Modeling and Simulation of Autonomous Mobile Robot Fleets for Automated Baggage Handling in Airports 4.0: A Fuzzy Agent Approach

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Abstract— **Airport 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. Modeling and simulation phases have therefore become essential to ensure the success of these integrations. The concept of Agent-Based Modeling and Simulation (ABMS) is perfectly suited to this context. 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 an agent with fuzzy knowledge (fuzzy agent). We developed a UML (Unified Modeling Language) model of the system, providing static and dynamic views of a simplified airport circuit, vehicles, and baggage. Three different strategies were tested to determine the number of autonomous vehicles needed to most efficiently handle 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. A discussion on the regulation of vehicle speeds is also included.**

Keywords- automatic baggage handling; autonomous mobile robots; ABMS; fuzzy agent; airport 4.0.

I. INTRODUCTION

This article considerably expands upon our previous conference paper [1] by providing additional information on all parts, especially by developing the fuzzy agent-based modeling section and its application for the case study. Industry 4.0 is the fourth industrial revolution after the invention of the steam engine, mechanization and mass production, computerization and robotization [2]. It brings the concepts of the Internet of Things (IoT), Cyber-Physical Systems (CPS), Machine to Machine (M2M), and intelligent robotics, including Autonomous Mobile Robots (AMR) [3]. Industry 4.0 assumes decentralized decision-making, interoperability, cyber assistance, predictive maintenance, eco-design and is user centered [4]. Industry 5.0 has complemented the previous one by amplifying the consideration of humans with Human machine connectivity and co-existence [5] and [6].

The concept of Industry 4.0 has extended to other types of structures and sectors [7], such as Supply Chain 4.0 [8] [9], Agriculture 4.0 [10] and [11], Health 4.0 [12], or Airport 4.0 [13]. However, the deployment of AMR fleets 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 [14]. Therefore, the 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 [15].

The use of simulation is justified by the high cost associated with developing experiments or tests on the real system, observing the behavior of static or dynamic processes and entities in the real world, or building a physical model [16]. Thus, in the context of Airport 4.0, the main advantages of simulating the operations carried out by an AMR fleet 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, and 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 [7], and safety assessment during coexistence and possible interactions between autonomous vehicles and human operators [17].

Numerous modeling and simulation approaches can be used in the field of Airport 4.0: Agent-Based Modelling and Simulation (ABMS), Discrete Event Simulation (DES), System Dynamics (SD), Virtual Reality (VR), Augmented Reality (AR), Artificial Intelligence (AI), Petri Nets (PN), Digital Twins (DT), and Hybrid Simulation (HS) [18]. ABMS is an increasingly used approach for modeling and simulating complex systems composed of autonomous agents interacting with each other and with their environment [19]. Thus, a strong analogy can therefore be drawn between a virtual agent and a physical (mobile) robot.

An autonomous baggage handling system in an airport is a complex and highly adaptive transportation system. So, different types of simulation frameworks and environments have been proposed for simulating complex systems involving AMRs capable of transporting luggage, mainly discrete event systems [20] or agent-based systems [21].

Numerous agent-based approaches are proposed for the modeling and simulation of both autonomous vehicles and transport systems [22]. They offer two-level simulation contexts, micro as well as macro, ranging from trajectory planning to optimal task allocation, while enabling collision and obstacle avoidance [23], addressing problems of traffic congestion, parking requirements, environmental implications or even the performance of autonomous vehicle systems [24].

One of the main problems of complex systems, such as automatic baggage handling systems in airports, results from 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 [25] and [26]. More specifically, it will allow for the adequate handling of variations in the incoming baggage flow, which requires adapting not only the number of vehicles handling the baggage, but also the distribution of these vehicles according to the different baggage entry points.

In [27] and [28], 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) and their potential values (fuzzy quantification), 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 agents simulating autonomous vehicles [29]. Also, the definition of fuzzy agents to manage the levels of imprecision and uncertainty involved in modeling the behavior of simulated vehicles seems quite appropriate [30].

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 fuzzy interaction values or fuzzy information acquired to assess its degree of affinity with other fuzzy agents or the degree of interest of this information in a specific situation.

Most of the control tasks performed by autonomous mobile robots (in simulated or real contexts) have been the subject of performance improvement studies using fuzzy logic: motion planning, navigation, and obstacle avoidance [31]; path planning [32], localization [33], and intelligent management of energy consumption [34]. However, although the simulation of AMR behavior based on fuzzy logic has been heavily studied since the 1990s [35] and [36] to the present day [37], mainly for navigation problems (trajectories and obstacle avoidance), no study addresses the simulation of mobile robot control in dynamic and uncertain environments in an exhaustive manner using fuzzy agents. This is the objective we set for ourselves, beginning by addressing the methodological framework for modeling these fuzzy agents. Furthermore, the case study in the Airport 4.0 domain, which we develop in Section III, provides us with an ideal framework for experimenting with fuzzy agent-based simulations that are consecutive, complementary, and correlated to the modeling phase.

To enhance the readability of this case study, we provide below 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 mobile robots, 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 a multi-partner collaborative project named ALPHA also had a significant place in this same research context.

The ALPHA project brought together a four-party consortium, including two industrial partners and two research laboratories. The aim of the project was to identify and validate a mobile robotics solution for the transportation of unit baggage in airports. The ALPHA project focused particularly on two key challenges: on the one hand, optimizing an AMR fleet based on minimal energy consumption; on the other hand, minimizing the complexity of the robotic solution under the constraint of many AMRs.

In the remainder of this article, we present the context of fuzzy multi-agent modeling, which allows us to simulate complex systems such as baggage handling systems in airports. In Section III, we propose a case study on simulation of AMR fleets for baggage handling in a greatly simplified airport area. Three strategies are presented with three different data sets. In Section IV, we analyze the results obtained by each of the strategies according to the performance criteria defined in the previous Section. Then, in Section V, we discuss the results obtained by varying speeds of AMRs. Finally, we conclude on the proposed fuzzy agent-based modeling and simulation, and then we present the perspectives for improvement in the short term.

