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THE USE OF ARTIFICIAL INTELLIGENCE IN AUTOMATED IN-HOUSE LOGISTICS CENTRES

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Abstract. *The paper deals with the problem of works transport organization in logistic center with the use of artificial intelligence algorithms. The presented approach is based on non-changeable path during travel along a given loop. The ordered set of containers requesting transport service was determined by fuzzy logic, while the sequence of containers in a loop was optimized by genetic algorithms. A solution for semi-autonomous transport vehicles wherein the control system informs the driver about optimal route was presented. The obtained solution was verified by a computer simulation.*

Keywords: logistics, fuzzy logic, intelligent transportation systems, genetic algorithms

ZASTOSOWANIE SZTUCZNEJ INTELIGENCJI W ZAUTOMATYZOWANYCH CENTRACH LOGISTYCZNYCH

Streszczenie. *Artykuł dotyczy problematyki sterowania transportem wewnątrzzakładowym w zautomatyzowanych centrach logistycznych z zastosowaniem metod sztucznej inteligencji. Zaprezentowane podejście zakłada predykcję niezmiennej trasy przejazdu środka transportu. Kolejność zbioru regałów wymagających obsługi transportowej jest determinowana przez logikę rozmytą, natomiast do optymalizacja trasy przejazdu wykorzystano algorytmy genetyczne. Zaprezentowano koncepcję środka transportu, w którym system sterowania informuje kierowcę dokąd ma jechać. Uzyskane rozwiązanie zostało zweryfikowane z wykorzystaniem metod symulacji komputerowej.*

Słowa kluczowe: logistyka, logika rozmyta, inteligentne systemy transportowe, algorytmy genetyczne

1. Introduction

Technological progress is an inherent feature of the evolution of economic and social systems [4]. One of the main trends accompanying the ongoing change is globalization [6, 7]. In turn, this phenomenon entails the need to improve logistics systems and processes. The consequence of this necessity is the emergence of modern logistic centers which due to their complex organizational complexity require sophisticated management methods [1]. With the development of information systems, the role of artificial intelligent (smart) systems has grown considerably, taking over more and more human tasks [3]. The systems of works transport control can be included to this set of logistic tasks [5]. Transport control within the logistics center is a continuous process. Due to its high complexity, many problems are NP-hard [2]. For this reason, IT systems using optimization and decision support algorithms work well in this problem. This article presents the concept of works transport control in a large logistics center. The presented concept uses fuzzy logic, evolutionary algorithms and deep learning (convolutional neural network).

2. Smart warehouse concept

The method presented in this paper concerns the operation of the works transport system at a large logistic center. Organization of the logistics center takes into account the division of the entire area into zones. The number of zones is selected so that one zone is handled by one mean of transport. Each zone contains dozens of shelves on which containers are stored. Each container has an RFID identifier. Parts stored in containers may also be tagged. It depends on the organization of given warehouse. Individual parts may also be stored in individually or collectively tagged packages. The logistics center is in fact a large warehouse that has to handle multiple deliveries and pick-up operations. A lot of transportation vehicles are moved within the logistics center, which, due to the zonal organization of the warehouse, does not collide with each other. Transporters can both deliver and receive parts (parcels).

Transporters perform loop-through rides. They leave the switching station and return there at the end of each loop. Transporters are driven by drivers, but drivers have their smartphones equipped with the right application in front of them. The application is dedicated to a specific, intelligent transport system. A ready to start new route vehicle receives assigned to it an ordered tasks vector. The tasks vector is fixed during whole loop execution. In the switching station, the transportation vehicle is loaded according to the delivery tasks waiting for it. When driving a loop, the conveyor goes by the planned route (ordered containers) shown on the smartphone. Transportation vehicle bypasses shelves with containers to which it either add parts or take them out in appropriate quantities. All details that should be done are visible on the smartphone screen. The system discreetly (e.g. by each second) receives the following information:

- current storage status of all containers,
- vector of parts that need to be delivered (what part and which container),
- vector of parts that need to be picked-up (what part and which container),
- information about which transport tasks have already been assigned to the mean of transport and which are not yet.

