Simulation of Drinking Water Infrastructures Through Artificial Intelligence-Based Modelling for Sustainability Improvement

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Abstract. The development of control systems for critical infrastructures requires testing and validating the proposals before using them in real environments. This work proposes the development of a new control system with an approach based on sustainability, which uses multi-agent systems as a basis, and which breaks away from traditional proposals focused on optimising energy costs. This new approach requires a thorough validation before its possible deployment, as it is based on distributed components that make independent decisions to generate complex emergent behaviour. In order to test its viability, a simulator has also been developed alongside the control system, which allows the behaviour of each agent to be analysed by subjecting it to tests using real data from the scenario to be controlled. Through this tool it is possible to observe each agent in the fulfilment of its functions, validate its behaviour, and check that the control system guarantees the supply of drinking water to a city, using the data obtained from that city as input. Through the simulator it is possible to analyse and represent different configurations of the control system over an infrastructure, thus being able to select the best option for the environment.

Keywords: WASUSI-MAS · Water supply simulator · Multi agent systems

1 Introduction

The use of artificial intelligence (AI) models makes it possible to make highly accurate estimates of the behaviour of complex non-linear systems, where hundreds of variables and actors involved need to be considered. AI is becoming increasingly important in resource management contexts, such as river flow prediction [1], energy management in construction [2] or solid waste management [3], where numerous technical, climatic, environmental, demographic, socio-economic and legislative parameters are involved. Today, one of the scarcest resources that must be managed efficiently is undoubtedly

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water, and more specifically drinking water. This is because, in recent years, water resources on a global scale have come under considerable pressure due to altered hydrological conditions and the spread of pollution resulting from climate change [4]. As a result, there are numerous studies that address the need to optimise water infrastructure management through all kinds of techniques, but most commonly through an energy optimisation approach [5]. This is because energy consumption in such systems is significant, and improving pump performance can greatly reduce energy costs [6]. In such work where optimisation must utilise large amounts of data, situations and conditions, IA plays a fundamental and very useful role in modelling, automating, and optimising critical water management applications [7].

However, today, an optimisation approach based solely on the energy efficiency of drinking water infrastructures does not meet the needs of environmental sustainability. This is because, energy optimisation is based on taking advantage of the hours when energy costs are lowest for the accumulation of drinking water in large reservoirs, i.e., producing the most water when energy is cheap [8]. There are several problems with this approach. Firstly, the stored water has been extracted from the ground, which decreases the water in aquifers and increases their deterioration, worsening water quality [9]. A sustainability-based approach dictates that only the water needed for consumption is abstracted, thus using aquifers as natural water reservoirs, which are even protective against surface pollutants and conserve water quality [10]. Secondly, by keeping the reservoirs filled to the maximum using cheap energy, the stored water exerts pressure on water infrastructures and pumping stations, which in the case of reservoirs that have their inlet at the bottom means that the higher the level in the reservoir, the more energy the pumps have to use to lift the water [11]. The use of storage tanks with their inlet/outlet at the bottom is beneficial for the maintenance of pressures in the infrastructure and therefore their use is common [12]. Figure 1 shows a classic drinking water supply infrastructure scheme, where groundwater is pumped to an above-ground reservoir that supplies a city. The more water is stored in the tank, the higher the water pumps have to pump.

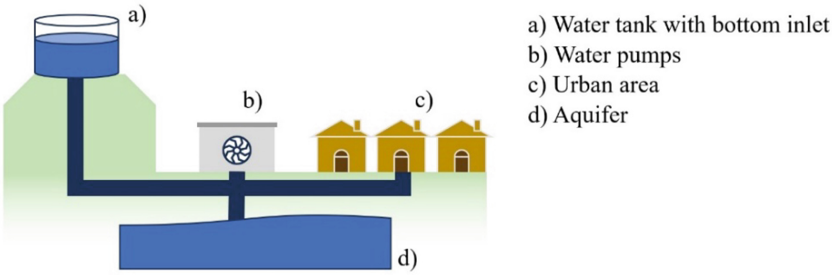

Fig. 1. Schematic of an infrastructure based on an overhead storage facility.

