Fuzzy Agent-Based Modelling and Simulation of Autonomous Vehicle Fleets for Automatic Baggage Handling in 4.0 Airports

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

Ouzna Oukacha
ECAM Louis de Broglie
IT and Telecommunications Laboratory
Rennes, France
email: ouzna.oukacha@ecam-ldb.fr

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

Egon Ostrosi
UTBM
ERCOS/ELLIAD EA4661
Belfort 90010, France
email: egon.ostrosi@utbm.fr

***Abstract*— Industry 4.0 offers a set of methods, techniques, tools, and technologies that are naturally relevant for the development of services in the airports of the future. Integrating these different concepts into an airport is not without its challenges, given the complexity of the systems in place. Modelling and simulation phases have therefore become essential to ensure the success of these integrations. In this paper, we presented a case study involving the simulation of autonomous vehicle fleets for baggage handling in a simplified airport, in which each vehicle is simulated by a fuzzy agent. We established a Unified Modeling Language (UML) model of the system, providing both static and dynamic views of the circuit and the vehicles. Three different strategies were tested, with the goal of determining the number of Autonomous Industrial Vehicles (AIV) that should circulate to handle the baggage arriving at the two entry points. Then, we presented our simulation results. These results allowed us to highlight the impact of various parameters, such as the number of simulations, the number of bags processed, the total simulation duration, and the total number of bags processed per hour.**

Keywords- automatic baggage handling; autonomous industrial vehicles; fuzzy agent-based simulation; airport 4.0.

I. Introduction

Industry 4.0 is the fourth industrial revolution after the invention of the steam engine, mechanization and mass production, computerization and robotization. It brings the concepts of the Internet of Things (IoT), Cyber-Physical Systems (CPS), Machine to Machine (M2M), and intelligent robotics, such as Autonomous Mobile Robots (AMR) or Autonomous Industrial Vehicles (AIV) [1]. Industry 4.0 assumes decentralized decision-making, interoperability, cyber assistance, predictive maintenance, eco-design and is user centred [2]. Industry 5.0 has complemented the previous one by amplifying the consideration of humans with Human machine connectivity and co-existence [3][4].

The deployment of fleets of autonomous vehicles (AMRs or AIVs) in the context of Airport 4.0 raises several challenges, all related to the actual level of autonomy of these "intelligent" vehicles: decision-making to maintain a required level of performance in carrying out tasks, traffic flow, vehicle localization, fault detection, collision avoidance, vehicle perception in changing environments, as well as acceptance by users and operators. Simulation, prior to the deployment of autonomous vehicles, makes it possible to consider the various constraints and requirements formulated by manufacturers and future airport users [5].

The main advantages of simulating the operations carried out by a fleet of autonomous industrial vehicles are the reduction of fleet development time and cost, the minimization of potential operational risks associated with the deployment of vehicles in a space shared with humans, but also the verification of fleet performance. This makes it possible to assess the feasibility of different scenarios for the circulation of autonomous vehicles at a strategic or operational level, the possibility of a rapid understanding of the operations carried out by these vehicles, the identification of improvements in the layout configurations of vehicle circulation areas [6], and safety assessment during coexistence and possible interactions between autonomous vehicles and human operators [7].

An autonomous baggage handling system is a complex and highly adaptive transportation system. So, different types of simulation frameworks and environments have been proposed for simulating complex systems involving autonomous vehicles (AMRs or AIVs), such as discrete event systems [8] or agent-based systems [9].

Many agent-based approaches are proposed for the modelling and simulation of autonomous vehicles [10]. They offer simulation contexts ranging from trajectory planning to optimal task allocation, while enabling collision and obstacle avoidance [11], addressing issues of traffic congestion, parking requirements, environmental implications or even the performance of autonomous vehicle systems [12].

One of the main problems of complex systems, such as automatic baggage handling systems in airports, results from

 ISBN: 978-1-68558-303-3

the acquired or transmitted data, which may be uncertain, insufficient or available in a fragmented manner due to the dynamics of the environments and the variation of acquisition times. Fuzzy logic then appears as a good solution to model and simulate the uncertainty and the unknown in these complex and adaptive systems [13][14].

In [15][16], Zadeh defines fuzzy logic and the notion of fuzzy sets, introducing the notion of linguistic variables whose values are generally vague, fuzzy, or relative, such as "low", "medium", "high", "most", or "a certain number". By defining these linguistic variables (fuzzy sets), as well as rules using them (fuzzy rules), it is then possible to build Fuzzy Inference Systems (FIS).

Fuzzy set theory is therefore particularly suited to the processing of uncertain or imprecise information that should lead to decision-making by autonomous agents [17]. Also, the definition of fuzzy agents to manage the levels of imprecision and uncertainty involved in modelling the behaviour of simulated vehicles seems quite appropriate [18].

Fuzzy agents can track the evolution of fuzzy information from their environment and from the agents themselves. By interpreting this fuzzy information, they can act and interact within a fuzzy multi-agent system. Thus, a fuzzy agent can discriminate a fuzzy interaction value to assess its degree of affinity (or interest) with another fuzzy agent.

