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Computational Intelligence in Control of AGV Multimodal Systems

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Abstract: The paper offers a new model for in-plant transportation control with the AGV. The controlling part is performed with the use of software constituting a hybrid information system employing fuzzy logic and genetic algorithms. Introducing the division of workspace into zones and switching stations resolved the problem of multimodality in transportation and potential collisions between AGVs. The concept model was verified by means of the developed simulation model of the production system with the transportation control system. The conducted simulation experiments confirmed high efficiency of the proposed solution.

Keywords: modelling, simulation, artificial intelligence, transportation control, transportation logistics, Automated Guided Vehicles.

1. INTRODUCTION

Logistics of in-plant transportation in modern production systems is inseparably connected with Automated Guided Vehicles (AGV) (Gola A. & Kłosowski G., 2018). Early AGV systems were developed at universities and research institutes, named commonly as mobile robots. Later the industry realized advantages of autonomous transport vehicles for repeating transport tasks. One main application area for AGVs is the intralogistics or manufacturing logistics, where the vehicles are mainly used for transporting raw materials, half-ready parts and ready products (Grzybowska K. & Kovács G., 2014). Even a brief study of trends in the development of in-plant transportation shows a growing significance of the AGV as a medium of high efficiency and cost-effectiveness (Juszczyński M. & Kowalski A., 2013). It was estimated that in the year 2000 over 20,000 different AGVs were present in the industry (Gottig H.H., 2000). AGV systems offer outstanding financial benefits to both cargo ship ports and their clients through realising delivery orders from the vessel to the land vehicle (Haefner L.E. & Bieschke M.S., 1998). A single AGV system may constitute a part of a larger system of *e.g.* smart flexible production system, such as in work, describing a complex system incorporating AGV, automated storage, sorting and part search system and the system of technological (Terkaj W., Tolio T. & Valente A., 2009; Gola A. & Świć A., 2013).

Among the biggest challenges faced by transportation systems it is the condition of multimodality that appears to take the leading role (Bocewicz G., Muszyński W. & Banaszak Z., 2015). AGVs are capable of transporting a single or a number of loads at a time. The size and weight of loads depends on several factors and is decided upon by the transportation system supervisors. In production systems the number of units in the AGV's transportation container is referred to as the container load (Świć A. & Gola A., 2013). The transport module may be equipped with a container or a palette. In general, the bigger the transport module, the lower the cost of a single load carrying operation (understood as a cost of carrying a single unit by a transportation module) (Sitek P. & Wikarek J., 2016). A larger-sized transport module translates to a smaller number of AGVs required in transportation.

The literature in the field of AGV transportation proposes various methods for the estimation of transport module size (Desrochers M., Desrosiers J. & Solomon M., 1992; Egbelu P.J., 1993; Moon S.W. & Hwang H., 1999). The findings generally indicate that at the designing stage of AGV systems it is critical to determine whether the transportation vehicles will be capable of one-load carrying or multi-load carrying (Burduk A. & Musiał K., 2016; Hoffa P., Jasiulewicz-Kaczmarek M. & Pawlewski P., 2015). Simulations indicate that AGVs of the latter type, *e.g.* carrying two transport modules at time reduce the number of transportation vehicles required to handle the orders of a given production system (Ozden M., 1988). Other research data suggested that increasing the load-carrying capacity of AGV reduces the average order delivery/pick-up time (Van der Meer J.R., 2000). However, literature analysis shows that the majority of researchers consider solely one-load carrying transportation vehicles.

The remaining sections of this paper are organized as follows: Section 2 presents the methodology of provided simulation research. Section 3 discusses the results

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confirming that the proposed solution is really efficient. Section 4 presents the main findings, presents conclusions and addresses prospective research objectives in control of AGV multimodal systems.

2. METHODOLOGICAL APPROACH

The reference model can be built on the basis of the rules of interaction, and ownership of the elements creating the system/layout. Such a model is introduced into the simulation system and is subject to testing. The observation of the built simulation model, based on the created reference model of such a studied occurrence, as well as the visualisation of the results produced by them, allows one to assess how the complex system may behave (Grzybowska K. & Kovács G., 2017). The subject of simulation was the model for in-plant transportation organised by means of a "*smart*" controller. The simulation focused on the behaviour of the control system (controller) against various organisational conditions of the analysed production system, including such aspects as multimodality of loads and AGV collision.

The tests were carried out with a computer simulator on a specially designed production system. The simulator included the sub-system of the in-plant transportation system, technological machines, a transportation vehicle and a smart controller.

The results of simulation provided the data for assessing the quality of the functional controller operating in the production system in question.

