Fuzzy Agent-Based Simulations of Cooperative Strategies for Task Allocation, Collision Avoidance, and Battery Charging Management of Autonomous Industrial Vehicles

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***Abstract*—The paper presents a multi-agent simulation using fuzzy inference to explore the task allocation, collision avoidance, and battery charging management of mobile baggage conveyor robots in an airport, in an integrated way. The approach leverages V2X cooperation to enable real-time communication between mobile robots and airport infrastructure, enhancing adaptability thanks to a distributed system, adapting to variations in the availability of conveyor agents, their battery capacity, infrastructure resource availability, and awareness of the activity of the conveyor fleet. Dynamic factors, such as workload variations and communication between the conveyor agents and infrastructure are considered as heuristics, highlighting the importance of flexible and collaborative approaches in autonomous systems. The results highlight the effectiveness of adaptive fuzzy multi-agent models to optimize dynamic task allocation, adapt to the variation of baggage arrival flows, improve the overall operational efficiency of conveyor agents, and collision avoidance, and reduce their energy consumption through V2X-enabled cooperation.**

Keywords-autonomous industrial vehicle; dynamic task allocation; collision avoidance; V2X cooperation; fuzzy agent; agent-based simulation; Airport 4.0.

I. Introduction

This article significantly extends our previous conference paper [1], which initially introduced a fuzzy agent-based simulation of task allocation and battery charge management. In this extended version, we incorporate collision avoidance mechanisms, integrate V2X communication for real-time coordination with infrastructure, and enhance the multi-agent framework to support richer, more realistic scenarios with improved adaptability and operational efficiency. The deployment of Autonomous Industrial Vehicle (AIV) fleets in the context of Airport 4.0 raises several issues, all related to their real level of autonomy: acceptance by employees, vehicle localization, traffic flow, failure detection, collision avoidance and vehicle perception in changing environments. Simulation makes it possible to take into account the various constraints and requirements formulated by manufacturers and future users of these AIVs. Before starting to test AIV fleet traffic scenarios in often-complex airport situations, it is wise, if not essential, to simulate these scenarios [2]. Moreover, one of the main advantages of using simulations is that the results can be used without the need to apply a scaling factor. The main advantages of simulating mobile robot or AIV operations are: reducing the time and cost of developing an AIV, minimizing potential operational risks associated with AIVs, allowing to assessment of the feasibility of different AIV circulation scenarios at a strategic or operational level, allowing a rapid understanding of the operations carried out by AIVs, and identifying improvements in the layout configurations of the facilities hosting these AIVs [3]. Simulation also provides flexibility in terms of AIV deployment and allows studying the sharing of responsibility between the central server and the robots (local/global or centralized/decentralized balance) for the different operational decisions. Another advantage of simulations is to introduce humans into the scenarios in order to verify and validate, before the actual deployment of autonomous mobile robots, the safety of the coexistence and possible interactions between these AIVs and human operators [4]. Agent-based approaches are often proposed for the simulation of autonomous vehicles. They offer simulation contexts ranging from trajectory planning to optimal task allocation while allowing collision and obstacle avoidance [5]. Our current research focuses on the use of fuzzy agents to handle the levels of imprecision and uncertainty involved in modeling the behavior of simulated vehicles [6]. Indeed, fuzzy set theory is well suited to the processing of uncertain or imprecise information that must lead to decision-making by autonomous agents, used in activities such as the simulation of AIVs in an airport or product design [7]. Fuzzy agents can track the evolution of fuzzy information from their environment and from agents [8]. By interpreting the fuzzy information they receive or perceive, fuzzy agents interact within the multi-agent system of which they are a part. For example, a fuzzy agent can discriminate a fuzzy interaction value to assess its degree of affinity (or interest) with another fuzzy agent [9]. Thus, we develop a comprehensive study on utilizing fuzzy inference within multi-agent simulations to optimize task allocation and battery management for mobile baggage conveyor robots in airports. The proposed simulation approach is designed to be highly adaptable, considering dynamic factors such as workload variations, battery capacities, and communication between agents and infrastructure. The results demonstrate that this adaptive fuzzy multi-agent model can significantly improve operational efficiency, adapt to variations in baggage arrival flows, and reduce energy consumption. This article is structured as follows: first in Section II, we present a state-of-the-art review of major concepts of fleets of AIV: task allocation, obstacle avoidance, battery recharging, V2X cooperation, and fuzzy agent-based simulation. Then, in Section III, we introduce a case study on fuzzy agent-based simulations of mobile baggage conveyors in an airport, where we present the simulation framework, the use of V2X cooperation, and task allocation strategies, both basic and fuzzy. We also integrate collision avoidance and speed adaptation into the simulations. In Section IV, we propose three improvements using fuzzy heuristics. Finally, we conclude on the proposed fuzzy dynamic task allocation strategies and present future research directions.

