Data preprocessing, aggregation and clustering for agile manufacturing based on Automated Guided Vehicles

Rafal Cupek[1], Marek Drewniak[2], Tomasz Steclik[3],

[1]Silesian University of Technology, Gliwice, Poland
[2]AIUT Sp. z o.o. (LTD), Gliwice, Poland
[3]Institute of Innovative Technologies EMAG Katowice, Poland

{rcupek@polsl.pl, mdrewniak@aiut.com.pl, tsteclik@ibemag.pl}

Abstract. Automated Guided Vehicles (AGVs) have become an indispensable component of Flexible Manufacturing Systems. AGVs are also a huge source of information that can be utilised by the data mining algorithms that support the new generation of manufacturing. This paper focuses on data preprocessing, aggregation and clustering in the new generation of manufacturing systems that use the agile manufacturing paradigm and utilise AGVs. The proposed methodology can be used as the initial step for production optimisation, predictive maintenance activities, production technology verification or as a source of models for the simulation tools that are used in virtual factories.

Keywords: Autonomous Guided Vehicles (AGV), AI-driven Analytics, Data clustering, Pattern searching

1 Introduction

Automated Guided Vehicles are one of major symbols of the fourth industrial revolution [1]. Their importance can be compared to the conveyor belt that was invented for producing the Ford Model T automobiles, which became the symbol of the second industrial revolution. However, the conveyor belt was not the reason for the changes in manufacturing, on the contrary, it was one of the results that came from the technological and social challenges that were visible at the beginning of the 20th century [2]. Similarly, the widespread introduction of AGVs should not be considered to be a new breakthrough technology (AGVs have been used by industry for more than twenty years), but should rather be considered to be an answer to the new technological challenges and a visible sign of the ongoing changes in manufacturing.

The new generation of manufacturing systems is characterised by a high degree of flexibility, which is required in order to cope with frequently changing customers' orders, low material buffers and agile production technologies. Moreover, production is often performed by robotic production stations that can execute many variants of the technological operations [3]. Contemporary manufacturing has to be supported by

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data mining mechanisms, artificial intelligence and cloud computing. AGVs are not stand-alone technological solutions because they have to cooperate and become a part of the highly advanced information services that are performed during the successive steps in the production chain. This means that AGVs have to cooperate with the advanced informatics tools that support the local optimisation of the ongoing production tasks and also have to support the automatic cooperation with production stands that are based on Machine-to-Machine communication. AGVs also have to be equipped with self-diagnostic tools, which are necessary for their predictive maintenance activities and have to support the new information architectures that are characterised by a high degree of autonomy and the distribution of the decision-making processes in manufacturing [4].

This research is focused on processing and managing the data that are collected by AGVs. The main research topics are data aggregation and clustering. The main research challenges were (i) to discover an unknown number of variants of transport orders performed by AGVs; (ii) to assign the subsequent, realised transport orders flowing in stream to the appropriate variant and (iii) to identify new, previously unknown variants of the transport orders.

The authors used two well-known clustering algorithms, K-means and DB-Scan, and used communication middleware that is based on the OPC UA standard. The authors consciously selected these “nonstreaming” clustering algorithms despite the fact that there are solutions that are dedicated to data that is flowing in a stream, for example, CluStream or Den-Stream, which are available in the MOA project [17]. The “streaming clustering algorithms” are primarily based on the concept of two steps (online and offline) and microclustering, which most often means high-speed computation. However, when the duration of a single transport cycle that is performed by an AGV (seconds, even minutes) is considered, the speed of a calculation is not crucial. The main reasons for selecting the above-mentioned "classic" clustering algorithms were (i) the authors were more interested in the possibility to immediately compare the incoming data (about the transport cycle being performed) with the existing reference clusters and anomaly detection [19] and (ii) “streaming clustering algorithms” enable clusters to “shift” in space when fluctuations occur in the incoming data values.

The main research contributions of the paper are (i) the proposed architecture for a data collection and aggregation system for AGV, which is presented in chapter two and (ii) the methodology for AGV data clustering and the experimental research that verified the proposed solutions, which is presented in chapter four. The presented results are part of the industrial research on the new generation of AGVs that are being designed and produced by AIUT LTD.