The object of the study was the production system, the transportation, and an AI-based hybrid control system of in-plant transportation. A repeated simulation of the parameterised model allowed us to obtain the suboptimal solution and to present the history of approaching the solution.

The control unit of the in-plant transportation in the simulated production system was a smart controller. The controller was designed as a hybrid mechanism, consisting of the fuzzy decision-making module and the optimisation module based on genetic algorithms.

The controller and the whole model for the simulation of the production system (technological machines, controller and the transportation) were developed by means of *MatLab* software with *Simulink* and *Stateflow* modules. Due to the fact that the elements of the study object (the production system) under simulation were technological machines and transportation, it was necessary to develop a mechanism that would enable simulation of the aforementioned. The simulation models of the machine tools and the transportation vehicle were designed using the *Stateflow* module, whereas the entire production system, *i.e.* particular elements (machine tools, transportation vehicles), controlling elements (controller software), and the information flow were simulated in the *Simulink* module by means of *MatLab* programming language. Fig. 2 shows the model upon the termination of an 8 hour's work of the production system simulation. The AGV was in motion for the total of 25,185 seconds, remained stationary for 3615 seconds; the two time periods together amount to 28,880 seconds, which is equal to an 8-hour long work shift.

The simulation model is both scalable and parameterised, and therefore its elements may be adjusted to obtain desired configurations of the production system (*e.g.* changing the number of technological machines, adjusting production parameters of particular technological machines, changing the fuzzy control rules, *etc*).

The conducted study involved simulation experiments aimed at validation of controller efficiency. The experiments were carried out in the developed simulation system, one of the elements of whose was the smart controller, similarly developed within the framework of this study. The experimental part was conducted in the production system consisting of 40 technological machines and one transportation vehicle. The parameters of the production system (*e.g.* the layout of the technological machines, the number of delivery/pick-up points, the number of transportation vehicles, material flow organisation, technological machine parameters *etc*) were based on an existing production system.

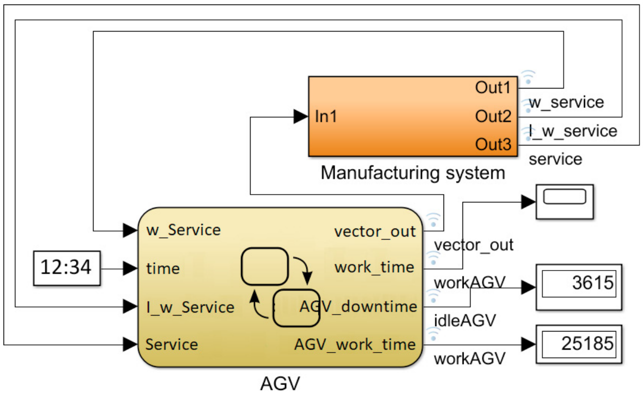

Fig. 2. The model of the simulated in-plant transportation control system (*MatLab/Simulink/Stateflow*)

The designed model simulates an in-plant transportation system in the production system. Simulation constitutes a time-efficient and cost-effective method for verification of various configurations of the production system, including an in-plant transportation system among others. Simulations enable selecting the optimal configuration for a given organisation, such as the number of transportation vehicles, the proper vector of workstations requiring transportation service in one loop, the adequate size of work-in-process stock. Having tested a selected model we may implement it in real conditions, which is a critical advantage of the method, which earmarks simulation as a perfect technique in the research and development of modern control systems, as well as the development of the existing ones (Sivanandam S., Sumathi S. & Deepa S.N., 2007; Kłosowski G. & Lipski J., n.d.; Furmann R., Furmannova B. & Więcek D., 2017).

Each delivery/pick-up point requires transportation service. In order for the transportation to take place, the decision must be made to determine whether a given point requires transportation service at a given time or not, and given that the answer is positive, what the actual transportation action required is (delivery or pick-up); for which purpose, the presented smart fuzzy logic controller module was designed.

The implementation of the controller requires that each technological machine should be fitted with measuring devices and equipped with its own fuzzy controller module. The system of sensors together with the controller modules work in a discrete system at a sample time of 1 second. At 1 second intervals, the fuzzy controller module of each technological machine is reached by input data, which are transformed to produce the output signal. The latter contains information regarding whether a given machine requires transportation service, if yes then what type of transportation and what priority of service it requires.

The fuzzy controller module of a single technological machine is a system where information is input in the form of a 3-element input vector, $\boldsymbol{W_x} = [x_1; x_2; x_3]$, consisting of the following elements:

x_1 – Machining progress [%]
x_2 – Waiting-for-delivery [%]
x_3 – Risk [1,2,...,10]

The output information is a 2-element vector, $\boldsymbol{W_y} = [y_1; y_2]$, where:

$y_1 \in \langle -1;1 \rangle$, if y1 > 0 then Delivery needed
$y_2 \in \langle -1;1 \rangle$, if y2 > 0 then Pick-up needed

The actual delivery or pick-up need is signalled when the output value is greater than 0. Simultaneously, the higher the value, the higher the priority of the transportation service signalled by a given workstation.