II. Major Concepts

A. Task Allocation

Task Allocation (TA) consists of optimally assigning a set of tasks to be performed by agents, actors, robots, or processes, grouped and organized within a cohesive system. This is the case for mobile multi-robot systems [10], AIV fleets [11], and applications in airports [12]. In the field of mobile robotics, the taxonomy presented in [13] has been defined to better characterize allocation and assignment functions to robots: Single Task for a Single Robot (STSR), Multiple Tasks for a Single Robot (MTSR), and Multiple Tasks for Multiple Robots (MTMR). These classifications enable tasks to be assigned to one or multiple robots, with various tasks being allocated to heterogeneous or multitasking robots. Moreover, De Ryck et al. [13] defined also: allocation modalities, such as instantaneous allocation or allocation extended in time. This last is linked to synchronization and precedent or time window constraints. As many combinations as exhaustively detailed by numerous surveys on the issue of multi-robot TA. Different solution models have been proposed for TA: based on optimization: exact algorithms, dynamic programming, (meta-)heuristics [10]; based on the Contract Net Protocol: inside an agent-based system, an initiating agent sends a call for proposals to all agents, chooses the best proposal received, and then informs all agents [11]; based on the concept of the market: announcement by an auctioneer, submission by bidders, selection by the auctioneer and award by the auctioneer [14]. Furthermore, different types of optimization objectives can be defined for this task allocation [13]: cost objectives (travel costs, such as time, distance, or fuel consumption), behavior objectives (ability of a robot to perform a task), reward objectives (payoff for performing a task), priority objectives (urgency to perform a task), and utility objectives (subtracting the cost from the reward or fitness). Task allocation and planning are often managed centrally, even semi-centrally when global and local planning are differentiated [15]. For the proper functioning of autonomous and dynamic systems, the requirements of flexibility, robustness and scalability, lead to consider decentralized mechanisms to react to unexpected situations. Autonomy and decentralization are two excessively linked notions to the extent that an autonomous system operates and makes decisions autonomously [16]. The problem of task allocation can also be thought of in a decentralized way [13]. For reasons of flexibility, robustness and scalability necessary in an Industry 4.0 or Airport 4.0 context, we are interested in decentralized task allocation solutions. These solutions, decomposed below, must be able to assign tasks to a fleet of robots. Particularly, solutions based on the market concept can easily be applied in a distributed context, where each mobile robot can become an auctioneer [17]. For each situation, a single mobile robot is appointed auctioneer and retains this role until the situation is definitively managed.

B. Obstacle Avoidance

Obstacle avoidance is a critical challenge in the deployment of AIV fleets, especially in dynamic and complex environments such as airports. It ensures safe and efficient navigation by preventing collisions with static and dynamic obstacles while maintaining operational efficiency. Currently, avoidance strategies are often implemented on a per-robot basis [18], without a coordinated collective approach. However, in the context of AIV fleets, a collective approach that incorporates multi-robot communication and coordination can significantly enhance adaptability and efficiency. Effective obstacle avoidance strategies must integrate three key components:

- Obstacle perception/detection: AIVs rely on onboard sensors (e.g., LiDAR, cameras, ultrasonic sensors) and perception algorithms to detect obstacles [19]. For this study, we assume that robots are already equipped with effective sensors and algorithms for detecting obstacles.
- Rerouting/trajectory planning: Once an obstacle is detected, AIVs must compute an alternative trajectory. While various rerouting methods exist, we focus on broader strategic decisions rather than specific algorithms of path planning or path finding [20, 21].
- Overall strategy decisions: Effective obstacle avoidance requires real-time decision-making mechanisms that adapt to both static and dynamic obstacles. This is the key focus of our study, as we are primarily interested in high-level decision-making mechanisms that enable effective obstacle avoidance in multi-robot systems. This includes multi-robot communication and coordination strategies, as well as real-time decision-making processes and algorithms.

Simulations play a crucial role in evaluating and optimizing obstacle avoidance strategies before real-world deployment.