2 Aggregating production records for an AGV

The operating principle for the control systems that are used in manufacturing can be based on the event-triggered mode, which is typical for high-level control (e.g. state machine based Sequential Function Chart SFC, which is defined under the IEC

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61131-3 standard or the distributed control architecture that is defined under the IEC 61499 standard) [5] or can follow a time-triggered periodic processing, which is typical for low-level control systems (e.g. a PLC running a Ladder or Function block diagram, which cyclically sample information from the sensors, execute the control logic and update the actuators) [6]. In both cases, the sources of information provide data streams (subsequent events or cyclically updated samples) that are quite difficult for data mining tools to directly analyse [7].

AGVs, which and use both control principles, are used to perform internal logistic tasks [8]. Time-triggered periodic data processing is used for the continuous control of an AGV's movement while the event-triggered mode is typical for communication with MES (Manufacturing Execution Systems) or high-level navigation support. Both types of data processing can be a source of valuable information for a data mining analysis. Each transportation task has a beginning and an end and can be characterised by one production record. Although from a technological point of view, the tasks that are performed by AGVs can be separated (one delivery can be transported by more than one AGV) or combined (several deliveries can be transported simultaneously) [x1], separating and joining transportation cycles was omitted for this research study. It was assumed that each transportation cycle included all of the operations that an AGV performs between the loading and unloading point.

In order to make the machine learning process effective and efficient, the streams of data that come from different sources have to be joined and grouped according to their relevance to the production steps being analysed. Next, the collected data have to be aggregated in order to create new information that reflects the statistically important features. This step combines the external engineering knowledge that can be expressed by the data models with the current information that is being collected from the production system. In this way, the streams of data from AGVs can be transformed into the discreet production records that are created by the aggregation functions.

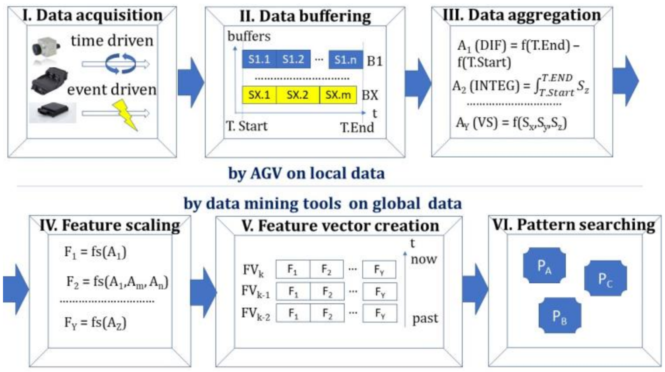

Fig. 1. AGV data processing methodology

The authors assumed that each aggregation function produces one scalar value according to the data model that is defined for a given AGV type. On the one hand, the information that is collected in one production record comes from different

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sources (e.g. sensors, control signals, machine states, messages transmitted from the parent system, independent security systems etc.), while on the other hand, each information source can be used many times by the different aggregation functions (different points of view on the same data source). The fusion of the aggregates forms a production record, which is an input vector for the data mining tools and characterises a single transportation cycle. Because this vector has the same structure for all of the transportation cycles (for a given data model), it is a convenient source of information for the data mining algorithms.

The proposed methodology (Fig. 1) for AGV data processing is composed of six steps: (i) data acquisition – sensors, control systems, supervisory systems, external events and other system provide a number of information streams. Data is exchanged based on a time-driven paradigm (where the samples are delivered cyclically according to a defined time interval) or by an event-driven paradigm (where the information is sent by its source in the event that a predefined event occurs); (ii) data buffering – the information has to be temporarily stored (buffered) in order to make its aggregation possible. The local storing is for a specific time period that is determined by the beginning and the end of each transportation cycle; (iii) data aggregation – each information buffer has to be transformed into a single scalar value that characterises the collected samples. The data stream from a single sensor can be processed by different aggregation functions (in order to detect the different features of a given signal) or an aggregate can be built on the data from multiple sensors (data fusion). Examples of the aggregates that were used in this research are DIF – the difference between the values at the beginning and at the end of a transportation cycle (e.g. for the energy consumption meters), INTEG – the integral of a parameter that is limited for a production cycle (e.g. the rotational speed of the drive wheels, which are integrated over the duration of the transportation cycle) or VS – the virtual sensors that generate new information that is based on one or more information sources and that includes any additional knowledge about the production technology; (iv) feature scaling, which is designed to change the values of the aggregates that are measured in the engineering units to a new artificial scale that reflects the technological importance of a given information source. This process differs from the classic normalisation that is used in data mining because the range of values cannot be predicted in advance (e.g. the duration of an operation may be extended many times due to the occurrence of a production error). Moreover, the standard normalisation procedure does not permit the technological significance of individual parameters to be taken into account; (v) feature vector creation, which is the step during which the data from the different aggregates are combined into the input feature vector and (vi) pattern searching, which on the one hand, is the output from the proposed aggregating methodology, while on the other hand, the database of the patterns that represent the repetitive transportation use cases can be used as the input for the subsequent stages of data mining.