The risk, in the range of 0-10, is estimated continually based on deviation of ideal service times, registered at particular delivery/pick-up points at a given moment. The risk is calculated at 1 second intervals, as it is the case with other output parameters of the system.

Ideal transportation service time is considered as the point when the remaining machining time of a current load is equal to the time required for unloading parts onto the workstation. However, thus optimised time leaves no margin for mistake or an unexpected problem, and is therefore burdened with significant risk. It is for the event of such a case that the formula describing the risk was specified to indicate the average risk value (R=5) when in delivery the number of units to be machined for a given transportation load l_p at the moment of delivery is equal to the number of units in the transported load p_t. When the delivery is carried out at an increased buffer stock ($l_p > p_t$), the risk decreases. On the other hand, when the number of parts to be machined at the moment of delivery is lower than the size of the container load – the risk increases. The optimal pick-up point is the moment when the machining of the last unit belonging to a machined load of parts is finished.

Fuzzy controllers cause that each workstation generates delivery and/or pick-up readiness signals at a real-time rate (1 second interval). This enables generation of the vector of workstations in need of transportation service at any given moment. The order of workstations in one loop of transportation service is determined by means of optimisation of the distance function with a genetic algorithm. This problem is a typical "travelling salesman problem", but for one detail: the start and the end of the path is at the same point, at the switching station.

The AGV completes the loop, which is determined by prediction. Each loop starts and ends in the switching station, which resolves the problem of multimodality, consisting in transporting material and products of dissimilar dimensions. Considering the limitations of the AGV, the vehicle is properly loaded at the switching station prior to commencing the route. Depending on the type of the AGV in service, it may be loaded unimodally: by loading identical containers with units. Should the design of the AGV permit it, the vehicle may be loaded with different containers and parts; in which case the smart transportation control system does not introduce any additional criterion of uniformity of load when planning each loop for the AGV.

Another solution to transportation problems in multimodal production systems is grouping machines according to machined part dimensions. Then, a single switching point may service multiple zones (Fig. 3). The emergence of different zones also deals with the issue of AGV collision, *i.e.* one AGV may be assigned to one servicing zone only, thus preventing collision.

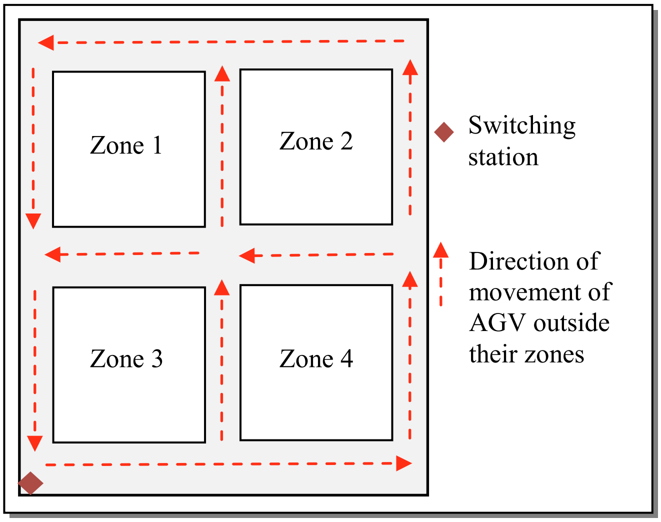

Fig. 3. Division of the logistics system into zones

3. RESULTS OF RESEARCH

The results of simulation experiments proved the effectiveness of the developed solution. Fig. 4 shows an optimized AGV route that includes all workstations.

The switching station location is shown in the lower left corner. It can be seen that the loop starts and ends at the switching station. The figure shows that one zone is operated by a single AGV, thus avoiding the possibility of collision with other transport vehicles. The switching station is where the parts taken from each workstation in the loop are unloaded from the AGV. After unloading, the automatic prediction of the vector of workstations requiring service in the next loop is performed. On this basis AGV is loaded with units or containers. Depending on the specifics of the AGV, the loads may be of different dimensions (multimodal AGV) or similar ones (unimodal AGV).