And thirdly, by having the storage at the maximum, when water consumption is high, inertia is produced that the pumping systems have to overcome. For example, during the first hours of the night when people come home from work, water is consumed in showers and kitchens, this generates an inertia of water towards the city, but when the water level in the reservoir drops and as energy is cheap at that time, water is pumped into the reservoir. This causes the pumps to be fighting against the inertia of the consumed water, which means higher energy consumption and unwanted overpressure towards the city. Figure 2 illustrates this effect.

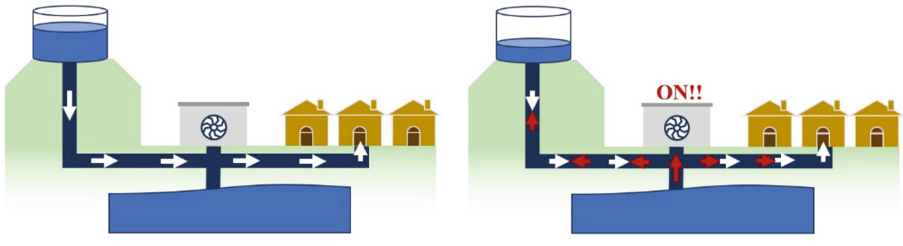

Fig. 2. Pumping start time where the pumping inertia is opposite to the consumption inertia.

To combat these three problems, this paper proposes the design of intelligent control systems capable of handling multiple objectives and priorities among them dynamically, through a multi-agent system (MAS). Multi-agent systems are an important branch of distributed artificial intelligence [13] that allows the decomposition of complex systems into different independent agents that collaborate with each other to achieve objectives. Each agent implies that it possesses local knowledge and information only about its own interests and goals, as it does not have to contain information from the whole system. This circumstance is beneficial in the management of infrastructures that may be distributed, very large, or that may change and evolve over time [14]. MAS is not only a field within IA, but also a field of research in associative areas such as economics, philosophy, sociology, or biology, where agent technology is used to achieve complex tasks in a distributed way, with solid results for years [15]. We can find works using MAS related to distributed energy infrastructure management. In renewable energy optimisation for hybrid systems, the study [16] proposes a MAS system where agents model the infrastructure elements and generate the optimal behaviour for the infrastructure. In [17], the creation of a simulator for an energy management system is proposed, where the agents model the communication between the elements, the execution of actions and the infrastructure components, and it is implemented through FIPA. Even the use of MAS has shown valid results in highly distributed, heterogeneous, and variable scenarios [18] where multi-level MAS systems coordinate multi-energy microgrid infrastructures.

The main distinction of our work is that the focus will be on minimising water storage to avoid unnecessary exploitation of aquifers, minimising the pressure due to the height of the stored water sheet and controlling overpressure. For this purpose, a simulator of a MAS has been developed in this work, which allows validating the control system by comparing it with the real behaviour and thus being able to check the points of improvement. Furthermore, this modelling has been carried out using the infrastructure and real data obtained from a small town of approximately 5,000 inhabitants in southeastern Spain. As it is based on a real scenario, the results allow us to quantify the benefit obtained on the real aquifers and infrastructures and thus validate the proposal.

The rest of the article is organised into the following sections: Sect. 2 contains a preliminary study of the characteristics of multi-agent systems, together with the definition of the necessary parameters for their design and implementation; Sect. 3 shows the objectives that the system must fulfil, each of them being an independent agent, with a series of parameters that condition each agent in its task; Sect. 4 explains the development of the simulator, from the technologies used to a certain level of code used; Sect. 5 finally draws the main conclusions of the work and sets out the lines of future work.

2 Design of the Multi-agent System

Our proposal is based on a Multi-agent Systems (MAS) approach. MASs were developed to solve large problems where data may be distributed and of different nature. In addition, they are particularly suited to problems with multiple methods of solving, multiple perspectives and/or multiple elements that can provide a solution to the problem. The purpose is to achieve objectives through a distributed system of sound, communication, processing, and control [19]. The use of the MAS paradigm in complex systems related to sensorisation has shown that it enables the generation of complex behaviour and is even capable of dealing with unknown situations [20], which means that it is not necessary to consider all possible states of the system, but rather to model the behaviour appropriately. The use of MAS as a possible solution to water resource management is relatively recent, as shown by the work of [21], but in this case, only optimisation focused on consumption is used, without considering other variables or the flexibility of the system to change both infrastructures and efficiency approach.

