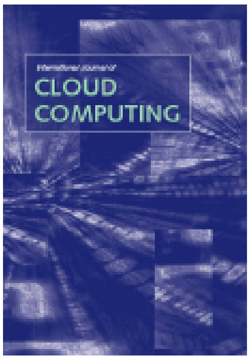

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Sawsan Alshattnawi, Anas M.R. AlSobeh

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A cloud-based IoT smart water distribution framework utilising BIP component: Jordan as a model

Sawsan Alshattnawi* and Anas M.R. AlSobeh

Computer Science Department,
Faculty of Computer Science and Technology,
Yarmouk University,
Irbid, Jordan
Email: Sawsan_kh@yu.edu.jo
Email: anas.alsobeh@yu.edu.jo
*Corresponding author

Abstract: Jordan is one of the poorest countries in terms of water resources, estimated to be below the poverty line. Due to high population growth and development, water supply and demand need a novel distribution water regime in Jordan. This paper presents a design-based smart water distribution model (SWDM), which integrates various technology solutions, such as behaviour-interaction-priority (BIP) components, cloud computing, and internet of things (IoT). This paper proposes a BIP-IoT model to introduce the SWDM, which provides a dynamic smart-design scalable model that is implemented over cloud components to cope with the increasing challenges of the water distribution regime in Jordan. The paper analyses the viability of this model and investigates an advantage in the reusable automation dynamic of SWDM's architecture. A composition component is integrated into the architecture that employs intelligence domain-independent planning to control execution. It also presents a high-level prototype cloud-based implementation of our proposed architectural model using AI data analysis algorithm.

Keywords: BIP component model; cloud computing; internet of things; IoT; water distribution network; wireless sensor network; WSN; smart water distribution management model; Jordan.

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Biographical notes: Sawsan Alshattnawi is an Associate Professor in the Department of Computer Science at Yarmouk University, Jordan since August 2015. She joined Yarmouk University academic staff as an Assistant Professor in 2009. She has received her PhD in Computer Science from Henri Poincaré University-Nancy 1, France in 2009. She received her BSc and MSc in Computer Science from Yarmouk University in 1994 and 2003, respectively. Her research interests include distributed systems, cloud computing, mobile computing, internet of things, security and data science. She has been granted many research and capacity development grants.

Anas M.R. AlSobeh is an Associate Professor of Information Systems at Yarmouk University in Jordan. He holds a PhD in Computer Science from the Utah State University, USA. He is the Director of the Refugees, Displaced Persons, and Forced Migration Studies Centre at Yarmouk University. He works with an international team to education and training needs in the context

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of forced migration. He has several running grants with many international funding agencies and coordinator for implementing projects related to refugees and the host community (HOPES-MADAD, H2020, Erasmus +). He is contributed in improvement processes to maximise productivity and streamline cross-functional collaboration. His research interests include data analysis, social media, software modelling and design, cloud computing, and web information security.

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1 Introduction

Based on recent statistics, Jordan is ranked as the second water-poorest country in the world. The Jordanian Ministry of Water and Irrigation faces severe difficulty in regulating the distribution of water between citizens and determining their drinking water needs. On the other hand, Jordan has borne tremendous pressure due to the flow of refugees which caused water demand to rise by 40% in the north, 10% in the south and by more than 21% of the average water demand of the kingdom of Jordan (Namrouqa, 2014).

Jordan has insufficient domestic supplies to satisfy demand which cause the increasing competition for water. The emerging problems posed by this climate include a call for a new water delivery system model to be designed and implemented (Byeon et al., 2015). It is evident that such a system is associated with high costs, which are closely linked to the distribution strategies and the network resources needed. IoT environments have a major capacity for water services surveillance and facilitate the opportunity to track the activities of water delivery and use. Usually, these environments have many heterogeneous sensors that track water environmental parameters (Lekidis et al., 2018).

Alongside IoT, emerging technologies such as cloud computing, behaviour-interaction-priority (BIP) components, and data analytics have been adopted in our design approach to create more efficient distributed-based architecture. This is now a developed area that is now being spun out into commercial applications, thereby a cloud computing technology providing the required resources for web-based applications with the requisite infrastructure, i.e., storage, platform, CPU, and service as demanded.