In addition to container metering (tagging), the system uses two subsystems:

- The <u>genetic algorithm</u>-based subsystem that optimizes the vehicle route (loop prediction) by minimizing the distance (the traveling salesman problem).
- The <u>fuzzy logic</u> subsystem assigns priority to the transport operation assigned to each container requiring service (delivery or pick-up). For example, if a container has already reached its maximum capacity or is approaching it, then the fuzzy logic subsystem automatically raises the pick-up priority for this container (real number from 0 to 1) and decreases the delivery priority. Where there are two or more containers that are designed to hold one type entity, the delivery will be directed to a container with a lower current fulfill level. In case of pick-up operation, higher priority container should have higher fulfill level.
- <u>Convolutional neural networks</u> for identifying (classifying) parts and selecting the best way of gripping parts during automated loading and unloading operations between the transport vehicle and containers.

3. Fuzzy logic to determine the hierarchy of transport tasks

In the described transportation system, each container in seconds intervals generates two types of information: delivery priority and priority of pick-up. This activity is realized because of the Fuzzy Logic based unit. The outline of the fuzzy logic system is shown in Fig. 1. It can be observed that the system has the following inputs:

x_1 – capacity [%] $0 \le x_1 \le 100$
x_2 – waiting time for pick up [%] $0 \le x_2 \le 100$
x_3 – risk $0 \le x_3 \le 10$

Variable x_1 reflects the current fill level of the container. Variable x_2 is estimated by comparing waiting times for receiving parts from a given container with similar times for other containers of a given zone. Variable x_3 specifies the level of due time risk associated with a part within given container. The level of risk can depend on many factors. For example, transport tasks involving parts with expire date or designated as priority may have an increased level of risk. Those parts should be handled prior to other transport tasks.

The fuzzy inference system has two following outputs:

y_1 – Delivery $-1 \le y_1 \le 1$, when $y_1 > 0$ then delivery
y_2 – Pick-up $-1 \le y_2 \le 1$, when $y_2 > 0$ then pick-up

In order to use the fuzzy inference system, each container should be metered and should be equipped with its own fuzzy controller unit. The sensor system together with the driver units operate in a discrete system with a sampling time of one second. At second intervals the fuzzy controller of the container receives input data that, after processing, generates an output signals. The received (output) information will be used to decide whether a container needs transport handling, what kind of handling it is and what is its priority.

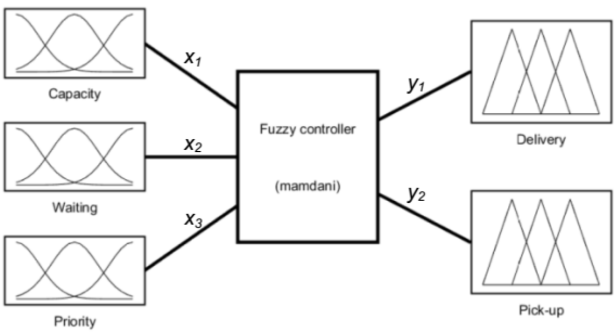

Fig. 1. Fuzzy inference system

The fuzzy controller performs the process of transferring the input vector into output based on the heuristics that are described by the following six linguistic rules:

1) If (Capacity is Low) or (Waiting is Short) or (Priority is Low) then (Delivery is Urgent)(Pick-up is Redundant).
2) If (Capacity is Average) or (Priority is Average) then (Delivery is Advisable)(Pick-up is Advisable).
3) If (Capacity is High) or (Waiting is Long) or (Priority is High) then (Delivery is Redundant)(Pick-up is Urgent).
4) If (Capacity is Average) or (Waiting is Short) or (Priority is Average) then (Delivery is Advisable)(Pick-up is Advisable).
5) If (Capacity is High) or (Waiting is Short) or (Priority is Average) then (Delivery is Redundant)(Pick-up is Advisable).
6) If (Capacity is Low) and (Waiting is Long) and (Priority is High) then (Delivery is Urgent)(Pick-up is Urgent).

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6) If (Capacity is Low) and (Waiting is Long) and (Priority is High) then (Delivery is Urgent)(Pick-up is Urgent)

The way of operation of the rules mentioned above, together with sample runs of the membership functions, is presented in Fig. 2. Each of the six rows of membership functions corresponds to one fuzzification rule. The first three columns of the membership functions correspond to the three input variables of the controller. The last, fourth and five, columns reflect the output parameters. The values of those parameters are computed through the determination of the centroid of a plane figure which is the result of compilation of several inference rule graphs (left right bottom corner of Fig. 2).

