Fuzzy Agent-Based Simulation of Integrated Solutions for Task Allocation and Battery Charge Management for Fleets of Autonomous Industrial Vehicles

Juliette Grosset
ECAM Rennes – Louis de Broglie
IMT Atlantique – IRISA, UMR 6074
Rennes, France
Email : juliette.grosset@ecam-rennes.fr

Alain-Jérôme Fougères
ECAM Rennes – Louis de Broglie
IT and Telecommunications Laboratory
Rennes, France
Email : alain-jerome.fougeres@ecam-rennes.fr

Moïse Djoko-Kouam
ECAM Rennes – Louis de Broglie
IETR, UMR CNRS 6164
Rennes, France
Email : moise.djoko-kouam@ecam-rennes.fr

Jean-Marie Bonnin
IMT Atlantique
IRISA, UMR 6074
Rennes, France
Email: jm.bonnin@imt-atlantique.fr

***Abstract*— The paper presents a multi-agent simulation using fuzzy inference to explore in an integrated way the task allocation and battery charging management of mobile baggage conveyor robots in an airport. This simulation approach offers high adaptability thanks to a distributed system, adapting to variations in the availability of conveyor agents, their battery capacity, knowledge of the context of infrastructure resource availability, and awareness of the activity of the conveyor fleet. Dynamic factors, such as workload variations and communication between the conveyor agents and infrastructure are considered as heuristics, highlighting the importance of flexible and collaborative approaches in autonomous systems. The results highlight the effectiveness of adaptive fuzzy multi-agent models to optimize dynamic task allocation, adapt to the variation of baggage arrival flows, improve the overall operational efficiency of conveyor agents, and reduce their energy consumption.**

Keywords-autonomous industrial vehicle; dynamique task allocation; fuzzy agent; agent-based simulation; Airport 4.0.

I. Introduction

The deployment of Autonomous Industrial Vehicle (AIV) fleets in the context of Airport 4.0 raises several issues, all related to their real level of autonomy: acceptance by employees, vehicle localization, traffic flow, failure detection, collision avoidance and vehicle perception in changing environments. Simulation makes it possible to take into account the various constraints and requirements formulated by manufacturers and future users of these AIVs.

Before starting to test AIV fleet traffic scenarios in often-complex airport situations, it is wise, if not essential, to simulate these scenarios [1]. Moreover, one of the main advantages of using simulations is that the results can be used without the need to apply a scaling factor.

The main advantages of simulating mobile robot or AIV operations are: reducing the time and cost of developing an AIV, minimizing potential operational risks associated with AIVs, allowing to assess the feasibility of different AIV circulation scenarios at a strategic or operational level, allowing a rapid understanding of the operations carried out by AIVs, and identifying improvements in the layout configurations of the facilities hosting these AIVs [2].

Simulation also provides flexibility in terms of AIV deployment and allows studying the sharing of responsibility between the central server and the robots (local/global or centralized/decentralized balance) for the different operational decisions. Another advantage of simulations is to introduce humans into the scenarios in order to verify and validate, before the actual deployment of autonomous mobile robots, the safety of the coexistence and possible interactions between these AIVs and human operators [3]. Agent-based approaches are often proposed for the simulation of autonomous vehicles. They offer simulation contexts ranging from trajectory planning to optimal task allocation, while allowing collision and obstacle avoidance [4].

Our current research focuses on the use of fuzzy agents to handle the levels of imprecision and uncertainty involved in modeling the behavior of simulated vehicles [5]. Indeed, fuzzy set theory is well suited to the processing of uncertain or imprecise information that must lead to decision-making by autonomous agents, used in activities such as the simulation of AIVs in an airport or product design [6].

Fuzzy agents can track the evolution of fuzzy information from their environment and from agents [7]. By interpreting the fuzzy information they receive or perceive, fuzzy agents interact within the multi-agent system of which they are a part. For example, a fuzzy agent can discriminate a fuzzy interaction value to assess its degree of affinity (or interest) with another fuzzy agent [8].