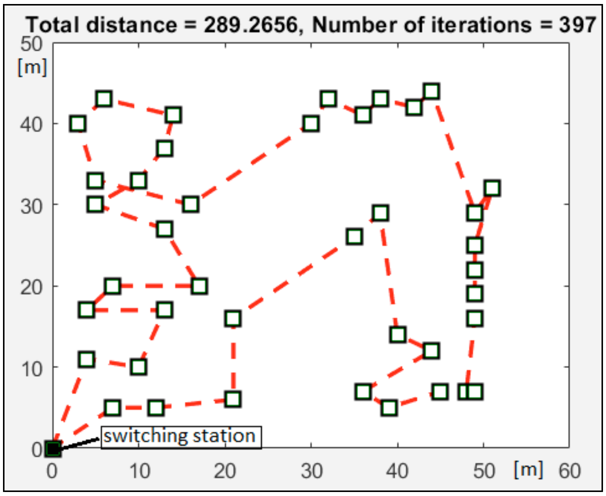

Fig. 4. All workstations with an optimized route

As was mentioned before, it is the optimisation performed by the genetic algorithm that is of the greatest relevance to the order of the AGV order vector. The optimization process is shown in Fig. 5. It can be seen that the initial distance of 1000 m was reduced to 289.3 m.

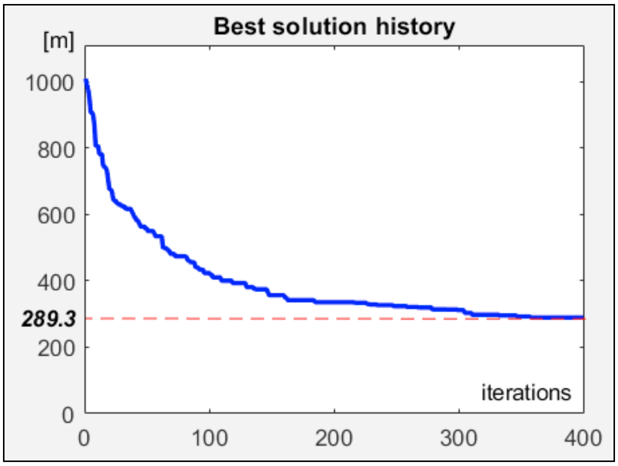

Fig. 5. Fitness function (route length) v. number of iterations of genetic algorithm

Fig. 6 shows two graphs. The top one shows the number of workstations in the zone that requested transportation service during the work shift. There were maximum 14 stations during one work shift that requested service (excluding the switching station), but there were also situations when there was only one station in need of service. It should be noted that individual peaks in the graph do not reflect particular loops of the transportation vehicle. While performing a single loop, the number of load carrying orders allocated to the transportation vehicle does not change, but the absolute number of stations requesting service may change swiftly. Therefore, based on the graph, it is difficult to determine how many times the transportation vehicle left the switching station. A significant variation of the graph means that AGV provided an effective service.

The bottom graph shows the level of risk of stopping the production of a selected workstation due to supply disruptions or part pick-ups during the work shift. At the start of the simulation, the risk was calculated as 5. After the first delivery, when it occurred that the waiting time for a transport service was short, the risk was reduced to below 0.8. Then it fluctuated slightly, however never exceeding 2.7. It means that during the simulation there was no need to deliver a machined part in more than one load. As a result, the buffer stock of the parts was kept at a constant, low level. The risk would be higher if the transportation vehicle was used more often.

In Fig. 7, the top graph indicates the buffer stock of the parts before machining. Delivery service is represented by vertical peaks recurring at short intervals. As can be seen, the supply is maintained at an average level of around 33 units, which is slightly higher than the basic load, which for this station amounts to 30 units.

In the bottom part of Fig. 7 the values of the output signal of the fuzzy controller of the technological machine in question, which pertain to the pick-up of the parts from this work station, are shown. At the start of the simulation, the value of the output signal is negative (less than 0.1). Then the signal level falls at a right angle to a level below (-0, 6). It is caused by a risk reduction that is recalculated at each delivery. At the top of the graph, at the same time as the value of parameter of "*urgency of delivery*" dropped, the first delivery of parts to the workstation in question was registered.

The top part of Fig. 8 shows a graph of the level of buffer stock of machined parts at a selected station. Vertical valleys in stock levels correspond to individual pick-ups of loads. The average stock level amounted to 15 units, which was less than the average stock level of parts prior to machining. It appears reasonable as maintaining a higher stock level at the machine input is intended to ensure continuity of production.

Stock of machined parts is not a critical parameter and it only causes a capital freeze. It should be kept at minimum as much as possible. The maximum buffer stock at the output of the technological machine amounted to approx. 32 units. The minimum level was close to zero. Such low stock level means that the AGV vehicle handled this station very efficiently.

In the bottom part of Fig. 8 the values of the output signal of the fuzzy controller of the technological machine in question, which pertain to the pick-up of the parts from this work station, are shown. At the start of the simulation, the value of the output signal is negative (less than 0.2). Next, the signal level falls at a right angle to a level below (-0, 6), which is caused by risk reduction recalculated at each delivery. At the top of the graph, at the same time as the value of parameter of "urgency of delivery" dropped, the first delivery of parts to the workstation in question was registered.