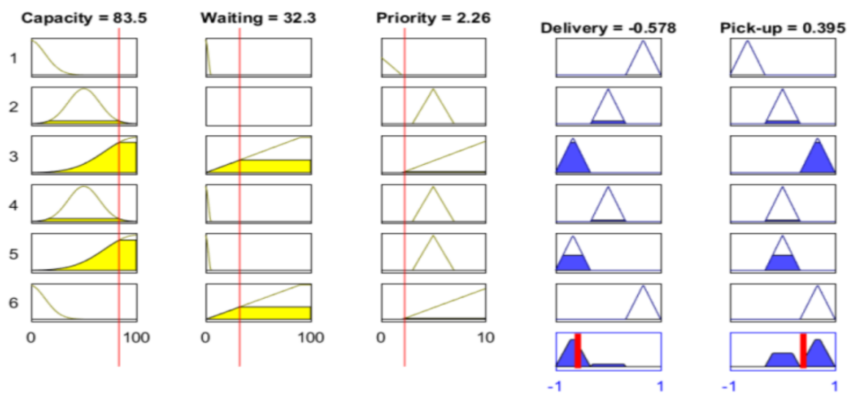

Fig. 2. Functioning of inference rules

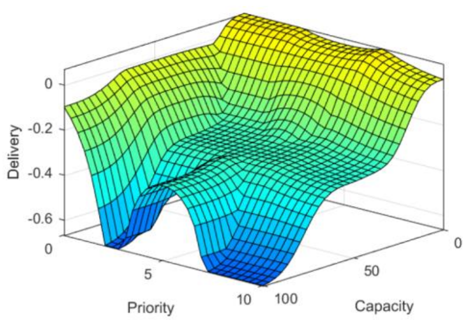

Fig. 3a. Response surface of the fuzzy controller

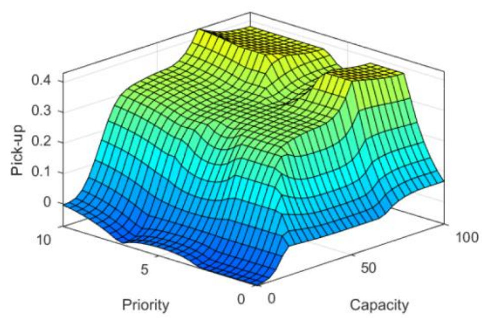

Fig. 3b. Response surface of the fuzzy controller

In the presented example, the Delivery variable is -0.578, Pick-up 0.395. It can be seen that a given container in a given second has much higher Pick-up priority than the Delivery. This is mainly due to the fact that given container is already fully filled up (Capacity 83.5%).

Figures 3a and 3b show the spatial diagrams illustrating relationships between two selected input variables (Priority and Capacity) and parts delivery and pick-up from the container. The irregular shape of both surfaces indicates a complex function which maps inputs as outputs. Therefore, it can be obvious that the task of describing these relationships with a mathematical formula would be very difficult. This fact explains to a high extent the sense and benefits of using fuzzy logic to solve decision problems connected with control processes.

4. Genetic algorithms for optimizing the route of a transport vehicle

One of the key elements of the vehicle transport control process is the choice of an optimal route. This is a problem known as the "symmetrical salesman problem". The solution to this problem is a structured vector of workstations that should be handled by the vehicle in a single pass loop. Because the salesman problem is a class of NP-hard problems, there is no deterministic method to solve this problem in polynomial time. That means that to solve the mentioned problem it is necessary to check all possible solutions, compare them and choose the best ones. The number of possible routes is permutation *1,2,3, ..., n* points (containers) lying on each route (n!).

The considered case of transportation problem has some characteristic features and limitations that distinguish it from the classical problem of the traveling salesman. Firstly, the transport vehicle always starts from one point - the switching station. It also has a pre-determined position (container) with the lowest priority that should be handled last. So it remains a problem to determine the order of services for the rest containers, that is, to properly sort the vector of containers requiring transport service between the switching station *n(1)* and the lowest priority container *n(i)*. The objective function is represented as an equation (1). Optimization is subject to the distance function that the transport vehicle must drive through in one loop of passage.

$$S(s_0, \mathbf{x}) = c_{s,l} \sum_{i=0}^{N} \left(s_{n(i)}, n(i), n(i+1) \right) \qquad (1)$$

where: $c_{s,l}$ – unit operating cost of *l*-th vehicle for distance *s* [PLN/m], *N* – total number of all containers, $n(i)$ – *i*-th container serviced by vehicle *n*, $S(s_0, \mathbf{x})$ – function of distance; s_0 is the distance of the beginning; **x** is the vector of containers that must be serviced in next loop, $s_{l,n(i)}, n(i), n(i+1)$ – distance of *l*-th vehicle between containers *n(i)* and *n(i+1)*.

