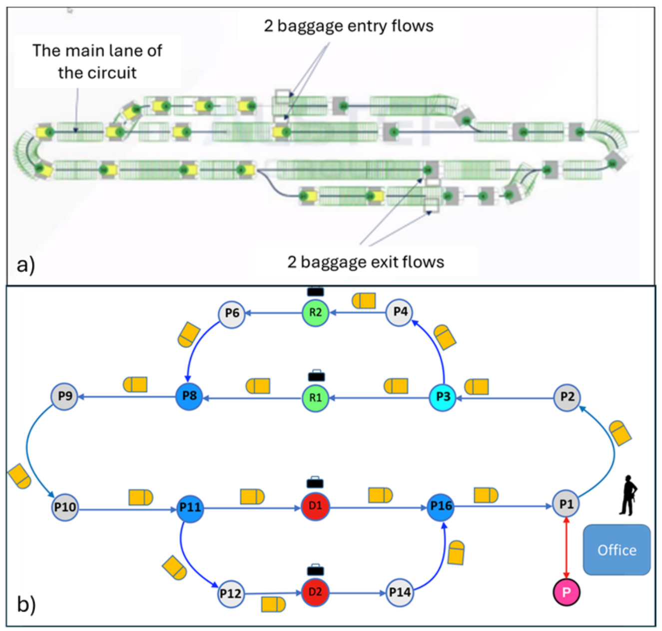
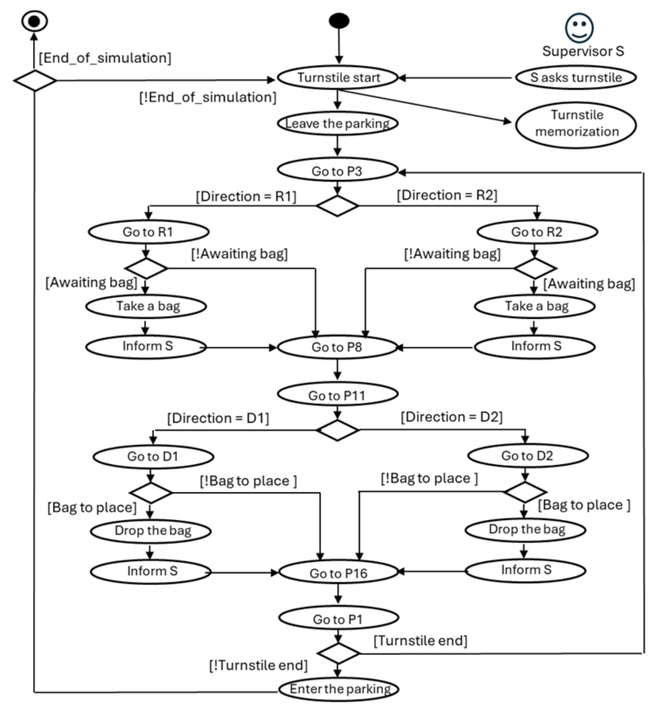
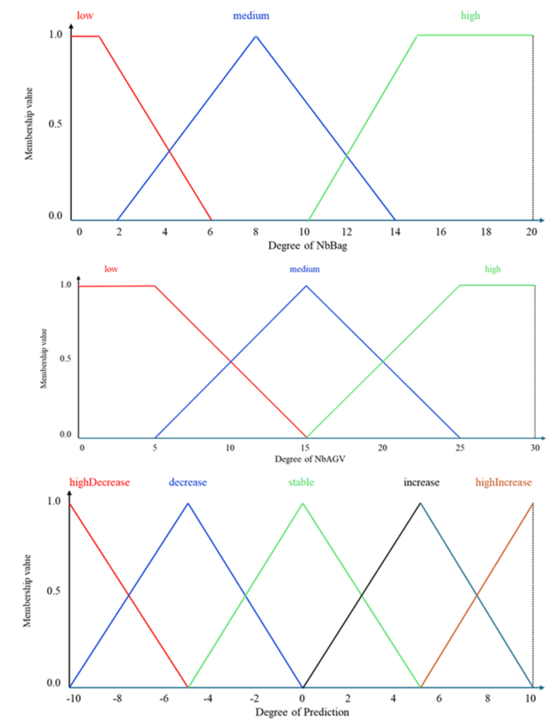
Fuzzy Agent-Based Modelling and Simulation of Autonomous Vehicle Fleets for Automatic Baggage Handling in 4.0 Airports

AISyS, Lisbon, 2 october 2025







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Context

Context and issue

In the context of **Airport 4.0**, technological building blocks have been defined, including the use of *automated guided vehicles* (**AGV**) or *autonomous industrial vehicles* (**AIV**)

However, the implementation and deployment of fleets of **AIVs** remain difficult due to:

- **Acceptability to employees**
- **Baggage and personal safety**
- **Vehicle location**
- **Traffic flow**
- **Perception of the dynamic environment**
- **…**

Our main issue is: *What types of solutions can improve automatic baggage handling by a fleet of AIVs deployed in an Airport 4.0?*

Context

Modelling and simulation of AIV fleet

- Before **testing baggage handling scenarios by AIVs** on a large scale in complex airport situations (several dozen AIVs), **it is essential to simulate these scenarios**.

