ two ANNs (Goodfellow et al., 2020). In this framework, a generative model G uses data from a data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G (this could be data from an intralogistics information system, for example). The training procedure for G is to maximize the probability of D making a mistake, and once G is trained, the data can be used for context-based simulation of an intralogistics system for design or logistics policy development. This is an emerging field of research and some articles such as the one by Basrur et al. (2021) have shown promising results. The authors use it to develop a traffic simulator in a maritime environment. The authors state that “the generator can simulate the travel time of vessels across different maritime zones conditioned on vessels’ speeds and traffic intensity. Experiments performed on the historical data from heavily trafficked Singapore strait show that our Ship-GAN system generates data whose statistical distribution is close to the real data distribution, and better fit than prior methods.”

Jackson et al. (2023) demonstrate a refined GPT-3 Codex to generate simulation models from a verbal prompt for queuing and inventory management systems. This development shows how simulation model development for logistics systems will be simplified in the future using large language models (LLMs, see Section 3.4).

3.3 Machine learning, deep learning, and reinforcement learning

As mentioned earlier, ML is a sub-field of AI that deals with complex input-output relationships. Several methods of ML that are reviewed in (Gambella et al., 2021) and presented as optimization problems. These include regression, classification, clustering, machine teaching and empirical model learning. ML algorithms are classified as supervised, unsupervised, or reinforcement learning (Gambella et al., 2021). In SL, the values of inputs and corresponding outputs are known. Training takes place on a subset of this known dataset. The objective is to minimize the margin of error while predicting the relationship between the input and output. However, in unsupervised learning (UL), the output variables are not available and the goal is to understand the features of the data and underlying associations. UL is useful for segmentation and clustering.

The decision space in intralogistics systems is usually modelled using optimization and/or simulation. SL does not explicitly model the decision space, although decisions taken in real-time could be recorded in a historical archive and used as an input in addition to other inputs that correspond to states of the system to evaluate what the outputs are.

It should be noted that neural network regression, modelled using ANNs, is particularly well suited for training (refer to the last paragraph of Section 1), a key feature of what would be required in intralogistics systems. This approach is often referred to as Deep Learning (DL) (Goodfellow et al., 2016) when there are at least two layers in the ANN.

The appropriate paradigm for explicitly modelling decision making in intralogistics is RL. Much of the intralogistics literature has focused on the "static" optimization problem using the methods of Operation Research (OR) or simulation. This can be seen in optimization papers such as the one by Briant et al. (2020). However, as noted in (Powell, 2022b,a), decisions in RL are taken at various points in time after observing the state of the system. These decisions then lead to newer states, setting up what is essentially a sequential decision approach. This represents a major paradigm shift, unifying classical optimization and AI, although the ideas in the continuum therein have evolved over time through Markov Decision Processes (Bellman, 1957) and Approximate Dynamic Programming (Powell, 2011), both considered essential ingredients of RL. An open research question is whether any of the mixed-integer linear programming (MILP) models in the intralogistics literature could also be embedded into the RL paradigm, assuming that they can be adapted to deal with rolling horizons.

However, since an RL based decision making algorithm can also be trained using a neural network regression, doing so results in what is called Deep Reinforcement Learning (DRL). The book by (Dong et al., 2020) first builds the foundations of DL and then covers widely used methods in DR, including implementations and applications.

While we have made these arguments within the virtual decision making domain, RL/DRL are also relevant to the physical domain. Naeem et al. (2020) review the literature on RL applied to robotics and autonomous control, communications and networking, and CV inter alia. The review by Lei et al. (2020) covers the following applications of DRL in autonomous Internet of Things (IoT): communication networks, cloud communicating systems, autonomous robots, smart vehicles, and smart grids.

In the physical intralogistics domain, we can think of an AMR with sensors and actuators. The sensors let the AMR know where it is and the actuators perform the load/unload function. The RL/DRL paradigm can not only be used for AMR task assignment but also direct its locomotive and transportation (load pickup/dropoff) tasks by appropriately defining the rewards in doing so.

3.4 LLM & RAG

Large language models (LLMs) have exploded in popularity with the advent of Generative Pre-trained Transformer (GPT) coined by OpenAI and distributed by them through their chatbot named ChatGPT. Min et al. (2023) present the concepts of LLM architectures while their survey covers LLM techniques for NLP through training, fine-tuning, prompting, and text generation. Retrieval augmented generation (RAG) has been proposed for knowledge-intensive tasks (Lewis et al., 2020). While this is still an emerging area of research, we expect in an intralogistics context that domain knowledge capture and retrieval would use this approach.