Our system is based on the definitions of [22], where each agent is described as an α element able to obtain information from its environment, what we call the $Percept_\alpha$, obtaining a perceived state Φ_α from the global environment. It can store this new perceived state, what we call Mem_α, in an internal state Σ_α, which will be the result of combining the perceived data and its own knowledge up to that moment. Using this perceived information and its own internal state, it can make decisions, called $Decision_\alpha$, and finally based on the decided action, execute it in the $Exec_\alpha$ system. Using formal definitions, developed for our proposal, an agent α is defined as:

$$\alpha = \langle \Phi_\alpha, \Sigma_\alpha, P_\alpha, \Gamma_\alpha, Percept_\alpha, Mem_\alpha, Decision_\alpha, Exec_\alpha \rangle \tag{1}$$

where:

- $\Phi_\alpha = \langle \varphi_1, \varphi_2, \varphi_3, \ldots, \varphi_n, \rangle$ and φ_i is a list of signal-value pairs of perceptions of the world, the information that an agent will extract from its context and that comes either from the managed system or from other agents producing new information.
- $\Sigma_\alpha = \langle \varsigma_1, \varsigma_2, \varsigma_3, \ldots, \varsigma_n, \rangle$ and ς_i is a list of signal-value pairs internal to the system, the information it will store internally.
- $\mathrm{P}_\alpha = \langle \rho_1, \rho_2, \rho_3, \ldots, \rho_n, \rangle$ and ρ_i is a list of signal-value pairs that define an action, an intention to change.
- $\Gamma_\alpha = \langle \gamma_1, \gamma_2, \gamma_3, \ldots, \gamma_n, \rangle$ and γ_i is a list of output signal-value pairs, called influences, which constitute the centre's attempt to change the state of the world by outputting new values it wishes to change in some element.

- *Percept*$_\alpha$: $W \rightarrow \Phi_\alpha$ function that generates a perception from the state of the world W.
- *Mem*$_\alpha$: $\Phi_\alpha \rightarrow \Sigma_\alpha$ function that generates a new internal state from the perceived state.
- *Decision*$_\alpha$: $\Phi_\alpha \, x \, \Sigma_\alpha \rightarrow P$ function that generates an action from the perceived and internal state.
- *Exec*$_\alpha$: $P \rightarrow \Gamma$ function that generates an influence from the action taken.

The execution of a given action by an agent at a given time does not directly imply the alteration of the state of the system but has to be taken as an attempt to change its state, i.e., to exert an influence γ of change. It is therefore the execution of all the actions decided, i.e., the sum of all the influences of each of the agents taking part in the system that actually generates a change from one state to another. Formally, the future state of the system $\sigma(t + 1)$ can be defined as the reaction, *React*, of the system in its current state $\sigma(t)$ together with the union of all the influences of the agents in the system:

$$\sigma(t+1) = React(\sigma(t), \bigcup_1^n (\gamma_i)) \text{ where each } \gamma_i \text{ is defined as}$$
$$\gamma_i = Exec_i(Decision_i(Percept_i(\sigma(t)),\ \varsigma_i(t))) \quad (2)$$

Each influence is independent and asynchronous from the others, i.e. this reaction function (2) will be executed each time a new influence is generated. Although function (2) only shows the union of all influences, there might be influences with higher weights than others, and therefore weights could be added to increase or decrease the impact of each influence. However, as will be seen below, in our case it will be an agent who will control this weighting, so the agent can also dynamically adjust the weights if necessary.

Figure 3 shows the description of the MAS system, and how the reaction function launches an attempt to change the influence on the water infrastructure. Note that the fact that actions are generated does not imply that the direct effect is as expected. For example, the current conditions may demand to start the water pumps, but if at the moment the action is performed the consumption is reduced, an unwanted overpressure may occur, which would be controlled again by the system.