The implementation should permit agile manufacturing including the use of big data analytics, cyber-physical systems and prediction technologies [10]. This can be divided into two parts: steps (i) – (v) can be performed in a distributed manner, while step (vi) should be performed on the global data using the data mining tools.

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However, the second part can also be parallelised when specific models of the aggregates are used by a number of the data mining tools that are used to simultaneously search for different transportation patterns. Another challenge is integrating the proposed approach with an actual manufacturing system. The analytical module has to combine the production data that comes from different AGVs that has actually been collected with the simulation data that has been created based on the relevant models. Additionally, the new models should be dynamically created and based on the collected data. This goal leads to the proposed system architecture that is shown in Fig. 2. The authors' research is based on the OPC UA communication middleware [11], which seems to be one of key enabling technologies for the new generation of manufacturing systems.

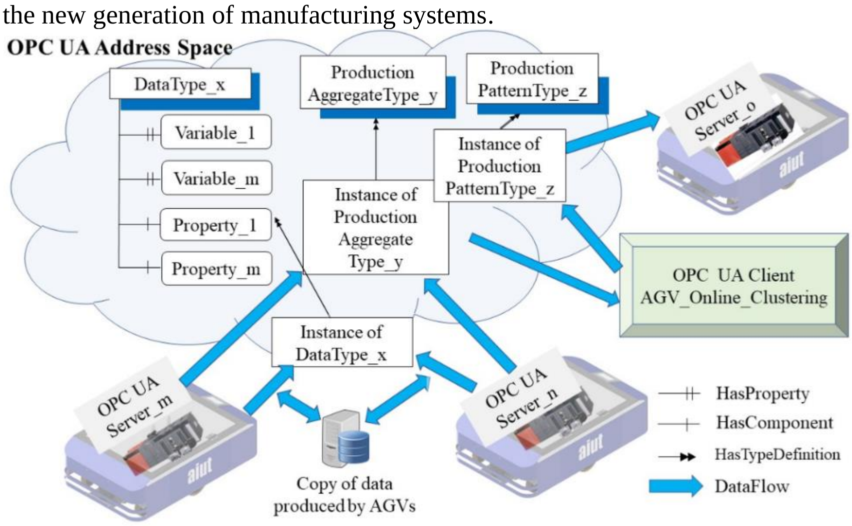

Fig. 2 Proposed system architecture.

The proposed architecture can be described by the following features: (i) the information models for the aggregated production records are transparent and are common for all of the AGVs. The definition is visible in the OPC UA address space and the object models that are used are the same for all of the OPC UA servers; (ii) many different models can be created and processed for the aggregates. Each record is identified according to the object-oriented approach by a class type that defines its content. New aggregates can be added based on the requirements that are generated by the data mining modules; (iii) the Historical Data Access mechanism, which is performed by OPC UA servers enables a later aggregation, which includes any new patterns that emerge in the data mining applications. It can also be used for simulations in virtual factories; (iv) the patterns for the transportation cycles are also visible in the OPC UA address space. These enable new fields of the data mining applications that support manufacturing decisions and (v) the data collected by the OPC UA servers can be accessed by many OPC UA clients in the parallel access mode. The parallel processing can be more efficient, e.g. in the event that the various patterns that are associated with the different data models have to be analysed.