This paper provides a simple and cost-effective framework called smart water distribution model (SWDM), which is a cloud-based IoT infrastructure that provides meaningful information across IoT devices. This model involves applying knowledge from various disciplines insights of the heterogeneous sensors by using BIP components. BIP enables the interpretation of context-awareness behaviours and interaction activities (AlSobeh and Magableh, 2018; Lekidis et al., 2015). It presents a real-time monitoring and controlling smart system for distribution based on interaction priority aspects and cloud integration (AlSobeh et al., 2020).

BIP components are defined by their behaviour, states and interfaces; they represent the system's states. Transitions are utilised to manoeuvre from a source to a destination state. Every time a transition is taken, component data (variables) is also allocated to new values, which are computed by user-defined roles (Lekidis et al., 2018). The SWDM is composed of a layered implementation of interactions and priorities. Its components embrace the principle of separating of concern (SoC) that can reduce complex model systems and increase reusability. Interactions represent synchronisation constraints that determine the flow of data among the interrelating components. Priorities are used to filter probable connections and then to monitor/track the SWDM evolved to satisfy administration criteria (AlSobeh and Magableh, 2018; Byeon et al., 2015; AlSobeh et al., 2020). As far as we know, no previous research has explored the use of the BIP model to design an intelligent water supply system. To illuminate this model, we characterise different aspects of BIP component in order to monitor the water distribution. The aim is to develop a more sophisticated SWDM system that defines the design rules for the ideal water distribution based on customers' needs through the IoT-based web application. It can support design flow to schedule the interactions or resolve conflicts when several intentions are enabled simultaneously. The most important advantage of this approach is that it can perform very well in BIP language to calculates an IoT component invariant for each component over-approximating its behaviour, according to consumption and distribution ratios readings, and then calculates the relation invariant that identifies the coordination restriction of all components of SWDM.

Our model is suitable for the intermittent water supply which is the case in our country, Jordan, and the third world counties. The few presented works are for the continuous water supply, the requirements and the design of two types are different, taking in consideration the difficulties and the cost to move from the intermittent to continuous water supply.

One practical advantage of the approach is that an intelligent water management distribution environment can perform context recognition based on the behaviours and interactions occurring in water fields utilising cloud computing and IoT technologies as an extension to the proposed paradigm in Alshattnawi (2017). This study is based on behavioural economics and analytics often suggest that presenting real-time knowledge to consumers will contribute to behavioural improvements (Padulano and Del Giudice, 2018). Our approach is inspired by the idea of SoC of computation and coordination to decompose the verification of component-based systems into two levels by taking advantage of the structural water flow features of SWDM's resources. The main achievements, including contributions to these concepts and the associated BIP approach that is required to optimise resources in:

a Monitoring/tracking-water consumption: real-time metering can help water suppliers understand customers' water consumption patterns and increase their awareness.

b Real-time monitoring of water supply loads and flow rates.

c Extracting a consumption pattern of each customer, which helps in expecting the future water pumping amount.

d Determining pumping periods per area: as it is known in intermittent water supply, water is pumped at regular intervals (a day, week, month, etc.) which does not correspond to the customers' needs and leave them with specific restrictions.

This paper is organised as follows: Section 2 explores the most recent research in this domain, Section 3 presents the system design and architecture, Section 4 present the implementation and the web application, Section 5 investigates the results and the conclusion and future work is presented in Section 6.

2 Background and literature

In the smart water domain, most researchers concentrate on detecting and localising underground burst events in real-time (Suresh et al., 2013; Srirangarajan et al., 2013; Wu and Liu, 2017; Whittle et al., 2013) and water quality treatment (Jothimani et al., 2017; Adu-Manu et al., 2017); a few of the works presented dealt with the problem of water distribution management.

The first work that gathers and processes data continuously on a real water distribution system presented in Whittle et al. (2010). Most works emerged to exploit ICT and some of them joined the ICT with new technologies such as IoT and cloud computing.