Moreover, most of the control tasks performed by autonomous mobile robots (simulated by agents or real) have been the subject of performance improvement studies using fuzzy logic: motion planning, navigation and obstacle avoidance [19]; path planning [20], localization [21], and intelligent management of energy consumption [22].

We believe it is useful to provide here some details about the research context that led to this publication. The academic collaboration between the authors, focusing on the dual theme of fuzzy logic and autonomous industrial vehicles, played an important role in the development of this article by combining expertise from each respective field. In addition, the industrial collaboration within the framework of the multi-partner collaborative project named ALPHA also had a significant place in this same research context. Thus, we find it important to share the following information regarding this second aspect: 1) the ALPHA project brought together a four-party consortium, including two industrial partners and two research laboratories; 2) the aim of the project was to identify and validate a mobile robotics solution for the transportation of unit baggage in airports; and 3) the ALPHA project focused particularly on two key challenges: on the one hand, optimizing an AGV fleet based on minimal energy consumption; on the other hand, minimizing the complexity of the robotic solution under the constraint of a large number of AGVs.

In this article, we start by presenting the context of fuzzy agent-based modelling and simulation. In Section 3, we propose a case study on simulation of autonomous vehicle fleets for baggage handling in a sample airport. Three strategies are presented with three different data sets. In Section 4, we analyse the results obtained by each of the strategies according to the performance criteria defined in the previous Section. Finally, we conclude on the proposed fuzzy agent-based modelling and simulation, and then we present the perspectives for improvement in the short term.

II. Fuzzy agent-based modelling and simulation

We indicated in the introductory section that many agent-based approaches are proposed for the modelling and simulation of complex systems, such as autonomous vehicles. We further assume that, equipped with reasoning and decision-making capabilities based on fuzzy knowledge, agents could simulate more complex, but also more realistic, situations.

A. Fuzzy agent-based application modelling

The modelling of an agent-based system or application, often discussed from a process or methodological point of view [23], requires adopting a local vision, to respect the fact that each agent is responsible for their knowledge and actions (agent autonomy), which are often decentralized.

Different models can be used to propose a methodology for designing an agent-based application, including: an agent model, to define the characteristics of an agent; a task model, to represent the tasks that can be performed by agents; an expertise model, to describe the knowledge of agents; a coordination model, to define the protocols and interactions between agents; an organization model, to describe the organization of the agent society; or a communication model, to describe the interactions between agents and users. Our agent modelling work mainly refers to the Agent Unified Modeling Language (AUML) [24].

In [25], we proposed a four-phase agent-based system modelling method (Figure 1): (1) create use case diagrams (the services provided by the system); (2) for each use case, create sequence diagrams specifying the interactions (message exchanges and scheduling) between the agents involved in these reference cases; (3) from the sequence diagrams, which allowed us to identify the agents, the system objects and their interactions, create the class diagram: the objects are associated with classes, the messages exchanged (service requests between objects) are translated by operations on the classes, the parameters associated with the operations are translated into class attributes – this diagram can possibly be completed by a collaboration diagram; (4) from the class diagram, define the behaviour of each agent (agent class) by means of a state or activity diagram (we also used Petri nets). The description of the roles played by the different cooperative agents mainly focuses on collaboration and sequence diagrams. We subsequently integrated an expertise model into the previous method, particularly in the form of knowledge and fuzzy inference rules [26].

We are now testing the integration of learning capabilities into fuzzy agents in the form of a basic but generic neural network or reinforcement learning processes. This is to give agents the ability to better adapt in unforeseen situations during their modelling, and to adjust their fuzzy knowledge when extracting it from human experts is difficult or problematic (uncertain knowledge or approximate fuzzy modelling).

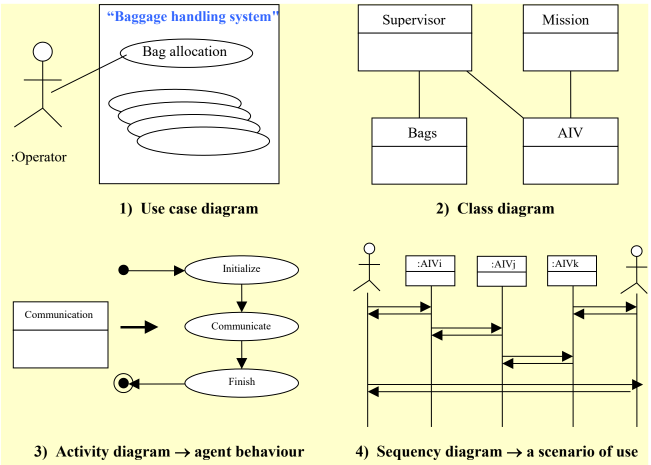

Figure 1. Agent-based system design: methodology adapted from AUML

B. *Fuzzy agent modelling*

An agent-based system is fuzzy if some of the agents that compose it have fuzzy behaviours or if the knowledge they use is fuzzy. This means that agents are modelled in such a way as to [18]:

- use fuzzy knowledge in their inferences; this knowledge consists of fuzzy linguistic variables, fuzzy linguistic values, and fuzzy rules [17];
- adopt fuzzy behaviours, following fuzzy inferences [27];
- and potentially implement fuzzy interactions, act in fuzzy organizations, or play fuzzy roles [28].