C. Battery Recharging

Effective energy management is crucial for AIVs as it directly affects their operational efficiency and autonomy. Managing energy resources involves monitoring battery status, detecting technical anomalies, and performing necessary maintenance, as highlighted by [22]. Optimizing energy consumption requires a holistic approach that considers operational availability, energy efficiency [23], collaboration with dynamic infrastructure, and adaptation to changing conditions. Battery recharging in AIVs must balance individual and collective energy needs to maximize system efficiency. This balance is achieved through two key decision-making principles: 1. Local Equilibrium – Each AIV optimizes its own recharging schedule to maintain operational readiness. An AIV may initiate recharging when its battery level drops below a predefined threshold, ensuring it can complete assigned tasks without disruptions. 2. Global Equilibrium – This approach considers the energy demands of the entire fleet and the surrounding infrastructure [24]. Coordinating fleet-wide energy consumption prevents congestion at charging stations, reduces power spikes, and improves overall system efficiency. Strategies such as staggered recharging schedules, shared infrastructure utilization, and workload-based energy distribution help maintain global equilibrium. To ensure effective energy management, AIVs must strike a balance between these two levels: - Individual Decision-Making: Each AIV must autonomously determine its recharging needs based on real-time energy levels, workload, and immediate operational requirements [22]. This minimizes the risk of energy depletion while maintaining vehicle autonomy. - Collective Coordination: Simultaneously, AIVs must communicate and synchronize their charging needs with one another and with the infrastructure. This prevents bottlenecks caused by simultaneous charging demands and enhances overall system efficiency. A key objective in battery recharging is to optimize recharging cycles to minimize energy costs and avoid excessive power consumption during low-demand periods. Poor anticipation of energy needs can lead to inefficiencies and reduced system availability. Since AIV workloads fluctuate—alternating between high-activity and low-intensity phases—aligning energy consumption with operational demand ensures continuous and efficient performance. Reducing energy consumption is a major challenge for mobile robots, requiring optimization through well-defined cost functions. Power consumption is often modeled based on parameters such as speed and motor force [25, 26]. Various optimization techniques have been proposed such as:

- Genetic Algorithms – Methods such as those in [27] utilize genetic algorithms to minimize energy consumption through an optimal fuzzy logic controller.
- Fuzzy Logic Optimization – Mamdani fuzzy logic [28] optimizes speed profiles (trapezoidal/triangular) for both straight and curved paths to reduce power consumption.
- Pontryagin's Maximum Principle (PMP) – Applied in the railway sector [29], this principle optimizes train speed trajectories based on braking distance and can be adapted for AIV movement strategies.
- Power Integral Functions – These models refine AIV movement strategies to minimize overall energy usage by optimizing acceleration and deceleration patterns.

D. V2X Cooperation

To effectively complete assigned tasks, AIVs must coordinate, cooperate, and exchange information on environmental perceptions. This cooperation relies on Vehicle-to-Everything (V2X) communication, which encompasses three key communication modes:

1) Vehicle-to-Vehicle (V2V) Communication – Direct information exchange between AIVs enhances coordination and task execution efficiency. While extensively studied in the literature, specific applications include decentralized intersection traffic light synchronization [30], cooperative lane-change simulations [31], and traffic light optimization strategies [32]. V2V enables AIVs to share navigation data and obstacle detection information, facilitating adaptive decision-making.
2) Vehicle-to-Infrastructure (V2I) Communication – AIVs communicate with the surrounding infrastructure, such as smart warehouses, to receive real-time updates on environmental changes [33]. This mode enhances safety and efficiency by allowing AIVs to receive alerts about obstacles, traffic flow modifications, and operational constraints, thereby optimizing navigation and avoiding collisions.
3) Vehicle-to-Pedestrian (V2P) Communication – In environments shared with humans, AIVs leverage V2P communication to ensure safety and seamless human-robot collaboration [34]. This interaction is crucial when an AIV encounters obstacles requiring human intervention, as it enables efficient coordination between human operators and autonomous systems.

Collectively, these three communication modes form the V2X framework [35], enabling AIVs to operate efficiently in dynamic environments through real-time data exchange and cooperative decision-making. The European Telecommunication Standards Institute (ETSI) has established standardized communication protocols for Intelligent Transport Systems (ITS), which have been adapted for AIV cooperation [36]. Two key message types support autonomous decision-making and coordination:

- Decentralized Environmental Notification Messages (DENM) – Defined by ETSI EN 302 637-3 [37], these messages serve as alerts during unexpected events, allowing AIVs to broadcast real-time incident notifications within a specific geographic area.
- Cooperative Perception Messages (CPM) – Standardized in ETSI TR 103 562 [38], CPMs facilitate situational awareness by transmitting obstacle detection and

navigation updates. AIVs receiving CPMs can dynamically adjust their routes, preventing disruptions and optimizing task execution. Beyond these existing standards, emerging V2V communication approaches further enhance cooperation. For example, a multi-agent control strategy for connected urban buses [39] enables real-time movement adjustments based on downstream traffic conditions. By integrating enhanced V2X communication strategies, AIV fleets can achieve higher resilience, adaptability, and operational efficiency in dynamic environments.