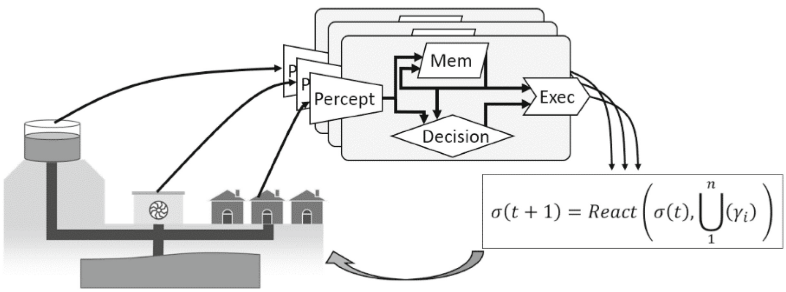

Fig. 3. MAS architecture for water supply control

Once the MAS architecture has been defined, we will define the internal *Percept, Mem, Decision* and *Exec* functions of each agent.

2.1 Percept

This function specifies the list of signals in the world that will be observed by an agent. It will be defined as a list of names of signals to which the agent will react by perceiving the state of the world, when one of them changes. Each agent will therefore define its observation list: *watchList = [singnal1, signal2, ..., signaln].*

2.2 Mem

The memorisation function is executed whenever there is a substantial change in perception that deserves to be stored. A threshold μ is defined, which when exceeded, generates a new internal state. To compare the current world state with the stored internal state, we use a distance function. Given an agent, and the list of perceived signals (φ) and the stored internal state (ς), at time instant (t), the distance function is defined as:

$$distance = \frac{\sum_1^n \left| \frac{\varphi(t)_i}{\max(\varphi_i)} - \frac{\varsigma(t-1)_i}{\max(\varsigma_i)} \right|}{n} \quad \text{where } | \text{ indicates absolute value} \tag{3}$$

The distance function calculates the difference between a perceived signal and the previous stored state. Furthermore, it divides each signal by its maximum in order to normalise the values and thus not to generate distortions by signals with high values versus signals with small values. Finally, the result of the summation is divided by the number of observed signals, generating a distance value between 0 and 1, where 0 implies that there has been no change and 1 implies that there has been a total change in all signals. *Mem* will store the new state of the world whenever *distance* $> \mu$. If we want the system to be very sensitive to changes, it will be enough to make $\mu = 0$, and then the system will react to any change. Each agent can be configured with a particular μ.

2.3 Decision

The decision function generates an action in case the centre detects a condition of interest to it. Generating an action implies generating output signals that will try to influence the world, trying to bring about a change. We can define this function as:

$$SetsignalValue(FundD(\varphi, \varsigma)) \ if \ PreD(\varphi, \varsigma) = true \tag{4}$$

where:

- *PreD* (φ,ς): is a precondition function that relates False or True to a percept and a given internal state: *PreD:* $\Phi_\alpha \times \Sigma_\alpha \rightarrow$ *Boolean.* Defines the trigger conditions.
- *FunD* (φ, ς): Function that associates the agent's perception and internal state with a list of output signals that define an action. *FunD:* $\Phi_\alpha \times \Sigma_\alpha \rightarrow P_\alpha$. Therefore, each centre will have to determine the signals that generate actions.

2.4 Excec

Finally, the execution function will be defined as a function that outputs the signals generated by *Decision*, provided that a certain execution precondition is met, i.e.:

$$PostE(\rho)if\ \ PreE(\varsigma) = true \tag{5}$$

The *PostE* function generates the output signals or influences. These can be the same signals defined by the action ρ. The *PreE(ς)* function allows the influence intent to be conditioned on the perceived state. If set to "true", influence is always generated.

3 Design of the Agents

To design the actors, it is necessary to specify the figures for the objectives of the system. There is an overall objective that must be met: to ensure water supply. This is achieved by maintaining a minimum level of water in the reservoir, so this objective will take priority over the other goals.

3.1 Goal 1

The first objective is to minimise the amount of water stored. To find out what the minimum and maximum values are, the behaviour of the city has been studied over several months in 2021 and 2022 (Fig. 4). The empirical study indicates that, most of the time, the water level moves approximately 0.5 m, in fact 72% of the measurements are within this range. The minimum level of the reservoir is set at 0.5 m, as below this water level there would be sediment entrainment. Therefore, values between [0.5 - 1] are required to maintain the water level at its optimum point.

