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Selection of optimal machine learning algorithm for autonomous guided vehicle's control in a smart manufacturing environment

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Abstract

Artificial intelligence is a field of research that is seen as a means of realization regarding digitalization and industry 4.0. It is considered as the critical technology needed to drive the future evolution of manufacturing systems. At the same time, autonomous guided vehicles (AGV) developed as an essential part due to the flexibility they contribute to the whole manufacturing process within manufacturing systems. However, there are still open challenges in the intelligent control of these vehicles on the factory floor. Especially when considering dynamic environments where resources should be controlled in such a way, that they can be adjusted to turbulences efficiently. Therefore, this paper aimed to develop a conceptual framework for addressing a catalog of criteria that considers several machine learning algorithms to find the optimal algorithm for the intelligent control of AGVs. By applying the developed framework, an algorithm is automatically selected that is most suitable for the current operation of the AGV in order to enable efficient control within the factory environment. In future work, this decision-making framework can be transferred to even more scenarios with multiple AGV systems, including internal communication along with AGV fleets. With this study, the automatic selection of the optimal machine learning algorithm for the AGV improves the performance in such a way, that computational power is distributed within a hybrid system linking the AGV and cloud storage in an efficient manner.

Keywords: Artificial Intelligence; Autonomous Guided Vehicles; Industry 4.0; Intelligent Control

1. Introduction

The growing development from static to dynamic production systems significantly increases the demands on intralogistics. This concerns both the demands on the flexibility of the systems, for example, with regard to fluctuating time and quantity requirements and the internal control of the systems. Therefore, neither orientation to fixed paths with predefined points for route determination nor exclusively centralized control is sufficient [1]. To cope with the new complexity that has arisen, besides classical analytical methods [2, 3] and simulative methods such as digital twins [4], artificial intelligence (AI) methods [5-8] are increasingly used. The dynamic selection of the appropriate artificial intelligence approaches for specific problem solving is a new challenge, especially in the case of changing framework conditions. In this context, the previous approaches [9-12] for algorithm selection mainly focus on the analytical derivation of the selection without sufficient inclusion of the empirical basis. In the presented approach, a framework is developed that considers both the analytical approaches and feedback with empirical data ('Data in the loop').

To this end, the functional requirements for AGVs are first briefly presented in section 2 and then assigned to the possible

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AI methods in section 3. Based on this, the framework for assigning the methods is derived in section 4. Finally, section 5 presents a summary and a brief outlook on further development.

2. Planning and control tasks for AGVs

According to [1], the tasks for AGVs can be divided into the following areas:

- Strategic tasks
- Tactical tasks and
- Operational tasks

2.1 Strategic tasks

For the strategic area occurs the determination of the guide path design [13, 14]. Within this design, the layout is defined over which the supply by the AGVs should take place. Besides the layout definition, other strategic decisions about the supply strategy (On-demand, milk run) can also be summarized in this area.
The supply of AGVs is closely connected to the routing and therefore, waiting times due to shortage or accumulation of materials can often be accounted to the AGV system. This is why a well-designed layout for the supply by AGVs is of utmost importance. [15] propose an approach that deals with the solution of the vehicle assignment problem, which relies on adaptive workstation clustering considering both the main characteristics of the material flow and the complex environment layout. Furthermore, [16] developed a cyber-physical system using multiagent system technology where AGVs and traffic commanders cooperate autonomously with each other to address the challenges of an efficient guide path design. Decision trees and reinforcement learning allow AGVs to choose the optimal rule-based strategy out of a pool of existing optional strategies in order to increase self-adaptive capability. This already illustrates the benefits of applied machine learning algorithms, which this paper takes closer into consideration in the next section.