WaterWiSeSG is a wireless sensor network (WSN) testbed. It is deployed on the drinking water distributions in Singapore and aimed to achieve three goals:

1 to implement a low-cost WSN for high data rate, and online monitoring of hydraulic parameters within a large range of the water distribution system in urban areas

2 to develop systems that enable remote detection of leaks and predict pipe burst events

3 to integrate monitoring of hydraulic parameters and water quality parameters.

The authors describe the components of the system and the flow of the data but there is no information about the management of water distribution after presenting the data analysis; they focus on detecting and determining the location of the leak.

The work presented in Byeon et al. (2015) achieved water sustainability by assessing water demand in areas with insufficient resources. The researchers used sensors with the communication network to monitor the quality of the resources in real-time, and to enhance the water distribution processes. They carried out work at an airport that has very limited resources. They measured and analysed the data on the water to verify the quantity and quality of the water and to assess the water balance for each water use. The system is built to balance the available water resources and e water demand.

The work presented by Hajebi et al. (2013) analysed the similarities between energy management and water management. The authors proposed a reference model for water smart grid similar to that used in the energy smart grids, mostly from the information and communication technology (ICT) point of view. They dealt with the flow of data in the water network, not the flow of water or the water grid itself. No information was provided on how to control and manage the distribution. Moreover, the availability of an effective monitoring system for the water grid would adequately locate leakages and promptly react to them; therefore, Mencarelli et al. (2012) concentrate on the deployment of sensor networks over wide rural or urban areas, hardware characteristics of sensors, and the batteries life and managements. No information about water distribution management to control the distribution process was tackled or discussed.

The system in Robles et al. (2015) presented a smart water management model combining internet of things (IoT) technologies with business processes coordination and decision support systems. The authors listed the main benefits of providing IoT in water management such as increasing efficiency, cost saving, increasing productivity, expansion of new and existing business models, and Internet-oriented. They defined the management exploitation layer, coordination layer, subsystems layer and administration layer and the interfaces that enable layer interaction. They also considered the physical model, which defines the physical elements executing water management processes in a hierarchical way, and also, the process model, which organises the execution of particular processes in water management subsystems.

The work presented in Sammaneh and Al-Jabi (2019) explored smart water management model requirements, a hieratical design is made to control the water distribution, no implementation or study is made to prove the feasibility of the model.

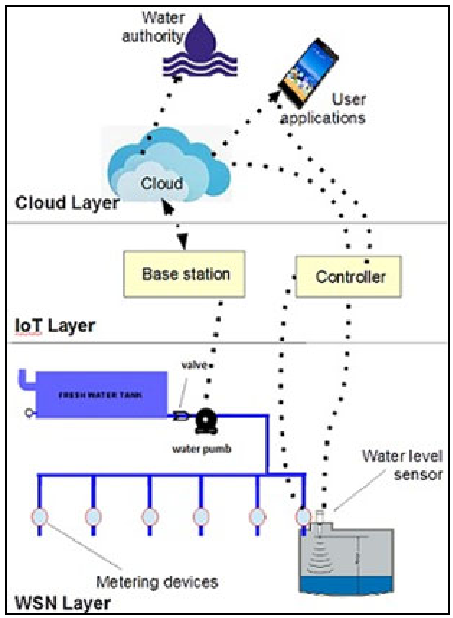
Some presented works described the use of various devices with their limitations for the smart management of water distribution networks. The work presented in Omarova et al. (2019) describes some of these devices such as pressure reducing valves, vibration sensors, and water quality sensors. Another work presented a specific requirement of water distribution systems in which the authors proposed in Hajebi et al. (2015) a water network partitioning into sub-networks to manage its complexity. The sub-networks were independent, and water cannot flow between different partitions.

While water supply in most developing countries like Jordan is intermittent, all presented research papers were, very limited and assumed a continuous water supply. Therefore, we would recommend that the infrastructure of the water network should be changed. The work in Hussein et al. (2020) described how to change the water supply pattern from intermittent to continuous. In this work, we propose water distribution structure architecture to the intermittent water supply.