Formally, a fuzzy agent-based system (1) and the fuzzy agents that compose it (2) can be defined as follows:

$$\widetilde{M}_\alpha = < \widetilde{A}, \widetilde{I}, \widetilde{P}, \widetilde{O} > \quad (1)$$

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

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

Where, for a fuzzy agent $\widetilde{\alpha}_i$, $\Phi_{\Pi(\widetilde{\alpha}_i)}$ is its function of observation; $\Phi_{\Delta(\widetilde{\alpha}_i)}$ is its function of decision; $\Phi_{\Gamma(\widetilde{\alpha}_i)}$ is its function of action; and $K_{\widetilde{\alpha}_i}$ is its set of fuzzy knowledge.

In the following case study, we will mainly develop fuzzy knowledge modelling. For the interested reader, we have extensively developed fuzzy modelling of other dimensions in the following articles [26][27][28][29].

III. CASE STUDY: SIMULATION OF AUTONOMOUS VEHICLE FLEETS FOR BAGGAGE HANDLING

In this section, we present a case study of a baggage handling system in an airport using a fleet of autonomous vehicles. We will successively propose the agent model of vehicle behaviour, the fuzzy logic modelling of their decision rules, and three baggage handling strategies to discuss the performance obtained in the following section.

A. *Presentation of the case study*

The case study presented in this paper proposes the simulation of baggage handling in a basic airport with two baggage entry flows and two baggage exit flows. The mobile robots (AIV) in charge of baggage handling travel a loop circuit shown in Figure 2.a. The AIVs are simulated by fuzzy agents, and the airport circuit is represented by a directed graph. This graph has 17 nodes (Figure 2.b): node *P0* represents the parking lot, nodes *R1* and *R2* represent the 2 baggage pick-up points, nodes *D1* and *D2* represent the 2 baggage drop-off points, and the other 12 nodes *Pi* represent characteristic points of the circuit (curve start points, curve end points, convergence points and divergence points).

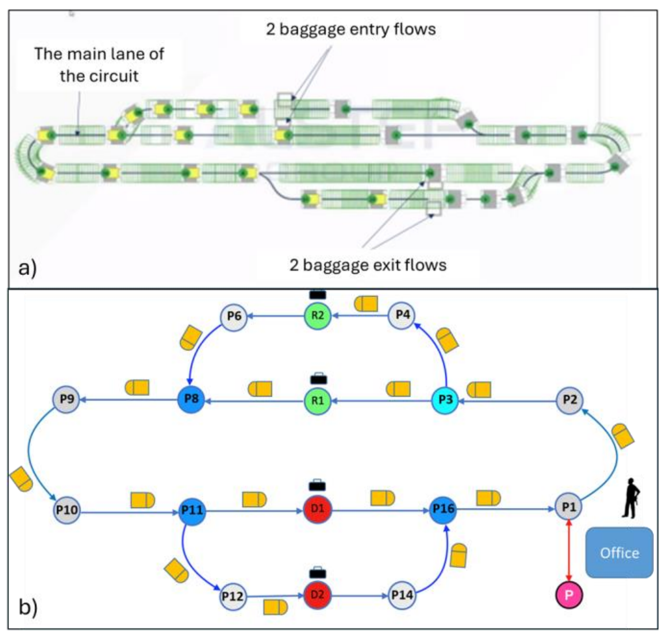

Figure 2. Simulation Application: a) the circuit, and b) the graph model

The application itself is developed in Python. Figure 3 presents its object and agent architecture in the form of a UML class diagram: static objects are represented in blue, and agents, therefore dynamic, are represented in red (only AIV agents are fuzzy agents). An infrastructure can be deployed in this environment. It includes a traffic plan and potentially active elements, such as beacons, tags, charging stations, etc. Static or dynamic obstacles (e.g., operators or broken-down AIVs) can also be activated in this simulation environment.

To study the performance of the solutions considered in this simulation, we defined the optimization system presented below (3): the objectives are to Minimize x, Maximize y, and Minimize z, where x is the number of AIVs, y is the baggage throughput per hour, and z is the recharge time of an AIV per hour (in ideal conditions where an AIV picks up one baggage each turn, a level of performance that we will analyse in the case study presented in Section 3, based on strategies deployed by the AIVs).

$$\begin{cases} 0 \leq x \leq Max(x) = {}^{L_{avg}}/_{d} \\ 0 \leq y \leq T_{avg} * Max(x) \\ 0 \leq z \leq 3600 \\ z = \left({}^{v_{avg}*3600}/_{C_{bat}}\right) * (t_0 + t_1) \\ T_0 = \left({}^{L_{avg}}/_{v_{avg}}\right) + (t_2 + t_3) \\ T_{avg} = {}^{(3600-z)}/_{T_0} \\ y = T_{avg} * x \end{cases} \tag{3}$$

Where $Max(x)$ is the maximum number of AIVs; L_{avg} is the average length of the circuit; d is the safety distance between 2 AIVs; C_{bat} is the average capacity of a battery; t_0 is the average charging time of a battery; t_1 is the average waiting time for a battery recharge; T_0 average duration of a circuit lap; t_2 is the time to pick up a bag; t_3 is the time to drop off a bag; T_{avg} is the average number of revolutions made by an AIV during one hour; and v_{avg} is the average speed of the AIVs on the circuit.