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3 The AGV that was used for the experiments

The AGV that was used for the research was a Formica-1, which is designed and manufactured by AIUT LTD. The unit was designed to perform transportation tasks including both the typical intra-logistics operations such as delivering resources to the production stations or to be used as a transportation carrier for the manufactured products. The Formica-1 is presented in Fig. 3.

Fig. 3. The Formica-1 AGV that was used in the experiments

An AGV can be equipped with various types of navigation methods. One of the most common is natural navigation, which is based on two onboard laser scanners that provide measurement data about the surroundings of a unit. The measurements are used to create a map of the production environment and later to compare what the AGV is currently observing in relation to this map. The techniques that are used to calculate the travelled distance and the heading of the machine are based on odometry. In order to provide the complete diagnostic information about the performed transportation tasks as well as the operation of all of the onboard devices, all of the signals from the automation control and industrial IT systems are passed through the unit controller. This controller gathers the data, adds timestamps and transmits it to third party diagnostic systems cyclically using a TCP/IP connection.

Depending on the purpose of the analysis of this data, different values are available: the process memories and statuses of work, the signals of the activity of specific devices, the measured energy and time, the distance travelled, velocities, directions, payload control, sensor indications etc. The data are grouped into functional structures, marked with specific identifiers and transmitted in the TCP frames. For this study, all of the data associated to the work statuses, diagnostic information, the activity of the devices, energy measurements and cycle determination were received and entered into the OPC UA server. The AGV was used in the testing area in AIUT LTD, where units are functionally tested before they are sent to and set up in the target production environments. The testing area has space for many production scenarios and therefore, the experiments were combined with preliminary customer tests, in which the AGV performed the transportation tasks in several variants. The data, which was recorded and stored for further data mining approach, was also gathered during the actual operation of the Formica-1. These data included the duration of a cycle; the energy that was required to implement it; the duration of the forward and backward movements; the rotational speed of the left and right drive wheels, which were integrated over the transportation cycle; the times when the LED

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lighting was activated (red, blue and green); the duration of the blinker signals, which were aggregated as virtual sensors and the downtime. The units that were used to measure these data were milliseconds, kilowatts and RPM x s.

Communication between an AGV and the data mining system is based on OPC UA, which utilises Webservices to communicate with the enterprise management systems and for the TCP-based communication with the control systems. In terms of security, OPC UA uses the solutions that are appropriate for a given family of protocols. The security of the information exchange is managed by a Secure Channel Service Set, which defines a long-running logical connection between an OPC UA client and a server. OPC UA is a scalable, reliable and safe middleware that can not only be used as a data connector but also as a translator for information models that can be used to match different information systems [12].

4 Pattern searching

The presented research was performed in a near-real environment during the preliminary tests of the Formica-1 before it was deployed at the customer's facility. During the course of the experiment, more than two hundred transport cycles of the AGV were logged, recorded and clustered. The pattern searching analytical module performed the clustering of production records that were collected from the AGV. The result was information about the clusters of transportation patterns and the assignment of the observed production cycles to these clusters. The main objectives of clustering were (i) to continuously monitor the work being performed by the AGV; (ii) to monitor the current condition of the AGV regarding it efficiency and the wear on its components (physical, power, executive); (iii) to detect any failures in the AGV; (iv) to detect any "problem spots" that could result in downtime and stoppages in realizing an order; (v) to detect any anomalies when realizing an order and (iv) to detect any new types or ways of outperforming the transportation cycles.

The work of the analytical module was divided into two phases: initialisation and production. The first phase was the one in which the analytical module was fed the data about the clean and undisturbed transport cycles that were considered to be correct in a given production scenarios – the observations that represented the assumed and possible states of the monitored object. The analytical module attempted to conclude how these cycles could be grouped (divided into clusters). It is worth mentioning that for the person analysing the work of the monitored object, the number of different states of the object remained unknown.

The production phase, which was next, was when the data flowed (as a stream) into the analytical module – the data that represented the observations that were actually recorded during the AGV's operation. The analytical module attempted to use the knowledge that was obtained in the initialisation phase and to qualify the obtained production records (data on the work that was performed by the AGV) into one of the previously discovered clusters. The analytical module enabled an analysis using one of the two tested methods that were (i) based on the K-means algorithm [13][14] and (ii) based on the DB-SCAN algorithm [16].