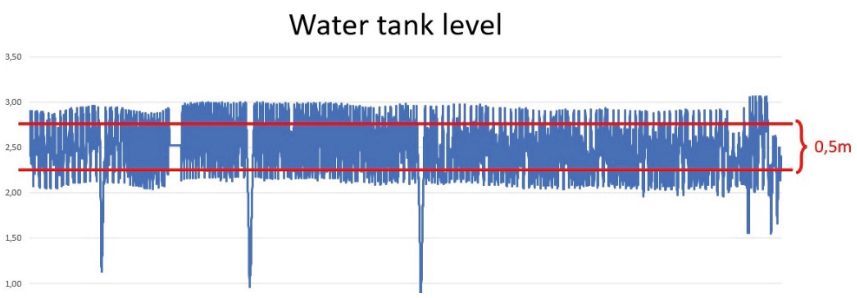

Fig. 4. Water tank level in 2021–2022

3.2 Goal 2

The second objective is to avoid pumping water during periods of peak consumption in the city, thus preventing the pumping stations from working against inertia. To this end, the behaviour of the city's consumption (Fig. 5) has been studied for 2021–2022 and it has been established that, above 50 m^3/h of consumption, it is desirable not to switch on the pumps, as long as goal 1 is met.

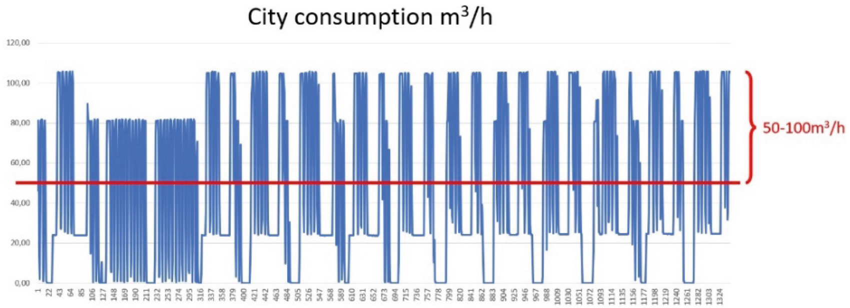

Fig. 5. City consumption in 2021–2022

3.3 Goal 3

The last objective is to maintain the pressure of the infrastructure around a reasonable value, avoiding too high or too low pressure. In this case, the reservoir is located at 47 m above sea level. Therefore, the minimum pressure should be 47 m water column (mwc). Since the maximum height of the tank level is set at 1 m in goal 1, the maximum pressure to be expected is 48 m water column. A margin of ±5% is applied to these values, which is the margin of error of the pressure gauges, so the pressure should be kept between [44.5–50.5] metres water column.

3.4 Agents

The system will be composed of several agents, one managing each objective, plus a coordinating agent, who will be responsible for coordinating the influences of the other agents. Each agent produces an influence on the system, in this case, the influence is the desire for the water pumps to start or stop. Each agent will produce an attempt to modify the state of the system, and we must consider that the intentions can be contradictory, and that is why a coordinating agent is necessary. To define the agents, it is necessary to define the internal functions of each agent.

Agent A_1 is responsible for achieving Goal 1. To do so, it will observe the water level in the tank and when it is close to the limits, it will generate an influence on the pumps, I_1, with a value between $[1, -1]$. Positive values indicate that it wants to start the pumps, a value of 0 indicates no influence, and a negative value indicates that it wants to stop the pumps. The strength of the desire will be between 0 and 1 for positive and between 0 and -1 for negative. Table 1 show the internal definition on A_1.

Agent A_2 will be responsible for Goal 2, so that it will monitor water consumption in the city and when it exceeds 50 m^3/h it will generate an influence, I_2, to detect the motors, i.e., it generates values between $[0, -1]$. In our infrastructures, to know the water consumed by the city, it is calculated by observing the amount of water generated by the pumps when they are on and the amount of water that enters or leaves the tank (positive flow indicates that it enters the tank, negative flow indicates that it leaves the tank) in the tank. Therefore, the water consumed is equal to the water produced by the pumps minus the flow of water in the tank. Table 2 show the internal definition on A_2.

Agent A_3 will manage Goal 3 by monitoring the water pressure. When the pressure is between its normal values, [44.5–50.5] mwc, the agent will produce a neutral influence, 0. When the pressure drops below the minimum, it will generate a maximum influence to start the pumps (value 1), and when the pressure exceeds the maximum, it will generate a maximum influence to stop them (value -1). Table 3 show this.