Thus, we develop a comprehensive study on utilizing fuzzy inference within multi-agent simulations to optimize task allocation and battery management for mobile baggage conveyor robots in airports. The proposed simulation approach is designed to be highly adaptable, taking into account dynamic factors such as workload variations, battery

 ISBN: 978-1-68558-192-3

capacities, and communication between agents and infrastructure. The results demonstrate that this adaptive fuzzy multi-agent model can significantly improve operational efficiency, adapt to variations in baggage arrival flows, and reduce energy consumption.

This article is structured as follows: first, we present a state-of-the art on the fuzzy agent-based allocation of tasks; then, we propose a case study on fuzzy task allocation where we compare five kinds of strategies; in Section 4 we present three improvements using fuzzy heuristics; finally, we conclude on the proposed fuzzy dynamic task allocation strategies, and then we present different work perspectives.

II. Fuzzy agent-based task allocation

This section presents a brief state of the art on task allocation and fuzzy agent-based simulation.

A. Task allocation

Task Allocation (TA) consists of optimally assigning a set of tasks to be performed by agents, actors, robots or processes, grouped and organized within a cohesive system. This is the case for mobile multi-robot systems [9], AIV fleets [10], and applications in airports [11].

In the field of mobile robotics, the taxonomy presented in [12] has been defined to better characterize allocation and assignment functions to robots: Single Task for a Single Robot (STSR), Multiple Tasks for a Single Robot (MTSR), and Multiple Tasks for Multiple Robots (MTMR). These classifications enable tasks to be assigned to one or multiple robots, with various tasks being allocated to heterogeneous or multitasking robots.

Moreover, De Ryck et al. [12] defined also: allocation modalities, such as instantaneous allocation or allocation extended in time. This last is linked to synchronization and precedent or time window constraints. As many combinations as exhaustively detailed by numerous surveys on the issue of multi-robot TA.

Different solution models have been proposed for TA: based on optimization: exact algorithms, dynamic programming, (meta-)heuristics [9]; based on the Contract Net Protocol: inside an agent-based system, an initiating agent sends a call for proposals to all agents, chooses the best proposal received, and then informs all agents [10]; based on the concept of the market: announcement by an auctioneer, submission by bidders, selection by the auctioneer and award by the auctioneer [13].

Furthermore, different types of optimization objectives can be defined for this task allocation [12]: cost objectives (travel costs, such as time, distance or fuel consumption), behavior objectives (ability of a robot to perform a task), reward objectives (payoff for performing a task), priority objectives (urgency to perform a task), and utility objectives (subtracting the cost from the reward or fitness).

Task allocation and planning are often managed centrally, even semi-centrally when global and local planning are differentiated [14]. For the proper functioning of autonomous and dynamic systems, the requirements of flexibility, robustness and scalability, lead to consider decentralized mechanisms to react to unexpected situations. Autonomy and decentralization are two excessively linked notions to the extent that an autonomous system operates and makes decisions autonomously [15]. The problem of task allocation can also be thought of in a decentralized way [12].

For reasons of flexibility, robustness and scalability necessary in an Industry 4.0 or Airport 4.0 context, we are interested in decentralized task allocation solutions. These solutions, decomposed below, must be able to assign tasks to a fleet of robots.

Particularly, solutions based on the market concept can easily be applied in a distributed context, where each mobile robot can become an auctioneer [16]. For each situation, a single mobile robot is appointed auctioneer, and retains this role until the situation is definitively managed

B. Fuzzy agent-based simulation

Many agent-based approaches are proposed for the simulation of autonomous vehicles. They offer simulation contexts ranging from trajectory planning [17] to optimal task allocation, while allowing collision and obstacle avoidance [18]. Our current research focuses on the use of fuzzy agents to handle the levels of imprecision and uncertainty involved in modeling the behavior of simulated vehicles [5]. Fuzzy set theory is well suited to the processing of uncertain or imprecise information that must lead to decision-making by autonomous agents [6].