II. FUZZY AGENT-BASED MODELING

The multi-agent paradigm is well-suited for modeling and simulating complex systems such as autonomous vehicles, which interact with each other and react within their dynamic environment [38]. However, for this approach to be effective, a rigorous modeling framework is necessary: the agent-based system must be characterized, quantified, and structured, and the agents' behaviors must be formally defined [19]. Furthermore, equipped with reasoning and decision-making capabilities based on fuzzy knowledge, the agents will be able to simulate more complex, and more realistic, situations [39]. The agents we design in this case study are therefore fuzzy.

A. *Fuzzy agent-based application modeling*

The modeling of an agent-based system or application, often discussed from a process or methodological point of view [40], 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 modeling work mainly refers to the Agent Unified Modeling Language (AUML) [41].

In [42], we proposed a four-phase agent-based system modeling methodology (Figure 1):

1) Create use case diagrams to represent the services provided by the system.
2) For each use case diagram, 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 class diagram can possibly be completed by a collaboration diagram).
4) From the class diagram, define the behavior 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 [43].

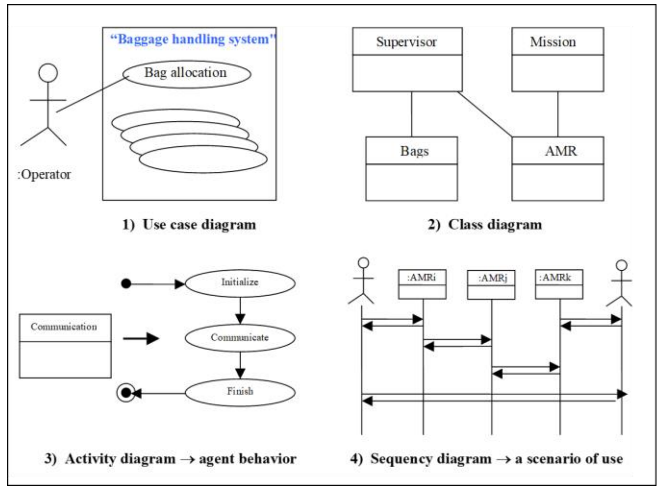

Figure 1. Agent-based system design: methodology adapted from AUML

B. *Fuzzy agent modeling*

An agent-based system is fuzzy if some of the agents that compose it sometimes have fuzzy behaviors, or if a part of the knowledge they use is fuzzy. This means that agents are modelled in such a way as to [30]:

- sometimes use fuzzy knowledge in their inferences; this knowledge then consists of fuzzy linguistic variables, fuzzy linguistic values, and fuzzy rules [29];
- sometimes adopt fuzzy behaviors, consequences of their fuzzy inferences [44];
- and potentially implement fuzzy interactions, act in fuzzy organizations, or play fuzzy roles [45].

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

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

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 case study presented in the following section, we will primarily develop the modeling of agents' fuzzy knowledge. This knowledge modeling is above all the result of methodological activity. Thus, the methodology we adopted comprises three steps:

1) the modeling of fuzzy data, that is to say the definition of the set *L(V, X, P)*, where *V* is the set of linguistic variables (for instance, "speed"), *X* is the set of possible values, the universe of discourse (for instance, "5 m/s"), and *P* is the set of partitions of the universe of discourse, called fuzzy subsets (for instance, "medium");
2) the quantification or fuzzification which consists of giving numerical values to the fuzzy subsets, to be able to determine that a given data has a membership value to one or more fuzzy subsets of the model (for instance, medium speed $\in [3, 6]$ in m/s);
3) the modeling of fuzzy rules so as to make fuzzy inferences from the fuzzy data supplied to the model, which consists of producing decision rules of the type: *IF A $\in$ V IS B $\in$ P THEN C $\in$ V IS D $\in$ P* (for example, "IF speed IS medium AND intersection IS near, THEN slowdown IS little").

To refine this fuzzy agent modeling methodology, we have extensively tested it in various engineering fields, such as product configuration in collaborative design process [43], integrated CAD product and adaptive manufacturing cell formation [44], collaborative design platform [45], and engineering design semantics elaboration [46].

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 mobile robots. We will successively propose the agent model of vehicle behavior, the fuzzy logic modeling of their decision rules, and three baggage handling strategies to discuss the performance obtained.

A. *Presentation of the case study*

The case study presented in this article proposes the simulation of the automatic baggage handling in a greatly simplified airport area comprising two baggage entry and exit flows (via baggage conveyor belt, for example), a parking lot equipped with battery charging stations, forty AMRs, and an operator who can intervene in case of a problem such as a malfunctioning AMR or baggage on the ground. The incoming baggage flow is simulated by the arrival of aircraft carrying a variable number of bags. As for AMRs, they can carry one bag at a time (in reality, baggage is classified by size, standard or specific, but we do not consider this distinction in our simulations).

The circuit followed by AMRs to transport bags from an entry point to an exit point is a loop circuit consisting of two branches, one for the two entry points and another for the two exit points (Figure 2). This circuit presents seven specific points that require AMR agents to adapt their behavior using strategies whose performance can be measured in both centralized (supervised agents) and decentralized (autonomous agents) modes. These strategies will require the agents to implement distributed artificial intelligence capacities (DAIC), such as communication (C), knowledge (K), and, with a view to improving the current simulator, learning (L) mechanisms. The correspondence between the problems inherent in these seven specific points and the strategies developed to address them is provided in Table I.

The baggage handling circuit of the airport has two baggage entry branches and two baggage exit branches, resulting in four different routes for the AMRs, with an average length of 313 m. The AMRs operate at four different speeds along the circuit: a slow speed of 3 m/s, a slightly higher speed of 4 m/s, a medium speed of 5 m/s, and a high speed of 7.5 m/s. Furthermore, baggage pickup and drop-off on the entry and exit points take 2 seconds.

The AMRs are simulated by fuzzy agents, and the airport circuit is represented by a directed graph. This graph has 17 nodes (Figure 3): 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).

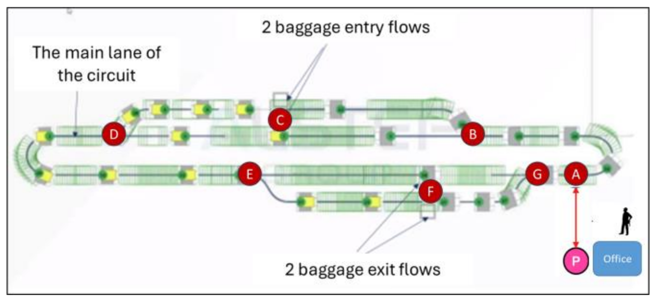

Figure 2. The circuit of the simulation Application: *A* is the input/output of the circuit; *B* and *E* are 2 points of divergence; *D* and *G* are 2 points of convergence; *C* are the 2 points of baggage collection; *F* are the 2 points of baggage drop-off; and *P* is the parking.