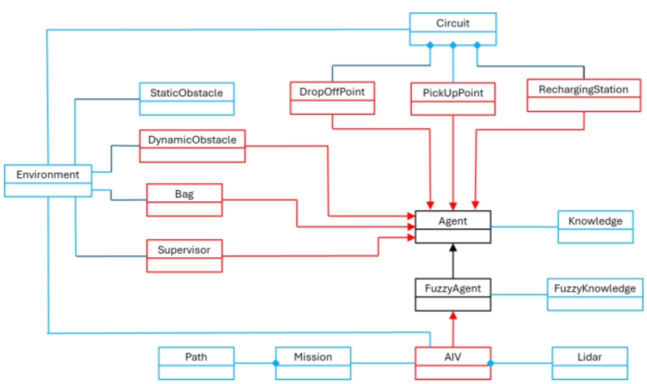

Figure 3. UML class-diagram of the fuzzy-agent based simulator.

An initial study focused on the sizing of the problem (traffic plan, number of AIVs, determination of applicable speeds, distances between AIVs, energy consumption of these AIVs, etc.) [5], followed by a Petri nets-based simulation of the AIV behaviour in function of strategies of baggage handling developed (Figure 4), allowed us to set the following parameters: $Max(x)=40$, $L_{avg}=313$, $v_{avg}=5$, $d=8$, $t_2=t_3=2$, and $z \approx 10\%$ of the AIVs operating time if t_1 is zero.

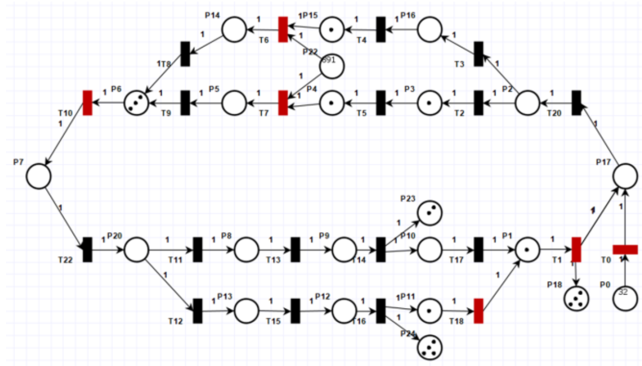

Figure 4. Petri net model of the circuit in Figure 2.a. It allows us to simulate a solution, while verifying that it retains the properties of liveness (non-blocking) and bounding of quantitative parameters such as the number of AGVs. The transitions in red indicate the possible evolution of the Petri net.

B. AIV behaviour and their fuzzy knowledge

As defined in the agent-based systems design methodology, one of the steps is to model the behaviour of the agents in the form of an activity or state diagram. The AIV agents in the simulation will have a behaviour adapted to the strategy implemented to process the baggage. Thus, Figure 5 presents the activity diagram of an AIV agent when it circulates according to the Round robin strategy (continuous looping if there is baggage to process).

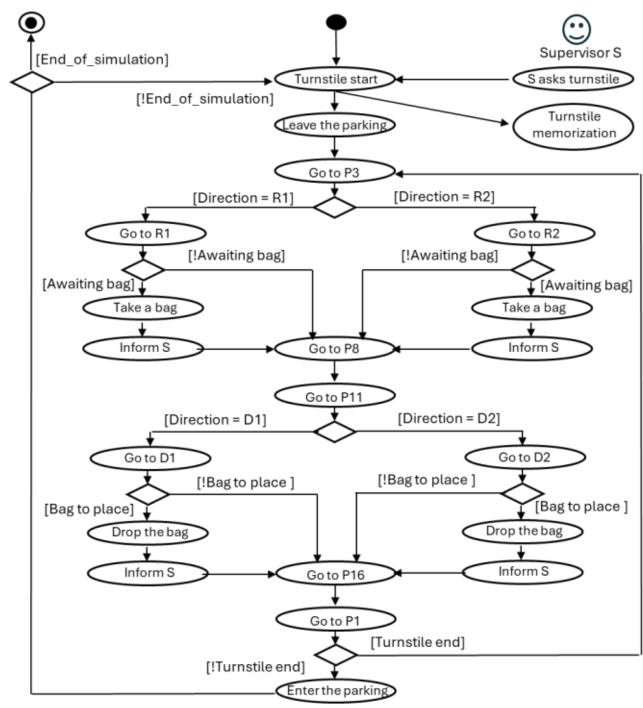

Figure 5. AIV behaviour based on “Round robin” strategy

AIVs are fuzzy agents that therefore have fuzzy knowledge. In this simulation, 2 types of fuzzy inferences are considered: the prediction of the number of AIVs that must circulate to process baggage, and the determination of the branch to choose to take a baggage (passage through R1 or R2).

