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► To cite this version:

Juliette Grosset, Alain-Jérôme Fougères, Moïse Djoko-Kouam, Jean-Marie Bonnin. Fuzzy agent-based simulation for managing battery recharging for a fleet of autonomous industrial vehicles. ASPAI 2024: 6th International Conference on Advances in Signal Processing and Artificial Intelligence, Apr 2024, Funchal (Madeira), Portugal. hal-04571994

HAL Id: hal-04571994

<https://imt-atlantique.hal.science/hal-04571994>

Submitted on 9 May 2024

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Type of Presentation:

Oral: In-person:
Poster: Virtual in Zoom:
The same: Pre-recorded video:

Topic: Applied Artificial Intelligence

Fuzzy agent-based simulation for managing battery recharging for a fleet of autonomous industrial vehicles

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Summary: The article presents a multi-agent simulation utilizing fuzzy logic to explore battery recharging management for Autonomous Industrial Vehicles (AIVs). This approach offers adaptability and resilience through a distributed system, accommodating variations in AIV battery capacity. Results highlight the efficacy of adaptive fuzzy multi-agent models in optimizing recharging strategies, enhancing operational efficiency, and curbing energy consumption. Dynamic factors like workload variations and AIV-infrastructure communication are considered in the form of heuristics, emphasizing the significance of flexible, collaborative approaches in autonomous systems. Notably, infrastructure capable of optimizing recharging based on energy tariffs can significantly reduce consumption during peak hours, emphasizing the importance of such strategies in dynamic environments. Overall, the study underscores the potential of incorporating adaptive fuzzy multi-agent models for AIV energy management to drive efficiency and sustainability in industrial operations.

Keywords: cooperative mobile robots, recharging battery management, fuzzy logic, multi-agent simulation, airport 4.0

1. Introduction

Industry 4.0 is coming with a high degree of digitalisation of industrial processes, but also a significant increase in communication and cooperation between the machines that make it up. This is the case with autonomous industrial vehicles (AIVs) and other cooperative mobile robots that are proliferating in factories or airports, and whose intelligence and autonomy are increasing.

The deployment of AIV fleets raises several issues, all of which related to their actual level of autonomy: acceptance by employees, vehicle localization, traffic flow, collision detection, and vehicle perception of changing environments. Simulation allows us to take into account the different constraints and requirements formulated by manufacturers and future users of these AIVs.

Before starting to test AIV traffic scenarios on a large scale in sometimes complex industrial or airport situations, it is essential to simulate these scenarios [1]. One significant benefit of running simulations is that usable results without the need to applying a scaling factor.

The main benefits of simulating AIV operations are extensively presented by Tsolakakis et al [2]: simulation reduces the development time and cost of an AIV, minimises the potential operational risks associated with the AIV, enables the feasibility of different AIVs scenarios to be assessed at a strategic or operational level, provides a rapid understanding of AIV operations (under conditions of limited data

availability), and identifies improvements in facility layout configurations hosting AIVs.

The simulation also provides flexibility in terms of deployment and redeployment, and enables us to study the sharing of responsibility between the central server and the robots (local/global balance) for the various operational decisions. Another advantage of simulations is to introduce humans into the scenarios in order to convince people, before the actual deployment of autonomous mobile robots, of the safe nature of the coexistence and possible interactions between these future mobile robots and human operators in industry [3].

Agent-based approaches are often proposed for the simulation of autonomous vehicles [4], including path planning in a large-scale context [5], or optimal task allocation with collision and obstacle avoidance [6].

Our current research focuses on the use of fuzzy agents to manage the levels of imprecision and uncertainty involved in modelling the behaviour of simulated vehicles [7]. Fuzzy set theory is well suited to the processing of uncertain or imprecise information that must lead to decision-making by autonomous agents [8]. The concept of the fuzzy agent can therefore be proposed as a partial implementation of this theory.