E. Fuzzy Agent-Based Simulation

Many agent-based approaches are proposed for the simulation of autonomous vehicles. They offer simulation contexts ranging from trajectory planning [40] to optimal task allocation while allowing collision and obstacle avoidance [41]. Our current research focuses on the use of fuzzy agents to handle the levels of imprecision and uncertainty involved in modeling the behavior of simulated vehicles [6]. Fuzzy set theory is well suited to the processing of uncertain or imprecise information that must lead to decision-making by autonomous agents [7]. Most of the control tasks performed by autonomous mobile robots have been the subject of performance improvement studies using fuzzy logic [42]: navigation [43], obstacle avoidance [44], path planning [45], motion planning [46], localization of mobile robots [47], and intelligent management of energy consumption [48, 49]. An agent-based system is fuzzy if its agents have fuzzy behaviors or if the knowledge they use is fuzzy [50]. This means that agents can have: 1) fuzzy knowledge (fuzzy decision rules, fuzzy linguistic variables, and fuzzy linguistic values); 2) fuzzy behaviors (the behaviors adopted by agents because of fuzzy inferences); and 3) fuzzy interactions, organizations, or roles. Table I below proposes a model of fuzzy agents corresponding to the principles stated above.

III. Case study: Fuzzy agent-based simulation of mobile baggage conveyors in an airport

This case study proposes the simulation of mobile robots conveying baggage fleet in an airport (we will keep the name ”AIV” for these conveyors). Fig. 1 shows the simulator's Human Computer Interface (HCI), which allows on the one hand, to visualize the arrival of baggage and the movements of 5 AIVs, and on the other hand, to follow the evolution of the different levels of indicators of the simulation (energy level, baggage level, charge level, and time level). The circulation scenario is detailed with a distance-oriented graph presented in Fig. 2.

Effective management of these AIVs requires an integrative approach that considers several factors, including the baggage arrival flow, the operational availability of the AIVs, their energy consumption, their communication, among themselves and with the infrastructure, and their adaptation to changing environmental conditions. In the case study, we analyze the

TABLE I
Fuzzy Agent Model Used in the Simulations

$$\tilde{M}_\alpha = \langle \tilde{A}, \tilde{I}, \tilde{P}, \tilde{O} \rangle \tag{1}$$

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

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

$\boldsymbol{\Phi_{\Pi(\widetilde{\alpha}_i)}}$: is the $\boldsymbol{\widetilde{\alpha}_i}$'s function of observation; $\boldsymbol{\Phi_{\Delta(\widetilde{\alpha}_i)}}$: is the $\boldsymbol{\widetilde{\alpha}_i}$'s function of decision; $\boldsymbol{\Phi_{\Gamma(\widetilde{\alpha}_i)}}$: is the $\boldsymbol{\widetilde{\alpha}_i}$'s function of action; $\boldsymbol{K_{\widetilde{\alpha}_i}}$: is the set of knowledge of the fuzzy agent $\boldsymbol{\widetilde{\alpha}_i}$.

$$\Phi_{\Pi(\widetilde{\alpha}_i)} : (E_{\widetilde{\alpha}_i} \cup I_{\widetilde{\alpha}_i}) \times \Sigma_{\widetilde{\alpha}_i} \to \Pi_{\widetilde{\alpha}_i} \tag{3}$$

$$\Phi_{\Delta(\widetilde{\alpha}_i)} : \Pi_{\widetilde{\alpha}_i} \times \Sigma_{\widetilde{\alpha}_i} \to \Delta_{\widetilde{\alpha}_i} \tag{4}$$

$$\Phi_{\Gamma(\widetilde{\alpha}_i)} : \Delta_{\widetilde{\alpha}_i} \times \Sigma \to \Gamma_{\widetilde{\alpha}_i} \tag{5}$$

$\boldsymbol{E_{\widetilde{\alpha}_i}}$: is the $\boldsymbol{\widetilde{\alpha}_i}$'s the set of fuzzy observed events; $I_{\widetilde{\alpha}_i}$: is the $\boldsymbol{\widetilde{\alpha}_i}$'s set of fuzzy interactions; $\boldsymbol{\Sigma_{\widetilde{\alpha}_i}}$: is the $\boldsymbol{\widetilde{\alpha}_i}$'s set of fuzzy states; $\boldsymbol{\Pi_{\widetilde{\alpha}_i}}$: is the $\boldsymbol{\widetilde{\alpha}_i}$'s set of fuzzy perceptions; $\boldsymbol{\Delta_{\widetilde{\alpha}_i}}$: is the $\boldsymbol{\widetilde{\alpha}_i}$'s set of fuzzy decisions; $\boldsymbol{\Gamma_{\widetilde{\alpha}_i}}$: is the $\boldsymbol{\widetilde{\alpha}_i}$'s set of fuzzy actions; $\boldsymbol{\Sigma}$: is the state of fuzzy agent-based system $\boldsymbol{\widetilde{M}_\alpha}$.

$$\widetilde{l}_l = \langle \widetilde{\alpha}_s, \widetilde{\alpha}_r, \widetilde{\gamma}_c \rangle \tag{6}$$

$\boldsymbol{\widetilde{l}_l}$: is a fuzzy interaction; $\widetilde{\alpha}_s$: is the fuzzy agent source of a fuzzy interaction; $\boldsymbol{\widetilde{\alpha}_r}$: is the fuzzy agent receiver of a fuzzy interaction; $\boldsymbol{\widetilde{\gamma}_c}$: is a fuzzy communication act (*inform, diffuse, ask, reply, and confirm*, are used in the basic model).