Fig. 4 shows a single loop of a transport vehicle optimized with genetic algorithm. The distance value obtained by optimizing the objective function was 284 meters. The resulting optimization was achieved after 200 iteration epochs.

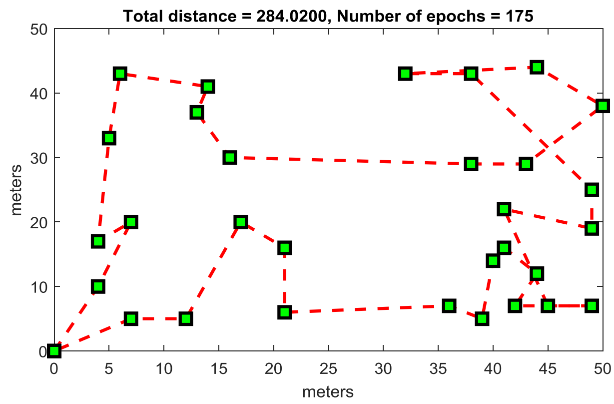

Fig. 4. Arrangement of containers in the zone in question

Fig. 5 shows the process of optimization. The falling curve reflects the decreasing value of the objective function that was obtained after the successive iterations. In this example we are dealing with the minimization of distance function, so the shape of the curve demonstrates the high efficiency of the applied genetic algorithm. The iteration process ends after 200 epochs. This is a parameter that has been set permanently to avoid too long conversion times.

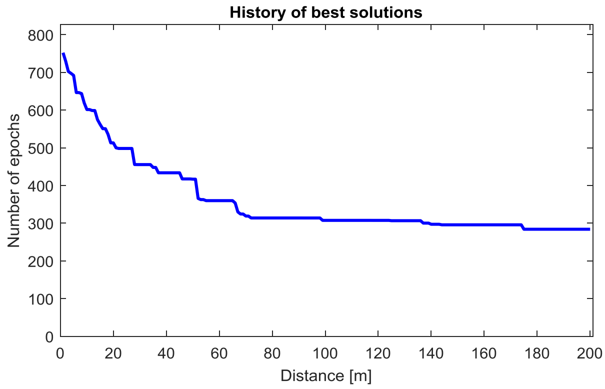

Fig. 5. Process of optimization

5. Simulation experiment

In order to verify control concepts using artificial intelligence algorithms, a simulation model of the logistics center was developed. The model incorporates elements such as a transport vehicle, a dedicated logistic zone consisting of 32 containers equipped with 32 fuzzy logic controllers.

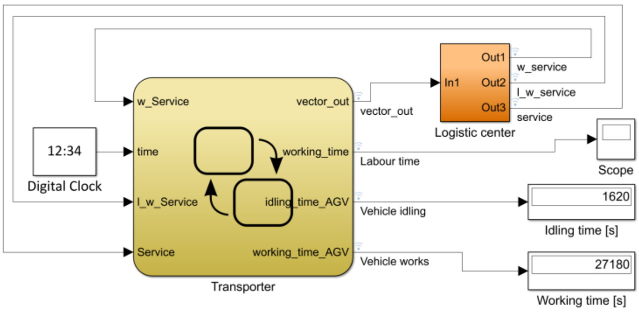

Fig. 6. Simulation model of transport system

Thanks to the above-mentioned controllers, the control system receives on-line, up-to-date information on the state of the containers. At the moment of completing the transport tasks vector, the control system makes a prediction of the next loop for the transport vehicle.

This is done on the basis of information about delivery and pick-up tasks. It also optimizes the route and current information on container occupancy, their priorities and risk. Fig. 6 shows a model of a developed transport system with its main components.

Based on the model, a number of simulation experiments have been performed. The eight hour shift divided into 28800 seconds was simulated. Results of one simulation run are presented in the figures below. Fig. 7 shows the Delivery signals distributed over time generated by the fuzzy controller. The horizontal axis is the time in seconds. Along the vertical axis the value of the Delivery parameter are presented. It can be seen that during the working shift there were seven deliveries (seven peaks) to the considered container.