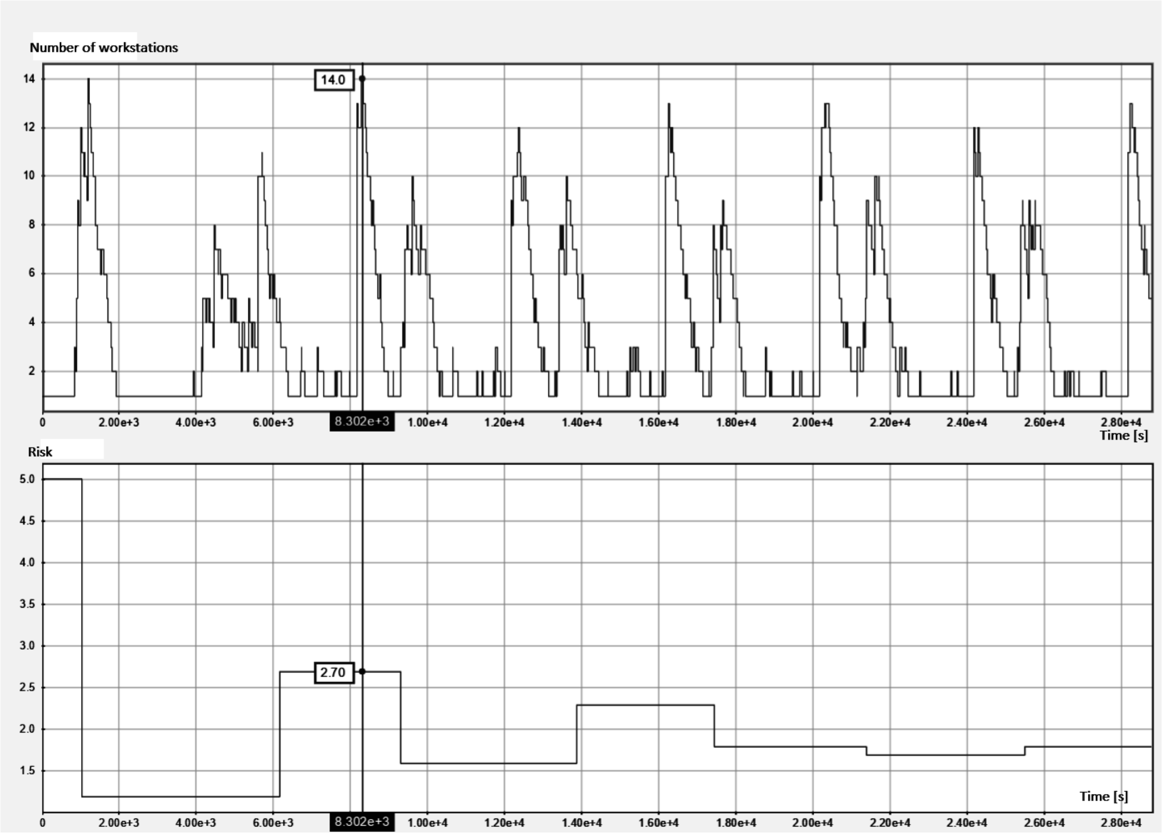

Fig. 6. Number of workstations need to be serviced (above) and level of risk (below) during 8 hours shift