Most of the control tasks performed by autonomous mobile robots have been the subject of performance improvement studies using fuzzy logic [19]: navigation [20], obstacle avoidance [21], path planning [22], motion planning [23], localization of mobile robots [24], and intelligent management of energy consumption [25].

An agent-based system is fuzzy if its agents have fuzzy behaviors or if the knowledge they use is fuzzy [26]. This means that agents can have: 1) fuzzy knowledge (fuzzy decision rules, fuzzy linguistic variables, and fuzzy linguistic values); 2) fuzzy behaviors (the behaviors adopted by agents because of fuzzy inferences); and 3) fuzzy interactions, organizations, or roles. The six equations below propose a model of fuzzy agents corresponding to the principles stated above and used in the simulations presented in this paper:

$$\tilde{M}_{\alpha} = < \tilde{A}, \tilde{I}, \tilde{P}, \tilde{O} > \; . \tag{1}$$

Where $\tilde{A}$ is a set of fuzzy agents; $\tilde{I}$ is a set of fuzzy interactions between fuzzy agents; $\tilde{P}$ is a set of fuzzy roles that fuzzy agents can perform; and $\tilde{O}$ is a set of fuzzy organizations defined for fuzzy agents (subsets of strongly linked fuzzy agents).

$$\tilde{\alpha}_i = \left\langle \Phi_{\Pi(\tilde{\alpha}_i)}, \Phi_{\Delta(\tilde{\alpha}_i)}, \Phi_{\Gamma(\tilde{\alpha}_i)}, K_{\tilde{\alpha}_i} \right\rangle . \tag{2}$$

Where $\Phi_{\Pi(\tilde{\alpha}_i)}$ is the $\tilde{\alpha}_i$ function of observation; $\Phi_{\Delta(\tilde{\alpha}_i)}$ is the $\tilde{\alpha}_i$ function of decision; $\Phi_{\Gamma(\tilde{\alpha}_i)}$ is the $\tilde{\alpha}_i$ function of action; and $K_{\tilde{\alpha}_i}$ is the knowledge of the fuzzy agent $\tilde{\alpha}_i$.

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

 ISBN: 978-1-68558-192-3

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

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

Where $E_{\tilde{\alpha}_i}$ is the $\tilde{\alpha}_i$ set of fuzzy observed events; $I_{\tilde{\alpha}_i}$ is the $\tilde{\alpha}_i$ set of fuzzy interactions; $\Sigma_{\tilde{\alpha}_i}$ is the $\tilde{\alpha}_i$ set of fuzzy state; $\Pi_{\tilde{\alpha}_i}$ is the $\tilde{\alpha}_i$ set of fuzzy perceptions; $\Delta_{\tilde{\alpha}_i}$ is the $\tilde{\alpha}_i$ set of fuzzy decisions; and $\Gamma_{\tilde{\alpha}_i}$ is the $\tilde{\alpha}_i$ set of fuzzy actions; Σ is the state of the fuzzy agent-based system $\tilde{M}_\alpha$.

$$\tilde{\iota} = < \tilde{\alpha}_s, \tilde{\alpha}_r, \tilde{\gamma}_c > . \quad (6)$$

Where $\tilde{\iota}$ is a fuzzy interaction; $\tilde{\alpha}_s$ is the fuzzy agent source of a fuzzy interaction; $\tilde{\alpha}_r$ is the fuzzy agent receiver of a fuzzy interaction; and $\tilde{\gamma}_c$ is a fuzzy communication act.

III. CASE STUDY: FUZZY TASK ALLOCATION SIMULATION

This case study proposes the simulation of mobile robots conveying baggage fleet in an airport (we will keep the name "AIV" for these conveyors). Figure 1 shows the simulator's HMI, which allows on the one hand, to visualize the arrival of baggage and the movements of 5 AIVs, and on the other hand, to follow the evolution of the different levels of indicators of the simulation (energy level, baggage level, charge level, and time level).