Most of the control tasks performed by autonomous mobile robots (*perception, localisation, mapping, path and task planning, navigation and motion control, obstacle avoidance, communication, and energy control* [9]) have been the subject of performance improvement studies using fuzzy logic:

- 1) navigation of mobile robots from conceptual, theoretical or application points of view [10], navigation of several mobile robots [11], navigation and control of a mobile robot in an unknown environment in real time [12], and comparison of navigation performance of mobile robots obtained using fuzzy logic or neural networks [13];
- 2) obstacle avoidance from conceptual and systemic points of view in an unknown dynamic environment [14];
- 3) path planning strategies focusing on obstacle avoidance [15] or global navigation [16];
- 4) motion planning [17];
- 5) localisation of mobile robots [18];
- 6) intelligent management of energy consumption [19].

An agent-based system is fuzzy if its agents have fuzzy behaviours or if the knowledge they use is fuzzy. This means that agents can have: 1) fuzzy knowledge (fuzzy decision rules, fuzzy linguistic variables, and fuzzy linguistic values); 2) fuzzy behaviours (the behaviours adopted by the agents as a result of fuzzy inferences); and 3) fuzzy interactions, organisations or roles [20].

Fuzzy agents can follow the evolution of fuzzy information coming from their environment and from the agents [21]. By interpreting the fuzzy information they receive or perceive, fuzzy agents interact within a multi-agent system; they can also interact in a fuzzy manner. For example, a fuzzy agent can discriminate a fuzzy interaction value to evaluate its degree of affinity (or interest) with another fuzzy agent [22].

2. Fuzzy agent-based simulation

The different elements of the fuzzy agent model are as follows [7]: (1) the agent-based fuzzy system; (2) the behaviour of a fuzzy agent, inspired by perceive-decide-act feedback loops [23]; (3-5) the behavioural functions of a fuzzy agent; (6) and the fuzzy interactions between two fuzzy agents.

Table 1. Fuzzy agent model used in our simulations [7,24].

$\tilde{M}_\alpha = \langle \tilde{A}, \tilde{I}, \tilde{P}, \tilde{O} \rangle \quad (1)$ <p>where A is a set of agents, $A = \{a_1, \dots, a_n\}$; \tilde{A} is a set of fuzzy agents, $\tilde{A} = \{\tilde{a}_1, \dots, \tilde{a}_m\}$ with $\tilde{A} \subseteq A$; \tilde{I} is a set of fuzzy interactions between fuzzy agents; \tilde{P} is a set of fuzzy roles filled by fuzzy agents; and \tilde{O} is a set of fuzzy organisations defined for fuzzy agents (subsets of strongly related fuzzy agents).</p>
$\tilde{\alpha}_i = \langle \Phi_{\Pi(\tilde{\alpha}_i)}, \Phi_{\Delta(\tilde{\alpha}_i)}, \Phi_{\Gamma(\tilde{\alpha}_i)}, K_{\tilde{\alpha}_i} \rangle \quad (2)$ <p>where, for a fuzzy agent $\tilde{\alpha}_i$, $\Phi_{\Pi(\tilde{\alpha}_i)}$ is its observation function, $\Phi_{\Delta(\tilde{\alpha}_i)}$ its decision-making function, $\Phi_{\Gamma(\tilde{\alpha}_i)}$ its</p>

action function and $K_{\tilde{\alpha}_i}$ its knowledge base.

$$\Phi_{\Pi(\tilde{\alpha}_i)} : (E_{\tilde{\alpha}_i} \cup I_{\tilde{\alpha}_i}) \times \Sigma_{\tilde{\alpha}_i} \rightarrow \Pi_{\tilde{\alpha}_i} \quad (3)$$

$$\Phi_{\Delta(\tilde{\alpha}_i)} : \Pi_{\tilde{\alpha}_i} \times \Sigma_{\tilde{\alpha}_i} \rightarrow \Delta_{\tilde{\alpha}_i} \quad (4)$$

$$\Phi_{\Gamma(\tilde{\alpha}_i)} : \Delta_{\tilde{\alpha}_i} \times \Sigma \rightarrow \Gamma_{\tilde{\alpha}_i} \quad (5)$$