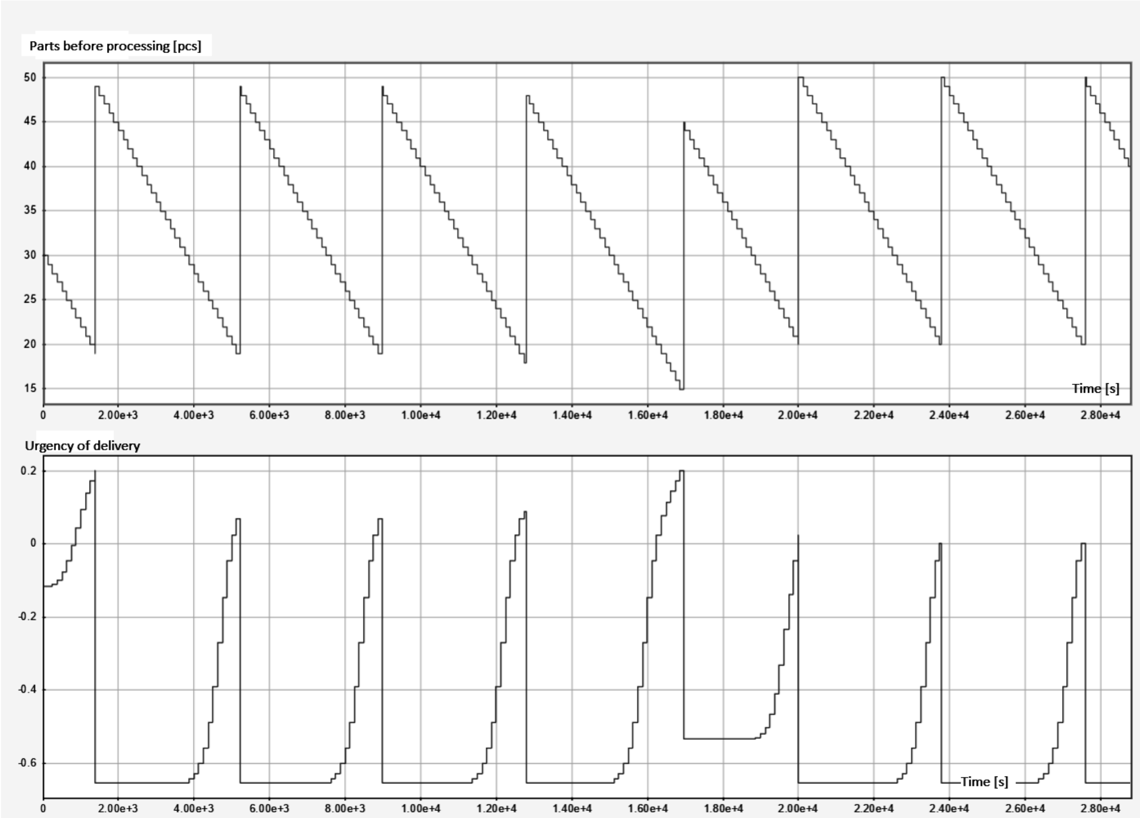

Fig. 7. Number of parts before machining (above) and urgency of delivery (below) for sample workstation