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4.1 Normalisation and rescaling of the values

Because the analytical module is intended for continuous operation and future transport cycles are not known, the authors could not normalise the source data values. The only process that the values were subjected to was rescaling – the problem was the different orders of magnitude that were obtained from the server. A single transportation cycle lasted for several dozen to several hundred seconds, while the values for the durations were presented in milliseconds. Similarly, the drive rotations were expressed in the number of rotations per minute, which led to poor results in the clustering. After the initial experiments, it was decided to use a single rescaling of the values function, where the basis of the time was a second. Therefore, all of the times were divided by 1000 and the RPM x s by 60. It was decided that the energy consumption should remain in kilowatts.

4.2 Initialisation phase

During the initialisation phase of the experiment, more than 37 transportation cycles of the AGV were logged and recorded. Because the logging was done during the functional tests of three transportation variants, authors expected that three different types of production scenarios would be obtained from the input data. However, this information and the detailed information about the exact number of registered transportation cycles remained invisible for the clustering system.

The method that was based on the K-means algorithm was divided into two stages: (i) when searching for the most optimal K (number of clusters), the most optimal K was selected using the elbow method (Fig. 4) [15] and (ii) dividing the observations into the K-discovered clusters and remembering the information about the centroids and standard deviation for each of them.

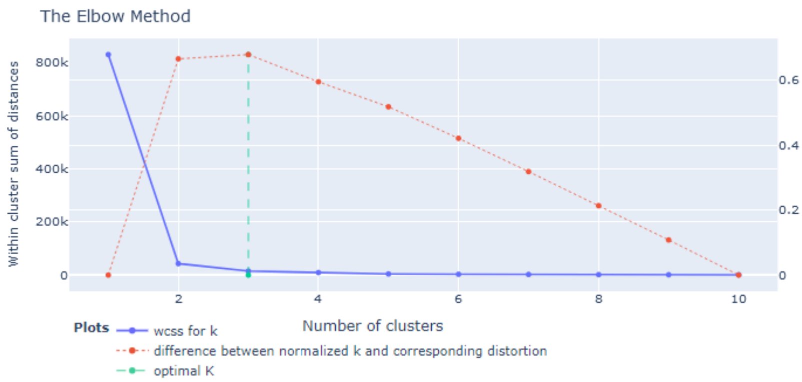

Fig. 4. The elbow method

The method that was based on the DB-Scan algorithm was also divided into two stages: (i) determining the maximum distance between the observations based on the average distance between N nearest neighbours (it was assumed that the maximum average distance on the histogram of the distances for the five nearest neighbours

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would be found, see Fig. 5) and (ii) dividing the observations into clusters taking into account the maximum distance between observations that was determined.