TABLE I. THE SEVEN PROBLEMATIC POINTS OF THE CIRCUIT

Points	Problem description	Strategies	DAIC
A	Management of AMR I/O on the circuit.	Round robin / On-demand / Prédiction	C, K, L
B	Managing the divergence between the two branches leading to R1 or R2	Random / Alternative / On-demand / Prediction	C, K
C	Baggage handling in R1 or R2	The absence of baggage is penalized.	C, K
D	Convergence management (collision avoidance) between the two branches comes from R1 or R2	Random / Alternative / Centralized or decentralized collision avoidance algorithm	C, K, L
E	Managing the divergence between the two branches leading to D1 or D2	Random / Alternative / On-demand / Prediction	C, K
F	Baggage drop-off management in D1 or D2	The absence of baggage is penalized	C, K
G	Convergence management (collision avoidance) between the two branches comes from D1 or D2	Random / Alternative / Centralized or decentralized collision avoidance algorithm	C, K, L

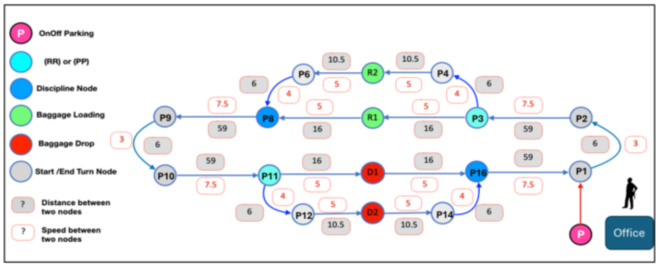

Figure 3. The circuit-directed-graph where nodes represent the characteristic points of the circuit, and edges are labeled with the segment lengths (distances between two nodes) and the permitted speeds on those segments.

The simulation application is developed in Python. Figure 4 presents the object and agent architecture of this simulator: Static objects are represented in blue, dynamic agents in red, and fuzzy agents in green. Infrastructure can be deployed in this environment. It includes a traffic plan (circuit composed of baggage entry and exit points, battery charging stations, and using a map), different types of test airports in which planes loaded with baggage arrive which will be processed by the AMRs (managing physical components, such as a Lidar, and abstract components such as a path), a supervisor which can possibly allocate baggage to AMRs according to specific strategies. Static or dynamic obstacles (e.g., operators or broken-down AMRs) can also be activated in this simulation environment.

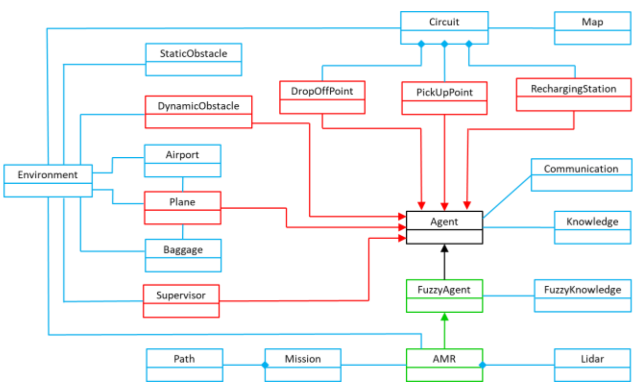

Figure 4. UML class-diagram of the fuzzy-agent based simulator.

The visualization of simulations and the evolution of performance indicators can be followed using the human-machine interface (HMI) shown in Figure 5. This HMI allows for the modeling and simulation of the dynamic behavior of the baggage handling system with its AMRs. It provides a graphical representation of the circuit elements and facilitates the analysis of flows and interactions at critical points. The main functionalities of this HMI are as follows:

- visualization of the complete circuit with the main lane, the two-baggage entry and exit branches, and the parking area,
- configuration of the parameters of AMR agents (speed, capacity, traffic logic and strategy, baggage arrival scenario),
- selection and control/tracking of a specific AMR agent,
- definition of incoming and outgoing baggage flows,
- visualization of queues/blockages at critical points in the circuit: intersections, convergence and divergence zones,
- visualization of performance indicator values distributed across three levels: simulation, bags, and AMR agent,
- monitoring battery charging in the parking lot,
- display of messages defined in the application in the console.

This interface is therefore an essential tool for testing different AMR and baggage management strategies, for analyzing the impact of flow variations on system performance, and for optimizing the circuit configuration before any physical experimentation. Thus, it allows us to measure indicators as varied as the maximum number of bags/h passing through the main track, the maximum number of bags/h passing through the two entry points, the maximum number of bags/h passing through the two exit points, or the number of AMR agents required for a maximum flow.

