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SMART WATER MANAGEMENT USING INTELLIGENT DIGITAL TWINS

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Abstract. Providing and distributing fresh water to large communities is a major global concern. In addition to its scarcity as well as to its wastage, this vital resource is being affected by challenging environmental conditions. New approaches are, therefore, urgently needed for an optimized, fair, and efficient use of fresh water. The adoption of emergent technologies is giving high hopes to reach this objective.

Among these technologies, digital twin is attracting increasing attention from the academic and industrial committees. This attention is particularly motivated by its expected values to any sector, including process optimization, cost reduction, and time to market shortening. In the specific field of water management, several solutions are being proposed, especially to detect leak detection and test water assets under a variety of working constraints. These solutions are still lacking intelligence and autonomy throughout the loop of data acquisition and processing as well as asset control and service generation and delivery. To this end, we are proposing in this paper a new framework based on multi-agent systems and DT paradigm to close gaps within this loop. Our multi-agent system is responsible of running data analytics mechanisms in order to assess water consumption and generate relevant feedbacks to users using, among others, a rewarding system to select the appropriate pricing policies. It is also responsible of simulating asset operations under specific working constraints for the purpose of failure and/or defect detection.

Keywords: Water management, digital twin, multi-agent systems

1 INTRODUCTION

Supplying and distributing fresh water are urgent and prominent issues in water resource management. They are being recognized as one of the worldwide matters under the attention of the United Nations. This attention is predominantly motivated by the scarcity of fresh water resources as well as by facts revealing that very large populations are having continuous difficulties to access fresh and clean water for drinking and sanitation purposes [29]. As huge volumes of natural water resources are being wasted and challenging environmental conditions are affecting the availability of water, considerable efforts (e.g., [29, 30, 31]) are focusing on the prevention of such wastage as well as the creation of smart solutions for efficient and fair supply of clean water. These solutions are particularly relying on the ever-growing computing power of computers and edge devices. They are also relying on emergent technologies, such as artificial intelligence (AI), internet of things (IoT), cyber physical systems (CPS), and digital twins.

The digital twin (DT) paradigm has become popular since its introduction by NASA in 2010 to enhance the simulation of physical models [1]. Due to the absence of any clear consensus on its meaning, its applications are currently very broad and fuzzy [9, 10]. Nevertheless, according to the common understanding, DT can create virtual copies of specific parts of a given system that are capable of interacting with their physical counterparts in a bidirectional way [6]. It can be defined as the virtual representation of a component, a product or a system by replicating all its physical features in order to enable real-time simulations [2]. These simulations are capable of touching all the aspects of industrial processes, from primary material extraction to product management and distribution [4]. They are also capable of providing additional services to the traditional simulations allowing, thereby, for better control and execution of operations as well as for enhanced decision-making processes [3]. The services provided by DT are bringing a wide range of values, such as reducing maintenance, optimizing operations, increasing user engagement, and reducing time to market. This is particularly facilitating synergies between the different phases of production and reduces the development time of a product with improvements in manufacturing. This is also making the contributions of DT indisputable in a wide range of application domains [5, 7]. This statement is supported by several studies. Indeed, according to Gartner [8], DT is representing a new technology with very high opportunities in terms of productivity growths over the next 5–10 years.

In the broad field of water management, the wastewater research community has been working hard in recent years to create new process models (e.g., [11, 12]), new process control strategies (e.g., [13, 14]) and new process monitoring systems (e.g., [15]). These efforts are aiming to bridge the gap between current operations and the state-of-the-art on control practices needed to efficiently and optimally run the multitude of processes involved in resource recovery, given constrained capital and operational budgets. The efforts undertaken by the wastewater resource community have been extended with DT-related capabilities, as shown by several products created by utility companies (e.g., Global Omnium and Consorcia d'Aigues de Tarragona [18]) as well as by several works addressing, for example, water distribution systems (e.g., [16, 17, 24]) or providing water metering applications (e.g., [19, 22]).