3.5 AI literature reviews in related areas

The review article by Rolf et al. (2023) proposes a classification framework for RL applications in supply chain management, a much broader field compared to our focus here on intralogistics. The elements of the framework include supply chain drivers, algorithms, data sources, and areas of application. They note that the Q-learning RL algorithm for inventory management is the most commonly reported application area in the literature. They also note that most applications are based on small problems to illustrate concepts but that the challenge is shifting to problems with large-scale data. To this end, the paper by Madeka et al. (2022) makes a contribution by presenting a DRL periodic review inventory control model with stochastic lead times, lost sales, correlated demand, and price matching considerations. This is shown to outperform both a model-free RL algorithm and the well known news-vendor solution through tests involving both simulations and real-world deployments at Amazon for a weekly dataset of about 80,000 sampled products from a marketplace. Cannas et al. (2023) use a multiple case study approach with 17 cases from six companies to show how AI applications can support operations and supply chain management processes using the supply chain operations reference (SCOR) model.

4. PRELIMINARY FRAMEWORK

We begin the preliminary framework development through the illustration in Fig. 1. The six-step iterative design framework of Peffers et al. (2007) involving problem identification, objective definition of a solution, design and development, demonstration, evaluation, and communication was kept in mind in doing so. We additionally considered AI methods and data requirements, the role of embedded and software agents, and domain specific requirements for AI in Intralogistics.

In Fig. 1, an intralogistics facility is controlled through a network which has wired, wireless, radio frequency (RF) connections to the cloud, internal partners (corporate office, other facilities within the company, etc.), and external partners (suppliers, transportation providers, customers, etc.). The network intelligently interacts with the physical control layer (in which sensors and actuators interact with physical devices), a human control layer (which interacts through displays, touch devices, input devices, etc.) with humans, and an agent control layer which interacts with intelligent or smart agents (Leitao et al., 2016). We can think of an AI-enabled layer as one which uses an AI framework but pragmatically would include decision making by humans or traditional automata.

The three AI enabled layers are expected to dynamically interact with each other. For example, a human being may be remotely piloting a gantry at a port with safety feedback from an intelligent agent, which would shut down the operation safely if it foresees an accident. Similarly, an intelligent agent may be watching for signs of worker fatigue and suggest a task activity break. The intelligent agent layer would naturally interact with the device layer as tasks are assigned or assumed (this interaction would ideally be two-way). The human assisted AI layer would conceivably enable device training for spatial awareness and fine-tuning a pick, place, or push handling requirement through a virtual or physical simulator in the human control layer. Conversely, the intelligent agent layer, with assistance from sensory inputs from the physical device layer would be used in task training. These examples are not merely hypothetical, current technologies allow for their deployment. In addition, layers are expected to be coupled with internal and external partners as well as the cloud.

Table 1 shows a classification of how AI can assist the various actors in intralogistics in training: the human, the intelligent agent, and the device. To train a human in such an environment within the cognitive context, an LLM with RAG is helpful. An example would be a systems designer who would like to estimate the throughput of various AS/RS designs. Within the physical context, VR simulations are already used in job training. Intelligent agents on the other hand, only exist in the cognitive (virtual) domain and would need to be trained using DL, or DRL in a simulation mode. With devices, the context is always physical and training occurs only in simulation mode. DRL is the most commonly used AI methodology for this case.

Table 1. AI Enabled Actor Assistance

Actor	Domain	Physical Reality	Digital Reality	Training Methodology
Human(s)	Cognitive or Physical	Yes	Maybe	LLM&RAG /VR Simulation
Intelligent Agent	Cognitive	No	Yes	DL/DRL Simulation
Device	Physical	Yes	Yes	DRL Simulation

Table 2 lists predominant AI methodologies for a few example intralogistics functions.