2.2 Tactical tasks

Within the tactical field, the summarized tasks cover the determination of the number of vehicles, battery management, scheduling, dispatching, and vehicle positioning.
Referring to AGVs, a central unit is responsible for taking control of scheduling, routing, and dispatching decisions [1]. Therefore, AGVs are less flexible in terms of decision-making, which results in a more static reaction to changes within a system and its corresponding environment instead of a dynamic adaption to the circumstances. There are diverse approaches to address this challenge. Considering multi-AGV scheduling systems, [17] established such a system by using the unidirectional directed graph method and combining the A* algorithm, which effectively solved conflict and collision problems. Furthermore, [18] present a smart AGV management system, which combines real-time data analysis and digital twin models to predict and optimize the schedule for material delivery. In comparison, [19] proposes a physical context-aware communication control method in order to ensure a collision-free and smooth AGV operation. They predict the time to intersections for all AGVs in communication with the central server. [15] provide a solution for vehicle assignment with modularity-based clustering that detects strong dependencies within AGV stations. Besides the described methods, [20] combine different algorithms in a super-algorithm that performs better than any of the components individually to improve the problem of project scheduling.

2.3 Operational tasks

In the operational area, the timely determination of the route and a deadlock resolution take place.
[21] classify path planning into offline and online path planning, static environmental path planning, dynamic environmental path planning as well as global and local path planning. Several algorithms are available such as A*, Dijkstra, D*Lite, or a combination of artificial potential field algorithms for optimal path planning [22]. Conventional AGVs follow fixed paths to move to predefined points on the determined route [1]. Due to this design, it would take most of the AGVs a substantial time to adapt to changes on a dynamic factory floor. [23] present a dispatch and navigation plan to serve the randomly constantly incoming orders to reduce time consumption for dynamic route planning. Furthermore, the application of multimodal deep Q learning increases fleet efficiency by multi-source data monitoring. Moreover, [24] present guidelines for when each algorithm should be used on a problem considering several algorithms for path planning as A* and D* lite.

3. Application of machine learning to planning and control tasks for AGVs

3.1 Machine learning paradigms

According to [25], machine learning approaches can be divided into the following three application classes: Supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL).

In the supervised learning approach, training is performed by explicitly evaluating the data with respect to the learning goal. Classification and regression issues can typically be clarified by employing the supervised learning approach.

For unsupervised learning, the data is processed without explicit evaluation for the learning approach. The algorithms determine patterns or structures via data exploration. The UL approach solves clustering or dimension reduction tasks.

In ML-paradigm reinforcement learning, learning is enabled via a reinforcing reward structure. For example, an AGV can maximize the number of delivered packages by avoiding obstacles [20].

3.2 Application of machine learning to AGV planning and control tasks

Diverse machine learning algorithms have an application in AGV planning and control. The most commonly used algorithms for those problem instances were neural networks, deep learning, including deep neural networks, reinforcement learning, and decision trees. To be able to evaluate current ML applications used for AGV planning and control, we conducted a literature analysis that investigated journals, conference papers, and scientific books. The sources are in English language, except they contributed substantially to defining the research gap, in this case German literature was taken into account as well. We searched the online databases Science Direct, Web of Science and Google Scholar and used a search term with the keywords "Automated guided vehicle", "Machine learning", "Artificial intelligence", "Planning", "Control", "Path planning", "Scheduling" to cover all areas of interest. Furthermore, the inclusion criteria for selected literature was to deal with a selection model for machine learning algorithms, AGV planning, control or scheduling, or machine learning algorithms applied to any of those application areas of AGVs. The following table illustrates an overview created from the literature analysis considering ML applications for AGVs, which explains the individual use cases of ML algorithms for certain AGV tasks more specifically. The algorithms are assigned to tasks related to one of the three categories: Selection of AGVs, timing, and routing. There are subcategories for the selection of AGVs, such as the prediction of future tasks and task selection. For timing, it is scheduling and dispatching and in the field of routing, algorithms can be applied for optimal path finding and path planning.