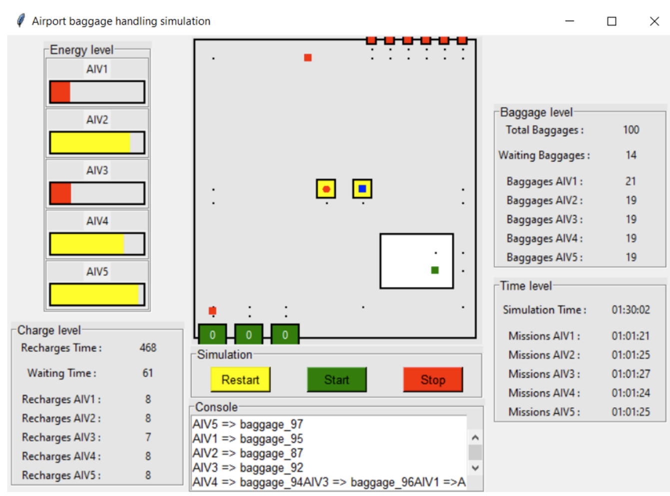

Figure 1. HCI of the simulation application

TA performed by a supervisor who questions AIVs to know their task completion costs.

The analysis is driven by three objectives aimed at optimizing TA: minimize x, maximize y, and minimize z. Where:

- x is the number of AIVs,
- y is the baggage throughput per hour,
- z is the recharge time of an AIV (in ideal conditions

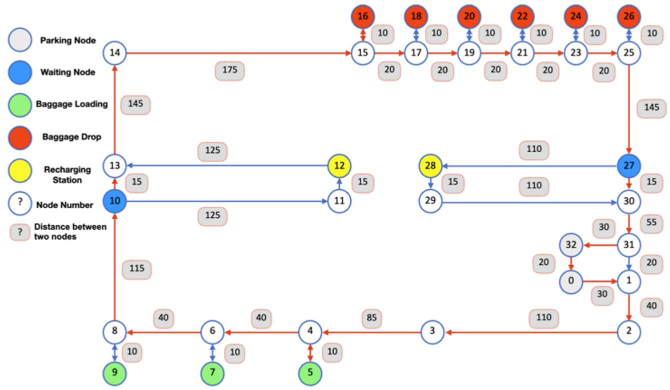

Figure 2. Oriented graph: distance in the environment in meters

where an AIV picks up one baggage per turn).

$$\begin{cases} 0 \leq x \leq \text{Max}(x) = \dfrac{L_{\text{avg}}}{d} \\ 0 \leq y \leq T_{\text{avg}} \times \text{Max}(x) \\ 0 \leq z \leq 3600 \\ z = \left(\dfrac{v_{\text{avg}} \times 3600}{C_{\text{bat}}}\right) \times (t_0 + t_1) \\ T_{\text{avg}} = \dfrac{v_{\text{avg}} \times (3600 - z)}{L_{\text{avg}}} \\ y = T_{\text{avg}} \times x \end{cases}$$

with:

- $Max(x)$ is the maximum number of AIVs.
- L_{avg} is the average length of the circuit.
- d is the safety distance between two 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_{avg} is the average number of revolutions made by an AIV during one hour.
- v_{avg} is the average speed of AIVs on the circuit.

Through 8 scenarios, we will progressively introduce fuzzy inferences to determine the costs of task completion, battery recharging and speed adjustment.

A. *The Simulation Framework*

Fig. 3 presents the agent model proposed to test our dynamic task allocation strategies for AIVs in simulation. The objective is to have an agent-based modeling and simulation system designed generically to test different scenarios, but also different types of circulation plans. An infrastructure is deployed in the environment. It is composed of a circulation plan and active elements, such as beacons, tags, the two charging stations and the two types of treadmill for baggage entry and exit. Static or dynamic obstacles (e.g., operators) may be present in the environment. AIV fuzzy agents perform missions defined by paths on the traffic plan. AIV fuzzy agents are equipped with a radar to avoid collisions and have knowledge about the environment and other agents to operate and cooperate. AIV fuzzy agents communicate with each other with different types of standardized messages. AIV fuzzy agents have fuzzy and uncertain knowledge, but also incomplete and fragmented, in order to adapt to situations that are themselves uncertain. Baggage are objects managed by the environment: arrival flow on the entry treadmill, tracking of its localization, and exit from the circuit on the exit treadmill.