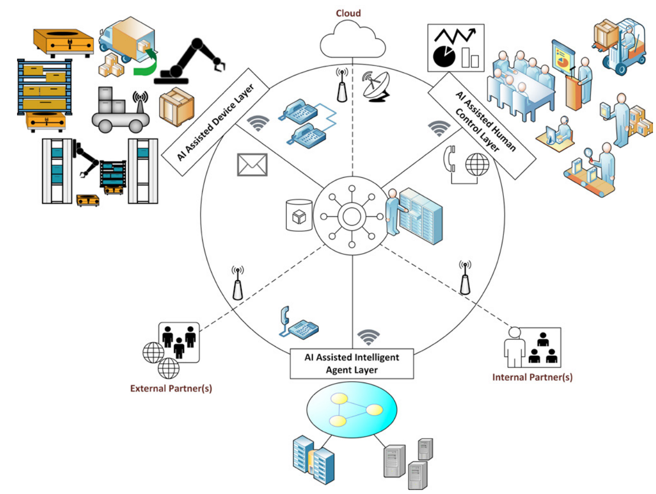

Fig. 1. An AI Enabled Intralogistics Network

Table 2. AI Assisted Layer Examples

Hierarchical Level	Function	High Level Goal	Methodology
Device Layer			
Planning	Motion Training	Spatial Awareness	Computer Vision/RL
Operations	Motion and/or Locomotion	Task Completion	RL
Intelligent Agent Layer			
Planning	Order Batching	Optimize Picking	RL
Operations	Individual or Swarm Control of AMRs	Task Assignment	RL
Human Interaction Layer			
Design	Warehouse Block Layout	Sizing and Dimensioning	DRL/RAG
Planning	Demand Forecasting	Estimate Lead Time	ML
Operations	Order Picking	Picking Instructions	Computer Vision and Face Recognition

Fig. 2 shows the role of data (both observed and simulated) in AI enabled intralogistics design, planning, and operations. It is well known that successful AI based implementations require massive and accurate data. There are two sources of data shown in this figure: observed and simulated. The simulated data is generated from the observed data through classical models such as Monte-Carlo simulation and distribution fitting. GANS and expert knowledge are introduced from the AI perspective. While the former was discussed already, expert knowledge in the intralogistics context include case picking rates, throughput, storage media sizing possibilities, etc. Such knowledge is important to decision making through the three levels of design, planning, and operations.

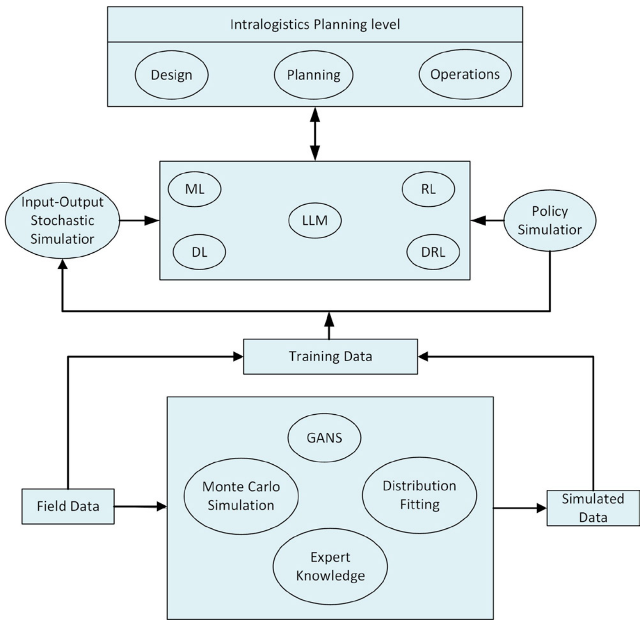

Fig. 2. Data and Simulation in AI Enabled Intralogistics

We next discuss the example of the online order batching problem described in Zhang et al. (2017) where pickers (manual or automated) are dispatched to retrieve a set of orders. The trade-off is to decide whether to batch orders from on existing set and start picking or to wait so that the net retrieval process is optimized. The decision space includes the decision to wait (do-nothing), batch orders into one or more picking routes, and the traversal pattern warehouse aisle network for each route. For simplicity, we assume that the input would be the existing orders and the output the total travel cost (or distance). In the context of Fig. 2, this problem falls under the operations level. Furthermore, RL could be used to solve the problem through policy simulations with future order data estimates coming from simulated data. DRL could be also used to train the RL model so developed.

5. BROADER ISSUES

While we focused on AI applications in logistics from an engineering perspective, AI itself is much broader and has connections to neuroscience, linguistics, ethics, psychology, organizational behaviour, and occupational safety and health and therefore can be seen as a toolbox of methods, that can be applied to various problems. Some of these broader perspectives are raised in the edited book by Lawless et al. (2020), which tries to examine "shared contexts" where both humans and machines are involved, as illustrated in our framework.