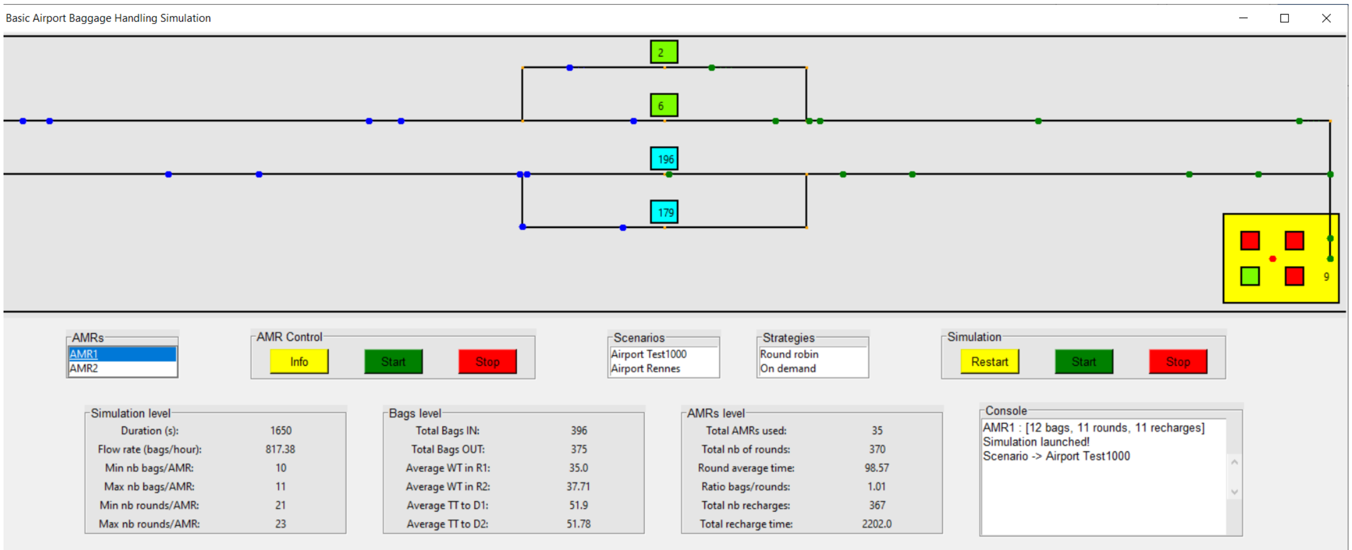

Figure 5. HMI of the simulation application.

To study the performance of the solutions considered in our simulations, we defined an optimization system where the objectives are:

1) to minimize the number of AMR, noted as x;
2) to maximize the bag throughput per hour, noted as y,
3) to minimize the recharge time of an AMR per hour, noted as z.

In ideal conditions, an AMR picks up one bag each turn, a level of performance that we will analyze in Section IV, based on three types of strategies deployed by the AMRs.

This optimization system (OS) is defined in Figure 6, where $Max(x)$ is the maximum number of AMRs; L_{avg} is the average length of the circuit; d_s is the safety distance between 2 AMRs; 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 AMR during one hour; and v_{avg} is the average speed of the AMRs on the circuit.

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

Given:

$L_{avg} = 313,\ v_{avg} = 5,$
$d_s = 8,\ t_1 = t_2 = 2$
$z \approx 10\%$ of AMR's activity, if $t_1 = 0$

Then for an hour:

$z = 10\% * 3600 = 360\ s$
$Max(x) = L_{avg} / d = 313 / 8 \approx 40$ AMRs
$T_0 = (L_{avg} / v_{avg}) + (t_2 + t_3) = 313 / 5 + 4 \approx 67\ s$
$y = \left({}^{(3600-z)}/_{T_0}\right) * x = 1897$ bags

Figure 6. Optimization system defined for this study.

An initial study focused on the sizing of the problem (traffic plan, maximum number of AMRs, determination of applicable speeds, distances between AMRs, energy consumption of these AMRs, etc.) [15], followed by a Petri nets-based simulation of the AMR behavior in function of strategies of baggage handling developed (Figure 7), allowed us to set the following parameters:

- $Max(x) = 40,\ L_{avg} = 313,\ v_{avg} = 5,\ d_s = 8,\ t_2 = t_3 = 2,$
- and $z \approx 10\%$ of the AMRs operating time if t_1 is equal to zero.

Following this initial study, we conducted our first simulations to determine the optimal number of AMRs to ensure the best baggage throughput on the route. The simulations involved 1,000 bags processed by AMRs implementing the "Round Robin" strategy. We varied the number of AMRs from 23 to 45 and obtained the best result with 31 AMRs (the shortest time to process the 1,000 bags), as shown in Figure 8. Figure 9 complements this study by showing the number of rounds traveled by all these AMRs during the different simulations, thus illustrating the energy impact associated with increasing or decreasing the number of AMRs (the distance traveled being converted into electrical consumption).

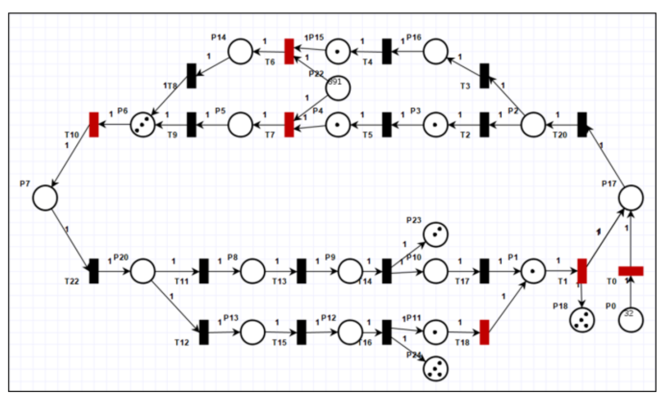

Figure 7. Petri net model of the circuit in Figure 2. It allows us to simulate a solution, while verifying that it retains the properties of liveness (non-blocking) and bounding of quantitative parameters such as the number of AMRs. The transitions in red indicate the possible evolution of the Petri net.

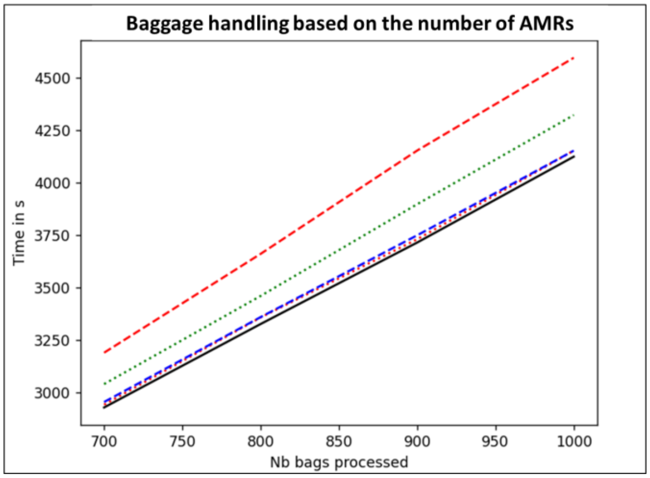

Figure 8. Partial graph representing the time taken to process 1000 bags by an AMR fleet comprising several vehicles varying from 23 to 39: 23 (red dashes), 27 (green dotted lines), 31 (solid black line), 35 (red dotted lines), and 39 (blue dashes).