For prediction, AIV agents have 3 linguistic variables (*NbBag, NbAIV, Prediction*, as shown in Figure 6) and 9 rules, such as (4):

IF *NbBag* ***IS*** *low* ***AND*** *NbAIV* ***IS*** *high*
THEN *Prediction* ***IS*** *highDecrease* (4)

As for the choice of branch *R1* or branch *R2*, the AIVs have 5 linguistic variables (*NbBagInR1, NbBagInR2, NbAIVToR1, NbAIVToR2, GoTo*, as shown in Figure 7) and 18 rules, such as (5):

IF *NbBagInR1* ***IS*** *low* ***AND*** *NbAIVToR1* ***IS*** *high*
THEN *GoTo* ***IS*** *R2* (5)

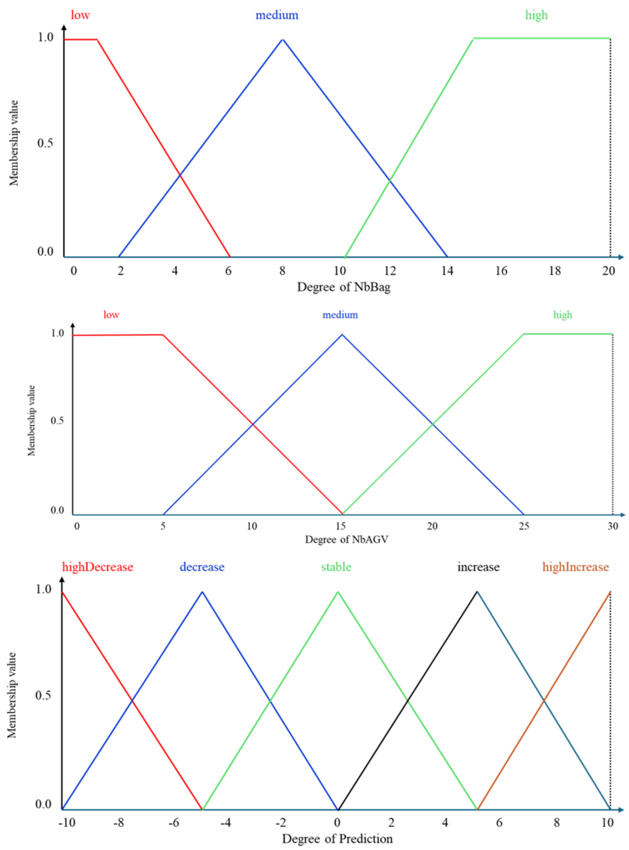

Figure 6. Linguistic variables to predict whether an AIV should circulate.

C. *The three considered strategies*

The goal here is to determine the number of AIVs that must circulate to process baggage arriving at both entry points. Three distinct strategies were simulated to test them and establish their performance on the system:

- **Round robin**. AIVs rotate around the circuit and pick up a bag if one is available on R1 or R2, depending on their route.
- **On-demand**. AIVs are assigned when baggage arrives and is available in the parking lot.
- **Fuzzy logic-based demand prediction**. The number of AIVs rotating around the circuit is calculated periodically based on predicted needs using fuzzy rules established by the operator. Other types of predictive strategies could be used, but as we have already shown the interest of fuzzy logic to efficiently solve this type of problem [30], we decided to develop this approach in this comparison of strategies.

Baggage arrival is a determining factor in the observable results for the three previous strategies. We have therefore defined different types of scenarios to cover many cases. Below we present the three main scenarios (without their variants):

- **Sc1 – Real data.** Baggage arrival is simulated based on aircraft arrivals at a sample airport, to better account for the variability of incoming baggage flow (high demand periods and low demand periods). These data cover a full day's traffic at the sample airport.

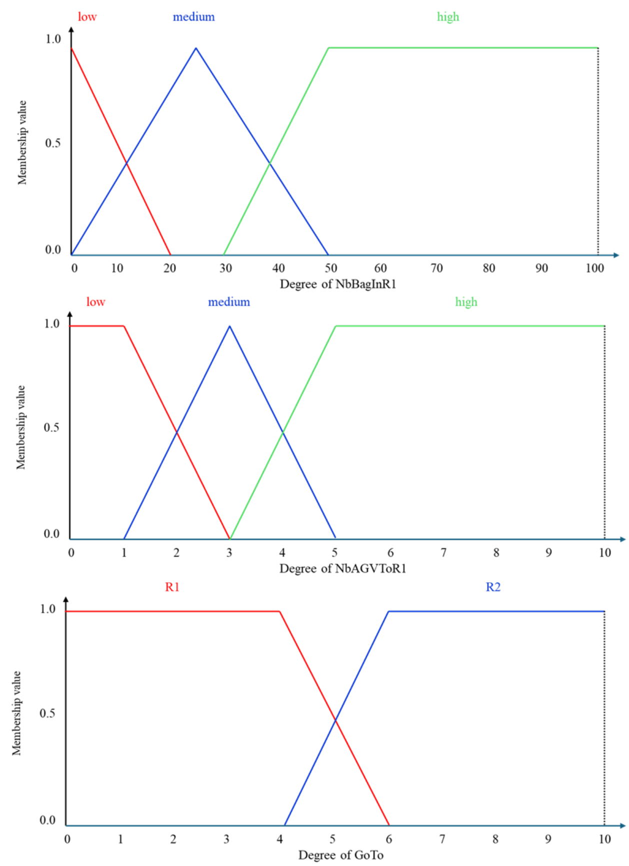

Figure 7. Linguistic variables for an AIV to choose one of the 2 branches.

