

Efficient Water Management through Intelligent Digital Twins

 Siva Sathyanarayana Movva

<https://orcid.org/0000-0148-4515-6305>

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Abstract

Purpose: Supplying and distributing fresh water to large populations is a significant global issue. In addition to the challenges posed by its scarcity and wastage, this essential resource is increasingly vulnerable due to adverse environmental conditions. Consequently, there is an urgent need for novel approaches to ensure the optimal, equitable, and efficient utilization of fresh water. The emergence of new technologies offers promising prospects for achieving this goal. One such technology, the digital twin, is gaining considerable attention from both academic and industrial communities. This attention is primarily driven by the anticipated benefits it offers across various sectors, including process optimization, cost reduction, and accelerated time to market.

Methodology: In the realm of water management, numerous solutions are being proposed, particularly aimed at detecting leaks and assessing water assets under diverse operational conditions. However, these solutions often lack sufficient intelligence and autonomy throughout the entire data acquisition and processing cycle, as well as in asset control and service provision. To address this gap, we propose a new framework in this paper, based on multi-agent systems and the digital twin paradigm.

Findings: Our multi-agent system is tasked with conducting data analytics to evaluate water consumption and delivering relevant feedback to users. This includes implementing a rewarding system to incentivize appropriate pricing policies. Additionally, the system simulates asset operations under specific constraints to facilitate the detection of failures or defects.

Unique Contribution to theory, practice and policy: We propose employing Markov Decision Process (MDP), a mathematical framework for decision-making, to model water consumption behaviors.

Keywords: *Digital Twin, Water Management, Water Consumption, Markov Decision Process (Mdp)*

I. INTRODUCTION

Supplying and distributing fresh water is a pressing global issue, recognized by the United Nations due to scarcity and difficulty of access for large populations. Efforts are focused on preventing water wastage and creating smart solutions using technologies like artificial intelligence (AI), internet of things (IoT), cyber physical systems (CPS), and digital twins. Digital twin (DT) technology, popularized by NASA, creates virtual copies of physical systems for real-time simulations and decision-making. DT brings value by reducing maintenance, optimizing operations, and shortening product development cycles. In water management, efforts include developing new process models, control strategies, and monitoring systems to efficiently manage resources. The wastewater research community has integrated DT capabilities into their work, leading to innovative products and solutions for water distribution and metering. Addressing global water scarcity is a critical challenge acknowledged by the United Nations. Efforts focus on minimizing water waste and implementing advanced technologies like AI, IoT, CPS, and digital twins. Digital twin technology, pioneered by NASA, enables virtual simulations of physical systems, aiding in maintenance, operations optimization, and product development acceleration. In water management, these efforts involve creating new process models, control strategies, and monitoring systems for efficient resource management. The wastewater research community has integrated digital twin capabilities, resulting in innovative solutions for water distribution and metering.

II. RELATED WORK

Digital Twins (DTs) are increasingly important across various industries and research areas due to the push for digitizing production processes and gaining insights from data using advanced methods like machine learning. In urban water systems, DTs replicate system components and dynamics virtually. They offer promising applications such as adaptive plant models, predictive maintenance, and plant-wide control mechanisms, leading to benefits like resource recovery, improved water quality, client engagement, and cost reduction. Successful case studies in the water distribution industry, including those by utility companies like Global Omnium and Consorcia d'Aigues de Tarragona, demonstrate the use of DTs to reduce water leakage and enhance services. These companies also utilize DTs for real-time data analysis to optimize pump operations, critical for efficiently serving high daily demands in water distribution systems. Authors in various studies have explored innovative approaches in water resource management. One study offers a thorough review of converting raw data into actionable insights, focusing on water resource recovery facilities. Another study introduces SWaRM, a smart water metering application, built on the Altior DT platform, facilitating integration with water company IT infrastructures. Altior enables the creation of DTs for various industrial sensors and devices, aiding in virtual network formation and real-world communication. In one of the studies, a DT-based application is discussed, capable of constructing hydraulic models from utility big data, aiding in scenario generation and real-time operation simulations for drinking water distribution networks. Additionally, a real-time DT solution for water distribution systems is proposed, utilizing data from multiple sources like GPS,

SCADA systems, and maintenance databases. A cyber-physical system (CPS) is proposed, incorporating a hydraulic simulator to develop an intelligent cyber water distribution system (WDS), ensuring equitable water distribution. Finally, a study presents a physical twin for simulating WDS scenarios, including communication failures and anomalies. The proposed approach runs real-time algorithms based on sensors' data for the sake of energy optimization and implementing and automated event-driven control.