Table 1. Analysis of applied machine learning algorithms for AGV tasks

	Neural Networks	Reinforcement Learning	Deep Learning	Decision Trees
Selection				
Prediction of future tasks			[26]	
Task selection	[27]	[27]		
Timing				
Scheduling	[26]	[16]		
Dispatching		[23]		
Routing				
Optimal path finding	[13, 14]	[5]		[13]
Path planning		[16]		[16]

3.3 Existing algorithm selection approaches

Building on the previous points, the selection of the best suitable machine learning algorithm for AGV planning and control tasks has the potential to improve the performance of AGVs on the shopfloor significantly. Algorithm selection refers to the problem of selecting the best algorithm for a specific instance of problems from a portfolio of algorithms [28]. [28] introduced four abstract models for considering the situations accordingly to requirements: The basic model, the model with selection based on features, alternate definitions of best for the models, and the model with variable performance criteria. Several researchers build on his approaches and develop algorithm selection models. Different approaches are available regarding the development of optimal algorithm selection models for multi-agent path finding [10, 27], but regarding AGV planning and control in general, there is still room for development in terms of automatic algorithm selection. The following illustration, figure 1, summarizes different algorithm selection approaches in the context of AGVs and provides a more detailed explanation of the individual, available approaches.

Referring to the conducted literature review, there were not many sources available that dealt with algorithm selection models applied on AGV scheduling or controlling. Figure 1 serves to illustrate what current researchers worked on and where the research is standing at the moment. The columns represent the main papers that developed an algorithm selection model, and the rows represent four categories that help to compare the approaches in terms of what the model is in general about, which algorithms are in the portfolio from which the model selects the most appropriate one, how the decision for a chosen algorithm takes place and if there are any validation procedures available. The selection of the evaluated papers is due to their data foundation and problem they intend to solve. They covered challenges from classification tasks, project scheduling, optimal path finding and dynamic vehicle routing. As they deal with different algorithm portfolios and algorithm selectors, they build a suitable foundation for further approaches on algorithm selection models for other data sources.

Within the presented models, the selection of algorithms in the portfolio was often in an ad hoc manner and arbitrary, but to be efficient, the algorithms should be competitive on the considered instance set [12]. Furthermore, the empirical evaluation of the models and validation has often been neglected. Therefore, this paper proposes an algorithm selection framework, which includes an empirical base to ensure validity.

4. Algorithm selection framework

The presentation of the algorithm selection framework is on two levels: The conceptual model and the implementation model. The conceptual model describes the structural design of the framework, and the implementation model describes the implementation architecture.

4.1 Conceptual model

The conceptual structure (Figure 2) builds on the following components:

- Problem classification
- Algorithm evaluation and
- Algorithm decision

Figure 1. Available algorithm selection approaches

Algorithm selection models

	Classification tasks in reverse logistics [11]	Dynamic vehicle routing problem [12]	Optimal multi-agent pathfinding [13]	Multi-agent pathfinding with shortest path embeddings [14]	Project scheduling problem [20]
Model description	Preselection of ML algorithms by developing a concept, where basic *supervised ML algorithms* and a set of criteria are selected and described	Algorithm selection model based on a *regression model*, that maps the relation between the characteristics and the solution quality of the algorithm	*Supervised learning algorithm* with a set of handcrafted specific features or a problem instance casted to an image to apply a *deep CNN* for classifying it	Portfolio of algorithms from which a *deep convolutional neural network* tries to find the fastest algorithm to solve a specific multi-agent path finding problem instance	*Empirical hardness model* that maps problem instance features to performance of an algorithm in order to create a super-algorithm
Algorithm portfolio	K-nearest neighbors, linear regression, logistic regression, SVM (with kernel), naïve bayes, decision trees, neural networks	MMASUS/Insert, MMASUS/US, Spiral8x8/Insert, Spiral/Insert, NN 2-Opt/Insert, NN 2-Opt/NN 2-Opt, NN 2-Opt/US	A*, Enhanced Partial Expansion A*, Increasing Cost Tree Search, Conflict-Based Search, Merging agents-CBS, state-of-the-art variant of CBS including proposed heuristic	Search based: Conflict-Based-Search and its state-of-the-art variant with improved heuristics; Optimization based: Branch-and-Cut-and-Price	Tabu-search algorithm, that can handle more general resource-constrained project scheduling problems and a hybrid genetic algorithm,
Algorithm selector	A suitable algorithm is selected by matching criteria and algorithms in order of their significance for preselection	For every algorithm, a regression model is created, and neural networks realize the selection of the most suitable algorithm	Regression approach (effort estimation and classification approach), learning algorithms: Tree-based and CNN with image-based features	CNN class, that treats algorithms as a classification task and an augmented version of this class, a graph embedding based model	M5P-Tree Model (Decision tree with regression models at the leaves) and M5 Rule model, that builds a set of rules
Model validation	No verification and implementation of concept yet	The criteria for the algorithms used for decision-making are based on several models, which increases the confidence in a criterion for an algorithm and thus for the decision	Accuracy, coverage and total runtime of model as metrics for the evaluation of the model	Ablation study in order to analyze architectural and design choices in the network by training variants of the model with different combinations of loss function	Model is built using training data; The results are only expected to be valid within the scope of that data