- **Simulations** take into account different **constraints** and **requirements**, such as:
  - ✓ **Useable results and performance of solutions without applying a scaling factor**
  - ✓ Reduced development time and costs
  - ✓ Feasibility and flexibility of deployment and redeployment
  - ✓ Identification of possible improvements in the configuration of the facilities hosting the AIVs
  - ✓ **Study of the responsibility between the central server and the AIVs (local/global balance): operational decisions**
  - ✓ **Introduction of a secure human presence (operators)**

Plan

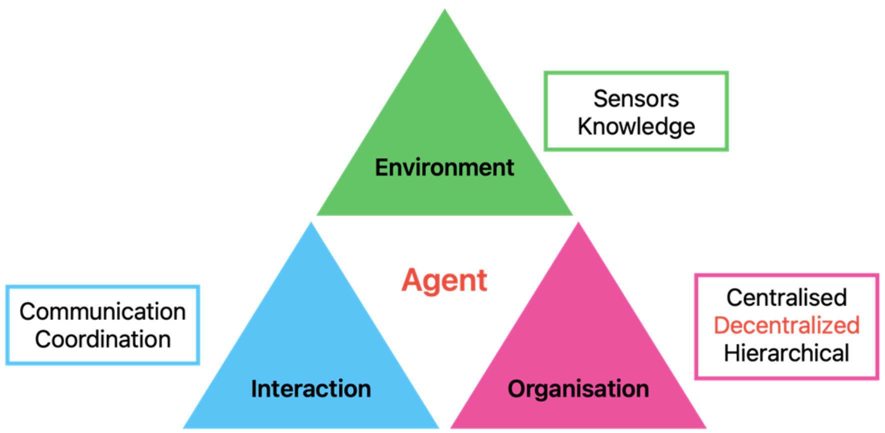
Contents of this presentation

- Our paper proposed a case study involving the simulation of AIV fleets for **baggage handling** in a simplified airport, in which **each AIV is simulated by a fuzzy agent**
- So, we first present the context of **fuzzy agent-based modeling and simulation**
- In second time, we present an **Agent Unified Modeling Language (A-UML) model of the system**, providing both static and dynamic views of the circuit and the vehicles
- Then, we present **three different strategies** for determining the number of AIVs that should circulate to handle the baggage arriving at the two entry points
- **Simulation results are also presented**. 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**
- Then, we finish by presenting conclusions, perspectives, and **extensions of our research**

Modelling

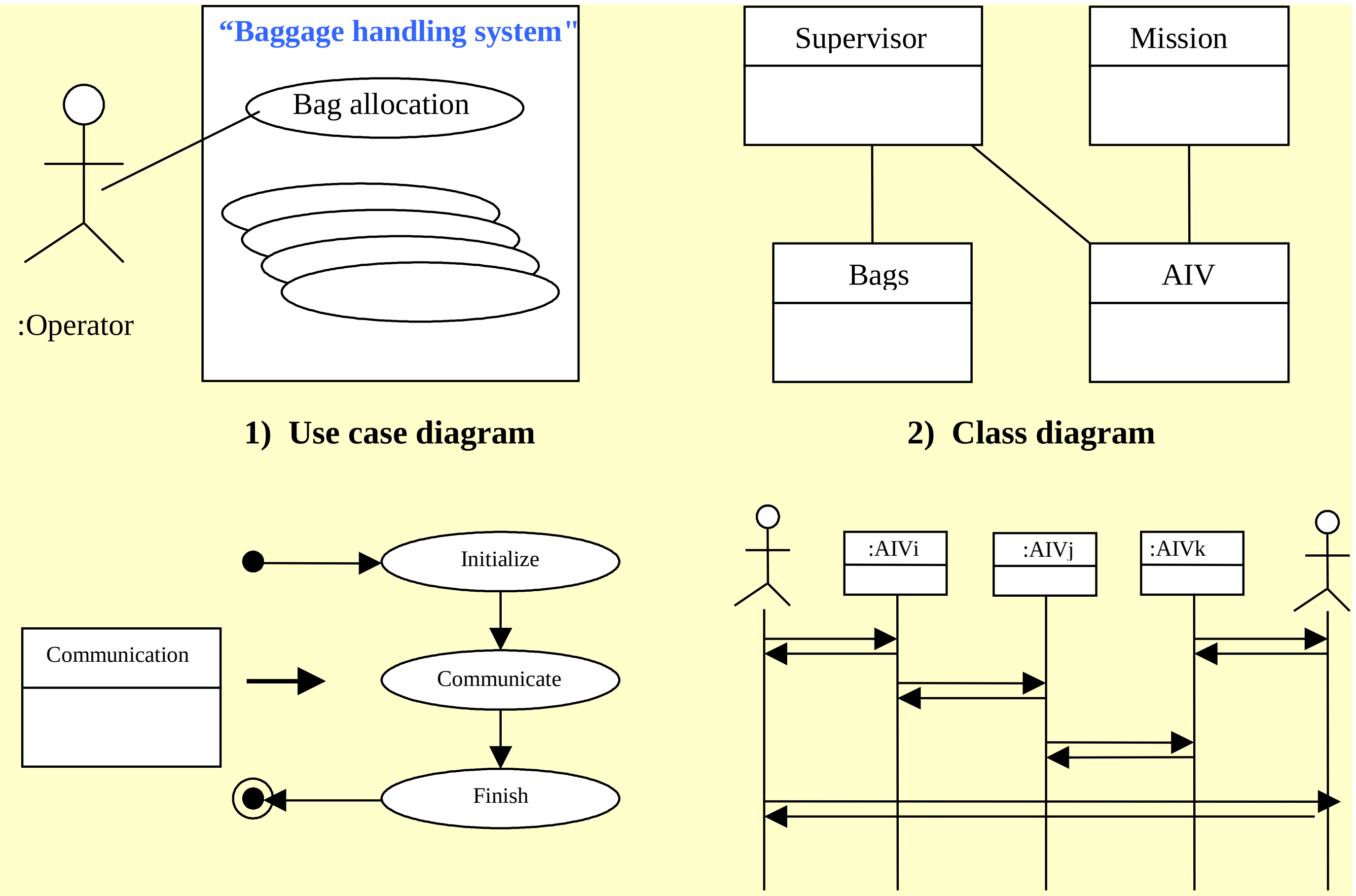
Agent-based application modelling

- To simulate an AIV fleet responsible for automatic baggage handling at an airport, we propose an **Agent-based approach**