This paper highlights the growing interest in adopting the Digital Twin (DT) paradigm for digitizing utility companies, especially in water systems. However, the literature indicates that its application in water management is still in its early stages. To address the need for smarter water consumption and optimization of scarce resources, new approaches are required. Multi-Agent Systems (MAS) offer promising capabilities for this purpose, as they have been successfully applied in water resources management. MAS involve multiple software agents with diverse behaviors and objectives, suited for solving complex problems in open, dynamic, and uncertain environments. Agents can operate autonomously, intelligently, negotiate, and collaborate to achieve common goals beyond their individual capacities

III. PROPOSED ARCHITECTURE

A. *Fundamentals*

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

- Automated meter reading: Personnel use handheld devices for walk-by or drive-by readings, transmitting data to a management system instantly or later.
- Advanced metering infrastructure: Dedicated gateways automatically retrieve readings from water meters, sending them via the internet to a remote data management system.

However, testing different sampling frequencies and pricing policies is challenging due to limitations in smart water meters. Predicting if a meter can provide specific readings under customized setups is difficult due to their limited capabilities and proprietary nature, which may require intensive processing and communication resources without guarantee of success.

This paper proposes a DT-based five-layer architecture for water resource management. The layers include: 1. Physical layer: comprising water-related assets like smart meters, gateways, and sensors. 2. Control layer: collecting data from the physical layer, utilizing analytics tools, and housing a decision-making module. 3. Digital twin layer: featuring digital replicas of water resources for testing actions and functionalities. 4. Application layer: delivering services, feedback, and recommendations on water consumption to clients. 5. Advising layer: analyzing and predicting consumer behaviors.

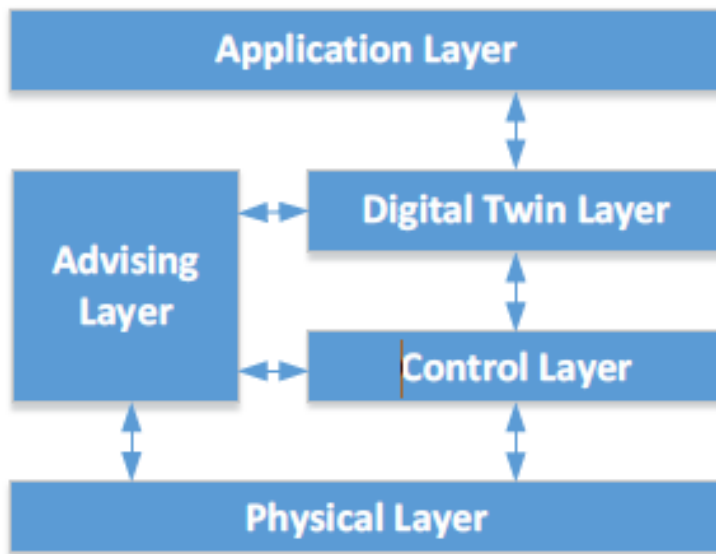


Figure 1. Proposed five-layer architecture

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.