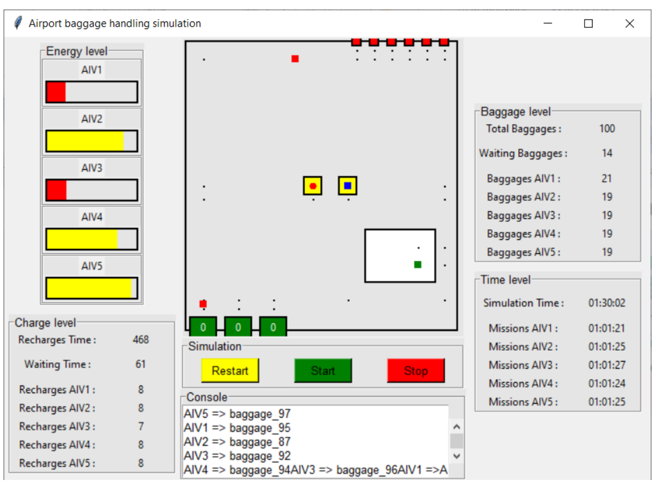

Figure 1. Simulation Application

Effective management of these AIVs requires an integrative approach that considers several factors, including the baggage arrival flow, the operational availability of the AIVs, their energy consumption, their communication, among themselves and with the infrastructure, and their adaptation to changing environmental conditions. In the case study, we analyze the TA performed by a supervisor who questions AIVs to know their task completion costs. Through 8 scenarios, we will progressively introduce fuzzy inferences to determine the costs of task completion, battery recharging and speed adjustment.

A. *The simulation framework*

Figure 2 presents the agent model proposed to test our dynamic task allocation strategies for AIVs in simulation. The objective is to have an agent-based modeling and simulation system designed generically to test different scenarios, but also different types of circulation plans.

An infrastructure is deployed in the environment. It is composed of a circulation plan and active elements, such as beacons, tags, the two charging stations and the two types of treadmill for baggage entry and exit. Static or dynamic obstacles (e.g., operators) may be present in the environment.

AIV fuzzy agents perform missions defined by paths on the traffic plan. AIV fuzzy agents are equipped with a radar to avoid collisions and have knowledge about the environment and other agents to operate and cooperate. AIV fuzzy agents communicate with each other with different types of standardized messages. AIV fuzzy agents have fuzzy and uncertain knowledge, but also incomplete and fragmented, in order to adapt to situations that are themselves uncertain. Baggage are objects managed by the environment: arrival flow on the entry treadmill, tracking of its localization, and exit from the circuit on the exit treadmill.

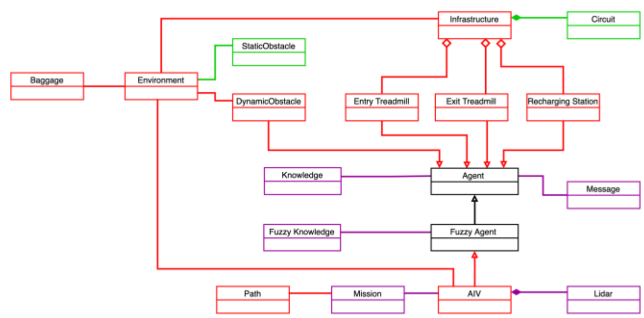

Figure 2. Simulator architecture: dynamic elements in red, static in green, and not related to the environment in purple.

B. *Task allocation with basic strategies*

In this section, we provide a comparative analysis of three basic types of auction-based task allocation strategies: random TA, FIFO TA, and AIV availability-based TA. Each of these strategies is tested in a scenario:

- *Sc1* (Random) is a TA scenario where missions are assigned to the AIV agents only randomly.
- *Sc2* (FIFO) is a TA scenario where missions are assigned to AIV agents using a queuing mechanism.
- *Sc3* (Available) is a TA scenario where missions are assigned to the most available AIV agents.

We simulated these three scenarios for 100 bags. We seek to minimize the maximum number of pending bags at a given time, the total simulation time, the average time to complete a mission per AIV agent, the number of missions completed per AIV agent during the simulation, and the activity rate per AIV agent. The simulation results are presented in Table 1.