In this paper, we have striven to be pragmatic as we present our framework and therefore resorted to fixed and hierarchical design, planning, and operations control levels. As Xian et al. (2023) point out in the knowledge mining robotics context, "directly using or adapting models to produce low-level policies and actions," there is the possibility of developing a "fully automated generative pipeline" where tasks and training could be scaled up through what the authors call empowered generalist robots. In this vision of an autonomous system future, these fixed control levels would blur and disappear.

6. CONCLUSION

The development of a framework for AI assisted intralogistics design, planning, and execution is extremely challenging for two reasons: 1) AI itself is fast evolving, and 2) Researchers and practitioners are rapidly developing new applications in response to gain competitive advantage. This article has looked into AI methodologies in the literature and identified ML, SL, UL, RL, DL, DRL, GANS, LLMs, and RAG, as currently the most relevant for intralogistics. As seen in Fig. 1, any framework needs to look integrally into how human, intelligent agent, and physical systems would work together. Such a framework also needs to mesh with broader supply chain process models such as SCOR.

Finally, since both, physical and virtual realities, co-exist in AI-assisted intralogistics design, planning and operations, the framework should drill down into how training and learning processes, the key enablers of AI, would look like at the human, intelligent agent, and physical actor levels. An interesting avenue to explore in this context would be the mixed simulation and machine learning workflow approach presented in ETP4HPC (2019), where the four steps are identified and maybe broadly summarized as data ingestion, pre-processing and cleaning real-world sensors or databases, in-depth analysis of the data, communication thereof with human users and intelligent agents, and the development of the "teacher loop" for Deep Learning.

ACKNOWLEDGEMENTS

The authors of this paper would like to acknowledge Mr. Simranjeet Singh Chadha's assistance in drafting the figures.

REFERENCES

Adel, A. (2022). Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas. *Journal of Cloud Computing*, 11(1).

Basrur, C., Singh, A.J., Sinha, A., and Kumar, A. (2021). Ship-gan: Generative modeling based maritime traffic simulator. In *Proceedings of the 20th International Conference on Autonomous Agents and MultiAgent Systems*, AAMAS '21, 1755–1757. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC.

Bellman, R. (1957). A markovian decision process. *Indiana Univ. Math. J.*, 6, 679–684.

Briant, O., Cambazard, H., Cattaruzza, D., Catusse, N., Ladier, A.L., and Ogier, M. (2020). An efficient and general approach for the joint order batching and picker routing problem. *European Journal of Operational Research*, 285(2), 497–512.

Brunetti, D., Gena, C., and Vernero, F. (2022). Smart interactive technologies in the human-centric factory 5.0: A survey. *Applied Sciences*, 12(16).

Cannas, V.G., Ciano, M.P., Saltalamacchia, M., and Secchi, R. (2023). Artificial intelligence in supply chain and operations management: a multiple case study research. *International Journal of Production Research*, 0(0), 1–28.

Davies, E.R. (2018). *Computer Vision Principles, algorithms, Applications, Learning 5th Edition*. Elsevier.

Dong, H., Ding, Z., and Zhang, S. (2020). *Deep Reinforcement Learning*. Springer Singapore.

ETP4HPC (2019). A blueprint for the new strategic research agenda for high performance computing. URL `https://www.etp4hpc.eu/hpc-vision-018.html`. Accessed: 2024-01-13.

Fottner, J., Clauer, D., Hormes, F., Freitag, M., Beinke, T., Overmeyer, L., Gottwald, S., Elbert, R., Sarnow, T., Schmidt, T., Reith, K.B., Zadek, H., and Thomas, F. (2021). Autonomous systems in intralogistics – state of the art and future research challenges. *Logistics Research*, 14(2).

Fragapane, G., de Koster, R., Sgarbossa, F., and Strandhagen, J.O. (2021). Planning and control of autonomous mobile robots for intralogistics: Literature review and research agenda. *European Journal of Operational Research*, 294(2), 405–426.

Fuentes-Pacheco, J., Ruiz-Ascencio, J., and Rendón-Mancha, J.M. (2015). Visual simultaneous localization and mapping: a survey. *Artificial Intelligence Review*, 43(1).