In spite of the promising results and its related high hopes, the application of DT in the water management field is still in an infancy stage [18]. New solutions are yet to be constructed to improve operations related to asset management, leak localization, optimization of the system operation, monitoring of water quality, planning of maintenance operations, early response to emergencies, etc. [19]. In the specific context of managing water consumption, we argue that these solutions should be endowed with autonomy and intelligence in order to deal with the right recurrent and non-recurrent requirements, at the right time. To this end, we are proposing in this paper a framework for water consumption management based on multi-agent systems as well as DT. Our framework is structured along five layers, within which water consumption data are managed based on intelligent software agents as well as a rewarding mechanism to identify the appropriate pricing policies and generate relevant feedbacks to users.

In the remainder of this paper, Section 2 will highlight the use of DT for the management of water consumption. Section 3 will describe the fundamentals of our framework as well as the rewarding mechanism and the approach used to select the pricing policy. Section 4 will outline some of our results. Section 5 will discuss the current progress of our work as well as our future plans. Section 6 will conclude the paper.

2 RELATED WORK

DTs are currently attracting increasing interest across several industrial and research application fields. This is particularly motivated by the growing focus on digitizing production lines and processes as well as the will of gaining more accurate insights from data using advanced methods (e.g., machine-learning and emerging visualization tools). In the specific field of urban water systems, the authors in [20] have defined DT as a set of systematic virtual replications of the components and dynamics of the water system. According to [21], one of the most promising applications are DT-based where adaptive plant models, predictive maintenance, and plant-wide control digitized mechanisms are used to enhance resource recovery, improve water quality, increase client engagement, and reduce costs. These benefits have motivated multiple successful water-related case-studies. For example, in the water distribution industry, DTs have been used by some utility companies (e.g., Global Omnium and Consorcia d'Aigues de Tarragona [18]) primarily to reduce water leakage and ultimately provide enhanced services to their clients. DTs have also been used by these companies to investigate pump operations based on real-time data acquisition, simulation, and analysis tools. These investigations are of paramount importance since water distribution systems are basically closed systems serving heavy daily demands [22] and operating unattended with constrained devices that are prone to failure.

Furthermore, in [9], the authors have presented a comprehensive review on transforming raw data into actionable insight, with a main focus on water resource recovery facilities. In [22], the authors have described a smart water metering application (called SWaRM) based on a DT platform (called Altior). SWaRM is created to enable an easy integration with the IT infrastructure of water companies. Altior, which focuses on industrial IoT applications and services, allows users to create DTs for a wide range of sensors and devices used in industrial applications. Examples of devices include data loggers, pressure sensors, and water meters. The platform Altior also allows users to build virtual networks and communicate with the physical world. In [19], the authors have presented a DT-based application that is capable of building a comprehensive hydraulic model using the information available on a utility big data platform. The application is capable of generating scenarios, simulating relevant real-time operations, and generating predictions about the drinking water distribution network. In [25], the authors have focused on water distribution systems and presented a solution to develop and maintain, in real time, a DT of a water distribution system (WDS). To meet the expected goals, the solution relies on data coming from a variety of sources, including GPS, the automated meter readings, SCADA systems, and operation and maintenance databases. In [16], the authors have proposed a cyber physical system (CPS) including a hydraulic simulator to build an intelligent cyber WDS that can monitor valves and accommodate water demands as equitably as possible, accordingly. In [17], the authors have built a small-scale physical twin which is capable of simulating a real WDS, considering several anomaly scenarios, including communication failure and pipe bursts. The proposed approach runs real-time algorithms based on sensors' data for the sake of energy optimization and implementing and automated event-driven control [19].

We argue in this paper that considerable efforts are being made to adopt the DT paradigm, particularly since it can be used as a promising tool to digitize utility companies providing water system [23]. Nevertheless, according to the current literature, the application of this paradigm for water management is still in an infancy stage [18, 21]. New approaches are particularly needed for smarter water consumption with options of testing a variety of operation scenarios as well as pricing policies to engage users toward optimizing the use of the scarce water resources. These capabilities can be obtained with the adoption of the multi-agent system (MAS) paradigm, which has been already applied to the field of water resources management (e.g., [32, 33, 34]). A MAS consists of multiple interacting software agents with varying behaviours and potentially conflicting objectives. It is suitable for modeling and solving complex problems which are particularly characterized with open, dynamic, and uncertain environments. In MAS, an agent can operate autonomously and intelligently as well as reason, learn, and adapt itself to meet its objectives. It can also negotiate, coordinate, and/or collaborate with other agents to achieve common goals, which are beyond their individual capabilities.