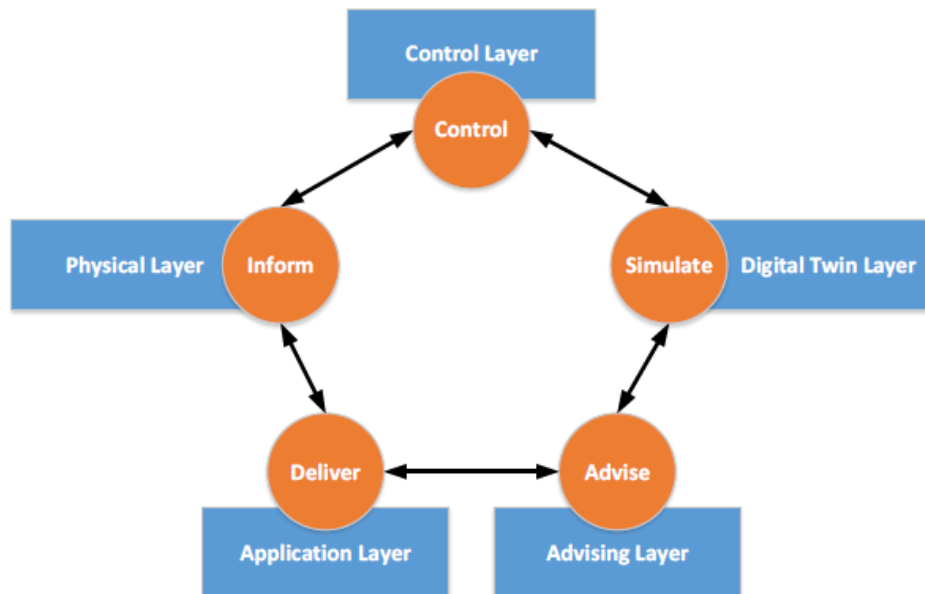


Figure 2. The Inform-Control-Simulate-Advise-Deliver (ICSAD) loop

The ICSAD loop assesses water consumption data to determine pricing and feedback for consumers. The Inform Agent (IA) preprocesses received readings, checking for quality, failures, or security issues. If any issues are found, a report is sent to the Control Agent (CA). The CA then involves the Digital Twin Agent (DTA) to investigate via simulations and provide feedback. If no issues are detected, the CA calculates consumption distortion to assess changes in water usage over a set period. The Feedback Agent (FA) in the application layer provides feedback to consumers based on their water consumption. If consumption remains consistent, the same feedback is given. If consumption improves, the Cumulative Agent (CA) calculates potential rewards. If cumulative rewards meet a threshold for better pricing, the FA offers more positive feedback and pricing details. Data and decisions from FA, CA, DTA, and IA agents are shared with the Advisor Agent (AA) for predictive processing. This process guides water consumption rewarding, pricing policy selection, and client feedback.

B. 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:

$$R(T) = a(pt(t))^b \quad (1)$$

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 define b in this paper as follows:

$$b = \frac{pt(t)}{\ln(pt(t))}. \quad (2)$$

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:

$$pt(t) = \lambda D(t) = \lambda \frac{C(t) - C(t-1)}{C(t-1)} \quad (3)$$

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.

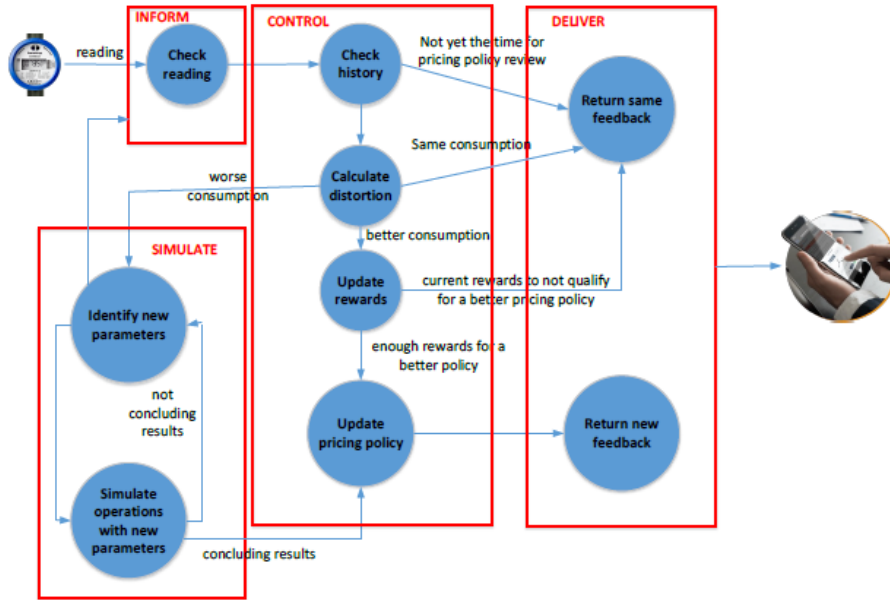


Figure 3. Multi-agent system for the management of water resources

B. 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 $P = p_1, p_2, \dots, p_n$ 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):

$$\begin{cases} f(R(t)) = p_{i+1}, & \text{if } R(t) > w(p_{i+1}) \text{ and } D(t) < \text{threshold1}, \\ f(R(t)) = p_{i-1}, & \text{if } |R(t)| > \text{threshold2} \text{ and } \text{Mean}(D(t-n), \dots, D(t)) > \text{threshold3}. \end{cases}$$

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.

C. Toward a Better Management of Water Consumption

Applying dynamic water consumption policies and offering effective feedback can encourage consumers to adjust their habits. Some Studies, advocate for using artificial intelligence, particularly reinforcement learning, to understand and improve user behaviors. We propose employing Markov Decision Process (MDP), a mathematical framework for decision-making, to model water consumption behaviors. MDP involves an agent interacting with its environment to maximize rewards through actions. 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} .