3 The system architecture

In this system, several devices and objects are combined, connected and communicated to design SWDM. It will consist of a heterogeneous WSN, which determines water consumption and leakages. It will also, make consumers aware of their consumption. Its objective is to control water distribution over a region and to ensure uninterrupted service to customers. SWDM consists of a set of modules: smart sensors, local network, IoT system (Arduino, Smart Valves and Raspberry Pi), cloud computing system, design-based BIP model, and visualisation water data. The overall configuration of the planned SWDM system is divided into three parts: user interface, microcontroller unit and water framework, as shown in Figure 1. SWDM architecture consists of a set of components that are represented in the WSN layer. They represent the building blocks of the system that encapsulate it compared to a component of the BIP model, each component having a set of actions and an interface. They can interact with others through the interface. The water flow sensors are installed at each home with water level sensors at each reservoir, the automatic valves are installed in the regional tanks which is controlled by the other system components. These sensors represent the building blocks of the whole system and the system behaviour depends on the data collected from these sensors. IoT layer includes a set of controllers which represents the IoT technology: different types of controllers will gather the data from different sensors (components) periodically and control the electric zone valve. A zone controller reads the water consumption measurements and turn on the zone water valve if the water consumption exceeds a desired level (threshold). The controller sends a request GET message using HTTP protocol. On the other hand, the cloud layer involves a set of schedulers deployed on the cloud computing storage: the scheduler manages the interaction of the components' actions. It is attached to a set of controllers to retrieve the concurrent local traces. The global state is constructed from the set of collected local traces. The collected data is analysed, and a pattern of consumption may be inferred to help the water authority to predict and manage the water distribution in Jordan.

Figure 1 The SWDM system architecture (see online version for colours)



Source: Alshattnawi (2017)

BIP supports the SWDM architecture design flow with well-defined separation of concerns and component-based structure principles. It identifies where customer interaction and ingenuity are needed to overcome design options, as well as activities that can be supported by SWDM to automate control tasks dynamically. Design-based BIP smart water model is implemented in automated transformations of cloud-based components on a well-defined architecture. Water flow design based on the BIP model includes the following distinct steps, as shown in Figure 2:

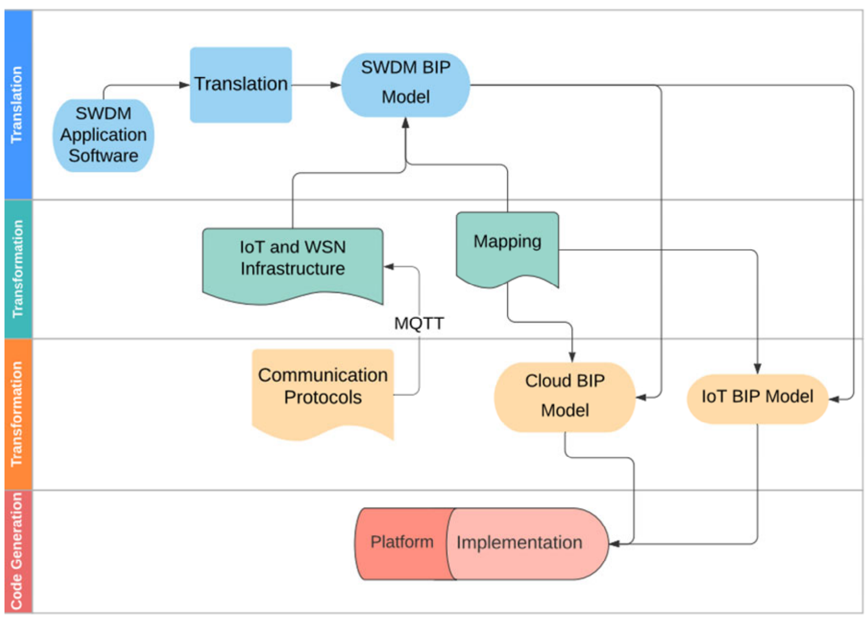
1 The translation of the SWDM program into a BIP model. This lets its illustration in a hard semantic SWDM including synchronous and water flow.