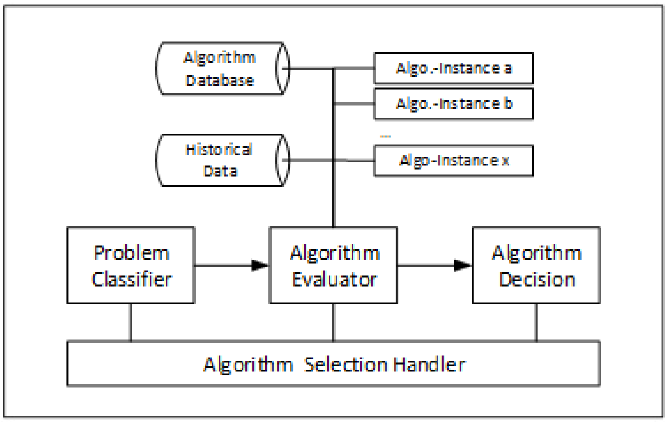
The *problem classification* component determines the appropriate algorithms based on input data. Within the phase of problem classification, a transformation of the technical problem to the abstract problem type occurs. The derivation of the suitable algorithms considers the available empirical data stock and falls back to the possible algorithms stored in a database. For example, if a problem is requested for the first time, only the heuristic algorithms or optimization approaches are offered for selection due to the lack of data.

The *algorithm evaluator* component performs an execution for the selected set of algorithms to determine the solution. For this purpose, instances are available to the evaluator for execution. These instances can pursue generic (e.g., mathematical optimization models) or specific solution approaches. For the solution determination, the algorithms based on training data also access the historical data.

The results of individual algorithms are passed with the model data to the *algorithm decision* component. Within this component, the decision for the most suitable algorithm is executed. In addition to the fulfillment of the target parameters, other parameters such as runtime and complexity are also considered in the decision-making process.

The *algorithm selection handler* controls the communication to the connected intralogistics systems and the internal communication between the components.

Figure 2. Conceptual model algorithm selection framework



4.2. Implementation model

Due to the dynamics of smart production systems, a static and time-stable selection of algorithms is critical. Therefore, the implementation of the algorithm selection framework must take into account the dynamic aspects and the increasing degree of autonomy [1] of AGV systems. The implementation model (Figure 3) includes the four areas:

- Place of execution
- Degree of autonomy
- Algorithm solver systems
- Type of results

Figure 3. Implementation model algorithm selection framework

	Modes		
Place of execution	Cloud	On Premise	hybrid
Degree of Autonomy	central	decentral	
Algorithm Solver Systems	Cloud	On Premise	hybrid
Type of Results	Data	Data + Model	Data + Model + Executer

4.2.1 Place of execution

On the one hand, the selection of the algorithms is critical to success, and, on the other hand, it should not place too high demands on the infrastructure for specific application groups, such as small and medium-sized enterprises. Thus, the operation of the framework must be possible both in an on-premise and in a cloud variant. If the selection of the algorithm contains confidential information, the execution can be split between the cloud and the on-premise area. For example, the historical data can be stored on an on-premise system to which only the local system has access.