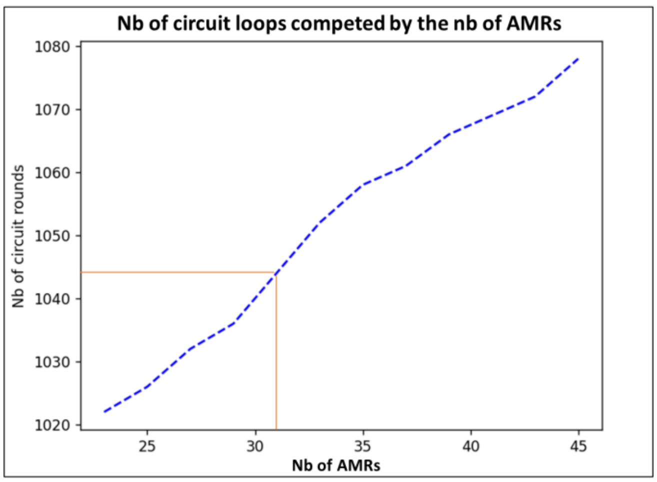

Figure 9. Graph representing the number of circuit laps completed by an AMR fleet comprising several vehicles varying from 23 to 45 (the optimum for bag processing with 31 AMRs is located on the curve).

B. Behaviors of AMRs

As defined in the agent-based systems design methodology, one of the steps is to model the behavior of the agents in the form of an activity or state diagram. The AMR agents in the simulation will have a behavior adapted to the strategy implemented to process the baggage.

Thus, Figures 10 to 12 present the Petri nets modeling the behavior of AMR agents, respectively: according to the “Round robin” strategy, which consists of continuously looping on the circuit as long as there is baggage to process (Figure 10); according to the “On-demand” strategy, which consists of allocating missions to AMRs when baggage arrives on the entry points (Figure 11); and according to the fuzzy logic prediction strategy (noted “FL Prediction” strategy), which consists of forecasting the need for AMRs in circulation based on baggage arrivals and the number of AMRs already present on the circuit (Figure 12).

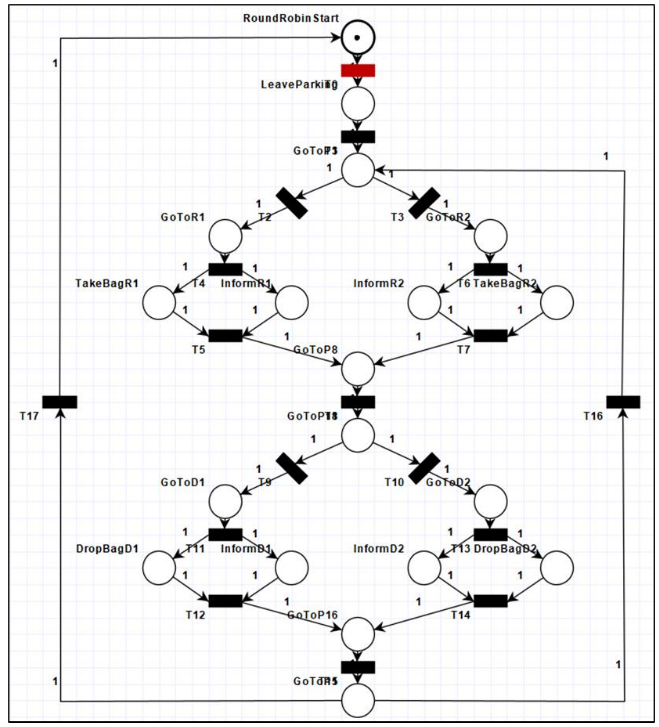

Figure 10. AMR agent behavior based on “Round robin” strategy

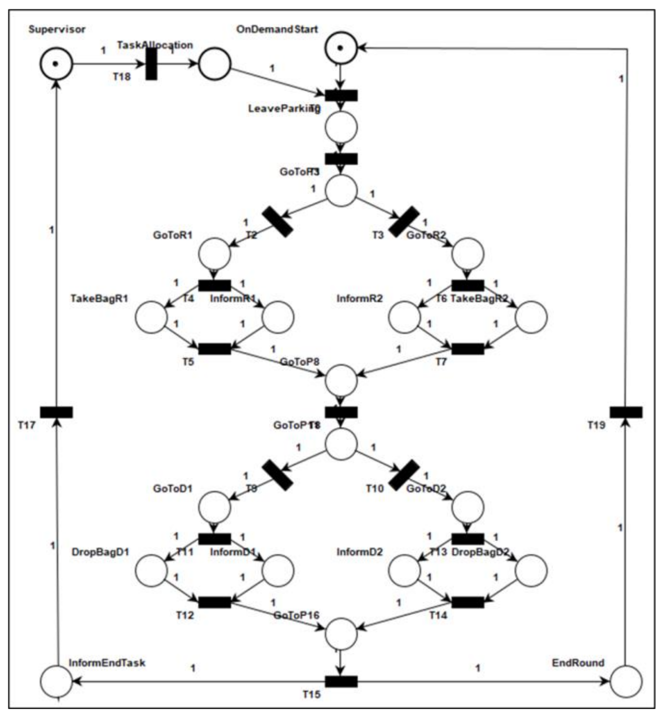

Figure 11. AMR agent behavior based on “On-Demand” strategy

C. Fuzzy knowledge of AMR agents

AMR agents are fuzzy agents that therefore have fuzzy knowledge. In this simulation, 2 types of fuzzy inferences are considered: the prediction of the number of AMRs that must circulate to process baggage, and the determination of the branch to choose to take a baggage (passage through R1 or R2). For the fuzzy knowledge acquisition phase, and therefore the determination of the linguistic variables and their different value ranges, we did not consult a domain expert. We defined an initial ad hoc model, which we refined through our simulations.