B. *V2X Cooperation in the Simulations*

To successfully complete their assigned tasks, AIVs must coordinate, cooperate, and share information about their tasks and environmental perceptions. They rely on ETSI messages, as described in Section II.D, to communicate their localization using CAM and report perceived obstacles using CPM and DENM, helping to prevent unexpected events. An additional type of V2V communication could further enhance cooperation among AIVs in task execution. For instance, if an AIV becomes blocked by an obstacle, breaks down, or is otherwise unable to complete its assigned task, it automatically sends a DENM. However, it would be beneficial for the AIV to also send a cooperative message, enabling it to delegate its task by providing the necessary information. In [42], we propose two new Cooperative Task Messages (CTM) designed specifically for task delegation. Similarly, [51] introduces a protocol with four new message types, including the Cooperative Response Message (CRM), which is used to communicate responses to cooperation requests. In our simulation model, AIV agents will use CRM messages as feedback to CTM messages, confirming their willingness to take on a delegated task. During the simulations, the sequence of communications between the supervisor, the AIV auctioneer, and multiple AIVs during the task allocation and reallocation process is illustrated in Fig.4. The supervisor initiates the process by sending a Cooperative Task Message (CTM) containing clustered tasks to an AIV acting as an auctioneer. The auctioneer then distributes these tasks by further clustering and auctioning them to other AIVs. This is done by sending a CTM [clustered auctioned tasks] to potential AIVs capable of performing the assigned duties. Once the auctioning phase is complete, the auctioneer allocates specific tasks by transmitting a CTM [allocated tasks] to the chosen AIVs. Each receiving AIV acknowledges the task assignment by sending a Cooperative Response Message (CRM) back to the auctioneer, confirming acceptance. Additionally, the same allocation mechanism is utilized for task reallocation. If an AIV encounters an obstacle, breaks down, or is unable to complete its assigned task, it can initiate a re-auction. In this scenario, the AIV itself takes on the role of an auctioneer, redistributing its pending tasks through CTM messages. The AIV that submits the most suitable bid will then integrate the reallocated tasks into its workload.

This structured communication process, visualized in Fig. 4, ensures effective task management and dynamic reallocation, enabling seamless cooperation among AIVs in an automated environment.

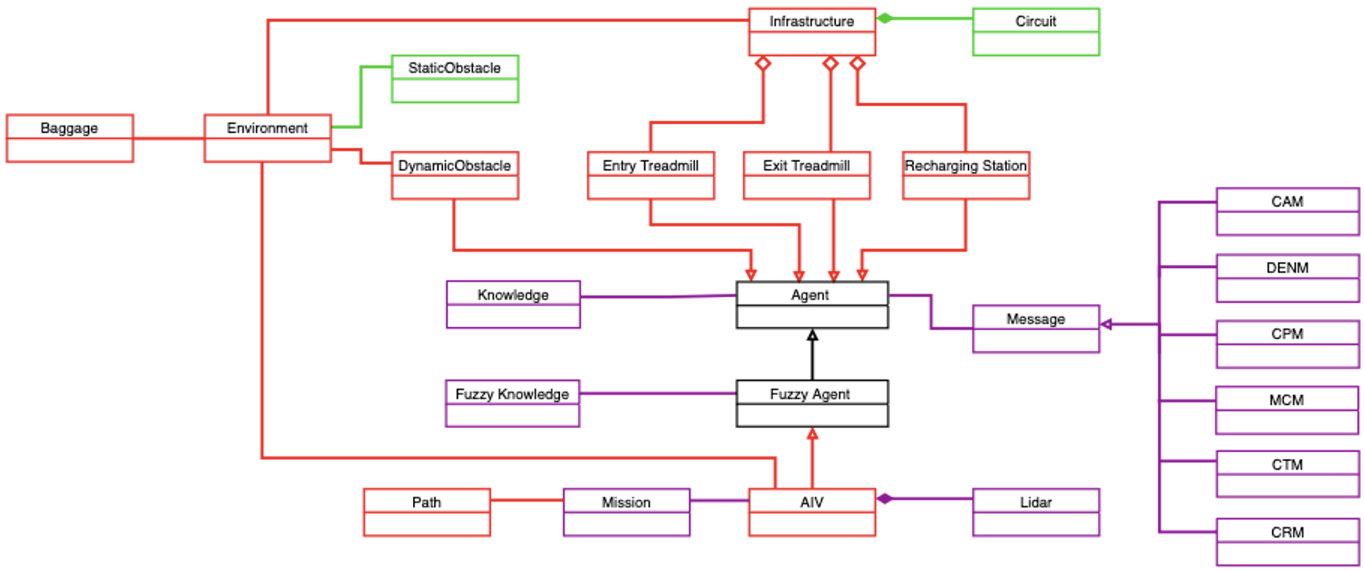

Figure 3. Simulator architecture: dynamic elements in red, static in green, and not related to the environment in purple.