- **Sc2 – Random Data**. Baggage arrival is randomly simulated over a period of one hour. Random data generation is performed upstream to create a single data set. This data set is then used to test the three strategies.

- **Sc3 – Mass data**. 1000 bags arrive continuously at the 2 entrances of the circuit. This involves performing a stress test for each strategy, regardless of the quality of each strategy's performance (e.g., a baggage waiting time threshold).

IV. RESULTS

Now, we present the results of the 9 simulations carried out according to the specifications formulated in the previous Section (3 scenarios x 3 strategies). The five performance criteria retained, with regard to the optimization system presented in (3), are: the duration of the simulation (i.e., the duration of processing of all baggage entering the simulated scenario), the number of baggage processed, the number of baggage processed per hour (throughput per hour), the number of circuit turns made by the AIVs to process all baggage, the average waiting time for baggage before being taken by an AIV, and the performance impact of AIV recharge times is estimated at 10% of AIV circulation time.

We will detail the results for each of the 6 criteria, then we will present the synthesis of these simulations.

Results regarding total simulation duration (Table 1)**.** With the exception of the 1h scenario in random baggage flow, the Round robin strategy always has the longest duration, the On-demand and FL Prediction strategies are more variable, with a shorter duration for On-demand when the baggage flow is continuous (test Mass data), and a lower duration for FL Prediction when the flow is more variable (flow depending on the arrival of aircraft at test Real data). Both FL Prediction and On-demand strategies optimize the processing time by activating AIVs when baggage arrives by determining the right traffic branches, which is not the case for AIVs in the Round robin strategy.

Results regarding the total number of bags processed (Table 2)**.** Two of the scenarios have a fixed number of bags (the test airport called Real data with a fixed number of bags of 1306, and the Mass data scenario with 1000 continuous bags); for the third scenario, with a random flow over 1 hour, the On-demand strategy is the least efficient (1864 bags), then the LF Prediction strategy (1956 bags), finally the most efficient is the Round robin strategy (2015 bags). On this criterion, the Round robin strategy is overall the most satisfactory, it is also on this criterion that it has its main advantage.

Results regarding the overall throughput of the 3 strategies (Table 3)**.** The two strategies of Round robin and On-Demand have the worst overall results. In continuous and variable flows, the Round robin strategy performs poorly (respectively 1578 and 1713 bags/h). On the other hand, in random flow over 1 hour, the On-demand strategy performs the least (1864 bags/h). The average and overall flow rate is unquestionably the best with the Prediction strategy (1807 bags/h on average over the 3 scenarios).

Results regarding the total number of turns made by the AIVs (Table 4)**.** For this criterion, the Round robin strategy is systematically the least efficient, and this significantly. 1664 rounds on average over the 3 scenarios for the Round robin strategy, against 1526 rounds on average for the FL Prediction strategy and 1390 rounds on average for the On-demand strategy. The average and overall number of AIV rounds is undoubtedly the best with the On-demand strategy (1390 rounds on average over the 3 scenarios); the allocation of an arriving bag to an AIV is indeed very efficient. For the FL Prediction strategy, the average results remain satisfactory (1526 rounds on average over the 3 scenarios), while those of the Round robin strategy are rather mediocre (1664 rounds on average over the 3 scenarios).

Results regarding the average waiting time for bags before being processed by an AIV (Table 5)**.** For this criterion, the Round robin strategy is twice the least efficient (for the one-hour random flow and for the variable flow of the Real data test), and the On-demand strategy is the least efficient for the continuous flow of 1000 bags. The On-demand strategy gives very satisfactory results on average for the 3 scenarios (22 s average wait for a bag), and the FL Prediction strategy also gives satisfactory performances for the three scenarios (23 s average wait for a bag).

Results regarding the performance impact of AIV recharge times (Table 6)**.** The AIVs run the same algorithm to determine whether they should recharge at a charging station located in the parking lot. The principles of the algorithm are as follows: 4 stations (corresponding to 10% of the 40 AIVs), recharge every 10 laps of the circuit (every 10 x 66s = 660s, on average), recharge if possible, when the AIVs are in the parking lot and recharge all the AIVs at the end of the simulation. Table 6 gives the results for a simulation with scenario 2 (one-hour simulation in random mode): number of recharges, total recharge time, and total duration of the simulation (3600s + final recharge for the AIVs to be fully charged again). The results provided by the on-demand strategy are the best, although at the cost of many recharges (when the AIVs return to the parking lot). The FL Prediction strategy offers a good compromise with interesting results that can be further improved by adjusting the values of the linguistic variables used in the fuzzy rules.