3 PROPOSED ARCHITECTURE

3.1 Fundamentals

Several options are being followed in order to extract readings from water meters. These options include:

1. The use of automated meter reading where a walk-by or a drive-by person uses a handheld device to read the meter and then send the readings to a management system in real time or offline; and
2. The use of advanced metering infrastructure where a dedicated gateways are used to pull out readings from water meters automatically and send them via internet to a remote data management system.

In these configurations, testing different patterns related to sampling frequency as well as pricing policies are not straightforward as smart water meters are not always capable of reporting consumption readings as per customized setups. This is particularly due to the commonly limited capabilities of smart water meters as well as their proprietary natures. These restrictions are making difficult, for example, to predict if a given smart water meter is capable of providing some requested readings under specific conditions that would require intensive processing and communication resources without failure.

In order to enable an alternative solution that would allow a better management of water assets and resources, we are proposing in this paper a DT-based five-layer architecture for the management of water resources (Figure 1). The physical layer includes all the water-related assets, including the smart water meters, the gateways, and the sensors. The control layer includes the data collected from the physical layer, the data analytics tools, and a decision-making module that is responsible of federating all the processing that concern the smart water solution. The digital twin layer includes the digital copies of the smart water resources. The purpose of this layer is to test actions on the actual devices, such as changing sampling frequencies, checking network connectivity, testing security routines, etc. The application layer is used to deliver services, feedbacks, and recommendations related to water consumption to clients. The advising layer is dedicated to the analysis and the predictions of the consumer behaviors.

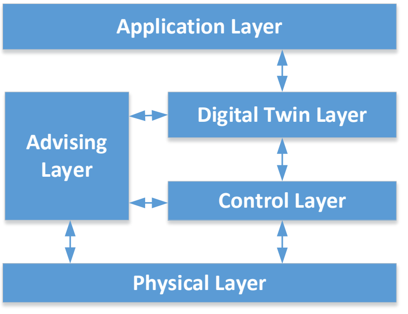

Figure 1. Proposed five-layer architecture

In order to maintain an effective flow of information between the five layers, we are proposing the use of the Inform-Control-Simulate-Advise-Deliver (ICSAD) loop reflected in Figure 2. The loop is controlled by a multi-agent system. The use of the multi-agent system paradigm is motivated by its proven autonomy, intelligence, and flexibility to solve complex problems in constrained, uncertain, and highly dynamic environments [26].

The operations between the components of the ICSAD loop is basically used to assess the water consumption readings and make an appropriate decision about the appropriate pricing policy that should be applied to the consumer as well as the appropriate feedback to be sent to him/her. More specifically, these operations are depicted in Figure 3, where the Inform Agent (IA) of a given smart water meter preprocesses any reading received, for example, by checking its quality, identifying reading failures, and/or identifying any security issue related to data acquisition or transmission. If any fault or security breach is detected then a report is sent to the Control Agent (CA). In this case, this agent will ask the Digital Twin Agent (DTA) to investigate the issue by running the appropriate simulations and returning back comments and recommends. If the readings are free of fault and security issues then the CA agent calculates the consumption distortion in order to identify if the water consumption during a predefined period of time (e.g., one week) has changed.