Random strategy: the maximum number of pending bags is high, the simulation time is also high, and the allocation of missions and the activity rates of AIV agents are poorly balanced (the average activity rate at 0.72 is low). The random strategy does not allow allocation to AIV agents that are a priori available, which very quickly leads to pending bags to be processed and therefore poor results.

FIFO strategy: this strategy brings a clear improvement in the results. The maximum number of pending bags is very low, the simulation time is very correct, the allocation is almost uniform (only the stops for recharging the batteries cause imbalances), and the occupancy rate of the AIV agents is much better (0.84).

Available strategy: this strategy produces the best results, except for the maximum number of pending bags. Allocating a mission to an AIV agent that is more available than the others are therefore improves the results. However, it is necessary to better manage the allocation based on pending bags and energy consumption to consolidate (or even optimize) this strategy.

TABLE I. TASK ALLOCATION SIMULATION RESULTS IN SCENARIOS SC1, SC2 AND SC3, FOR 100 BAGS.

Scenarios	Random	FIFO	Available
Maximum nb of pending bags	19	4	8
Simulation time	2270s	1942s	1846s
Average mission time per AIV (in s)	[81,81,83,83,81]	[80,82,83,81,83]	[81,80,81,83,81]
Nb of missions completed by AIV	[26,26,14,14,20]	[21,21,19,21,18]	[22,21,20,19,18]
Work rate per AIV	[0.93,0.93,0.51, 0.51, 0.71]	[0.87, 0.89, 0.81, 0.88, 0.77]	[0.97, 0.91, 0.88, 0.85, 0.79]

C. *Task allocation with fuzzy strategies*

In this section, we propose an analysis of task allocation by auction based on a fuzzy inference approach. As a reminder, fuzzy logic allows us to better understand natural, uncertain, imprecise and difficult to model phenomena by relying on the definition of *if-then fuzzy* rules and membership functions (linguistic variables) to *fuzzy sets* [27].

Two scenarios are studied. The first, *Sc4*, implements a TA strategy in which each AIV agent uses a fuzzy model with 3 linguistic input variables (availability of the AIV agent, distance from the baggage drop-off location, energy level of the AIV agent) to determine the cost of handling a mission (picking up and dropping off a baggage). The second, *Sc5*, takes the strategy of *Sc4* and adds energy management with a second fuzzy model. With this new fuzzy model, the AIV agents determine whether they will need to recharge during a mission, which allows them to refine calculation of the mission cost. The linguistic variables used in this scenario are: availability of the AIV agent, distance from the baggage drop-off location, energy level of AIV agent, and distances of the 2 charging stations.

Fuzzy strategy in *Sc4*. The results with this new strategy are generally good: low maximum number of pending bags, good overall simulation time, good distribution of missions between AIV agents and good average AIV activity rate (0.88). However, few elements of uncertainty are considered (3 linguistic variables at the input and one at the output). The introduction of other fuzzy elements (nuances in the simulation parameters) should improve the results, particularly in terms of maximum number of pending bags and management of battery recharges.

Fuzzy strategies in *Sc5*. In this new scenario, the raw results of the TA are slightly worse than in *Sc4*: same maximum number of pending bags, slightly longer overall simulation time, worse distribution of missions between AIV agents and worse average AIV occupancy rate (0.82). However, the overall recharge time is lower in this scenario, which can allow a greater availability of AIV agents (an area of improvement for the next scenarios).