Fig. 8 illustrates the distributed demand pick-up signals generated by the fuzzy controller of the given container during the shift. The horizontal axis is the time in seconds. The vertical axis is the Pick-up value. It can be seen that in case of given container there were eight pick-up operation during the 8-hours shift.

Fig. 9 shows the pick-up times for a given container from the time the shipping order occurred. It can be seen that the longest wait times ranged in 900 seconds. In addition, the moments in which subsequent transport operations follow are in line with Fig. 8.

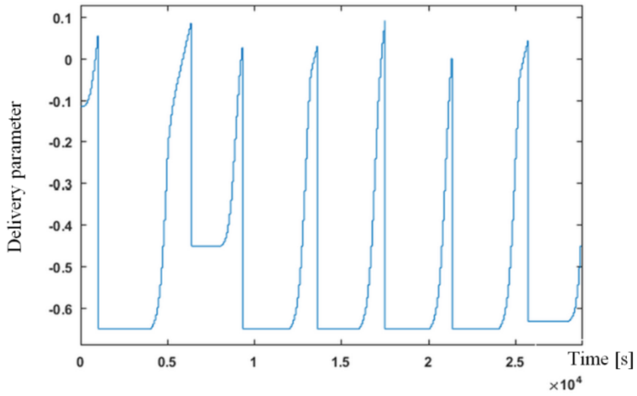

Fig. 7. Delivery tasks in time for given container

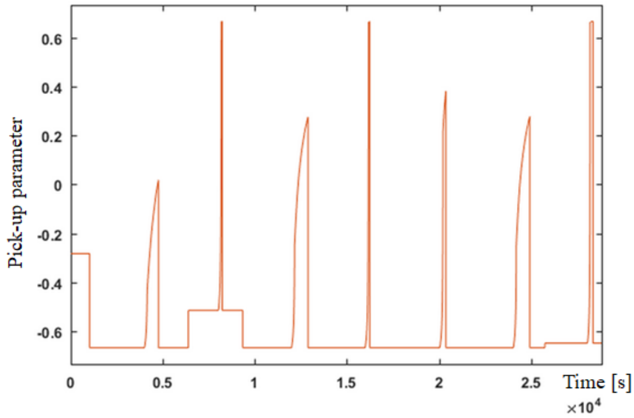

Fig. 8. Pick-Up tasks in time for given container

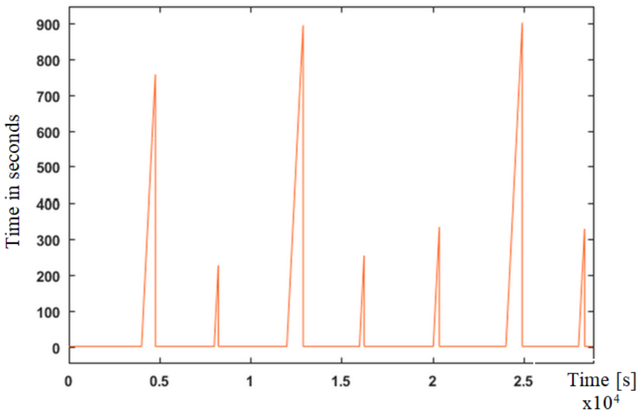

Fig. 9. Waiting times of pick-up services for given container

6. Deep learning for handling parts

In the case of automated transport systems important role play gripping robots and automatic manipulators allowing for proper grasping of parts for loading or unloading. Good grip problem is important because the operations of carrying parts and parcels are crucial from a safety point of view (protection against collapse or parts destruction) and time minimization of transport operations.

To automate mentioned above handling operations convolutional neural networks (CNN) can be used. For this purpose, it would be useful to gather the appropriate image database for the parts together with the correct ways to capture them. Conventional neural networks, thanks to their ability to extract important images, are suitable for classifying objects. In this case, CNN's first step would be to make a proper classification of the part. Then, knowing what kind of parts is being handled, the network should match the grip parameters such as approach angle, grip position and thrust.

7. Conclusions

This paper presents the original concept of artificial intelligence in handling the smart logistics center. A fuzzy inference system was developed to generate signals to assign priority to each container in the warehouse. A genetic algorithm was used to optimize the route of means of transport operating at the logistics center. A simulation model was developed, consisting of: a mean of transport, 32 containers equipped with 32 fuzzy logic units and a genetic algorithm unit. Simulation experiments were conducted because of which the behavior of the transport system during the 8-hour shift was investigated. The obtained results confirmed the effectiveness of the presented smart control concept.

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