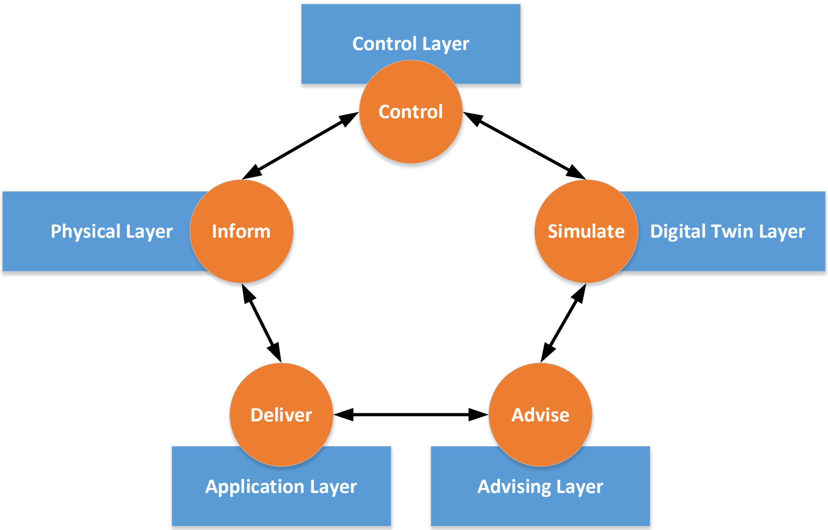

Figure 2. The Inform-Control-Simulate-Advise-Deliver (ICSAD) loop

If the consumption remains relatively the same then the Feedback Agent (FA), which is located in the application layer, will keep the same feedback provided to the consumer. If the consumption is better than the previous predefined period of time then the CA agent will calculate the rewards that could be obtained. If the cumulative rewards so far do not qualify for a better pricing policy then the same feedback is kept. If the cumulative rewards qualify for a better pricing policy then the FA will generate a more encouraging feedback along with related water consumption and pricing details. It is important to mention here that data collected, their related analysis, as well as any decision taken by the IA, CA, DTA, and FA agents will be shared with the Advisor Agent (AA) for further predictive processing. In addition to shedding light on this issue, we will outline in what follows the process of water consumption rewarding mechanism, selecting water pricing policies, and generating feedback to clients.

3.2 Water Consumption Rewarding Mechanism

In order to encourage clients to reduce their water consumptions and reward them accordingly, we are proposing in this paper to calculate the cumulative rewards of a given consumer as follows:

$$R(T) = a(pt(t))^b$$

where $pt(t)$ refer to the points obtained at time against the water consumption, a is a constant, and b represents how the reward would change when $P(t)$ changes. We

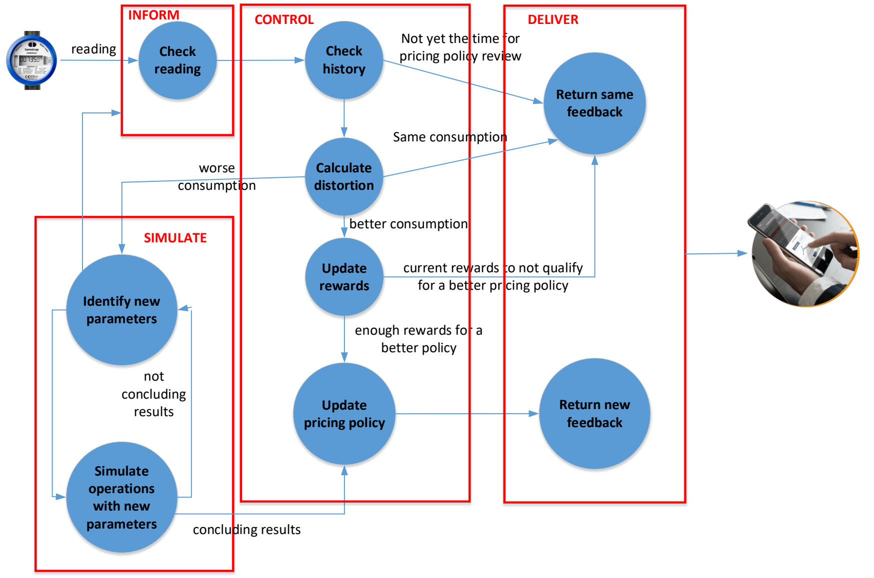

Figure 3. Multi-agent system for the management of water resources

define b in this paper as follows:

$$b = \frac{pt(t)}{\ln(pt(t))}.$$

In the above equation, the parameter will increase slowly as the number of points at time t (i.e. $pt(t)$) increases. This number is going to be calculated as follows:

$$pt(t) = \lambda D(t) = \lambda \frac{C(t) - C(t-1)}{C(t-1)}$$

where $D(t)$ is the water consumption distortion, $C(t)$ and $C(t-1)$ refer to the water consumptions at time slot t and $t-1$, respectively. The parameter λ ($\lambda < 0$ since the distortion must be negative to mean that the water consumption has decreased at time t compared to time $t-1$) is selected in a way to make sure that the number of points will not be strongly correlated with the distortion.