TABLE II. TASK ALLOCATION SIMULATION RESULTS IN SCENARIOS SC4 AND SC5, FOR 100 BAGS

Scenarios	Sc4	Sc5
Maximum nb of pending bags	6	6
Simulation time	1843s	2000s
Average mission time per AIV (in s)	[80, 81, 80, 81, 82]	[81, 80, 81, 84, 83]
Nb of missions completed by AIV	[21, 21, 21, 19, 18]	[23, 19, 21, 19, 18]
Work rate per AIV	[0.91,0.92,0.91,0.84,0.80]	[0.93,0.76,0.85,0.80,0.75]

TABLE III. RECHARGE SIMULATION RESULTS IN SCENARIOS SC4 AND SC5, FOR 100 BAGS

Scenarios	Sc4	Sc5
Recharge time	546s	490s
Waiting time for recharges	34s	16s
Nb of recharges	39	33
Distribution of nb of recharges per AIV	[8, 8, 8, 8, 7]	[8, 6, 7, 6, 6]

IV. IMPROVEMENT USING FUZZY HEURISTICS

Now, we propose to increase the relevance of previous auction TA scenarios based on a fuzzy inference approach, by integrating other types of realistic constraints concerning battery recharging and AIV agent speed adjustment made possible by a stronger knowledge of the fleet traffic and mission management context (increased awareness). Three scenarios are studied (*Sc6*, *Sc7* and *Sc8*) to show that specific heuristics allow us to treat certain situations quite finely and to increase the collective/global performances of the AIV agents. The results are presented in Table 4 for task allocation and Table 5 for battery recharging.

Sc6 consists of completing scenario *Sc5* to determine in which station the AIV agents can recharge in order to minimize the waiting times for recharging, based on knowledge of the context of occupation of the stations and the needs of the other AIV agents (therefore more awareness for the agents). The linguistic variables used in this sixth scenario are the following: the availability of the AIV agent, the distance from the baggage drop-off location, the energy level of the AIV agent, the distances of the 2 recharging stations and the availability of the recharging stations.

Sc7 takes up the strategy of *Sc6* and adapts the recharging rate (80 or 100%) in order to increase their availability if the flow of incoming baggage increases and therefore if the number of pending bags is likely to increase. The linguistic variables used in this seventh scenario are: the availability of the AIV agent, the distance from the baggage drop-off location, the energy level of the AIV agent, the distances from the 2 charging stations, the availability of the charging stations and a variable energy charge rate.

Sc8 consists of increasing *Sc7* by adapting/regulating the speed of the AIV agents according to the flow of baggage arrivals and therefore the potential increase in the number of pending bags to be processed, but also according to the speed, the proximity of other AIV agents (use of observed and safety distances). The linguistic variables used in this eighth scenario are as follows: the availability of the AIV agent, the distance from the baggage drop-off location, the energy level of the AIV agent, the distances of the 2 charging stations, the availability of the charging stations, a variable charging rate (80 or 100%) and urgency in relation to the number of pending bags.

Results of fuzzy inferences in *Sc6*. This is the implementation of a first heuristic to improve the TA but also the recharge decision. The objective is to minimize the waiting time for a recharge when an AIV agent must be available to take baggage. The results for TA are slightly better than in *Sc5*: the same maximum number of pending bags, a slightly shorter overall simulation time, a rather homogeneous average mission completion time, a better distribution of missions between AIV agents, and an average AIV activity rate that is roughly the same (0.82). However, if the overall recharge time is the same, the waiting time for recharges is significantly lower (14s).

Results of fuzzy inferences in *Sc7*. Second heuristic proposed in order to increase the availability of AIV agents so that they can take baggage according to their arrival flow while minimizing the waiting time for their recharges. In this scenario, the results for TA are significantly better than in the *Sc6* scenario: the same maximum number of pending bags, but a shorter overall simulation time, a more homogeneous average mission completion time, a better distribution of missions between AIV agents and a higher average AIV activity rate (0.84). Regarding battery recharges, the results are of the same order for both scenarios: an identical overall recharge time, with in *Sc7*, a slightly higher waiting time for recharges (18s).