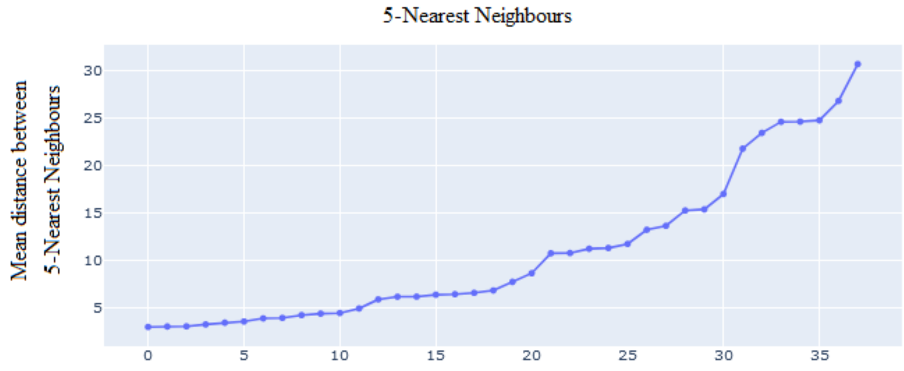

Fig. 5. Histogram of distances for the five nearest neighbours

Obtained results of the initialisation phase. According to the initial suppositions, both methods divided the observations into identical clusters: 19 transportation cycles were assigned to the type 1 production pattern, 10 cycles to the type 2 production pattern and 9 cycles to the type 3 production pattern. The results were then discussed with the person who had ordered the transport cycles. It was found that all of the cycles were recognised, and that the orders were grouped correctly. Because an input vector that consisted of seventeen features was selected for analysis, in order to be able to present the graphical division into the clusters for the purposes of visualisation, the number of dimensions was reduced to three [18]. In Fig. 6, the authors present this division but only in the space of two dimensions ("cycle time" and "cycle energy"). These two features were selected as the most representative. The other parameters were the duration of the forward and backward movements, the rotational speed of the left and right drive wheels integrated over the entire transportation cycle, the times that the LED lighting was activated (red, blue and green), the duration of the blinker signals (aggregated as virtual sensors) and downtime. The presented figure clearly shows the clusters that represent the various assumed transport cycles that were implemented by the AGV.

The method that was based on the DB-Scan required more attention when determining the maximum distance in combination with the minimum number of observations that were included in a cluster. This results directly from the the way in which the algorithm operates, which treats any observations that cannot be categorised (as a core/border point) as noise. The research showed that several attempts usually led to the expected effect (the correct number of clusters, the appropriate distance and the minimum number of observations that formed a cluster).

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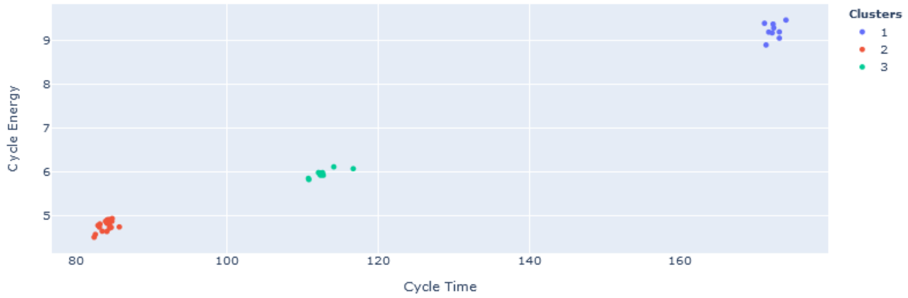

Fig. 6. Clustering results in two dimensions

4.3 Production phase

In the production phase, the analytical module used the previously acquired knowledge about the clusters for the new, received data and then attempted to assign them into one of them. For the K-means-based method, the process was as follows: using the information about the number of clusters and centroids to assign each of the new observations (received in a stream after each subsequent completed cycle) to the nearest one and compare the distance with the value of the standard deviation for that cluster. For the second method (DB-Scan-based method), the process was as follows: assign new, received observations into clusters by comparing their distance to every core points with the maximum distance and radius that was assumed during the initialisation phase.

Obtained results of the production phase. During this part of the experiment, there were 168 transport cycles, streamed and fetched during the AGV's operation. For the transport cycles whose realisation was not disturbed in any way (116 transport cycles), both methods divided those observations into the correct clusters. For the observations in which the values for some of the features deviated from the standard values (there were 31 anomalies with differences of between 10%-25%), both methods behaved differently. The first method required the observations to be assigned to the nearest cluster, regardless of whether it was the correct one or not. Because the differences in the values for the individual parameters for the transport cycles belonging to different clusters were significant (e.g. the difference in the duration of the order execution was greater than 30%), all of the anomalies were correctly assigned. For the second method, 18 of those observations were marked as noise. A detailed analysis of these observations showed that this procedure was correct because the values of the features for these observations differed from the standard ones to such an extent that the distances exceeded the radius that had been declared in the initialisation phase.

During the research, additional erroneous transport cycles were also discovered (there were 21 such cycles), which could not be qualified for any of the clusters. These were the situations in which the AGV was in a state of a safety failure that was caused by a poorly planned route or a downtime of tens of minutes. For the first

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method, four cycles were clustered correctly. For the second method, two were assigned correctly, some were classified as noise (5 of the 21) and the rest to were assigned bad clusters.

The research results are summarised and presented in Table 1.