3.3 Selecting Water Consumption Policies

In order to motivate consumers to make a better use of the scarce water resources, we are assuming in this paper that $P = p_1, p_2, \ldots, p_n$ pricing policies exist, with the following assumptions:

- Policy p_i is more competitive from a consumer perspective than policy p_j $(i < j)$.
- Policy p_i requires less resources (e.g., less data acquisition and processing energy) than policy $p_j(i < j)$.

The decision on the pricing policy to be applied to the client is decided by the following function (we assume that the current policy is p_i):

$$\begin{cases} f(R(t)) = p_{i+1}, \text{ if } R(t) > w(p_{i+1}) \text{ and } D(t) < \textit{threshold}1, \\ f(R(t)) = p_{i+1}, \text{ if } R(t) > \textit{threshold}2 \text{ and } \textit{Mean}(D(t-n), \ldots, D(t)) > \textit{threshold}3. \end{cases}$$

The first line of the equation is applicable in the case of upgrading the pricing policy (i.e. going for a better policy). This is going to happen when the cumulative number of rewards is higher than the weight $w(p_{i+1})$ of the new policy and the current consumption distortion $D(t)$ is lower than a given threshold (recall: the distortion is a negative value in the case of a better water consumption).

The second line of the equation is applicable in the case of downgrading the pricing policy. More precisely, the new policy will be p_{i-1} if the current distortion is higher than a predefined threshold (i.e. Threshold 2) and the mean of n previous positive distortions is higher than a given threshold (i.e. Threshold 3). The parameter n could be set to a fixed value or may change depending on the consumption behavior of the client.

3.4 Toward a Better Management of Water Consumption

Providing appropriate feedbacks as well as applying dynamic water consumption policies would motivate and/or constraint consumers to adapt their water consumption habits. In order to understand, assess, and provide means toward better users' behaviours, several studies (e.g., [27, 28]) have demonstrated the benefits of using artificial intelligence approaches. Following the recommendations found in the literature, we are proposing the use of reinforcement learning tools in order guess water consumption behaviors and consequently improve feedbacks to be provided to consumers. More specifically, we propose to rely on Markos Decision Process (MDP), which is a mathematical framework for modeling decision-making in given situations. The outputs of these decisions are partly controller by a decision-maker as well as partly random. In MDP, which is also used to describe an environment in reinforcement learning, an agent interacts with its environment by performing actions while trying to obtain maximum rewards. The process of MDP at any given time stamp t could be described with:

1. The environment is in state S_t;
2. The agent performs an action A_t;
3. The environment produces a reward R_t (depending on A_t and S_t); and
4. The environment shifts to the next state S_{t+1}.

In the current paper, the agent AA (see Section 3.1), is following the MDP process. To this end, we highlight in Table 1 the different components of this process. We also highlight in Figure 4 the typical transition diagram that is going to be used in the MDP.

MPD Process	Water Consumption Scenario
States	A consumer may have several states, based on his/her water consumption behaviour. More specifically, and for the sake of illustration, we assume in this paper that these states are as follows: 1. Normal (in this state, the water consumption is within predefined ranges defined by the water service provider authority); 2. Rewarding (in this state, the consumer gets rewards against the points collected for low water consumptions); 3. Probation (in this state, the water consumption is relatively high, based on predefined limits); and 4. Penalizing (in this state, the consumer is penalized for repetitive high consumption)
Rewards	For each water consumption state, there will be a reward (alternatively a penalty) calculated based on readings. These rewards will be calculated based on the explanations given in Section 3.3
State transition probabilities	Based on the data and information received from the IA, CA, DTA, and FA agents over time, the AA agent will calculate transition probabilities between the different consumption states. These probabilities will be regularly revised to reflect new readings and new consumption behaviours. Furthermore, the AA agent will, in parallel, calculate specific probabilities, that we call here probabilities of improvement. A probability of improvement p will mean to the consumer that if he/she follows the recommendations of the AA agent then there is p chance that his/her consumption state would transit to a better state.
Actions taken by the agent	Based on the current consumption state as well as the last readings, the agent will predict the next state into which the consumer would be. In order to prevent any transition into an undesirable state (namely Probation and Penalizing), the agent will recommend some actions to the consumer (e.g., reduce water consumption during specific hours of the day). These recommendations would help him/her, for example, to get a better pricing plan.