Results of fuzzy inferences in *Sc8*. A third heuristic was proposed in order to adjust speed of the AIV agents to minimize the maximum number of pending bags when the flow of baggage arrivals increases. The results for TA are much better than in *Sc7*: the same maximum number of pending bags, but a much lower overall simulation time (a consequence of the adaptation of speeds of AIV agents when necessary), an average time of completion of the missions and a distribution of the missions between the AIV agents always homogeneous, and finally, a lower average occupancy rate of the AIV agents (0.79), because the last two AIV agents are less requested due to the adaptation of the speeds of the first 3, in particular their increase in speed to respond to the increase in the flow of baggage arrivals. As for the battery recharges, the results are less good: the increase in the speeds of the AIV agents has an energy cost!

TABLE IV. TASK ALLOCATION SIMULATION RESULTS IN SCENARIOS SC6; SC7 AND SC8, FOR 100 BAGS

Scenarios	Sc6	Sc7	Sc8
Maximum nb of pending bags	6	6	6
Simulation time	1964s	1896s	1675s
Average mission time per AIV (in s)	[79,79,80,80,81]	[79,80,80,80,80]	[67,65,67,65,67]
Nb of missions completed by AIV	[22,22,20,16,20]	[22,22,21,18,17]	[22,22,22,19,15]
Work rate per AIV	[0.88, 0.88, 0.81, 0.65, 0.82]	[0.92, 0.93, 0.89, 0.76, 0.72]	[0.88, 0.85, 0.88, 0.74, 0.6]

TABLE V. RECHARGE SIMULATION RESULTS IN SCENARIOS SC6, SC7 AND SC8, FOR 100 BAGS

Scenarios	Sc6	Sc7	Sc8
Recharge time	490	490	736
Wait time for recharges	14	18	119
Nb of recharges	33	33	49
Distribution of nb of recharges per AIV	[7, 7, 7, 5, 7]	[7, 7, 7, 6, 6]	[11, 11, 11, 9, 7]

V. CONCLUSION

We developed a multi-agent simulation platform to test different scenarios of task allocation management for mobile baggage conveyor robots (AIVs) in the context of Airport 4.0. This approach offers a flexible adaptation to the different aspects of AIV autonomy management and facilitates possible adjustments needed for deployment at an airport site. The use of a distributed multi-agent system provides temporary autonomy in case of central infrastructure failure, and can improve the management of individual AIV functions, such as task allocation, battery charging, speed regulation, etc.

To establish a basis for comparison of auction-based task allocation strategies with the fuzzy approach we wanted to develop, we started by defining three basic scenarios implementing random, FIFO and AIV availability strategies. We then tested a task allocation scenario with a basic fuzzy model, and then we made several improvements to this scenario by extending the AIV's fuzzy decision model to: (1) recharging the AIVs batteries, (2) determining the recharging station, (3) determining the most relevant recharging rate, and (4) regulating the speed of the AIVs so that they adapt to the variation of the baggage arrival flow.

The simulation results show that integrating adaptive fuzzy multi-agent models for managing task allocation, energy recharging management, determining the most favorable infrastructure elements (charging stations) and speed adaptation, can improve the operational efficiency of AIV fleet. These results highlight the importance of flexible and collaborative approaches to improve the performance of autonomous systems in dynamic environments.

We plan to continue integrating fuzzy models into AIV agent behavior simulations and to add learning capabilities (e.g., based on neural networks [28]) to them in order to increase the relevance and efficiency of their decisions in the collective management of their autonomies.

Acknowledgment

The authors would like to thank the Brittany region for funding the *VIASIC* and *ALPHA* projects, as part respectively of the ARED-2021-2024 call for projects, and the PME 2022 call for projects entitled “Accelerate time to market of digital technological innovations from SMEs in the Greater West”.

References

[1] X. Hu and 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] A.-J. Fougères, “A Modelling Approach Based on Fuzzy Agent,” Int. J. of Computer Science Issues, Vol. 9, Issue 6, 2013, pp. 19-28.

[6] A.-J. Fougères and 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.

[7] N. Ghasem-Aghaee and T. I. Ören, “Towards Fuzzy Agents with Dynamic Personality for Human Behavior Simulation,” Proc. of SCSC 2003, Montreal, Canada, 2003, pp. 3–10.