Table 1. Definition of the internal elements and functions of the agent A_1.

Element	Values	
watchList	HWT (height of water in the tank)	
μ	0,01	
FunD	$I_1 = 1$ $I_1 = 2*(1 - HWT)$ $I_1 = -1$	if HWT $\leq$ 0,5 if 0,5 < HWT < 1 if HWT $\leq$ 1
PostE	I_2	

Table 2. Definition of the internal elements and functions of the agent A_2.

Element	Values	
watchList	WTF (water tank flow), WPF (water pumps flow)	
μ	0,01	
FunD	$I_2 = 0$ $I_2 = -1$	if WPF-WTF < 50 if WPF-WTF $\geq$ 50
PostE	I_2	

Table 3. Definition of the internal elements and functions of the agent A_3.

Element	Values	
watchList	WP (water pressure)	
μ	0,01	
FunD	$I_3 = 1$ $I_3 = 0$ $I_3 = -1$	if WP $< 44{,}5$ if $44{,}5 \leq$ WP $\leq 50{,}5$ if WP $> 50{,}5$
PostE	I_3	

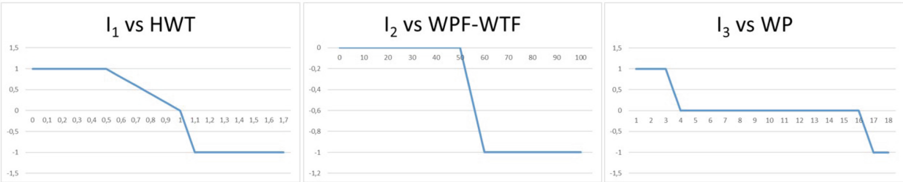

Fig. 6. Influence values of A_1, A_2 and A_3

Figure 6 shows the graphs with the values of the influences produced by each agent. The coordinating agent AC_1 will be responsible for mediating between all influences, giving priority to I_1 over the others, as maintaining the water supply is mandatory (Table 4).

Table 4. Definition of the internal elements and functions of the agent AC_1

Element	Values
watchList	I_1, I_2, I_3
μ	0
FunD	$I_4 = 0.5{*}I_1 + 0.3{*}I_2 + 0.2{*}I_3$
PostE	I_4

The behaviour of this coordinating agent could be expressed in many ways. It has been chosen to carry out a static weighting of the influences of the rest of the agents, but it could also be dynamic, so that, for example, depending on the season of the year, it would give more weight to I1, so that in summer it gives priority to having stored water, or depending on the time of day to I2, so that, during working hours, it would give more priority to not turning on pumps during the moments of greatest consumption and therefore, of inertia in the water flows.

4 Simulator Development

To validate the proposal, we have developed a MAS simulator, which uses as input the real consumption data of the city of 5000 inhabitants taken as an example. For the development of the system, we have used the Angular framework programmed in TypeScript and libraries of graphical representation of data [23]. These technologies have been chosen for the development of the simulator for two reasons. First, the aim is to use platform-independent web technologies. Secondly, in this way, the logic of the agents is executed on each client's computer, but, if necessary, the logic can be moved to a specialised server, ensuring the scalability of the proposal. Each agent has been designed as a class of type Agent as shown in the Fig. 7.

For each agent, it will only be necessary to define its *FunD* decision function, which generates the corresponding influence. Whenever there is a change in any of the input signals, the agents evaluate the state of the world and make decisions accordingly, generating influences that try to alter the state of the pumps (Fig. 8).

```
export class Agent {
  watchList:string[] = [];              // signals watched
  mu:number = 0;                        // distance threshold
  memory:SignalInterface[] = [];        // internal memory
  perception:SignalInterface[] = [];    // perception of agent
  influence=0;                          // influence of agent
  percept(word:SignalInterface[]){
    this.perception=signalsOfWachList(word);
    this.mem();
  }
  mem() {
    if (distance(perception,memory)>mu) this.memory = perception
    this.decision()
  }
  decision() {
    this.influence = FundD(this.perception, this.memory)
    this.exec()
  }
  exec() { return this.influence }
}
```

Fig. 7. Class Agent used as a base class for all agents.