Table 1. Dynamic water consumption policies based on rewards and penalties

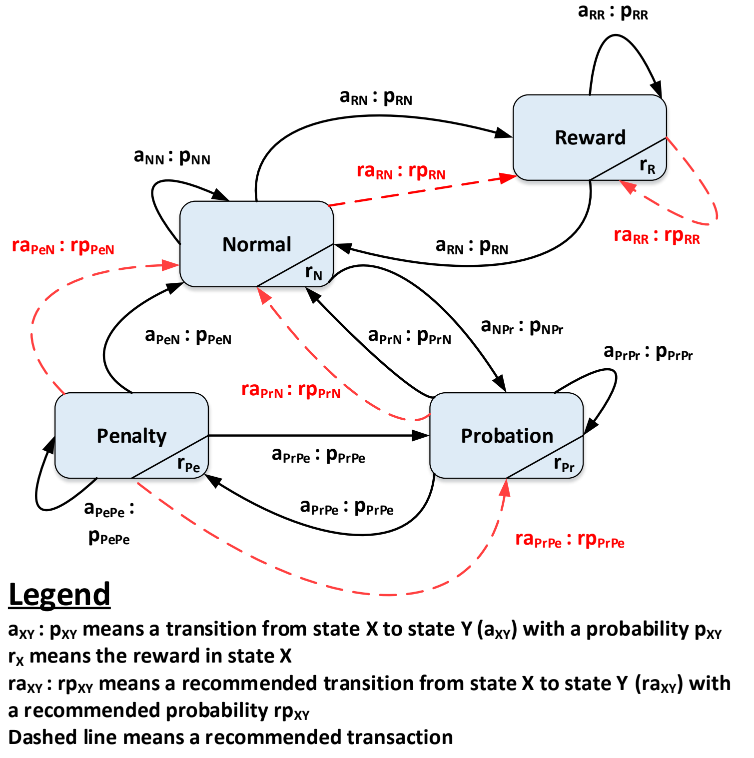

Figure 4. Typical transition diagram for water consumption

4 IMPLEMENTATION AND RESULTS

In order to give a proof of concept of our approach, we installed 100 smart water meters in the area highlighted in Figure 4. The high-level setup of our system is depicted in Figure 5. In the backend of our solution, we implemented our multi-agent system using the GAMA platform, as recommended in [25].

The data pushed out from the system is managed by a web-based solution that allows the manager of the smart water metering system to control the water assets and check their operations (Figure 6).

Our solution provides users with several options (Figure 7) to check their water consumptions. More specifically, Figure 7 a) shows the dashboard of the user, Figure 7 b) depicts the readings coming from a specific smart meter for a given day, Figure 7 c) gives the cumulative daily water consumption during a given month, Figure 7 d) reflects the average weekly water consumption, Figure 7 e) highlights the water consumption per day during a given month, Figure 7 f) gives the total water consumption for several months, and Figure 7 g) presents the percentage of water consumption for several months.