Where, for a fuzzy agent $\tilde{\alpha}_i$, $E_{\tilde{\alpha}_i}$ is the set of fuzzy events observed, $I_{\tilde{\alpha}_i}$ all its fuzzy interactions, $\Sigma_{\tilde{\alpha}_i}$ all its fuzzy states, $\Pi_{\tilde{\alpha}_i}$ all its fuzzy perceptions, $\Delta_{\tilde{\alpha}_i}$ all its fuzzy decisions, $\Gamma_{\tilde{\alpha}_i}$ all its fuzzy actions, and Σ is the state of the fuzzy multi-agent system \tilde{M}_α .

$$\tilde{I}_i = \langle \tilde{\alpha}_s, \tilde{\alpha}_r, \tilde{\gamma}_c \rangle \quad (6)$$

Where, for fuzzy interaction \tilde{I}_i , $\tilde{\alpha}_s$ is the fuzzy source agent, $\tilde{\alpha}_r$ is the destination fuzzy agent, and $\tilde{\gamma}_c$ is a fuzzy communication act (*inform, diffuse, ask, reply, ...*).

3. Case study: autonomous management of battery recharging

We present an adaptable fuzzy multi-agent model (Figure 1) that addresses the challenges of energy management for AIVs. Efficient management of AIVs requires a holistic approach that takes into account several factors, including operational availability, energy consumption [25], collaboration between AIVs and the dynamic infrastructure, and their adaptation to changing conditions. We aim to optimise recharging based on energy costs, as a low workload combined with frequent recharging can increase the overall energy consumption of the system. In addition, poor anticipation can limit system availability.

AIV missions do not follow a uniform distribution in terms of frequency, creating periods of intense activity and others that are quieter. It is therefore essential to link the energy consumption of AIVs to the amount of work carried out and their operational availability.

To avoid an overload of recharging requests due to too many simultaneous requests, the AIVs need to work together by communicating with each other or via the infrastructure. As for automatic recharging, although it solves the problem of the number of charges, it requires space and consumes energy. Even a 2 to 3% reduction in energy consumption is significant for certain warehouses and airports. For the introduction of fleets of autonomous vehicles in the industry of the future, it therefore seems necessary to fine-tune the number of recharging points. This sizing can be improved by taking into account the possibilities for communication between the AIVs, which can collectively avoid critical (urgent) recharging.

3.1 . Description of the simulation framework

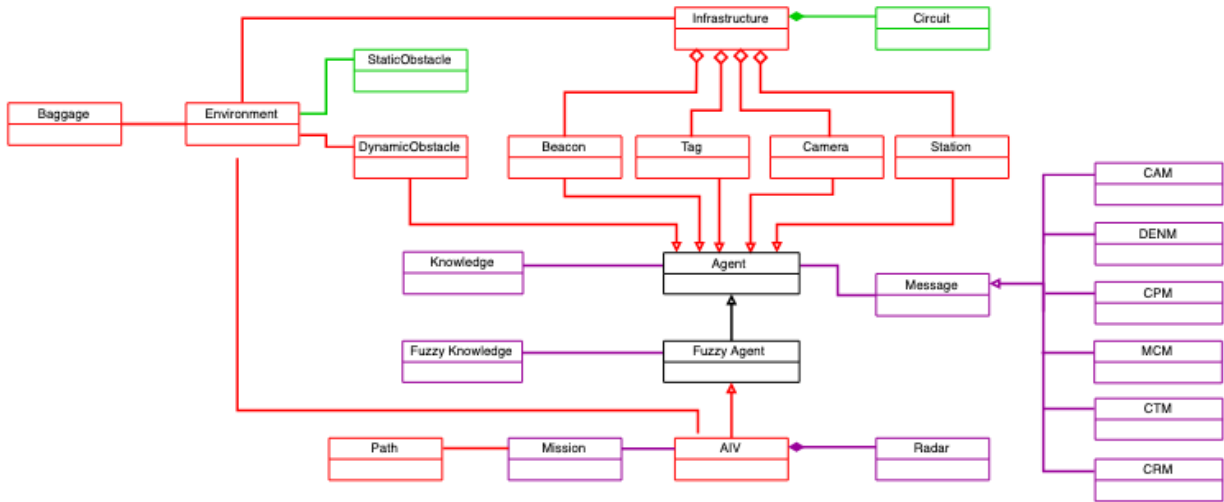


Fig. 1. Simulator architecture: dynamic elements in red, static in green, and not related to the environment in purple.