In the upper area, the initial parameters of HWT, city consumption and initial infrastructure pressure can be set. When starting the simulation (Start button), the system uses the actual city consumption to calculate the status of the pumps. The simulator shows the status of each signal in the graph below. Simulations have been performed using data from 2021 and 2022, with hourly measurements. The results are discussed below.

4.1 Achievement of Goal 1

The behaviour of this agent aims to keep the water level in the tank stable, between 0.5 and 1 m in height. Figure 9 shows the water level (blue line) and the city's consumption

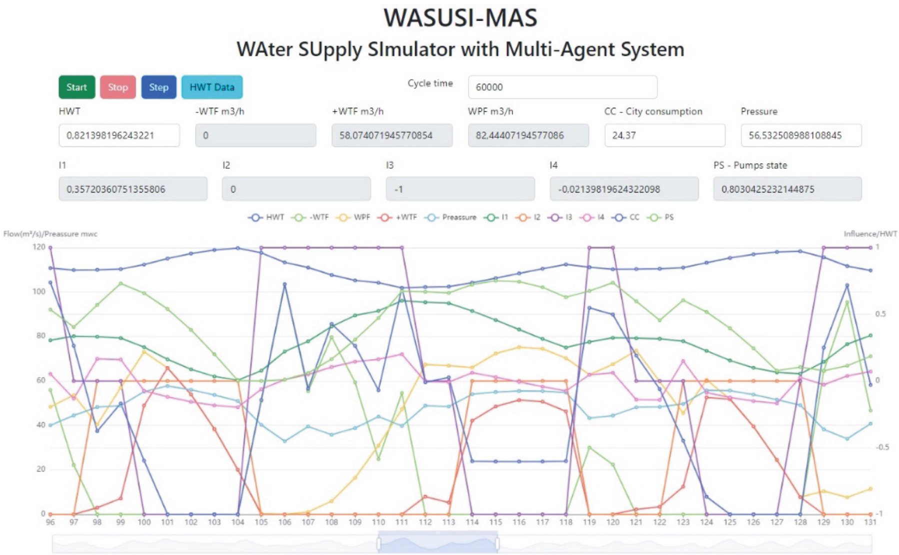

Fig. 8. Interface from WASUSI-MAS.

(green line), and we can see that this level has been always kept stable. Irrespective of the city's consumption demand, at no time has the constant supply been lost, nor has it dropped below 0.5 m, which would have resulted in sediment being washed away.

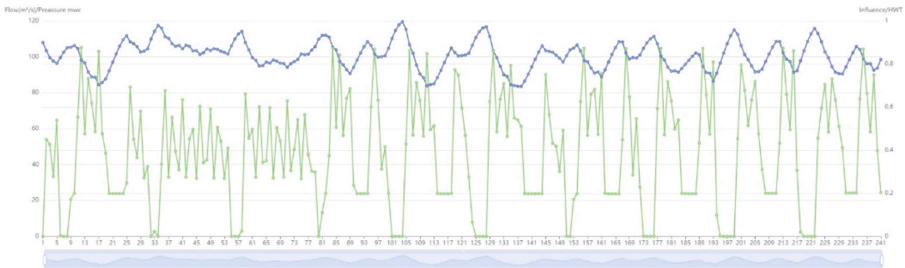

Fig. 9. City consumption and tank level (Color figure online)

Figure 10 shows how the influence generated by agent A_1 decreases when the water level in the tank approaches the maximum values, and how it increases when the water level in the tank decreases.

4.2 Achievement of Goal 2

The A_2 agent aims to reduce the pumps being switched on when there is high consumption in the city, because this prevents the pumps from working against the inertia of the