TABLE I. SIMULATION DURATION FOR THE 3 STRATEGIES (S)

Scenarios	Real data	Random data	Mass data
Round robin	2744	3600	2280
On-demand	2686	3600	2196
FL prediction	2515	3600	2252

TABLE II. NUMBER OF BAGS PROCESSED BY THE 3 STRATEGIES

Scenarios	Real data	Random data	Mass data
Round robin	1306	2015	1000
On-demand	1306	1864	1000
FL prediction	1306	1956	1000

TABLE III. FLOW RATE OF THE THREE STRATEGIES (bags/h)

Scenarios	Real data	Random data	Mass data
Round robin	1713	2015	1578
On-demand	1750	1864	1639
FL prediction	1868	1956	1597

TABLE IV. NUMBER OF TURNS COMPLETED BY THE AIVS

Scenarios	Real data	Random data	Mass data
Round robin	1622	2074	1298
On-demand	1306	1864	1000
FL prediction	1376	2021	1182

TABLE V. AVERAGE WAITING TIME PER BAG BEFORE (S)

Scenarios	Real data	Random data	Mass data
Round robin	41	57	14
On-demand	26	21	20
FL prediction	29	22	19

TABLE VI. IMPACT OF THE RECHARGING OF AIV BATTERIES

Scenarios	Number of recharges	Total duration of recharges	Total duration of simulation
Round robin	195	11760	3823
On-demand	622	9810	3683
FL prediction	198	11658	3793

Finally, we can discuss the benefits of using the communication capabilities of AIV agents. Indeed, adding communication between the AIVs and the infrastructure improves the performance of the Round Robin strategy (2% higher throughput and up to 11% fewer rounds for the AIVs). This communication also improves the results of the algorithm that determines whether an AIV needs to recharge. Indeed, by passing near the parking lot where the charging stations are located, the infrastructure can communicate to the AIV if one of the 4 stations is available. This information allows the AIVs to avoid waiting, especially to maintain a good level of baggage processing performance during periods of dense and continuous flow.

V. CONCLUSION AND PERSPECTIVES

In this article, we presented the context of fuzzy agent-based modelling and simulation. We introduced the general framework for modelling fuzzy agent-based applications, highlighting the fact that in such systems, each agent is responsible for its own knowledge and actions, which makes it an autonomous entity within the system.

It is important to note that the modelling of fuzzy agents is based on the fuzzy nature of knowledge, behaviours, and interactions.

We presented a case study involving the simulation of autonomous vehicle fleets for baggage handling in a simplified airport, in which each vehicle is simulated by a fuzzy agent. This simplification allows us to establish a baseline configuration to which we can add more complex and dynamic situations encountered in real airports, such as the introduction of baggage checkpoints requiring baggage drop-off and pick-up by the same or a different AIV.

We established a UML model of the automatic baggage handling system, providing both static and dynamic views of the circuit and the vehicles. Three different strategies were tested, with the goal of determining the number of AIVs that should circulate to handle the baggage arriving at the two entry points.

Finally, we presented our simulation results. These results allowed us to highlight the impact of various parameters, such as the number of simulations, the number of bags processed, the total simulation duration, and the total number of bags processed per hour.

We plan to continue improving the performance of fuzzy models in simulations of AIV agent behaviour for autonomous baggage handling in airports. This may consist of adding neural network-based learning capabilities [31][32], to increase the relevance and efficiency of their decisions in the collective management of their autonomies and in compliance with the performance expected by airport operators.

Another extension of our research consists of continuing work started recently, still in a simulation approach, on the incorporation of human-robot coworking aspects to maintain system performance, simulate the management of incidents occurring on the circuit or other types of problems difficult to solve for AIVs alone, and thus improve practical credibility for Airport 4.0 stakeholders.

ACKNOWLEDGMENT

The authors would like to thank the French Brittany region for funding the *ALPHA* project as part of the PME 2022 call for projects entitled “Accelerate time to market of digital technological innovations from SMEs in the Greater West.”

REFERENCES

[1] A. G. Frank, L. S. Dalenogare, and N. F. Ayala, “Industry 4.0 technologies: Implementation patterns in manufacturing

 ISBN: 978-1-68558-303-3

companies," International journal of production economics, vol. 210, pp. 15-26, 2019.

[2] E. Oztemel and S. Gursev, "Literature review of Industry 4.0 and related technologies," Journal of intelligent manufacturing, vol. 31, no. 1, pp. 127-182, 2020.

[3] X. Xu, Y. Lu, B. Vogel-Heuser, and L. Wang, "Industry 4.0 and Industry 5.0—Inception, conception and perception," Journal of manufacturing systems, vol. 61, pp. 530-535, 2021.

[4] A. Akundi, et al., "State of Industry 5.0—Analysis and identification of current research trends," Applied System Innovation, vol. 5, no. 1, pp. 27, 2022.

[5] O. Oukacha, A.-J. Fougères, M. Djoko-Kouam, and E. Ostrosi, "Computational ergo-design for a real-time baggage handling system in an airport," Sustainability, vol. 17, no. 9, pp. 3794, 2025.

[6] N. Tsolakis, D. Bechtsis, and J.S. Srai, "Intelligent autonomous vehicles in digital supply chains: From conceptualisation, to simulation modelling, to real-world operations," Business Process Management Journal, vol. 25, no. 3, pp. 414-437, 2019.

[7] A. Hentout, M. Aouache, A. Maoudj, and I. Akli, "Human–robot interaction in industrial collaborative robotics: a literature review of the decade 2008–2017," Advanced Robotics, vol. 33, no. 15–16, pp. 764–799, 2019.

[8] R. Skapinyecz, "Examining the collision avoidance problem of AGVs in a discrete event simulation environment," Academic Journal of Manufacturing Engineering, vol. 22, no. 4, pp. 52-65, 2024.