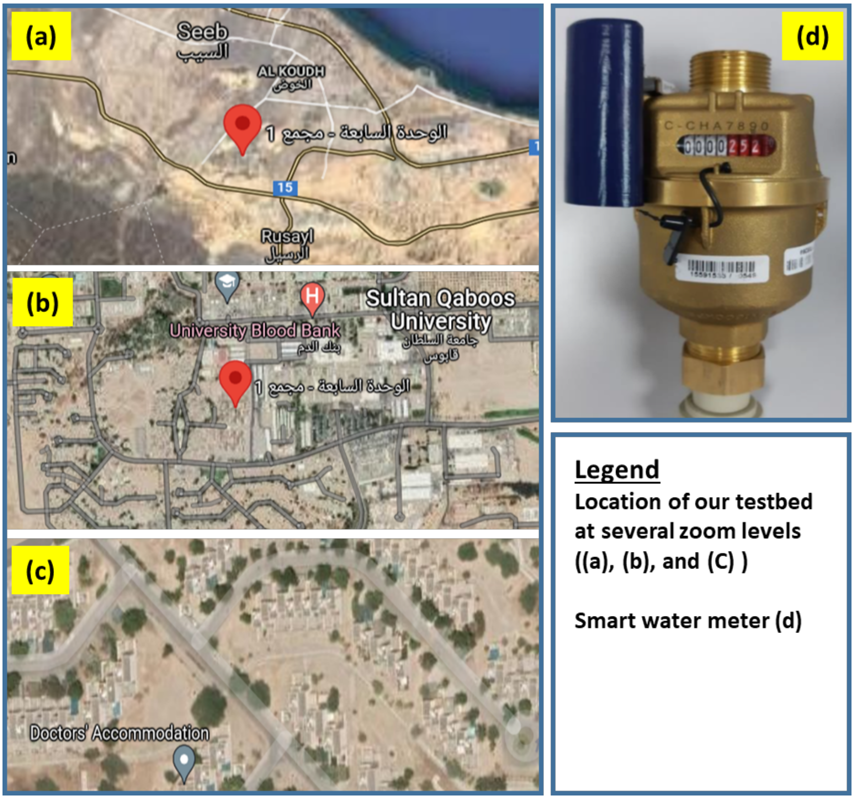

Figure 5. Location of our testbed along with a sample of smart water meters used

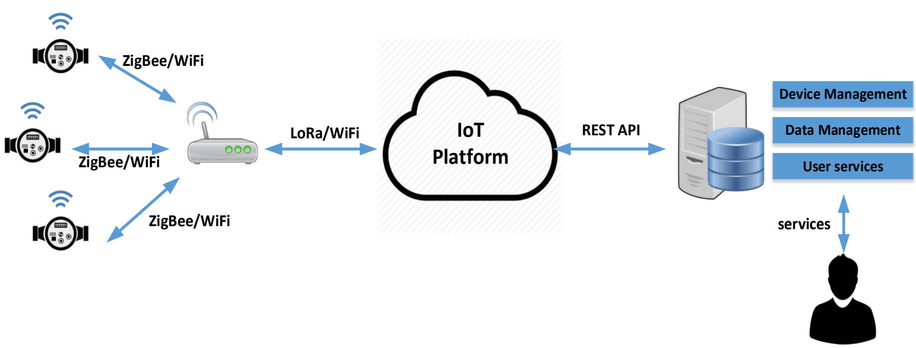

Figure 6. System overview

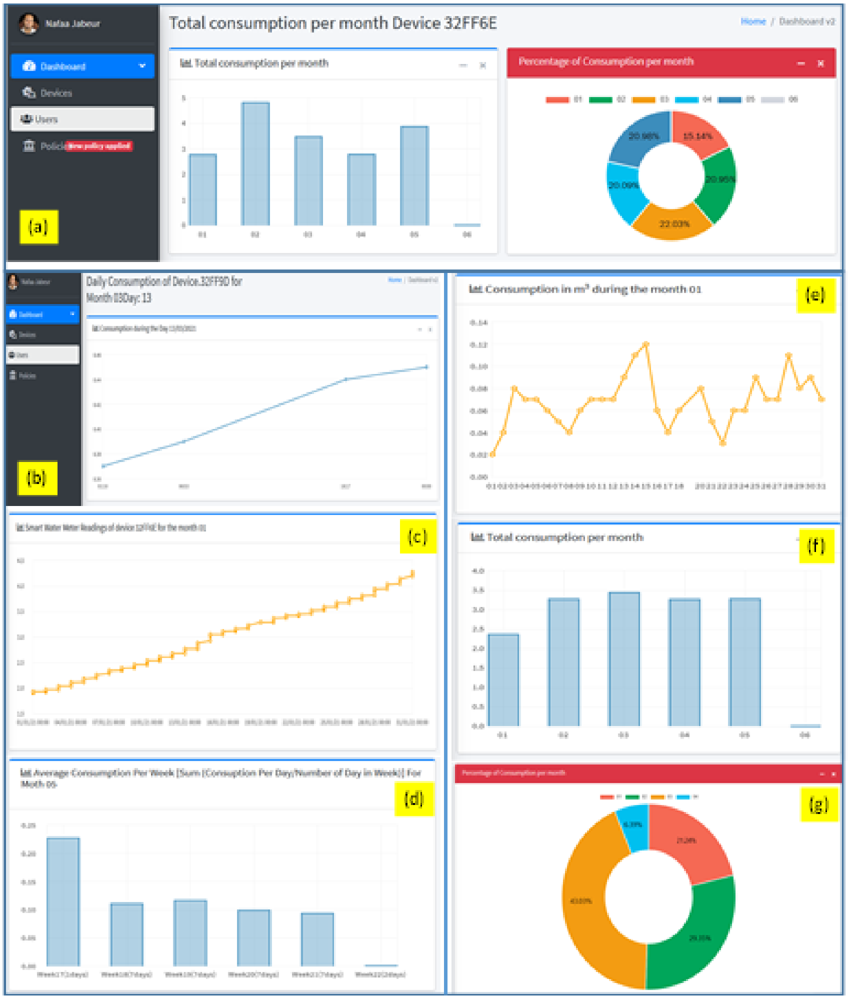

Figure 7. Examples of services provided to consumers about their water consumptions

Based on the user's water consumption, our solution will apply the appropriate pricing policy, as discussed in Section 3.3. This is currently reflected with the use of different colors, as shown in Figure 7.

5 DISCUSSION

Our current implementation is capable of providing consumers with real-time feedbacks on their water consumptions. It is also capable of identifying the appropriate pricing policies against these consumptions. In spite of this performance, several shortcomings must be solved in order to extend the current solution. More specifically, the following challenges must be investigated:

Integration of DT: The current implementation does not yet support the expected DT functionalities, such as the simulation of smart water operations under specific circumstances. In this regard, in addition to exhibiting several communication failures, the deployed IoT network does not allow for the testing of variable sampling rates. For this reason, the ongoing developments are focusing on the use of DT-related simulations in order to understand and predict IoT failures as well as the behaviours of smart water meters while delivering consumption readings as per specific timings.

Extending DT with intelligence: The use of multi-agent system is enabling a smart and autonomous management of water consumption performance. Making DT-related functions intelligent would improve the operations of the solution. For example, an intelligent agent assigned to a given smart water meter A may take the outputs of the DT of the meter and do the necessary testing on another similar meter B. This is particularly relevant if the meter A is currently unavailable or does not support specific operations.