To test different autonomous management strategies for solving the problem of AIVs recharging batteries, we defined an initial scenario, which we will refer to as the basic scenario (Figure 2). We made several improvements to this basic scenario and compared the number of missions carried out (1), the number of recharges performed (2), the average time taken to complete a mission in seconds (3), and waiting times for recharging in seconds (4). We also varied the charge threshold at which an AIV must recharge its battery. We then introduced a fuzzy inference system to determine the recharge time. We also varied the values of the fuzzy model (fuzzy linguistic values).

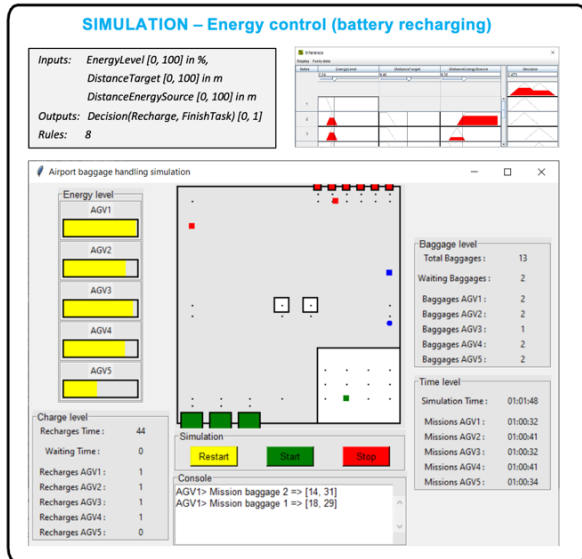


Fig. 2. Simulation Application

3.2 Comparisons between thresholds and fuzzy logic models

In this section, we delve into a comparative analysis between different thresholds and fuzzy logic models. We propose 3 different scenarios:

- Scenario 1 (or 'Sc1'), which corresponds to a Basic Scenario.
- Scenario 2 (or 'Sc2'), where different threshold values are tested in the context of scenario 1.
- Scenario 3 (or 'Sc3'), where AIVs use a fuzzy logic model for recharge.

We simulated these three scenarios for 1000 baggages (a discussion regarding the scenario results is provided in the following three sections). The temporal results are shown in Table 3. We aim to discern the optimal threshold configurations that maximise mission throughput, minimise recharging frequency, and optimise resource utilisation, thereby improving the overall efficiency of autonomous management strategies for recharging the AIV battery.

Table 2. Time results for 1000 baggages for Sc1, Sc2 and Sc3

Scenarios	Sc1	Sc2	Sc3
Number of baggages	1000	1000	1000
Total recharge time (s)	3675	3535	3561
Total simulation time (hour:minutes:seconds)	04:36:46	04:35:11	04:34:58

3.2.a Basic Scenario

In the "Basic Scenario", AIVs have a single threshold model set at 30% for recharge. This scenario makes it possible to compare performance in terms of mission processing time (overall and individual time), number of recharges, and waiting time for recharges

(access to a free station). The AIVs results for Scenario 1 are shown in Table 3.

Table 3. AIVs results for Scenario 1

Indicators	AIV1	AIV2	AIV3	AIV4	AIV5	Global
Thresholds	30	30	30	30	30	
(1)	201	200	199	200	200	1000
(2)	67	67	66	67	67	334
(3)	80	80	80	80	80	80
(4)	0	0	0	11	23	34

3.2.b Different threshold values

Scenario 2 enables us to compare different threshold values for AIVs recharge. When we compare with thresholds varying between 15% and 30%, the overall mission processing time is slightly lower, and the number of recharges and overall recharge time are also lower (295 and 3535, respectively). The performance of AIV1 with the lowest threshold (15%) is obviously the best, although there is a greater risk of not being able to reach a station due to a lack of charge in the event of an incident!