[9] F. Gehlhoff, N. Jobs, and V. Henkel, "Agent-Based Control of Interaction Areas in Intralogistics: Concept, Implementation and Simulation," Logistics, vol. 9, no. 2, pp. 52, 2025.

[10] J. Huang, et al., "An overview of agent‐based models for transport simulation and analysis," Journal of Advanced Transportation, vol. 2022, no. 1, pp. 1252534, 2022.

[11] J. Grosset, A.-J. Fougères, M. Djoko-Kouam, and 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, no. 3, pp. 249–266, 2024.

[12] P. Jing, H. Hu, F. Zhan, Y. Chen, and Y. Shi, "Agent-based simulation of autonomous vehicles: A systematic literature review," IEEE Access, vol. 8, pp. 79089-79103, 2020.

[13] A. Azadegan, L. Porobic, S. Ghazinoory, P. Samouei, and A. S. Kheirkhah, "Fuzzy logic in manufacturing: A review of literature and a specialized application," International Journal of Production Economics, vol. 132, no. 2, pp. 258-270, 2011.

[14] H. H. Tang and N. S. Ahmad, "Fuzzy logic approach for controlling uncertain and nonlinear systems: a comprehensive review of applications and advances," Systems Science & Control Engineering, vol. 12, no. 1, pp. 2394429, 2024.

[15] L. A. Zadeh, "Fuzzy sets. Information and control, vol. 8, no. 3, pp. 338-353, 1965.

[16] L. A. Zadeh, "Outline of a new approach to the analysis of complex systems and decision processes," IEEE Transactions on systems, Man, and Cybernetics, vol. 3, no. 1, pp. 28-44, 1973.

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

[18] A.-J. Fougères, "A Modelling Approach Based on Fuzzy Agent," Int. J. of Computer Science Issues, vol. 9, no. 6, pp. 19-28, 2013.

[19] A. Meylani, et al., "Different Types of Fuzzy Logic in Obstacles Avoidance of Mobile Robot," Int. Conf. on Electrical. Eng. and Computer Sc., 2018, pp. 93-100.

[20] B.K. Patle, et al., "A review: On path planning strategies for navigation of mobile robot," Defence Technology, vol. 15, no. 4, pp. 582-606, 2019.

[21] M. Alakhras, M. Oussalah, and M. Hussein, "A survey of fuzzy logic in wireless localization," EURASIP J. on Wireless Com. and Networking, vol. 1, pp. 1-45, 2020.

[22] M.F.R. Lee and A. Nugroho, "Intelligent Energy Management System for Mobile Robot," Sustainability, vol. 14, no. 16, pp. 10056, 2022.

[23] P. K. Biswas, "Towards an agent-oriented approach to conceptualization," Applied Soft Computing, vol. 8, no. 1, pp. 127-139, 2008.

[24] B. Bauer and J. Odell, "UML 2.0 and agents: how to build agent-based systems with the new UML standard," Engineering Applications of Artificial Intelligence, vol. 18, pp. 141–157, 2005.

[25] A.-J. Fougères, "Agents to cooperate in distributed design," in the IEEE International Conference on Systems, Man and Cybernetics, (SMC'04), The Hague, Netherlands, October 10-13, 2004, vol. 3, pp. 2629-2634.

[26] E. Ostrosi, A.-J. Fougères, and M. Ferney, "Fuzzy Agents for Product Configuration in Collaborative and Distributed Design Process," Applied Soft Computing, vol. 8, no. 12, pp. 2091–2105, 2012.

[27] A.-J. Fougères and E. Ostrosi, "Holonic Fuzzy Agents for Integrated CAD Product and Adaptive Manufacturing Cell Formation," Journal of Integrated Design and Process Science, vol. 23, no. 1, pp. 77-102, 2019.

[28] A.-J. Fougères and E. Ostrosi, "Multiple Fuzzy Roles: Analysis of their Evolving in a Fuzzy Agent-Based Collaborative Design Platform," In: Lecture Notes Studies in Computational Intelligence (LNCSI), Edited by K. Madani, A. Dourado, A. Rosa, J. Filipe and J. Kacprzyk, Springer International Publishing Switzerland, 2016, p.207-226, ISBN: 978-3-319-23391-8, 978-3-319-23392-5 (e-book).

[29] A.-J. Fougères and E. Ostrosi, "Fuzzy engineering design semantics elaboration and application," Soft Computing Letters, vol. 3, pp. 100025, 2021.

[30] J. Grosset, A.-J. Fougères, M. Djoko-Kouam, and J.-M. Bonnin, "Fuzzy Agent-Based Simulations of Cooperative Strategies for Task Allocation, Collision Avoidance, and Battery Charging Management of Autonomous Industrial Vehicles," International Journal on Advances in Systems and Measurements, vol. 18, no. 1&2, pp. 8-18, 2025.

[31] D. Luviano-Cruz, et al., "Multi-agent reinforcement learning using linear fuzzy model applied to cooperative mobile robots," Symmetry, vol. 10, no. 10, pp. 461., 2018

[32] H.M. Yudha, T. Dewi, and 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.