4.2.2 Degree of autonomy

The framework supports a centralized as well as a decentralized organization. In the case of the centralized approach, the selection is performed by a defined entity that performs all selection tasks. In the case of a decentralized or usually partially decentralized organization, the selection can be made on different levels. A decentralized organization is beneficial for time-critical problems that can be solved with algorithms that are not computationally intensive. In addition, individual AGVs are being equipped with increasingly powerful IT systems.

4.2.3 Algorithm solver systems

The software systems required for solving the individual algorithms can be implemented analogously to the higher-level solution either on an on-premise solution or on a cloud solution. Especially for time-critical tasks, such as extensive training data or complex optimization algorithms, ready-made and scalable cloud solutions can be used. Cloud solutions can furthermore be a cost-saving way of implementation for selection decisions that are only temporarily necessary in relatively stable production systems. Since the architecture of the framework structurally supports different solution instances, these can, of course, also be used in a hybrid form.

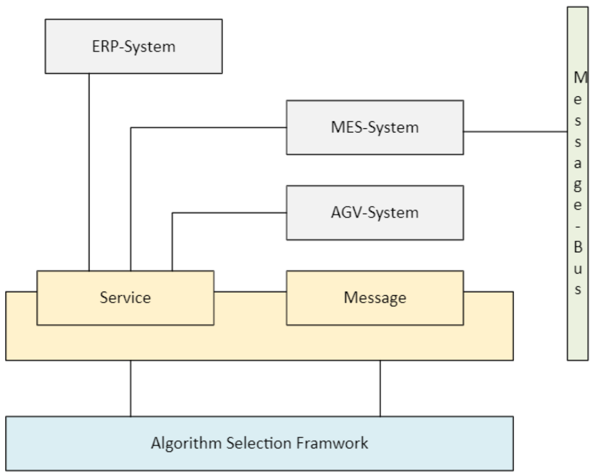
4.2.4 Type of results

The algorithm selection framework's original task is to determine the suitable algorithm. Particularly in the case of ML algorithms, in addition to the actual algorithm, corresponding model data, for instance in the form of a trained neural network, are sometimes necessary for the execution.

4.3 Integration Model

In order to ensure good integration into existing IT infrastructures, it must be possible to connect newer standardization approaches, such as the VDA 5050 standardization [29] on the one hand, and legacy systems on the other. To guarantee this, the integration is basically ensured via a service-oriented approach, which can be operated in passive mode (request-response) as well as in active mode (active message control via message systems). The basic functionality of the algorithm selection system is connected to the systems via an integration layer (see Figure 4). This ensures with the changes and advancements of the systems to be expected that only the respective assignment between the inquiring system and the algorithm selection system must be changed. The assignment layer can be static or dynamic via the inclusion of semantic information [30].

Figure 4. Implementation of integration layer



5. Conclusion and Outlook

The presented approach demonstrates how the selection of algorithms can be realized via the framework for productive use. In addition to the selection, it supports the execution of the algorithms with corresponding data and model sets. The feedback also supports the dynamic adaptation to changing conditions and the flexibility regarding the place of execution. The restrictions of the existing static approaches are thereby overcome and a stepwise integration into the IT systems of different structure is thus ensured. Due to the gradual introduction, the knowledge gained in each phase can be taken into account in order to support both the secure development of algorithm know-how and the development of the necessary database. Future potentials of the approach lie, in particular, in the inclusion of more flexible AMR and the structural consideration of further dynamic data such as employee movement data.

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