Multi-Agent Systems

A methodology adapted from AUML for Agent-based system design



1) Use case diagram

2) Class diagram

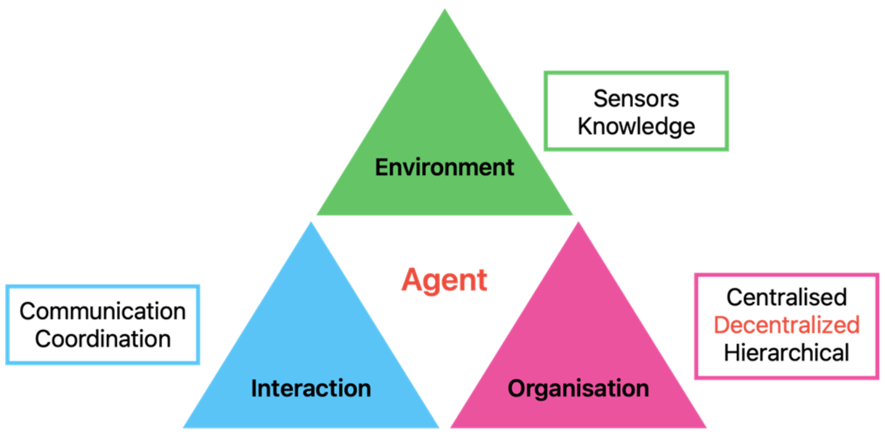
3) Activity diagram → agent behaviour

4) Sequency diagram → a scenario of use

Modelling

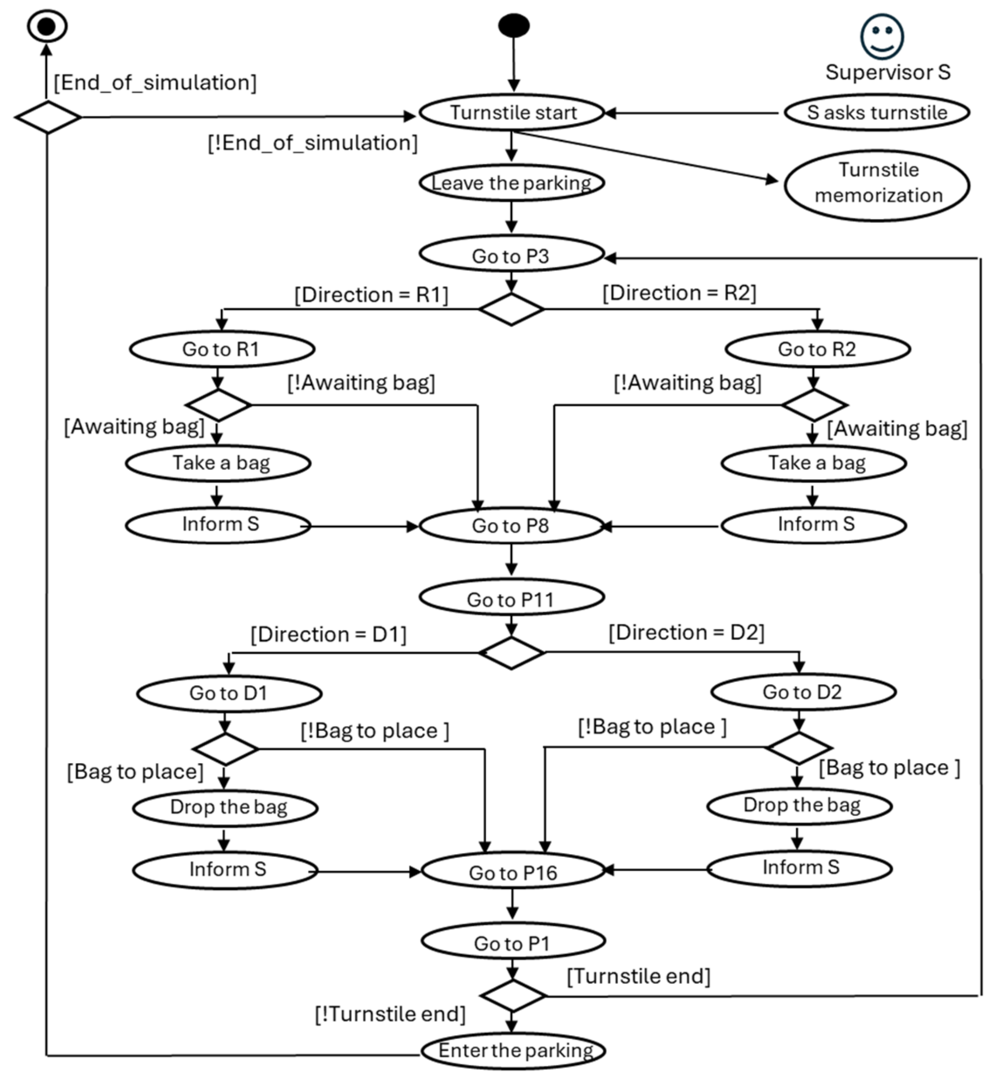
Agent-based application modelling

➢ To simulate an AIV fleet responsible for automatic baggage handling at an airport, we propose an **Agent-based approach**



Multi-Agent Systems

Example of an AIV behaviour/activity diagram for a Round robin strategy (cf. case study)



Modelling

Fuzzy agent-based modelling

- The **use of fuzzy agents** allows to manage the levels of imprecision and uncertainty in the behaviors of simulated AIV

- An agent-based system is fuzzy if the agents that compose it have **fuzzy behaviors** or if the **knowledge they use is fuzzy**