[8] E. Ostrosi, A.-J. Fougères, M. Ferney, “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.

[9] A. Khamis, A. Hussein, A. Elmogy, “Multi-Robot Task Allocation: A Review of the State-of-the-Art,” in Studies in Computational Intelligence, vol. 604, 2015, pp. 31–51.

[10] K. Karur, N. Sharma, C. Dharmatti, J. E. Siegel, “A survey of path planning algorithms for mobile robots,” Vehicles, Vol. 3, Issue 3, 2021, pp. 448-468.

[11] S. El-Ansary, O. M. Shehata, E. S. I. Morgan, “Airport Management Controller: A Multi-Robot Task-Allocation Approach,” Proc. of the 4th Int. Conf. on control, mechatronics and automation, 2017, pp. 26-30.

[12] M. De Ryck, M. Versteyhe, F. Debrouwere, “Automated guided vehicle systems, state-of-the-art control algorithms and techniques,” J. of Manufacturing Systems, Vol. 54, 2020, pp. 152-173.

[13] A. Hussein and A. Khamis, “Market-based approach to multi-robot task allocation,” Int. Conf. on Individual and Collective Behaviors in Robotics (ICBR), IEEE, 2013, pp. 69-74.

[14] S. Mariani, G. Cabri, F. Zambonelli, “Coordination of autonomous vehicles: Taxonomy and survey,” ACM Computing Surveys (CSUR), Vol. 54, Issue 1, 2021, pp. 1-33.

[15] W. de Paula Ferreira, F. Armellini, L. A. De Santa-Eulalia, “Simulation in Industry 4.0: A State-of-the-Art Review,” Computers & Industrial Eng., Vol. 149, 2020, pp. 106868.

[16] A. Daoud, F. Balbo, P. Gianessi, G. Picard, “ORNInA: A decentralized, auction-based multi-agent coordination in ODT systems,” Ai Communications, Vol. 34, Issue 1, 2021, pp. 37-53.

[17] N.M. Kou, C. Peng, X. Yan, Z. Yang, “Multi-agent path planning with non-constant velocity motion,” Proc. of the 18th Int. Conf. on Autonomous Agents and MultiAgent Systems, 2019, pp. 2069-2071.

[18] J. Grosset , A. Ndao, A.-J. Fougères, M. Djoko-Kouam, C. Couturier, 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.

[19] 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,” Integrated Computer-Aided Engineering, Vol. 31, Issue 3, 2024, pp. 249–266.

[20] V. Yerubandi, Y. M. Reddy, M. V. Kumar, “Navigation system for an autonomous robot using fuzzy logic,” Int. j. of scientific and research pub., Vol. 5, Issue 2, 2015, pp. 5-8.

[21] A. Meylani, A. S. Handayani, R. S. Carlos, “Different Types of Fuzzy Logic in Obstacles Avoidance of Mobile Robot,” I. Conf. on Electrical. Eng. and Comp. Sc., 2018, pp. 93-100.

[22] B. K. Patle, A. Pandey, D. R. K. Parhi, “A review: On path planning strategies for navigation of mobile robot,” Defence Technology, Vol. 15, Issue 4, 2019, pp. 582-606.

[23] A. Nasrinahar and J. H. Chuah, “Intelligent motion planning of a mobile robot with dynamic obstacle avoidance,” J. on Vehicle Routing Algorithms, Vol. 1, Issue 2, 2018, pp. 89-104.

[24] 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.

[25] M. F. R. Lee and A. Nugroho, “Intelligent Energy Management System for Mobile Robot,” Sustainability, Vol. 14, Issue 16, 2022, 10056.

[26] 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.

[27] L. A. Zadeh, “Fuzzy sets,” Information and control, Vol. 8, Issue 3, 1965, pp. 338-353.

[28] H. M. Yudha, T. Dewi, N. Hasana, “Performance comparison of fuzzy logic and neural network design for mobile robot navigation,” Int. Conf. on Electrical Eng. and Comp. Sc., 2019, pp. 79-84, 2019.