2 The development of a BIP model-based abstract IoT and WSN model represents the SWDM software, an IoT execution software model, and a map of the SWDM software model's IoT components into the processing elements of the platform. The model obtained considers the constraints of the IoT hardware architecture and water flow execution times. The limitations of design include mutual exclusion caused by the exchange of physical infrastructure such as water pumps, meters and planning strategies aimed at maximising the usage of water resources.

3 The generation of a concrete SWDM model obtained from an abstract IoT and cloud type expresses a high degree of communication structures such as interactions and priorities to enforce the platform for action using water delivery primitives. This transformation usually involves IoT and cloud interactions with asynchronous message passing using communication protocols (MQTT primitives).

4 The cloud BIP model generation sets of elements/instances interact with the same scheduler unit. This transformation allows effective implementation by avoiding overhead flow because of coordination between all components. The scheduler unit is deployed on the cloud (Amazon Web Service) to store and manage all the collected data. It handles data transmission among components and translates them into Timed Automata (TA). It is utilised to analyse the timing behaviour of the IoT and network components, which reflects the status transformation between IoT components and the physical environment for water distribution. SWDM utilises the theory in Chen et al. (2020) to contemplate the nature of interaction status with the large-scale water IoT sensors in zones, functional BIP and incompleteness of the IoT components.

Figure 2 The design-based BIP model for SWDM and water data transmission in zone (see online version for colours)



At each execution step, the SWDM model's state is represented by the current control locations (e.g., home in each zone) and the values of resident variables (e.g., tank) of all atomic components) sensors' data). The adaption of BIP (Lekidis et al., 2018) in SWDM software enables:

1 to define randomly features of IoT sensors invariants

2 to deliver a strictly semantics for the matching structure of IoT components and cloud computing services through interactions and priorities.

Practically, random behaviour at the low-level of atomic BIP-based IoT sensors is gotten as probabilistic values. These are added to probability distribution functions and are modified during transformation, wherever they get arbitrary values consequently. The interaction on transformation is also covered by semantic matching. After implementing priority rules, when multiple interactions are allowed, a probabilistic option between them is made using a user-specified probability distribution (Lekidis et al., 2015).

3.1 System grid description

The water grid infrastructure is responsible for distributing water to subscribers which corresponds to water availability and users' needs as much as possible. The water grid consists of tanks, valves, pumps and pipes. The main water provider distributes water into different zones, feeding the homes within their ranges. The amount of water supplied to each zone (*x*) is defined by the following equation:

$$x = \sum_{i=1}^{n} yi \tag{1}$$

where *x*: the amount of water pumped by the main provider to different zones. *y*: the amount of water received by each subscriber. n: number of subscribers/customers.

Each home is equipped with one or more reservoirs. The consumption amount of water (*z*) could be calculated at any time. In addition, the amount of water in each reservoir should be calculated. The amount of water pumped for all zones by the main provider is:

$$z = \sum_{j=1}^{m} xj \tag{2}$$

where *m* is the number of zones. The consumed water amount by all zones plus the conserved water must be equal to *y*; if the amount is less than *y* then a leakage may be detected.

3.2 Smart water system components (SWDM) design

SWDM components include hardware and software that make up an information system. Regarding the hardware, it includes many hardware components such as Raspberry Pi, node MCUs ESP, potentiometer, relays, resistors, wires, breadboards, water level sensor, water flow sensor, LEDs, sensing, processing, power units, pump, etc. The sensors are controlled by the Raspberry Pi controller which is connected to the internet by Wi-Fi connection and it is used to collect experimental data from sensors. Raspberry Pi also sends and receives the data or command to/from the cloud for performing the real-time operation using MQTT protocol. The software comprises Arduino integrated development environment (IDE) for the microcontroller. Sublime 3 software integrates GUI programming using HTML, CSS, JavaScript, and Bootstrap. While PHP 7 is used for programming the backend website, MySQL integrates database programming and cloud computing system by AWS.