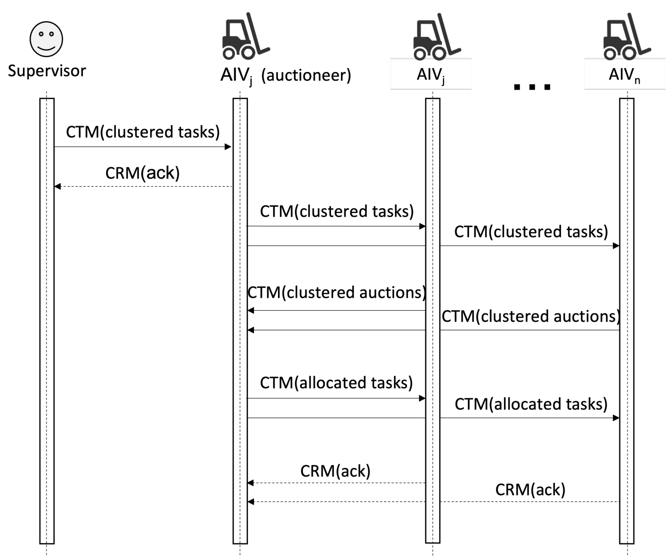

Figure 4. CTM and CRM exchanged during task allocation

C. Task Allocation with Basic Strategies

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

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

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

Random strategy: the maximum number of pending bags (19) is high, the simulation time is also high, and the allocation of missions and the activity rates of AIV agents are poorly balanced (the average activity rate at 0.72 is low). The random strategy does not allow allocation to AIV agents that are a priori available, which very quickly leads to pending bags being processed and therefore poor results.

FIFO strategy: this strategy brings a clear improvement in the results. The maximum number of pending bags (4) is very low, the simulation time is very correct, the allocation is almost uniform (only the stops for recharging the batteries cause imbalances), and the occupancy rate of the AIV agents is much better (0.84).

Available strategy: this strategy produces the best results, except for the maximum number of pending bags (8). Allocating a mission to an AIV agent that is more available than the others, improves the results. However, it is necessary to better manage the allocation based on pending bags and energy consumption to consolidate (or even optimize) this strategy.

D. Task Allocation with Fuzzy Strategies

In this section, we propose an analysis of task allocation by auction based on a fuzzy inference approach. As a reminder, fuzzy logic allows us to better understand natural, uncertain, imprecise and difficult to model phenomena by relying on the definition of if-then fuzzy rules and membership functions (linguistic variables) to fuzzy sets [52]. Two scenarios are studied. The first, Sc4, implements a TA strategy in which each

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

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

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

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

TABLE IV
RECHARGE SIMULATIONS RESULTS IN SCENARIOS SC4 AND SC5, FOR 100 BAGS

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

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

Fuzzy strategy in Sc4. The results presented in Table III and Table IV, with this new strategy are generally good: low maximum number of pending bags (6), good overall simulation time, good distribution of missions between AIV agents and good average AIV activity rate (0.88). However, a few elements of uncertainty are considered (3 linguistic variables at the input and one at the output). The introduction of other fuzzy elements (nuances in the simulation parameters) should improve the results, particularly in terms of maximum number of pending bags and management of battery recharges.

Fuzzy strategies in Sc5. In this new scenario, the raw results of the TA are slightly worse, as shown in Table III and Table IV, than in Sc4: same maximum number of pending bags (6), slightly longer overall simulation time, worse distribution of missions between AIV agents and worse average AIV occupancy rate (0.82). However, the overall recharge time is lower in this scenario, which can allow a greater availability of AIV agents (an area of improvement for the next scenarios).

E. Integration of Collision Avoidance and Speed Adaptation

Managing traffic situations on the circuit sometimes requires speed adaptations for AIVs. This is particularly the case for managing intersections between AIVs or for managing distances between AIVs. Obstacle avoidance may also need to be managed. However, although we have considered it in previous studies [41], we do not address it in this study. Fuzzy AIVs agents have fuzzy knowledge to adapt their speeds. This knowledge is mainly activated to respect the priority to the right when exiting baggage claim areas, when exiting baggage drop-off areas and when exiting battery charging areas. For this, four fuzzy linguistic variables were defined, three for the inputs to the fuzzy inference system (7, 8, 9) and one for the output (10):