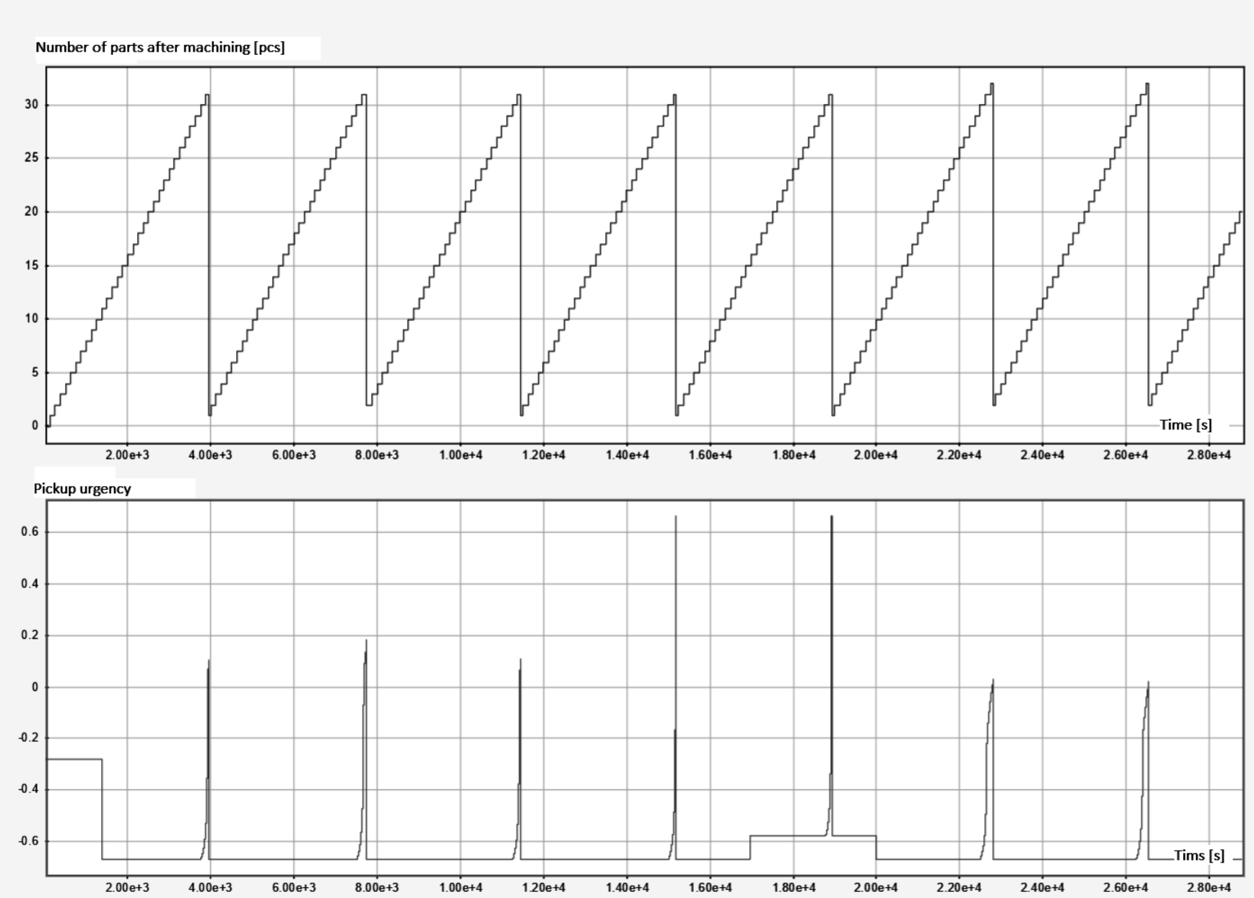

Fig. 8. Number of parts after machining (above) and urgency of pickup (below) for sample workstation

Fig. 9 shows the times of all runs of the transportation vehicle between (n) and (n + 1) delivery/pick-up points. This graph does not apply to a single workstation but to a transportation vehicle that covers the entire production system. The bars indicate the times of individual runs. It can be seen that the AGV, for the most part, has carried out transportation orders, and that the breaks were relatively infrequent. The maximum travel time between stations does not exceed 160 seconds.

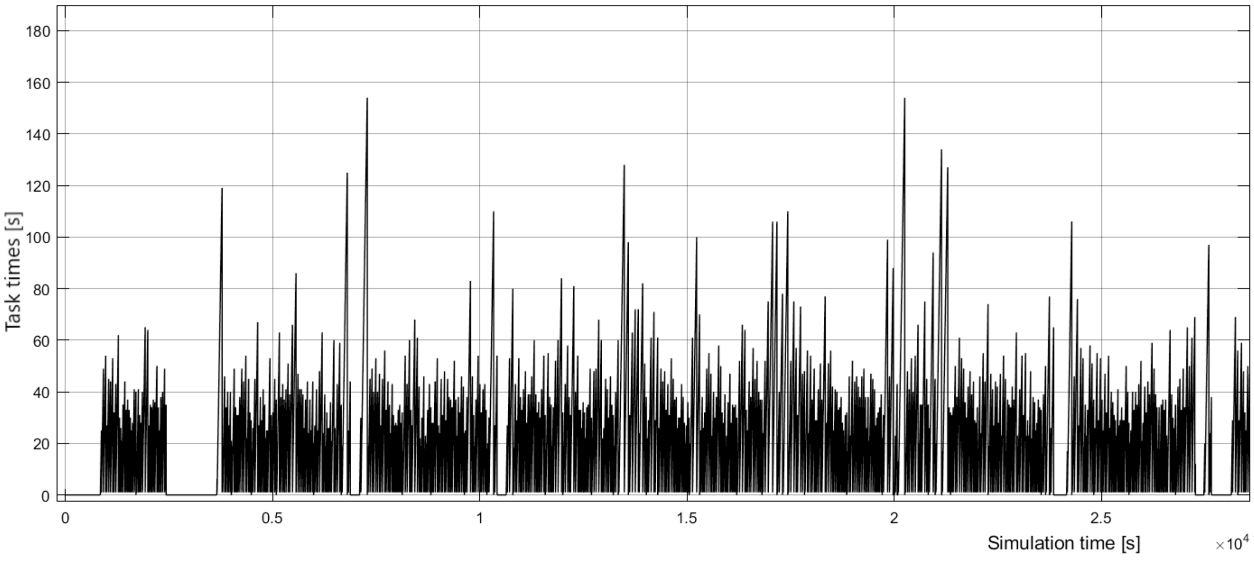

Fig. 9. Durations and numbers of logistic tasks of AVG during 8 hours shift

4. CONCLUSIONS

As a result of the research, a parametric model based on fuzzy logic and genetic algorithms was developed to optimize the control of in-plant transportation in various configurations of the production process. The results also confirmed that the use of a smart fuzzy logic controller employing an optimized genetic algorithm is an effective solution also for large AGV systems. The assumption is proved by the fact that during the simulation the controller was able to efficiently and continuously control a system consisting of 40 workstations, while in-plant transportation control systems based on linear programming algorithms were unable to control systems effectively in case when the number of stations exceeds 15 (with one AGV vehicle) (Johnson M.E. & Branddeau M.L, 1993).