Based on the BIP modules, the IoT resources, WSN includes sensors and intelligent instruments in the real world, and even virtual cloud computing services in SWDM system. The SWDM's physical component senses the state of water flow and level variables; these variables can be collectively referred to as the IoT module functions and cloud computing services. All water instruments and sensors are scheduled by cloud instance.

The SWDM's interface allows users to access the system. The interface has been implemented as a software application for consumers. The web application is simple, yet it includes all the key elements of the SWDM framework, representing the IoT system's core features, i.e., microcontrollers. The primary function of a microcontroller is to provide a translation of data to/from hardware and communication components through the user interface. Hardware components are connected directly to the microcontroller via wires. The controller can control and monitor the water level system such as starting/ stopping the water pumping to fill the water tank. The communication unit which acts as a mediator between the user interface and the microcontroller is responsible for sending and receiving data as reference variables.

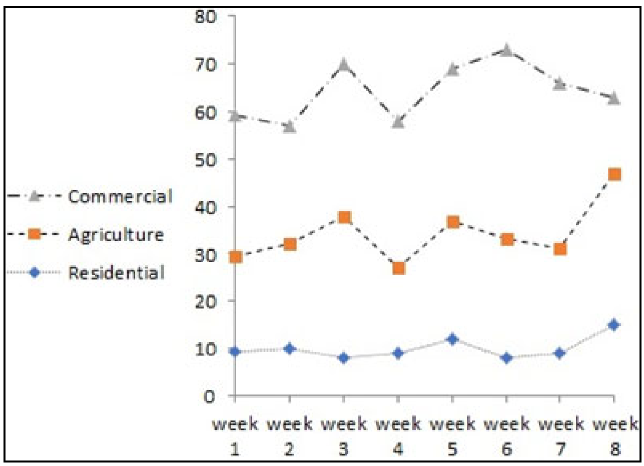
4 Data modelling and the smart water web application

Our data collection system is packed and unfettered. The system gives you freedom of data collected per customer. Simply, we continue collecting data as usual, then we synchronise data when we reconnect our devices to the internet. The main controller unit collects data from sensors that will be sent to the AWS server to build our dataset and then to be analysed before visualised it to the user interface. MQTT allows devices to post information about a specific status record to a server that acts as a medium for MQTT messages. It then pushes the information to customers who have previously subscribed to the customer's record over AWS cloud.

Figure 3 Setup and install a SWDM system in a real environment (see online version for colours)

The dataset is obtained from a constructed real model in the university campus as shown in Figure 3. This figure shows an example of the SWDM system and a laptop computer to display the input and feeding list for the agriculture zone. We distributed the system into three different types of areas: residential (southern housing for staff), commercial (restaurants), agriculture (the agricultural area in the southern plot). Each zone is managed by a pipeline, e-valves, water level and point sensors, wireless Wi-Fi and controllers of computations that store the intermediate results. Figure 3 illustrates the installed SWDM which coded to record data through detect water flow and consumption in litre per hour by Android and PHP, randomly. The system records consumption data, the overall volume, and the everyday usage of water resources on cloud-based repository system. The data collected is analysed in real-time on the data mining analytic instance and stored as time series in a shared cloud-based database system. Each zone has a range of random numbers according to the zone's nature. The data is collected over 365 days from three zones; the water flow sensor read is taken every hour, and the supplying process is done at the beginning of the week. Samples of the consumption amount for these three zones are shown in Figure 4. These assumptions are taken from the real status of the water demand. To avoid mistake, the overall water usage achieved by adding formulations consumption makes 5% of the error in determining the value of local use.