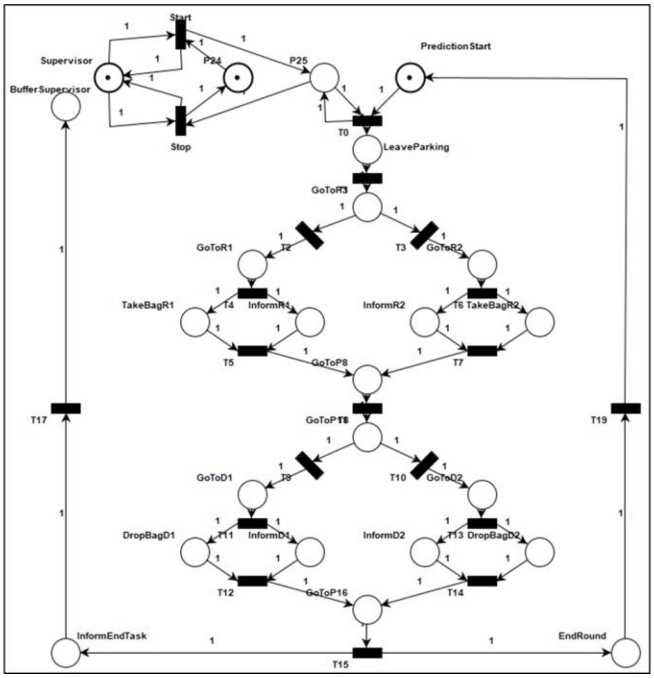

Figure 12. AMR agent behavior based on “Prediction” strategy

To predict the number of AMRs expected to circulate on the circuit at a given time, AMR fuzzy agents use 3 linguistic variables (Figure 13) and 9 rules (Table II):

- **NbBag**. This variable represents the number of bags waiting at entry points *R1* and *R2*. It is described by three linguistic values: *low*, *medium*, and *high*. The universe of discourse varies depending on the simulations and the requirement for the maximum number of bags waiting. For the present case study, we defined the interval from 0 to 20 bags. Thus, *low*, whose membership function is trapezoidal, has the value interval [0, 6]; *medium*, whose membership function is triangular, has the value interval [2, 14]; and *high*, whose membership function is trapezoidal, has the value interval [10, 20].
- **NbAMR**. This variable represents the number of AMRs circulating on the circuit at a given time. It is described by three linguistic values: *low*, *medium*, and *high*. The universe of discourse varies depending on the simulations and the circuit size (depending on the circuit, an initial study determines the maximum number of AMRs that can circulate while respecting safety distances). For the present case study, we have defined the interval from 0 to 40 AMRs. Thus, *low*, whose membership function is trapezoidal, has the interval [0, 15]; *medium*, whose membership function is triangular, has the interval [5, 25]; and *high*, whose membership function is trapezoidal, has the interval [15, 30].
- **Prediction**. This variable indicates the number of AMRs that should be brought into the circuit or removed from the circuit at a given time. It is described by five linguistic values: *highDecrease*, *decrease*, *stable*, *increase*, and *highIncrease*. The universe of discourse varies according to the frequency of the predictions (if this frequency is low, the interval will be wider than that of a higher frequency). For the present case study, we have defined the interval as -10 to 10. Thus, *highDecrease*, whose membership function is trapezoidal, has the interval [-10, -5]; *decrease*, whose membership function is triangular, has the interval [-10, 0]; *stable*, whose membership function is triangular, has the interval [-5, 5]; *increase*, whose membership function is triangular, has the interval [0, 10]; and *highIncrease*, whose membership function is trapezoidal, has the value interval [5, 10].

TABLE II. THE 9 RULES USED FOR FUZZY INFERENCE "PREDICTION"

Rule ID	Rule
R1	`IF NbBag IS Low AND NbAMR IS High` `HEN Prediction IS HighDecrease`
R2	`IF NbBag IS Low AND NbAMR IS Medium` `THEN Prediction IS Decrease`
R3	`IF NbBag IS Low AND NbAMR IS Low` `THEN Prediction IS Stable`
R4	`IF NbBag IS Medium AND NbAMR IS High` `THEN Prediction IS Decrease`
R5	`IF NbBag IS Medium AND NbAMR IS Medium` `THEN Prediction IS Stable`
R6	`IF NbBag IS Medium AND NbAMR IS Low` `THEN Prediction IS Increase`
R7	`IF NbBag IS High AND NbAMR IS High` `THEN Prediction IS Stable`
R8	`IF NbBag IS High AND NbAMR IS Medium` `THEN Prediction IS Increase`
R9	`IF NbBag IS High AND NbAMR IS Low` `THEN Prediction IS HighIncrease`

To choose which branch leading to R1 or R2 they will take at a given time, the AMR fuzzy agents use five linguistic variables: (Figure 14) and 18 rules (Table III):

- **NbBagInR1** and **NbBagInR2**. These variables represent the number of bags waiting at entry points *R1* and *R2*. They are described by three linguistic values: *low*, *medium*, and *high*. The universe of discourse varies depending on the simulations and the requirement for the maximum number of bags waiting. For the present case study, we defined the interval from 0 to 100 bags. Thus, *low*, whose membership function is trapezoidal, has the value interval [0, 20]; *medium*, whose membership function is triangular, has the value interval [0, 50]; and *high*, whose membership function is trapezoidal, has the value interval [30, 100].

- **NbAMRToR1** and **NbAMRToR2**. These variables represent the number of AMRs circulating on the circuit at a given time. They are described by three linguistic values: *low*, *medium*, and *high*. The universe of discourse varies depending on the simulations and the branch size. For the present case study, we have defined the interval from 0 to 10 AMRs. Thus, *low*, whose membership function is trapezoidal, has the interval [0, 3]; *medium*, whose membership function is triangular, has the interval [1, 5]; and *high*, whose membership function is trapezoidal, has the interval [3, 10].
- **GoTo**. This variable indicates the branch that the AMRs should take at a given time. It is described by two linguistic values: *R1* and *R2*. The universe of discourse is defined as the interval 0 to 10, and the two membership functions of *R1* and *R2* are trapezoidal. Thus, *R1* has the interval of value [0, 6] and *R2*, has the interval of value [4, 10].