Gambella, C., Ghaddar, B., and Naoum-Sawaya, J. (2021). Optimization problems for machine learning: A survey. *European Journal of Operational Research*, 290(3), 807–828.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep Learning*. MIT Press.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2020). Generative adversarial networks. *Commun. ACM*, 63(11), 139–144.

Grosse, E.H., Sgarbossa, F., Berlin, C., and Neumann, W.P. (2023). Human-centric production and logistics system design and management: transitioning from industry 4.0 to industry 5.0. *International Journal of Production Research*, 61(22), 7749–7759.

Jackson, I., Saenz, M.J., and Ivanov, D. (2023). From natural language to simulations: applying ai to automate simulation modelling of logistics systems. *International Journal of Production Research*, 1–24.

Khurana, D., Koli, A., Khatter, K., and Singh, S. (2023). Natural language processing: state of the art, current trends and challenges. *Multimedia Tools and Applications*, 82(3).

Lawless, W., Mittu, R., and Sofge, D. (eds.) (2020). *Human-Machine Shared Contexts*. Elsevier.

Lei, L., Tan, Y., Zheng, K., Liu, S., Zhang, K., Xuemin, and Shen (2020). Deep reinforcement learning for autonomous internet of things: Model, applications and challenges.

Leitao, P., Karnouskos, S., Ribeiro, L., Lee, J., Strasser, T., and Colombo, A.W. (2016). Smart agents in industrial cyber-physical systems. *Proceedings of the IEEE*, 104(5), 1086–1101.

Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., Yih, W.t., Rocktäschel, T., Riedel, S., and Kiela, D. (2020). Retrieval-augmented generation for knowledge-intensive nlp tasks. In H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, and H. Lin (eds.), *Advances in Neural Information Processing Systems*, volume 33, 9459–9474. Curran Associates, Inc.

Madeka, D., Torkkola, K., Eisenach, C., Luo, A., Foster, D.P., and Kakade, S.M. (2022). Deep inventory management.

Min, B., Ross, H., Sulem, E., Veyseh, A.P.B., Nguyen, T.H., Sainz, O., Agirre, E., Heintz, I., and Roth, D. (2023). Recent advances in natural language processing via large pre-trained language models: A survey. *ACM Comput. Surv.*, 56(2).

Murrenhoff, A. (2023). Requirements for generating learning environments for autonomous systems behavior in a digital continuum. In *Progress in Material Handling Research, 16th Proceedings*. Digital Commons@GeorgiaSouthern.

Naeem, M., Rizvi, S.T.H., and Coronato, A. (2020). A gentle introduction to reinforcement learning and its application in different fields. *IEEE Access*, 8, 209320–209344.

Peffers, K., Tuunanen, T., Rothenberger, M., and Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, 24, 45–77.

Powell, W.B. (2011). *Approximate Dynamic Programming: Solving the Curses of Dimensionality*. Wiley.

Powell, W.B. (2022a). *Reinforcement Learning and Stochastic Optimization: A Unified Framework for Sequential Decisions*. Wiley.

Powell, W.B. (2022b). *Sequential Decision Analytics and Modeling*. Now Publishers.

Rolf, B., Jackson, I., Müller, M., Lang, S., Reggelin, T., and Ivanov, D. (2023). A review on reinforcement learning algorithms and applications in supply chain management. *International Journal of Production Research*, 61(20), 7151–7179.

Rosheim, M.E. (1994). *Robot Evolution: The Development of Anthrobotics*. Wiley.

Suleiman, Z., Shaikholla, S., Dikhanbayeva, D., Shehab, E., and Turkyilmaz, A. (2022). Industry 4.0: Clustering of concepts and characteristics. *Cogent Engineering*, 9(1).

Xian, Z., Gervet, T., Xu, Z., Qiao, Y.L., Wang, T.H., and Wang, Y. (2023). Towards generalist robots: A promising paradigm via generative simulation.

Zhang, J., Wang, X., Chan, F.T., and Ruan, J. (2017). On-line order batching and sequencing problem with multiple pickers: A hybrid rule-based algorithm. *Applied Mathematical Modelling*, 45, 271–284.

Zou, J., Han, Y., and So, S.S. (2009). Overview of artificial neural networks. In D.J. Livingstone (ed.), *Artificial Neural Networks: Methods and Applications*, 14–22. Humana Press, Totowa, NJ.