Table 4. AIV results for Scenario 2

Indicators	AIV1	AIV2	AIV3	AIV4	AIV5	Global
Thresholds	15	20	25	30	35	
(1)	202	200	200	199	199	1000
(2)	50	57	57	66	67	295
(3)	79	80	80	77	80	79.2
(4)	31	38	27	2	13	111

3.2.c Fuzzy logic model

In comparison with Scenario 1, where AIVs have a threshold of 30%, in Scenario 3, AIVs use a fuzzy basic model. The results presented in Table 5 demonstrate an improvement in overall and individual AIV times (79.4 secondes on average instead of 80 secondes) and fewer recharges (285 recharges instead of 334).

Table 5. AIV results for Scenario 3

Indicators	AIV1	AIV2	AIV3	AIV4	AIV5	Global
FL model	FL	FL	FL	FL	FL	

(1)	200	200	200	200	200	1000
(2)	57	57	57	57	57	285
(3)	80	80	80	80	77	79.4
(4)	0	19	0	15	0	34

3.3 Increases in fuzzy logic criteria

To improve the results of the previous simulations, we made 3 types of adaptation (heuristics), taking into account more realistic constraints and the possibility of AIVs communicating with each other and with infrastructure elements such as charging points:

- 1) adaptation of recharging according to the needs of the AIVs and the availability of the charging points (centralised scenario by supervision and decentralised scenario by communication between the AIVs and the charging points);
- 2) adaptation of recharging according to the rate of baggage arrival and the resulting variation in activity (the number of missions to be performed by the AIVs in a unit of time is no longer constant);
- 3) adapting the speed of the AIVs according to the rate of baggage arrival (centralised scenario by supervision and decentralised scenario by communication between the AIVs and the charging points).

The objective of this section is to show that specific heuristics allow certain situations to be dealt with fairly finely and increase the collective/overall performance of AIVs. We simulated these three improved scenarios for 1000 baggages. The temporal results are shown in Table 6.

Table 6. Time results and configuration for 1000 baggages for Sc4, Sc5 and Sc6

Scenarios	Sc4	Sc5	Sc6
Number of baggages	1000	1000	1000
Total recharge time (s)	3528	3574	11807
Total simulation time (hour:minutes:seconds)	03:59:06	03:51:08	02:25:00
Maximum number waiting baggages	486	650	499
Average Baggages Waiting	242	322	266

3.3.a Adapting recharging to demand and the availability of charging points

Scenario 4 simulates the adaptation of charging to demand and the availability of charging points. The AIV results are shown below, in Table 7. The effectiveness of this heuristic is clearly visible, especially for AIV1: 15 fewer recharges than for

AIV5, and 16 fewer than for AIV4. The total recharging time is also shorter than for scenarios 1 and 2: 3528 seconds instead of 3675 seconds and 3535 seconds.

Table 7. AIV results for Scenario 4

Indicators	AIV1	AIV2	AIV3	AIV4	AIV5	Global
Thresholds	15/15	20/15	25/20	30/20	35/25	
(1)	202	201	200	200	197	1000
(2)	50	56	57	66	65	294
(3)	69	69	69	69	69	69
(4)	117	11	44	14	0	186

3.3.b Adaptation of recharging according to the baggage arrival rate

Scenario 5 simulates an adaptation of recharging as a function of the baggage arrival rate and therefore of the variation in induced activity (the number of tasks to be carried out by the AIVs). Table 8 shows that the adaptation of recharging enables AIVs to complete their missions more quickly than in scenario 4. In fact, they complete 1 mission in 66 seconds on average, compared with 69 seconds for Scenario 4.