Table 1. Research results

	K-means-based method	DB-Scan-based method
correct passes	116/116 correct	116/116 correct
anomalies (difference <= 25%)	31/31 correct	13/31 correct 18/31 marked as noise
erroneous passes	4/21 correct 17/21 bad assignment	2/21 correct 5/21 marked as noise 14/21 bad assignment

Discussion of results. Using the method based on the K-means algorithm permitted the analysis of the individual incoming observations. The advantage of this method is its speed. However, its disadvantage is that each observation must be assigned to one of the clusters. This can lead to incorrect assignments that are difficult to identify quickly and is possible if the distances and the standard deviations for individual features are analysed (keeping in mind the differences in the values for the individual parameters for the transport cycles belonging to different clusters).

Using this method to discover new clusters (e.g. by starting the implementation of new types of transport cycles, which were unknown in the earlier stages) might not be an easy task and requires restarting the initialisation phase with all the data that had already been collected (point 4.2). This process can be performed at any time when: (i) there are several cycles for which the distance from the centroid is significant (a significant change in the standard deviation value) or (ii) the fact that a new type of transport cycle has occurred has been confirmed by the person ordering the work.

Using the method based on the DB-Scan algorithm also was determined to be relatively easy. As was the case of the previous method, all of the production cycles that did not have any anomalies or errors were assigned to the appropriate clusters. Although the behaviour of this algorithm was definitely different for the disturbed passes, it cannot be said that identifying them was easy. In some cases, the anomalies were assigned as noise, and in these cases, they were immediately identified. At the same time, some of the anomalies were assigned incorrectly and only a small proportion was correctly assigned. In a situation in which the observations that were classified as noise were individual cases and at the same time the values for the individual features did not differ significantly from the others, this could indicate the need to increase the distance that defines the cluster boundary (due to the fluctuations in the values). On the other hand, when the observations begin to resemble clusters, it could mean that it is a seed of a new cluster.

During the research, it was observed that the DB-Scan-based method was quite sensitive to changes in the values of the features, even if they were part of the observations that should belong to the same cluster, which made it possible, for

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example, to discover any incorrect AGV settings for several passes. An example could be a situation in which an AGV carries out a transport order, but instead of moving forward, part of the route was reversed by 180 degrees. A similar situation occurred for the routes in which the steering angles for some of the turnings were slightly larger, which was associated with the activation of the turn signals by the AGV.

Finally, it could be difficult for the end user to specify two parameters for the method using the DB-Scan: how many nearest neighbours should the smallest cluster consist of and what should the maximum distance between the observations be, which means that it OR they belong to a given cluster. This is especially important when analysing the observations for which there is no reference point.

However, with this method, it is possible to observe the formation of new clusters – if the subsequent observations (transport cycles) begin to form a new cluster and their number is sufficient to create it. However, correctly recognising a new cluster and assigning transport cycles to it using this method should begin with restarting the initialisation phase with all of the previously registered observations.

5 Conclusions

In this paper, the authors present industrial research on the methodology and system architecture that can support gathering, preprocessing, aggregating and clustering data for AGV-based internal logistics. The methods, which are based on K-means and DB-Scan, for clustering production records were verified in a near-real test environment. This work and the obtained results show that it is possible to use classical clustering algorithms for data that is flowing in a stream. It seems that using them would be easier than using the stream algorithms, especially in systems where the processing time is not a critical parameter. The proposed methods make it possible to detect an unknown number of clusters, correctly assign incoming observations to the appropriate groups and observe the formation of new clusters. Both of the proposed methods are divided into two phases, where the first phase is creates the reference point and the second is the operational phase. For both methods, it is possible to run the first phase at any time that is selected by the user, which results in the creation of a new reference model. It is important to emphasise that the results of the conducted experiments show that the two proposed methods behave differently in the case of any anomalies. OPC UA-based communication middleware makes it possible to separate the machine learning process from the data gathering and preprocessing. The knowledge about the AGV sensors and its technological meaning is stored in and expanded on by the OPC UA address space. This knowledge can be easily shared between AGVs and is also available for other systems, in particular, for data mining applications. The production patterns that are discovered by the data mining part can be used for production optimisation, predictive maintenance activities or as a source of models for the simulation tools.

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