The developed controller enables troubleshooting several problems at once. First of all, it determines when to place a request for the transportation service (delivery and/or pick-up) by the point of delivery /pick-up. Secondly, it optimises the route of the transportation vehicle. Thirdly, it determines the level of risk associated with the delivery/pick-up failure. Lastly, it takes specific countermeasures (to accelerate or delay delivery/pick-up requests sent out by delivery/pick-up points and decide on the size of a delivery to ensure adequate buffer stocks). The controller is dynamic (works in real time with discretisation in seconds).

Division into zones combined with the use of predictive loops of AGVs with one switching station is a solution to the problem of multimodality and potential collision with other transport vehicles.

By using optimized mechanisms based on genetic algorithms, it is possible to conduct simulation tests that lead to the development of heuristic techniques. These techniques should facilitate shortening calculation time by the AGV vehicle dispatch control system in large transportation systems, considering the multimodality of load, collision avoidance, bottlenecks and delays.

REFERENCES

Bocewicz G., Muszyński W. & Banaszak Z. (2015) Models of multimodal networks and transport processes. *Bulletin of the Polish Academy of Sciences, Technical Sciences*. 63 (3), 635–650.

Burduk A. & Musiał K. (2016) Optimization of chosen transport task by using generic algorithms. *Lecture Notes in Computer Science*. 9842, 197–205.

Desrochers M., Desrosiers J. & Solomon M. (1992) A new optimization algorithm for the vehicle routing problem with time windows. *Operations Research*. 40 (2), 342–354.

Egbelu P.J. (1993) Concurrent specification of unit load sizes and automated guided vehicle fleet size in manufacturing system. *International Journal of Production Economics*. 2949–64.

Furmann R., Furmannova B. & Więcek D. (2017) Interactive Design of Reconfigurable Logistics Systems. *Proceedia Engineering*. 192, 207–212.

Gola A. & Kłosowski G. (2018) Application of fuzzy logic and genetic algorithms in automated works transport organization. *Advances in Intelligent Systems and Computing*. 620, 29–36.

Gola A. & Świć A. (2013) Design of storage subsystem of flexible manufacturing system using the computer simulation method. *Actual Problems of Economics*. 142 (4), 312–318.

Gottig H.H. (2000) Automation and Steering of Vehicles in ports. *Port Technology International*. 10, 101–111.

Grzybowska K. & Kovács G. (2014) Sustainable supply chain - supporting tools. In: Ganzha M., Maciaszek L., & Paprzycki M. (eds.). *Preprints of the Federated Conference on Computer Science and Information Systems*. pp. 1351–1359.

Grzybowska K. & Kovács G. (2017) The modelling and design process of coordination mechanisms in the supply chain. *Journal of Applied Logic*. 2425–38.

Haefner L.E. & Bieschke M.S. (1998) ITS opportunities in port operations. *Transportation Conference Proceedings*. 131–134.

Hoffa P., Jasiulewicz-Kaczmarek M. & Pawlewski P. (2015) Multidimensional approach to the supply chain. In: Dolgui A., Sasiadek J., & Zaremba M. (eds.). *15th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2015*. IFAC-Papers OnLine. Elsevier. pp. 2121–2126.

Johnson M.E. & Branddeau M.L (1993) An analytic model for design of a multivehicle automated guided vehicle system. *Management Science*. 39 (12), 1477–1489.

Juszczyński M. & Kowalski A. (2013) Achieving desired cycle times by modelling production systems. *Computer Information Systems and Industrial Management*. 476–486.

Kłosowski G. & Lipski J. (2006) *Genetic algorithms in work transport optimization*.

Moon S.W. & Hwang H. (1999) Determination of unit load sizes of AGV in multi-product multi-line assembly production systems. *International Journal of Production Research*. 37 (15), 3565–3581.

Ozden M. (1988) A simulation study of multiple-load-carrying automated guided vehicles in a flexible manufacturing system. *International Journal of Production Research*. 26 (8), 1353–1366.

Sitek P. & Wikarek J. (2016) A Hybrid Programming Framework for Modeling and Solving Constraint Satisfaction and Optimization Problems. *Scientific Programming*. [Online] Article ID 5102616.

Sivanandam S., Sumathi S. & Deepa S.N. (2007) Introduction to Fuzzy Logic using MATLAB. *Springer-Verlag Berlin Heidelberg*. 11–127.

Świć A. & Gola A. (2013) Economic Analysis of Casing Parts Production in a Flexible Manufacturing System. *Actual Problems of Economics*. 141 (3), 526–533.

Terkaj W., Tolio T. & Valente A. (2009) Design of Focused Flexibility Manufacturing Systems (FFMSs). In: Tolio T. (ed.). *Design of Flexible Production Systems*. Springer. pp. 137–190.

Van der Meer J.R. (2000) *Operational control of internal transport*. ERIM Ph.D. Series Research in Management.