Table 1 highlights the different components used in MDP 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	<p>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:</p> <ol style="list-style-type: none"> 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	<p>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</p>
State transition probabilities	<p>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.</p>
Actions taken by the agent	<p>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.</p>

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

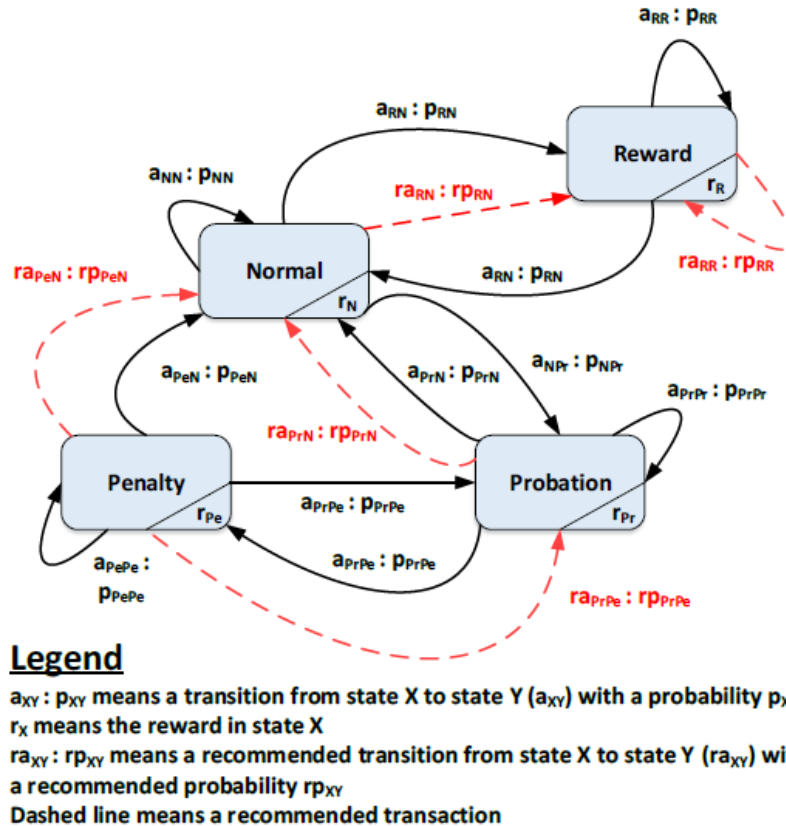


Figure 4. Typical transition diagram for water consumption

IV. IMPLEMENTATION AND RESULTS

To illustrate the viability of our approach, we deployed 100 smart water meters within the area delineated in Figure 4. Utilizing the GAMA platform, we developed the backend of our solution, implementing a multi-agent system. Data generated by the system is managed through a web-based interface, enabling the administrator of the smart water metering system to oversee water assets and monitor their functionality (refer to Figure 6).

Our solution offers various functionalities to users (refer to Figure 7) for monitoring their water usage. Specifically, Figure 7 a) showcases the user dashboard, Figure 7 b) displays readings from a specific smart meter for a particular day, Figure 7 c) presents the cumulative daily water consumption over a given month, Figure 7 d) illustrates the average weekly water consumption, Figure 7 e) outlines the daily water consumption trends over a given month, Figure 7 f) provides the total water consumption over several months, and Figure 7 g) illustrates the percentage breakdown of water consumption over several months.