TABLE III. THE 18 RULES USED FOR FUZZY INFERENCE "GOTO"

Rule ID	Rule
R1	`IF NbBagInR1 IS Low AND NbAMRToR1 IS High THEN GoTo IS R2`
R2	`IF NbBagInR1 IS Low AND NbAMRToR1 IS Medium THEN GoTo IS R2`
R3	`IF NbBagInR1 IS Low AND NbAMRToR1 IS Low AND NbAMRToR2 IS Medium THEN GoTo IS R1`
R4	`IF NbBagInR1 IS Medium AND NbAMRToR1 IS High THEN GoTo IS R2`
R5	`IF NbBagInR1 IS Medium AND NbAMRToR1 IS Medium THEN GoTo IS R1`
R6	`IF NbBagInR1 IS Medium AND NbAMRToR1 IS Low THEN GoTo IS R1`
R7	`IF NbBagInR1 IS High AND NbAMRToR1 IS High THEN GoTo IS R2`
R8	`IF NbBagInR1 IS High AND NbAMRToR1 IS Medium AND NbAMRToR2 IS Medium THEN GoTo IS R1`
R9	`IF NbBagInR1 IS High AND NbAMRToR1 IS Low THEN GoTo IS R1`
R10	`IF NbBagInR2 IS Low AND NbAMRToR2 IS High THEN GoTo IS R1`
R11	`IF NbBagInR2 IS Low AND NbAMRToR2 IS Medium THEN GoTo IS R1`
R12	`IF NbBagInR2 IS Low AND NbAMRToR2 IS Low AND NbAMRToR1 IS Medium THEN GoTo IS R2`
R13	`IF NbBagInR2 IS Medium AND NbAMRToR2 IS High THEN GoTo IS R1`
R14	`IF NbBagInR2 IS Medium AND NbAMRToR2 IS Medium THEN GoTo IS R2`
R15	`IF NbBagInR2 IS Medium AND NbAMRToR2 IS Low THEN GoTo IS R2`
R16	`IF NbBagInR2 IS High AND NbAMRToR2 IS High THEN GoTo IS R1`
R17	`IF NbBagInR2 IS High AND NbAMRToR2 IS Medium AND NbAMRToR1 IS Medium THEN GoTo IS R2`
R18	`IF NbBagInR2 IS High AND NbAMRToR2 IS Low THEN GoTo IS R2`

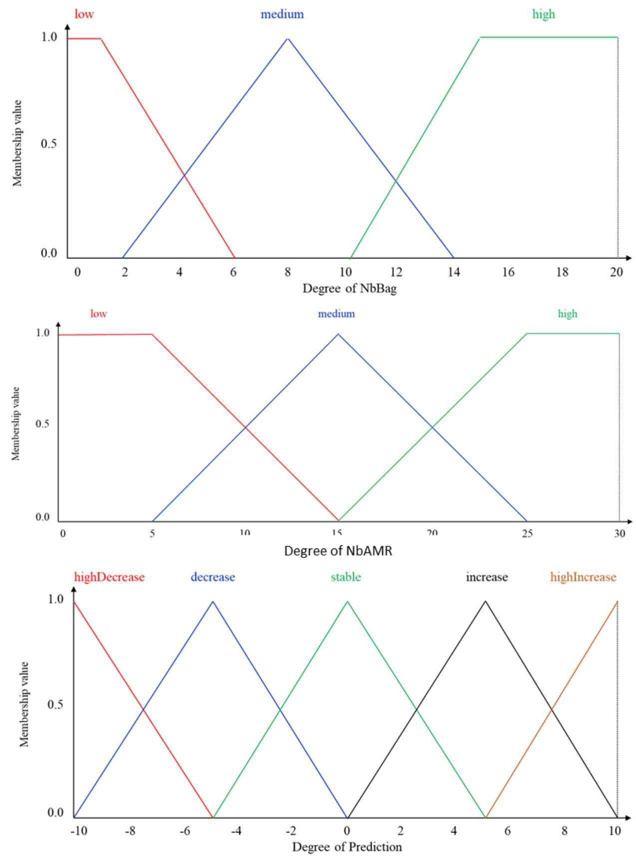

Figure 13. Linguistic variables to predict whether an AMR should circulate.

D. The three strategies considered

The objective is to determine an efficient strategy for handling baggage arriving at the two entry points of the circuit, based on two criteria: ensuring the best baggage throughput and limiting the energy consumption of the AMRs (i.e., minimizing the total distance traveled by the fleet's AMRs). Three distinct strategies were simulated to test them and establish their performance on the system:

- **Round robin**. The AMR agents perform a continuous rotation around the circuit and pick up baggage if any is available at the circuit's entry point according to their route (passing through R1 or R2).
- **On-demand**. Baggage arriving at R1 or R2 is assigned to available AMR agents in the parking area or along the route. An AMR agent that has dropped off baggage at D1 or D2 returns to the parking area if it has no new baggage assigned.
- **Fuzzy logic-based demand prediction**. The number of AMR fuzzy agents 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 [47], 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 this airport (for instance, the French airport of Rennes).

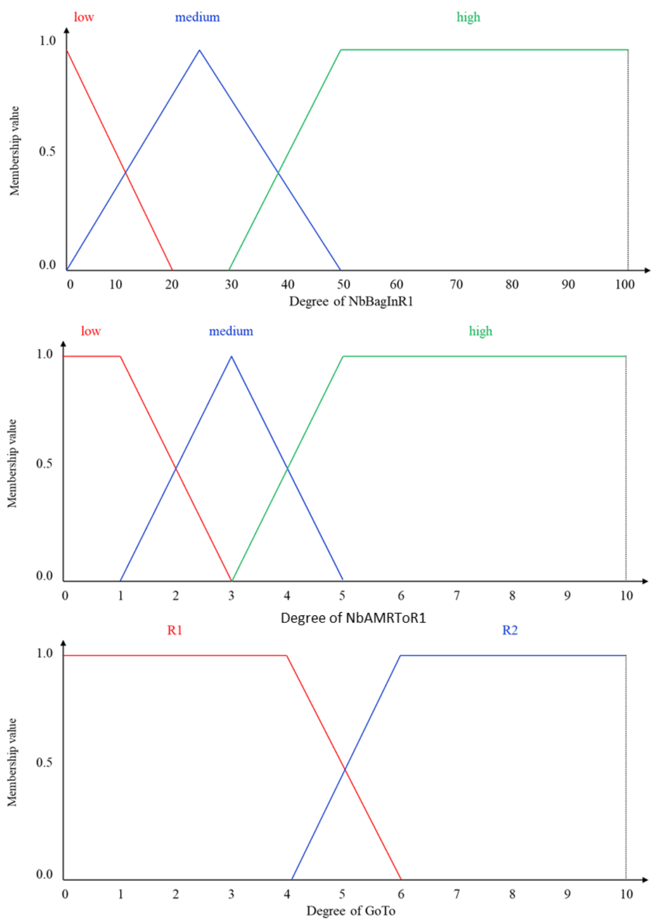

Figure 14. Linguistic variables for an AMR to choose one of the 2 branches.