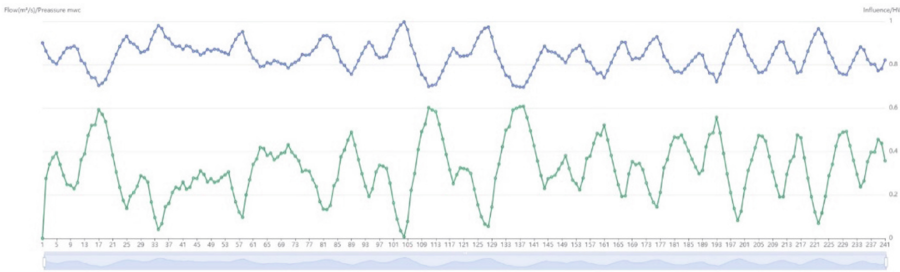

Fig. 10. Water level in the tank against the influence of A1

water flow when it circulates towards the consumption area. In Fig. 11, the influence of A_2 is shown in orange, the city consumption in green, and the pump status in blue. It can be seen that the agent has a negative influence, it tries to stop the pumps when the consumption is high. As soon as the consumption decreases from 50 m^3/h, the agent generates the neutral influence 0, allowing the pumps to be activated according to the rest of the parameters. When the agent A_2 produces the influence 0, the pump can increase its power, this can be seen as the blue line rises in the graph.

Fig. 11. Pump performance against the influence of A_2 (Color figure online)

4.3 Achievement of Goal 3

The A_3 agent aims to keep the pressure within desirable operating levels between 44.5 and 50.5 mwc. In Fig. 12, the purple line shows the influence of A_3, the dark blue line shows the pump status, and the light blue line shows the pressure in the infrastructure. In this case, A_3 has a negative influence when the pressure is very high, as the pumps are in operation. When the pressure decreases, A_3 generates a neutral influence, leaving the pumps working. Lastly, when the pressure is too low, A_3 produces a positive influence, which boosts the work of the pumps.

The simulator is available in the public repository [24] along with sample data for simulations. This simulator could be used as a basis for the development of other control systems on other infrastructures.

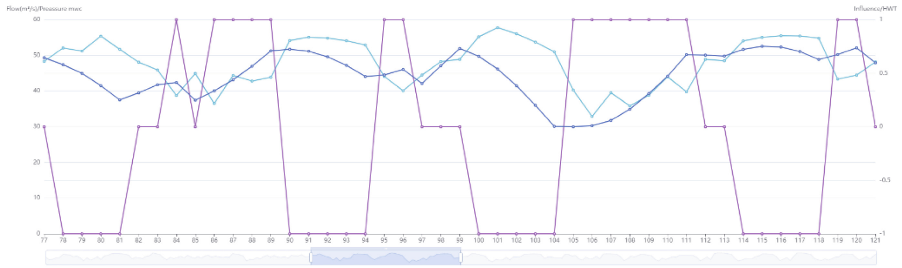

Fig. 12. Evolution of the pressure against the influence of A_3 (Color figure online)

5 Conclusions and Future Work

This work has proposed the design and development of a drinking water supply infrastructure simulator, which uses a multi-agent system for its control. The use of MAS allows us to introduce goals to be met by the control system, without the need to worry about the exhaustive modelling of the physical system, or that the goals are consistent with each other. Based on the MAS, a tool has been built, WASUSI-MAS, through which the simulation of the system can be carried out on the data of a real infrastructure. This makes it possible to obtain a control system focused on sustainability, capable of reducing the amount of water stored in the reservoir and maintaining an efficient operating range in the infrastructures, preventing the system from working under adverse circumstances such as high pressures or water inertia. In the simulation, it has been verified that the agents fulfil their goals, generating the desired behaviour. In addition, the simulator has been shared in a public repository so that it can be used freely.

However, when dealing with the management of critical systems, it is necessary to increase the number of tests and simulations, extending to anomalous or exceptional situations, to ensure that the operation will be as desired. Until then, the simulator can be used to propose various improvements to the agents, or to model more complex scenarios or scenarios with new goals. Future work includes increasing the number of tests and the creation of scenarios that are not only based on historical data.

Based on this work, several ways are open. On the one hand, work on the incorporation of prediction agents. The current simulator uses historical consumption data to generate the desired behaviour. This implies that the MAS is limited to being solely reactive. The inclusion of prediction agents could provide a much more sophisticated MAS, with influences based not only on current data, but also on future data. On the other hand, work is underway to generate a library of predefined agents, agents specialised in different goals. This line of work would generate great potential for the simulator, as it would allow the MAS control system to be composed, simulate its operation with real infrastructure datasets, compare different configuration options, and thus be able to generate safe and stable control systems.

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