Deploying the MDP: The amount of data collected so far is not enough to determine accurate probabilities related to the transitions between the consumption states (see Section 3.4). Our future works will focus on running data analytics models in order to infer these probabilities.

Testing the impact of the solution on consumers' behaviours: Decent work is still needed in order to assess any change of water consumption behaviours following the feedbacks provided to consumers as well the use of varying policy plans. This work will be particularly important in order to identify the appropriate recommendations and their related probabilities, as explained in Section 3.4.

6 CONCLUSION

Managing water consumption effectively remains of paramount importance. The use of emerging technologies, including IoT and big data analytics, is making this task easier. Recent works are increasingly relying on the paradigm of digital twins (DTs). Several research and commercial solutions are, consequently, being proposed, as reported in the literature. In spite of the progress shown so far, the use of DT in the field of water management remains limited. We proposed in this paper a DT-based framework for a smart management of water consumption. Our solution is using a multi-agent system solution to extend our framework with intelligence and autonomy toward a better use of water resources.

Our current prototype is able to oversee the ongoing status of smart water meters as well as provide insights to user about their water consumptions from different perspectives. The multi-agent system is capable of managing the data collected, identifying the appropriate pricing policies, and generating the relevant outputs to the consumers. Nevertheless, the DT part is still in progress. Our future work will, therefore, focus on implementing all the related functions and test them in our testbed setup.

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