- **Sc2 – Random Data**. Baggage arrival is randomly simulated over a period of one hour. This 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 nine simulations carried out according to the specifications formulated in the previous Section (three scenarios were tested, each using three different strategies). The five performance criteria selected, in accordance with the optimization system presented in Figure 6, are:

1) The simulation duration, i.e., the processing time for all baggage entering the simulated scenario, as well as the battery recharge time for all AMR agents that have been in operation.
2) The hourly throughput, i.e., the number of bags processed per hour (adjusted to an hourly rate if necessary).
3) The number of circuit loops completed by the AMR agents to process all the baggage.
4) The average waiting time for baggage at entry points before it is taken over by an AMR agent.
5) The impact of AMR agent charging times on performance (this impact is estimated by default at 10% of the AMR operating time).

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

Results regarding total simulation duration (Table IV)**.** With the exception of the 1 hour 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 AMR agents when baggage arrives by determining the right traffic branches, which is not the case for AMR agents in the "Round robin" strategy.

Results regarding the total number of bags processed (Table V)**.** 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 VI)**.** 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 “FL Prediction” strategy (1807 bags/h on average over the 3 scenarios).

Results regarding the total number of loops made by the AMR agents (Table VII)**.** 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 AMR agent loops 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 AMR agent 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 AMR agent (Table VIII)**.** 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 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 AMR agent recharge times (Table IX)**.** The AMR agents 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 AMRs), recharge every 10 laps of the circuit (every 10 x 66s = 660s, on average), recharge, if possible, when the AMR agents are in the parking lot and recharge all the AMR agents at the end of the simulation. Table IX 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 AMRs to be fully charged again). The results provided by the on-demand strategy are the best, although at the cost of many charges (when the AMRs 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 IV. 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 V. 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 VI. 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 VII. NUMBER OF LOOPS COMPLETED BY THE AMR AGENTS

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

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

V. Discussion

The previous section presented the results obtained from fuzzy agent-based simulations. The objective was to evaluate the performance of the AMRs on a reference circuit (Figure 2), to validate the hypotheses formulated in the first theoretical study, to identify critical points, and to measure the impact of operational parameters on:

- Average transit/circulation times and delay distribution. The AMRs follow predefined paths, allowing the average time required to complete a mission to be measured. The influence of traffic density and priorities can therefore be quantified and then analyzed.
- Blockages and waiting times at intersections and convergence/divergence zones. Intersections and convergence points are identified as critical areas where queues form. Simulations were used to determine the average queue length and the probability of blockage for different configurations.
- Overall throughput and use of critical zones. The maximum number of AMRs that can circulate simultaneously without degrading throughput was estimated at 31, allowing the optimal circuit capacity to be determined.
- The impact of different control strategies on system operation.

This approach made it possible to compare the performance of the proposed solutions and to identify the optimal conditions for stable, smooth, and efficient operation of AMRs. Thus, the performance of a looped circuit using AMRs depends on a delicate balance between: transport capacity (entry and exit points, distances), the speed and synchronization of pickups/deposits, and flow management at intersections (convergence/divergence). Incorrect sizing or an imbalance between these factors quickly leads to saturation, while a harmonized configuration ensures the smooth, stable, and efficient flow of traffic.

Regarding the speeds of the AMRs on the circuit (speeds arbitrarily defined in Figure 3), the simulations highlighted what the preliminary analysis had already revealed:

- An average speed (5 m/s) promotes a more balanced distribution between the main and secondary tracks and allows for a higher number of AMRs without loss of flow.
- A maximum speed (7.5 m/s) locally increases the flow on the main track but requires limiting the number of AMRs on the circuit to avoid congestion.

We then sought to determine the optimal speed distribution strategy on the circuit, allowing us to reduce the duration of a mission while minimizing energy consumption. Four strategies were thus simulated:

- **StrategySpeed_1**: The speed strategy illustrated in Figure 3.
- **StrategySpeed_2**: the same speed profile as *StrategySpeed_1* for all stops, except that the average speed of 5 m/s is replaced by the maximum speed of 7.5 m/s.
- **StrategySpeed_3**: all speeds are set to the minimum value of 3 m/s.
- **StrategySpeed_4**: the same speed profile as *StrategySpeed_1*, except that on long-distance segments the maximum speed of 7.5 m/s is replaced by the average speed of 5 m/s.

The duration of an AMR mission on the circuit (Figure 3) differs for each of the four speed strategies, as it depends on a fixed travel distance and on a varying speed profile. It can therefore be shown that the maximum system throughput, defined as the number of baggage units that can be handled per unit of time, is higher when using *StrategySpeed_1*.

The maximum system throughput, denoted by λ_{max}, is given by the ratio between the maximum number of AMRs $Max(x)$ and the average duration of a circuit lap T_0. For instance, using the speed profile shown in Figure 3, if the number of AMRs present on the circuit is 31 and an AMR takes 60 s on average to complete one lap, λ_{max} will be defined by (3):

$$\lambda_{max} = Max(x) / T_0 = 31 / 60 = 0.52 \text{ bags/s} \qquad (3)$$

Assuming that the maximum number of AMRs, $Max(x)$, is fixed for all four strategies, the minimum mission durations T_0 can be ranked according to the speed strategies as follows: *StrategySpeed_2*, *StrategySpeed_1*, *StrategySpeed_4*, and *StrategySpeed_3*. This ranking can be explained by the fact that the mission duration varies only with the speed profile, since all other parameters are fixed, as shown in the mathematical model presented in Figure 6. Consequently, the maximum system throughput λ_{max} follows the same ranking.

However, *StrategySpeed_2* consumes more energy than *StrategySpeed_1*, since the cost function we established in [15] increases with speed.

VI. Conclusion and Perspectives

In this article, we have presented a fuzzy agent-based modeling and simulation framework with the aim of better understanding the dynamic and uncertain situations encountered in the activity of complex systems such as baggage handling systems in airports.

We introduced the general framework for modeling 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 also important to note that the modeling of fuzzy agents is based on the fuzzy nature of knowledge, behaviors, 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 AMR.

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 AMRs 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 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 [48] and [49]. This is to give AMR agents the ability to better adapt in unforeseen situations during their modeling, and to adjust their fuzzy knowledge when extracting it from human experts is difficult or problematic (uncertain knowledge or approximate fuzzy modeling).

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 AMRs alone, and thus improve practical credibility for Airport 4.0 stakeholders.

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