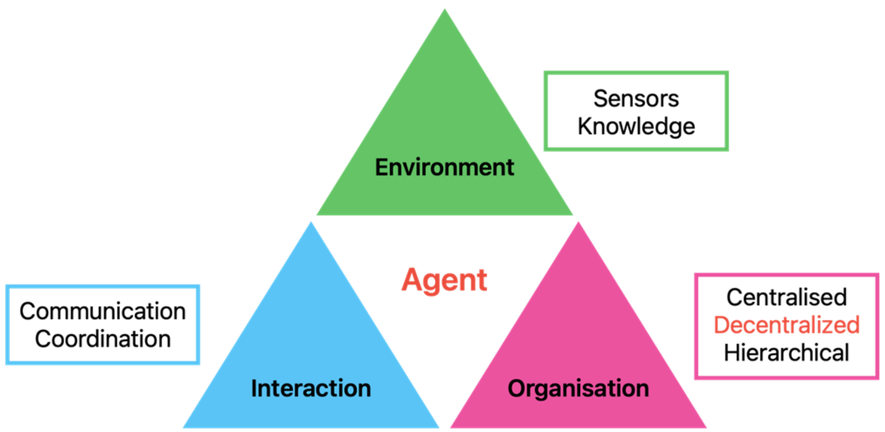
This means that fuzzy agents can have:

- ✓ **fuzzy knowledge** (fuzzy decision rules, fuzzy linguistic variables and fuzzy linguistic values)
- ✓ **fuzzy behaviors** (defined by FIS)
- ✓ **fuzzy interactions, organizations or roles**

Modelling

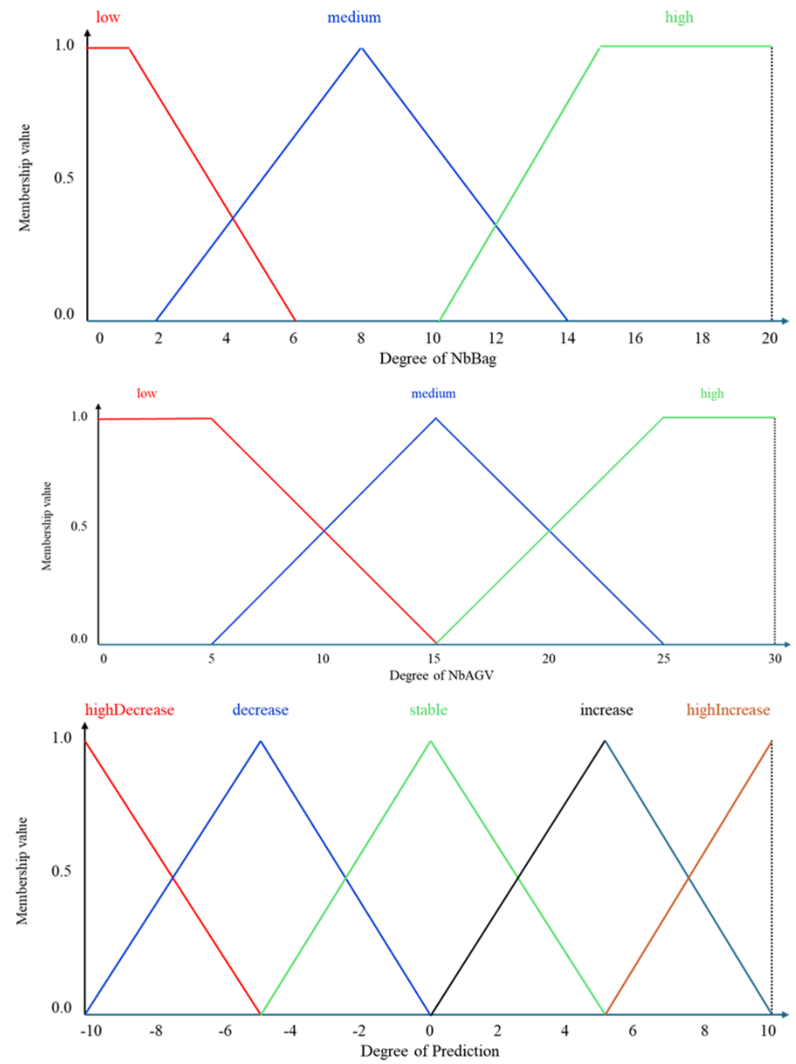
Fuzzy agent-based modelling

➢ To simulate an AIV fleet responsible for automatic baggage handling at an airport, we propose an **Agent-based approach**