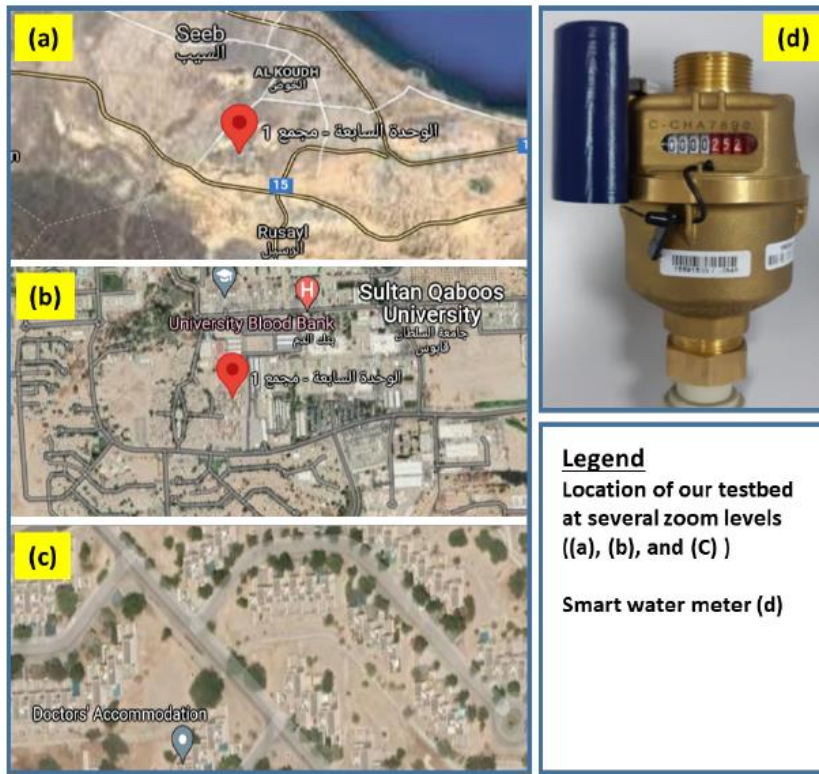


Figure 5. Location of our testbed along with a sample of smart water meters used

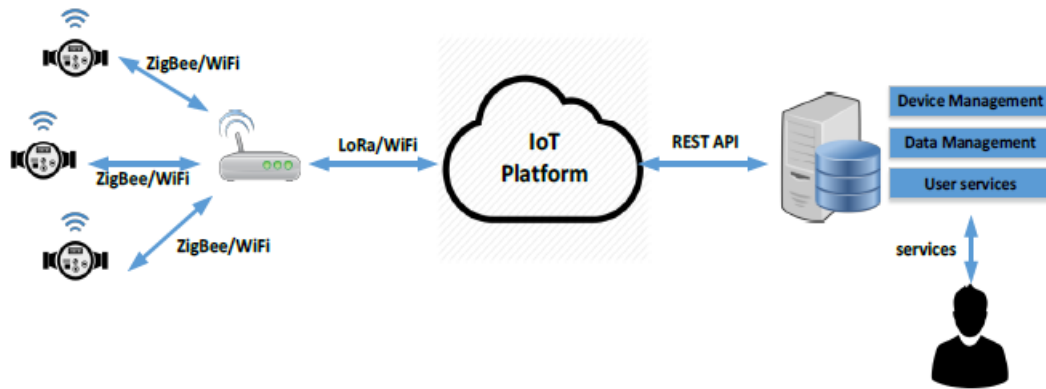


Figure 6. System overview



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

Based on the user's water consumption, the appropriate pricing policy will be used. This is currently reflected with the use of different colors, as shown in Figure 7.

V. 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 Digital Twins (DT): The current setup lacks support for anticipated DT features, such as simulating smart water operations under specific conditions. Additionally, the deployed IoT network faces communication issues and lacks flexibility in testing variable sampling rates. Consequently, ongoing developments prioritize utilizing DT-based simulations to comprehend IoT failures and predict behaviors of smart water meters, especially concerning timely consumption readings.

Enhancing DT with intelligence: Leveraging a multi-agent system enables intelligent and autonomous management of water consumption performance. Incorporating intelligence into DT

functions would enhance solution operations. For instance, an intelligent agent assigned to a smart water meter A could utilize DT outputs to conduct necessary testing on a similar meter B, particularly if meter A is unavailable or lacks certain capabilities.

Implementing Markov Decision Processes (MDP): The current data collection is insufficient for accurately determining transition probabilities between consumption states. Future efforts will focus on deploying data analytics models to infer these probabilities.

Assessing the solution's impact on consumer behaviors: Further analysis is necessary to evaluate changes in water consumption behaviors following consumer feedback and varying policy plans. This assessment is crucial for identifying appropriate recommendations and their associated probabilities.

VI. CONCLUSION

Study: Effectively managing water consumption remains a top priority, and the integration of emerging technologies like IoT and big data analytics is simplifying this task. Digital twins (DTs) are increasingly being utilized, with various research and commercial solutions emerging in the literature. Despite advancements, the adoption of DTs in water management is still limited.

Conclusions: In this paper, we propose a DT-based framework for intelligent water consumption management. Our approach incorporates a multi-agent system to enhance intelligence and autonomy, aiming for optimized water resource utilization. Our current prototype monitors smart water meters in real-time and provides users with comprehensive insights into their consumption patterns.

Recommendations: The multi-agent system handles data management, identifies suitable pricing strategies, and delivers relevant information to consumers. However, the DT aspect of our framework is still under development. Future efforts will focus on implementing and testing additional functionalities within our testbed setup.

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