Table 8. AIV results for Scenario 5

Indicators	AIV1	AIV2	AIV3	AIV4	AIV5	Global
Thresholds	20	20	20	20	20	
(1)	201	200	201	200	200	1000
(2)	57	57	58	57	57	286
(3)	66	66	66	66	66	66
(4)	0	46	0	0	24	70

3.3.c Adapting the speed of the AIVs to the flow of baggage arrivals

In scenario 6, we propose to adapt the speed of the AIVs to the flow of baggage arrivals. Compared with scenario 5, the 30% threshold has been adapted (the 20% threshold causing too many load faults due to the increase in energy consumption in cases of faster speed). The overall simulation time is much shorter despite a much longer overall reload time, as presented in Table 6. Moreover, Table 9 shows that the throughput is a little better controlled since the baggage waiting time is 266 seconds in this scenario instead of 332 seconds for scenario 5, presented in Table 8.

Table 9. AIV results for Scenario 6

Indicators	AIV1	AIV2	AIV3	AIV4	AIV5	Global
Thresholds	20	20	20	20	20	20
(1)	199	203	198	203	197	1000
(2)	195	200	194	200	194	983
(3)	41	40	41	40	41	40.6
(4)	330	39	342	20	343	1074

4. Conclusions

We have developed a multi-agent simulation, including fuzzy logic, to test various scenarios of battery recharging management. This approach offers a flexible adaptation to the various aspects of AIV management and facilitates any adjustments required for deployment on the industrial site. The use of a distributed system provides temporary autonomy in the event of failure of the central infrastructure, taking into account the individual differences in the battery capacity of the AIVs.

The simulation results demonstrate that incorporating adaptive fuzzy multi-agent models for AIV energy management can significantly optimize recharging strategies, improve operational efficiency, and mitigate energy consumption, particularly by considering dynamic factors such as workload variation, communication between AIVs and infrastructure elements. In fact, an infrastructure capable of optimising recharging according to energy tariffs is advantageous, particularly with the ability to cut consumption over an hour. These findings will underscore the importance of flexible, collaborative approaches in enhancing the performance of autonomous systems in dynamic environments.

We plan to continue integrating fuzzy models into our AIV simulation agents in order to increase the relevance and effectiveness of their decisions in the management of their energy recharge.

References

- [1] X. Hu, B.P. Zeigler. A Simulation-based Virtual Environment to Study Cooperative Robotic Systems, *Integrated Computer-Aided Engineering*, Vol. 12, Issue 4, 2005, pp. 353-367.
- [2] N. Tsolakis, D. Bechtsis, J.S. Srai. Intelligent autonomous vehicles in digital supply chains: From conceptualisation, to simulation modelling, to real-world operations, *Business Process Management J.*, Vol. 25, Issue 3, 2019, pp. 414-437.
- [3] A. Hentout, M. Aouache, A. Maoudj, I. Akli. Human-robot interaction in industrial collaborative robotics: a literature review of the decade 2008-2017, *Advanced Robotics*, Vol. 33, Issue 15-16, 2019, pp. 764-799.
- [4] P. Jing, H. Hu, F. Zhan, Y. Chen, Y. Shi. Agent-based simulation of autonomous vehicles: A systematic