Multi-Agent Systems

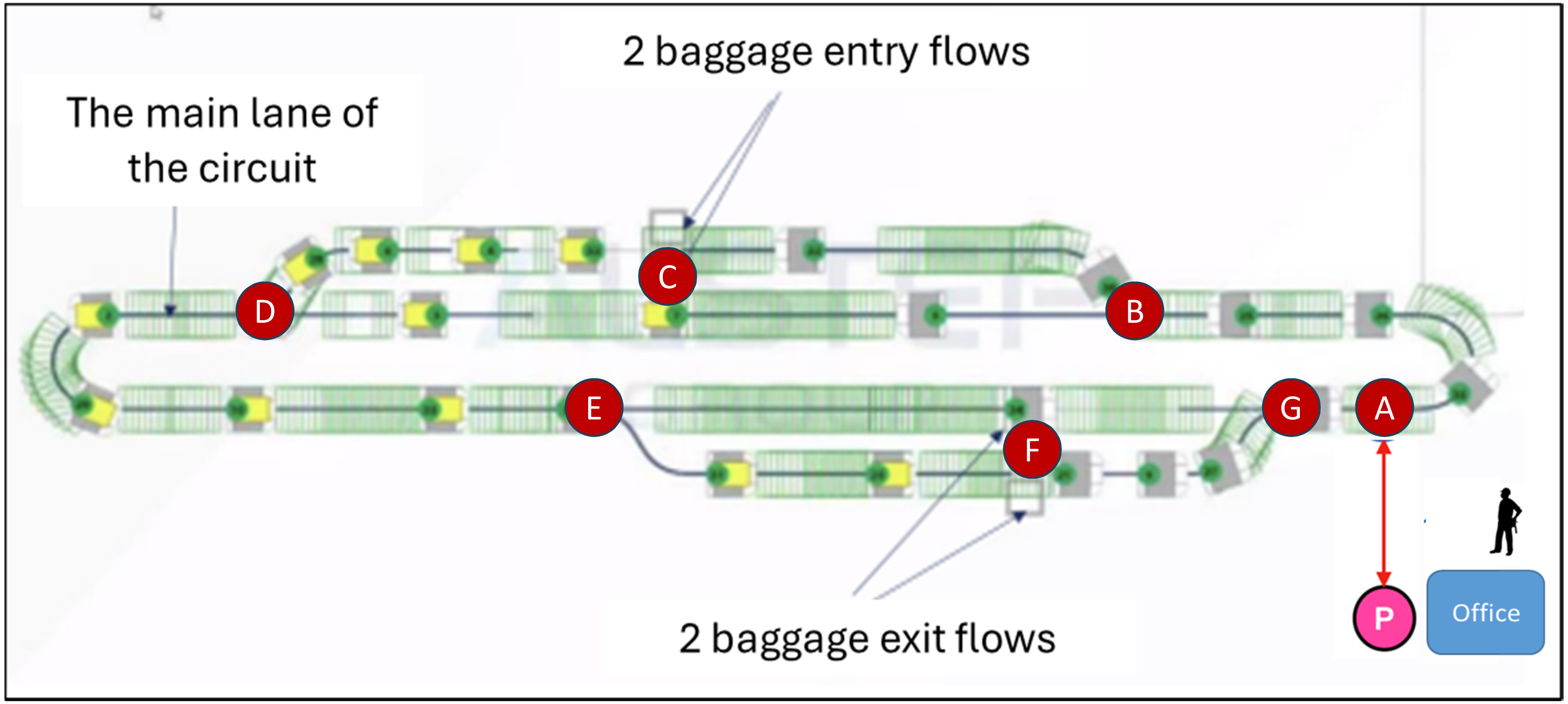
Example of fuzzy linguistic variables for a fuzzy Prediction strategy (cf. case study)



Case study

The case study

The case study proposes the **simulation of mobile robots conveying baggage fleet in an airport**

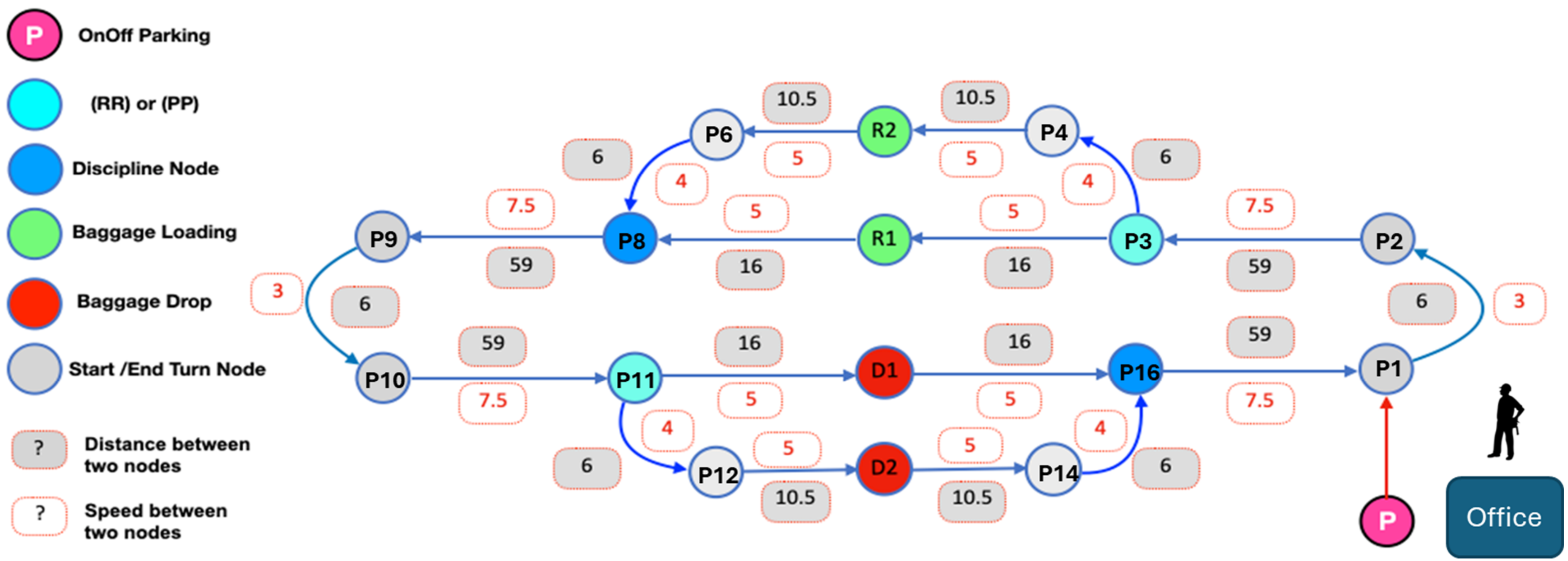


A: input/output of the circuit | B/E: divergence points | D/G: convergence points
C: Baggage collection points | F: Baggage drop-off points

The case study

Modeling in the form of a circuit graph:

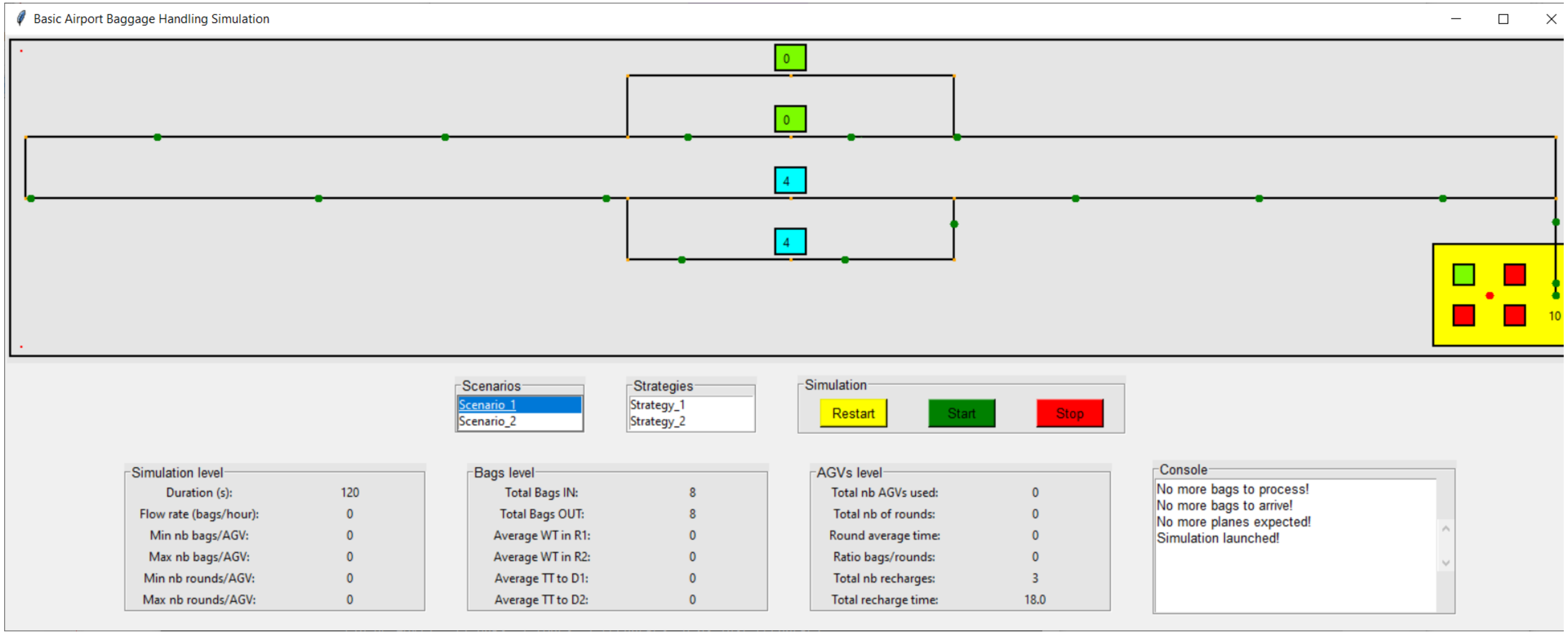
- ✓ nodes → **characteristic points** of the circuit ($P_{0..16}$, $R_{1,2}$ and $D_{1,2}$)
- ✓ edges → **distances** between these points and **maximum speeds** between these points



The case study

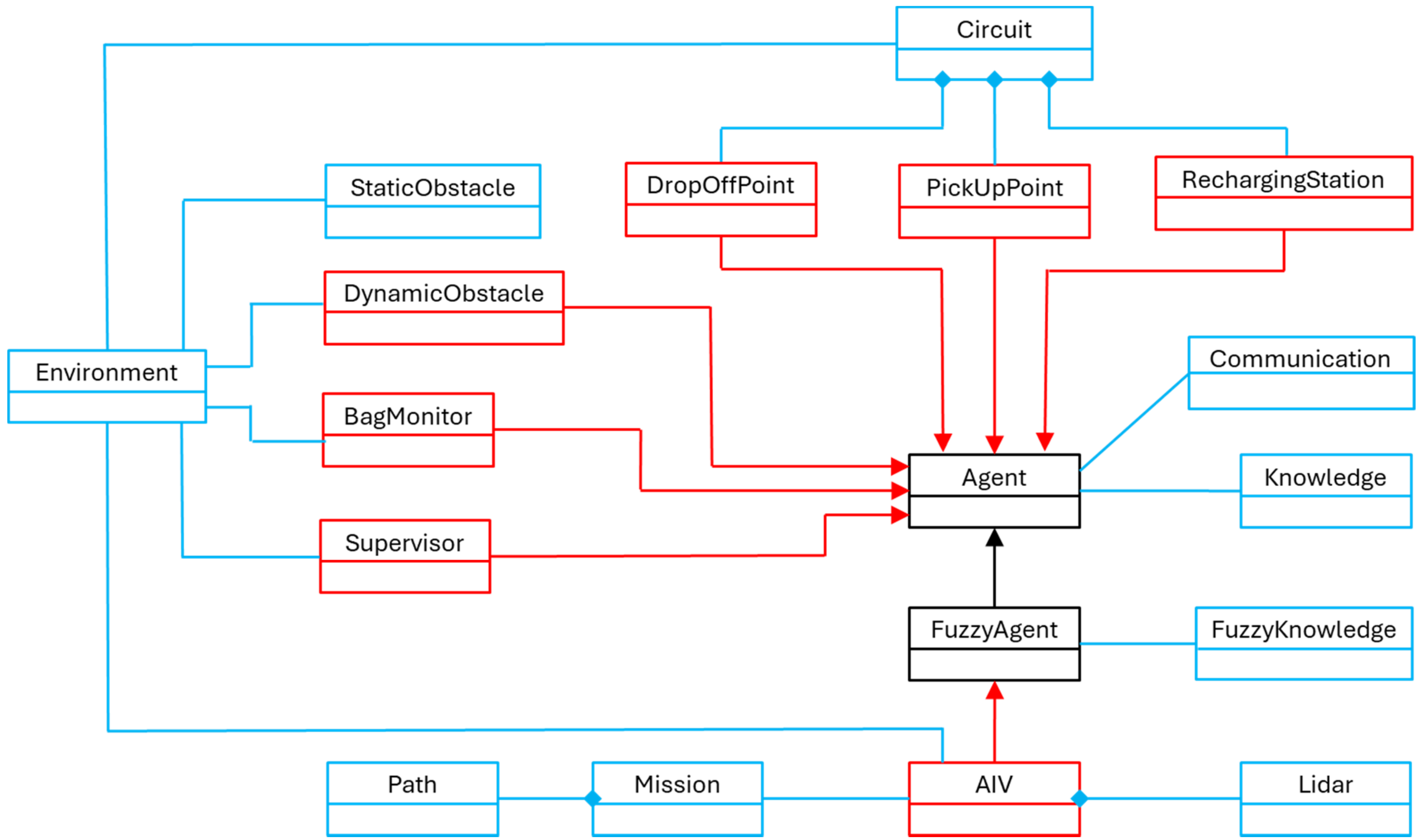
The figures below show the simulator's HMI, which allows:

- ✓ to **visualize the arrival of baggage** and **the movements of AIVs (max = 41)**,
- ✓ and to follow the **evolution of the different levels of indicators of the simulation** (**Simulation level, Bags level, AIVs level, and Console**).



Case study

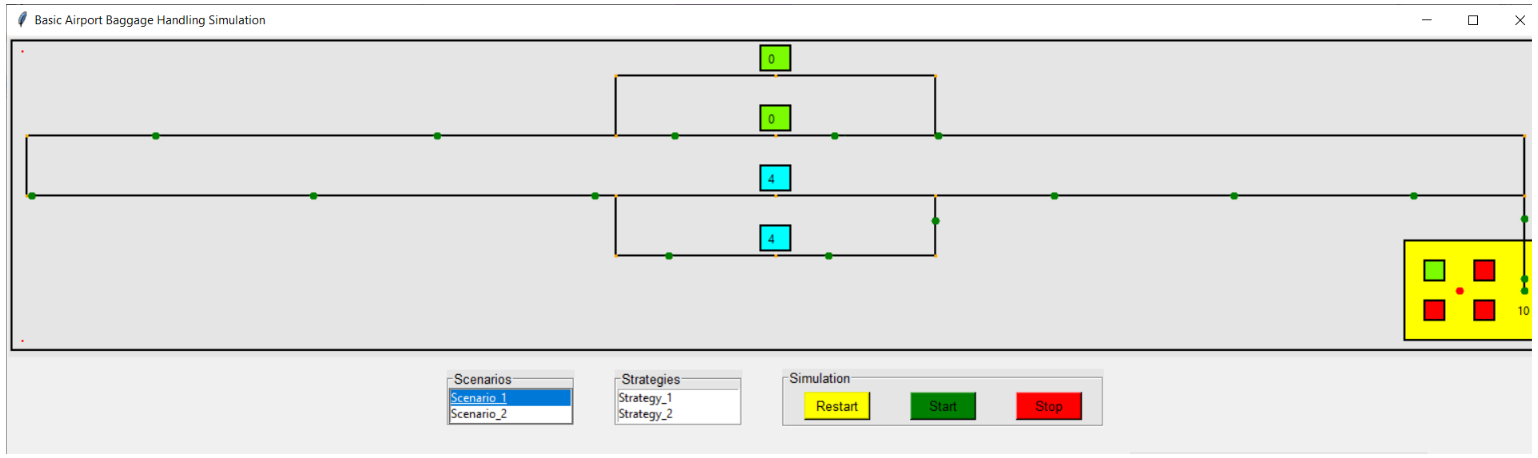
The simulation framework



Legend:	- static object	- dynamic object	- agent (thread)