- $AIV\_right\_distance$ (near, medium, far) (7)
- $AIV\_distance$ (near, medium, far) (8)
- AI_speed (slow, medium, fast) (9)
- $AIV\_speed\_adaptation$ (slow, medium, fast) (10)

The AIVs fuzzy inference system for adapting their speeds works through the activation of 15 fuzzy rules such as the following (11):

$IF\ AIV\_right\_distance\ IS$ near $AND\ AIV\_distance\ IS$ far $AND\ AIV\_speed\ IS$ medium $THEN\ AIV\_speed\_adaptation\ IS$ slow (11)

IV. IMPROVEMENT USING FUZZY HEURISTICS

Now, we propose to increase the relevance of previous auction TA scenarios based on a fuzzy inference approach, by integrating other types of realistic constraints concerning battery recharging and AIV agent speed adjustment made possible by a stronger knowledge of the fleet traffic and mission management context (increased awareness). Three scenarios are studied (Sc6, Sc7 and Sc8) to show that specific heuristics allow us to treat certain situations quite finely and to increase the collective/global performances of the AIV agents. The results are presented in Table V for task allocation and Table VI for battery recharging. Sc6 consists of completing scenario Sc5 to determine in which station the AIV agents can recharge in order to minimize the waiting times for recharging, based on knowledge of the context of occupation of the stations and the needs of the other AIV agents (therefore more awareness for the agents). The linguistic variables used in this sixth scenario are the following: the availability of the AIV agent, the distance from the baggage drop-off location, the energy level of the AIV agent, the distances of the 2 recharging stations and the availability of the recharging stations. Sc7 takes up the strategy of Sc6 and adapts the recharging rate (80 or 100%) in order to increase their availability if the flow of incoming baggage increases and therefore if the number of pending bags is likely to increase. The linguistic variables used in this seventh scenario are: the availability of the AIV agent, the distance from the baggage drop-off location, the energy level of the AIV agent, the distances from the 2 charging stations, the availability of the charging stations and a variable energy charge rate (80 or 100%). Sc8 consists of increasing Sc7 by adapting/regulating the speed of the AIV agents according to the flow of baggage arrivals and therefore the potential increase in the number of pending bags to be processed, but also according to the speed, the proximity of other AIV agents (use of observed and safety distances). The linguistic variables used in this eighth scenario are as follows: the availability of the AIV agent, the distance from the baggage drop-off location, the energy level of the AIV agent, the distances of the 2 charging stations, the availability of the charging stations, a variable charging rate (80 or 100%) and urgency in relation to the number of pending bags.

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

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

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

TABLE V
TASK ALLOCATION SIMULATION RESULTS IN SCENARIOS SC6; SC7 AND SC8 FOR 100 BAGS

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

TABLE VI
COMPARISON OF SCENARIOS SC6, SC7, AND SC8

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

V. CONCLUSION

We developed a multi-agent simulation platform to test different scenarios of task allocation management for mobile baggage conveyor robots (AIVs) in the context of Airport 4.0. This approach offers a flexible adaptation to the different aspects of AIV autonomy management and facilitates possible adjustments needed for deployment at an airport site. The use of a distributed multi-agent system provides temporary autonomy in case of central infrastructure failure, and can improve the management of individual AIV functions, such as task allocation, battery charging, collision avoidance, speed regulation, etc. To establish a basis for comparison of auction-based task allocation strategies with the fuzzy approach we wanted to develop, we started by defining three basic scenarios implementing random, FIFO and AIV availability strategies. We then tested a task allocation scenario with a basic fuzzy model incorporating cooperative V2X communication and collision avoidance mechanisms. Then, we made several improvements to this scenario by extending the AIV's fuzzy decision model to: (1) recharging the AIVs batteries, (2) determining the recharging station, (3) determining the most relevant recharging rate, and (4) regulating the speed of the AIVs so that they adapt to the variation of the baggage arrival flow. The simulation results show that integrating adaptive fuzzy multi-agent models for managing task allocation, energy recharging management, determining the most favorable infrastructure elements (charging stations), cooperative task allocation through V2X, and speed adaptation with collision avoidance, can improve the operational efficiency of AIV fleet. The adaptive model not only improves task allocation and energy management but also ensures safer and more coordinated operations by dynamically adjusting speed and preventing collisions. These results highlight the importance of flexible and collaborative approaches to improve the performance of autonomous systems in dynamic environments. We plan to continue integrating fuzzy models into AIV agent behavior simulations and to add learning capabilities (e.g., based on neural networks [53]) to them in order to increase the relevance and efficiency of their decisions in the collective management of their autonomies. Moreover, to ensure our simulations better reflect real-world operations, we also plan to study the impact of unexpected events, such as security attacks or mis-behavior of AIVs, and to integrate corresponding mechanisms into our scenarios.

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