- literature review, *IEEE Access*, Vol. 8, 2020, pp. 79089-79103.
- [5] N.M. Kou, C. Peng, X. Yan, Z. Yang, et al. Multi-agent path planning with non-constant velocity motion. In Proc. of the 18th Int. Conf. on Autonomous Agents and MultiAgent Systems, 2019, pp. 2069-2071.
- [6] J. Grosset, A. Ndao, A.-J. Fougères, M. Djoko-Kouam, C. Couturier and J.-M. Bonnin. A cooperative approach to avoiding obstacles and collisions between autonomous industrial vehicles in a simulation platform, *Integrated Computer-Aided Engineering*, Vol. 30, Issue 1, 2023, pp. 19-40.
- [7] A.-J. Fougères. A Modelling Approach Based on Fuzzy Agent. *Int. J. of Comp. Science Issues*, Vol. 9, Issue 6, 2013, pp. 19-28.
- [8] A.-J. Fougères, E. Ostrosi. Fuzzy agent-based approach for consensual design synthesis in product configuration. *Integrated Computer-Aided Engineering*, Vol. 20, Issue 3, 2013, pp. 259-274.
- [9] M. De Ryck, M. Verstehey, F. Debrouwere. Automated guided vehicle systems, state-of-the-art control algorithms and techniques. *J. of Manufacturing Systems*, Vol. 54, 2020, pp. 152-173.
- [10] T.S. Hong, D. Nakhaeinia, B. Karasfi. Application of Fuzzy Logic in Mobile Robot Navigation, in *Fuzzy Logic: Controls, Concepts, Theories and Applications*, Edited by Elmer P. Dadios, United Kingdom: IntechOpen, 2012.
- [11] S.K. Pradhan, D.R. Parhi, et al. Fuzzy logic techniques for navigation of several mobile robots. *Applied soft computing*, Vol. 9, Issue 1, 2009, pp. 290-304.
- [12] V. Yerubandi, Y.M. Reddy, M.V. Kumar. Navigation system for an autonomous robot using fuzzy logic. *Int. j. of scientific and research publications*, Vol. 5, Issue 2, 2015, pp. 5-8.
- [13] H.M. Yudha, T. Dewi, N. Hasana, et al. Performance comparison of fuzzy logic and neural network design for mobile robot navigation. Int. Conf. on Electrical Eng. and Comp. Sc., pp. 79-84, 2019.
- [14] A. Meylani, A.S. Handayani, R.S. Carlos, et al. Different Types of Fuzzy Logic in Obstacles Avoidance of Mobile Robot. Int. Conf. on Electrical. Eng. and Computer Sc., pp. 93-100, 2018.
- [15] A. Shitsukane, W. Cheriuyot et al. A survey on obstacles avoidance mobile robot in static unknown environment. *Int J Comput*, Vol. 28, Issue, 2018, pp. 160-173.
- [16] B.K. Patle, A. Pandey, D.R.K. Parhi, et al. A review: On path planning strategies for navigation of mobile robot. *Defence Technology*, Vol. 15, Issue 4, 2019, pp. 582-606.
- [17] A. Nasrinahar, J.H. Chuah. Intelligent motion planning of a mobile robot with dynamic obstacle avoidance. *Journal on Vehicle Routing Algorithms*, Vol. 1, Issue 2, 2018, pp. 89-104.
- [18] M. Alakhras, M. Oussalah, M. Hussein. A survey of fuzzy logic in wireless localization. *EURASIP J. on Wireless Com. and Networking*, Vol. 1, 2020, pp. 1-45.
- [19] M.F.R. Lee, A. Nugroho. Intelligent Energy Management System for Mobile Robot. *Sustainability*, Vol. 14, Issue 16, 2022, 10056.
- [20] E. Ostrosi, A.-J. Fougères, M. Ferney. Fuzzy Agents for Product Configuration in Collaborative and Distributed Design Process. *Applied Soft Computing*, Vol. 8, Issue 12, 2012, pp. 2091-2105.
- [21] N. Ghasem-Aghaee, T.I. Ören. Towards Fuzzy Agents with Dynamic Personality for Human Behavior Simulation. Proceedings of SCSC 2003, Montreal, Canada, 2003, pp. 3-10.
- [22] E. Ostrosi, A.-J. Fougères, M. Ferney et al. A fuzzy configuration multi-agent approach for product family modelling in conceptual design, *Journal of Intelligent Manufacturing*, Vol. 23, Issue 6, 2012, pp. 2565-2586.
- [23] Y. Brun, G.D.M. Serugendo, et al. Engineering self-adaptive systems through feedback loops. In *Software engineering for self-adaptive systems*. Springer, Berlin, Heidelberg, 2009, pp. 48-70.
- [24] J. Grosset, A.-J. Fougères, M. Djoko-Kouam, J.-M. Bonnin. 'Multi-agent Simulation of Autonomous Industrial Vehicle Fleets: Towards Dynamic Task Allocation in V2X Cooperation Mode'. 1 Jan. 2024, 1 - 18, DOI: 10.3233/ICA-240735.
- [25] H. Lasi, P. Fettke, H.G. Kemper, et al. Industry 4.0. *Business & information systems engineering*, Vol. 6, Issue 4, pp. 239-242, 2014.