Case study

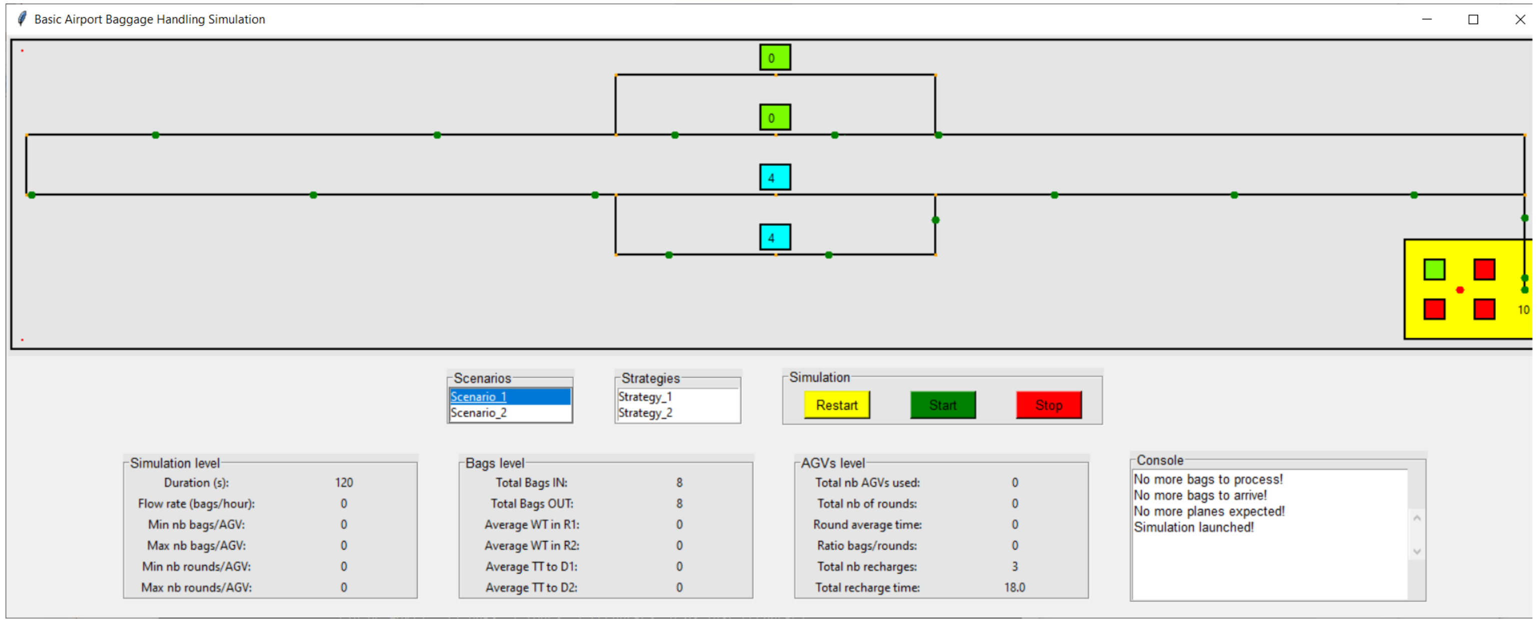
3 Strategies and 3 Scenarios



- We provided a comparative analysis of 3 basic types of strategies:
  - ✓ **Strategy_1:** ***Round robin***
  - ✓ **Strategy_2:** ***On-demand***
  - ✓ **Strategy_3:** ***Fuzzy logic-based demand prediction***
- Each of these strategies is tested in the three following scenarios:
  - ✓ **Scenario_1:** ***Real data (based on reference airport)***
  - ✓ **Scenario_2:** ***Random data (during 1 hour)***
  - ✓ **Scenario_3:** ***Mass data (1000 bags arriving continuously)***

Case study

3 Strategies and 3 Scenarios



- We seek to:
  - ✓ **Minimize the number of AIVs**: (1) used, and (2) circulating on the circuit at a given time
  - ✓ **Maximize the number of bags processed per hour**
  - ✓ **Minimize the total recharge time of AIVs per hour**

Results

Simulation time for the 3 strategies (in s)

Scenarios	Real data (test airport)	Random data (1h)	Mass data (1000 bags)
Round robin	2744	3600	2280
On-demand	2686	3600	2196
FL prediction	2515	3600	2252

1) Round robin strategy always has the longest duration
2) Both FL Prediction and On-demand strategies optimize the processing time by activating AIVs when bags arrive by determining the right traffic branches, which is not the case for AIVs in the Round robin strategy

Results

Number of bags processed by the 3 strategies

Scenarios	Real data (test airport)	Random data (1h)	Mass data (1000 bags)
Round robin	1306	**2015**	1000
On-demand	1306	**1864**	1000
FL prediction	1306	1956	1000

1) /!\ 2 scenarios have a fixed number of bags (1306 bags for test airport, and 1000 bags for mass data)
2) On this criterion, the Round robin strategy is overall the most satisfactory, it is also on this criterion that it has its main advantage (AIVs continually passe in front of the baggage claim)

Results

Flow rate of the 3 strategies (bags/h)

Scenarios	Real data (test airport)	Random data (1h)	Mass data (1000 bags)
Round robin	**1713**	**2015**	**1578**
On-demand	1750	**1864**	**1639**
FL prediction	**1868**	1956	1597

1) The 2 strategies of Round robin and On-Demand have the worst overall results
2) The average and overall flow rate is unquestionably the best with the Prediction strategy (1807 bags/h on average over the 3 scenarios)

Results

Number of complete rounds made by AIVs

Scenarios	Real data (test airport)	Random data (1h)	Mass data (1000 bags)
Round robin	**1622**	**2074**	**1298**
On-demand	**1306**	**1864**	**1000**
FL prediction	1376	2021	1182

1) **For this criterion, the Round robin strategy is systematically the least efficient, and this significantly**
2) **The average and overall number of AIV rounds is undoubtedly the best with the On-demand strategy (the allocation of an arriving bag to an AIV is indeed very efficient)**

Results

Average waiting time per bag before (in s)

Scenarios	Real data (test airport)	Random data (1h)	Mass data (1000 bags)
Round robin	**41**	**57**	14
On-demand	**26**	**21**	**20**
FL prediction	29	22	19

1) The Round robin strategy is twice the least efficient
2) The On-demand strategy gives very satisfactory results (22s average wait for a bag)
3) The FL Prediction strategy also gives satisfactory performances (23s average wait for a bag in the 3 scenarios)

Results

Impact of the recharging of AIV batteries

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

1) This table gives the results for a simulation with scenario 2: one-hour simulation in random mode (note that total duration of the simulation = 3600s + final recharge for the AIVs to be fully charged again)
2) The results provided by the on-demand strategy are the best, although at the cost of many recharges (when the AIVs return to the parking lot)
3) 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

Conclusion

Conclusion and perspectives

- **We presented fuzzy agent-based modelling and simulation** in the context of Airport 4.0
- **We developed a multi-agent simulation platform to test different scenarios of automatic baggage handling processed by** mobile baggage conveyor robots (AIV).
- This approach offers **a flexible adaptation to the different aspects of AIV autonomy management** and facilitates possible adjustments needed for deployment in an airport site.
- Results allowed us to highlight the impact of various parameters, such as the number of simulations, the number of bags processed, the total simulation duration, and the total number of bags processed per hour.
- We plan to **continue integrating fuzzy models into AIV agent behavior simulations, and then to add learning capabilities** (e.g., based on neural networks) to them in order to increase the relevance and efficiency of their decisions in the collective management of their autonomies.

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Thank you for your attention !

Do not hesitate to contact us …

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