Figure 4 A sample of data collected for the three zones (see online version for colours)



One of the most popular data mining techniques is the K-means clustering algorithm. It is easily adapted to our data sample to ensure convergence easily and it is applied to analyse our dataset and extract knowledge that allows the system to make the right decision. The dataset contains data without defined categories or groups. Since K-means clustering is one of the popular unsupervised machine learning algorithms, it is used to divide a region of interest from a large background in which there is no structured data (Sood et al., 2018; Radhakrishnan and Wu, 2018). Also, anonymous data, can be utilised for improving software system evaluation by analysing the water data and offering perceptions regularity based on its results. Consumption data was spread as data clusters represented by variable K on the basis of the characteristics given. They were clustered into two groups for normal and abnormal usage of water; this enables the SWDM system to detect the abnormal values and notify the water supplier/admin and the user about this status. Therefore, the forecasting for the next period will be done by computing the seasonal average. It promotes sustainable management and user awareness and aims to elicit feedback from stakeholders about the system and consumption. Water suppliers evaluate the system, are non-intrusive and can be managed easily. Moreover, they guarantee that awareness of daily/weekly/monthly/year consumption formulas generates more interest in water use.

In this context, we designed a web-based SWDM application, which is utilised by AWS, MQTT broker, JavaScript, and MYSQL database to focus on real-time monitoring and management that provides predictive and trend analysis of water flow and usage. In the cloud-based server-side, JavaScript and PHP are used to create a visualised data service, which consumes RESTful API by publish-subscribe pattern. The cloud-based SWDM provides service using BIP behaviour using data frequently and across an elastically scalable shared data grid for data management and support monitoring. The SWDM application monitors the flow of water and its consumption in the different zones mentioned earlier. It also predicts the appropriate timing and the amount of flowing water by analysing the results of a set of the historical time frame K-means clustering findings and provides prediction and recommendation regarding the overload or lack of water supply over the timeline.

5 Results and discussion

This model utilised IoT components to collect data from the mounted flow sensors, publish and subscribe fragments, and analyse consumption pattern. In Jordan, the consumption pattern is more dynamic so the behaviour model is accustomed to many changes according to the nature of areas. In SWDM application, the administrator can explore the extracted information and the predicted value; in addition, the predicted value is managed or controlled by the water supply administrator even if there is any urgent situation. In all cases the predicted values must be managed by the administrator when it is largely different from the last predicted value. The predicted values about the data are collected and managed in a way that leads to different results and brought into a map of water consumption areas as shown in Figures 6 and 7. The field value represented a variable spread over the entire zone. To conduct a preliminary analysis of the collected data, we use a machine learning technique, i.e., K-means algorithm, to analyse the data collected, to learn the correlation and regularity of the data, and to predict water usage. In this model, we used the PHP Apache Math Library with the K-means method to quickly and objectively provide the first set of clustering results on system services alert and to provide new predictions based on historical differences.

Initially, the SWDM application randomly reads several different points in the data and groups each data point to the nearest central point. Once the IoT sensors start reading water flow, the BIP behaviours pattern is designed as an asynchronised mode to avoid overcrowding flow from distributed values and sensors. A behaviour pattern is adopted for event processing to deal with the different level point in various zones. For each level point, it is possible to compute immediate, daily and overall consumption as shown in Figure 5 with an indication of the type of field usage. Moreover, some of the outputs of the used metrics analysis can be reported as follows:

a percentage of water consumption monthly and yearly

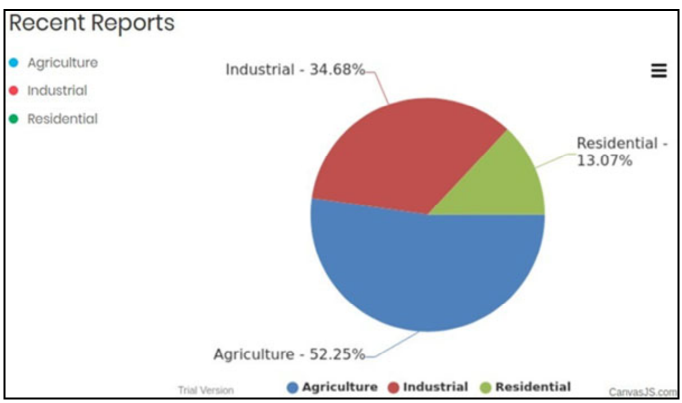
b average of daily volume consumption for a month

c variation of hourly water usage during a day over three zones

d average of water flow for one month.

Figures illustrate data of water flow consumption for three zones and report heterogeneity values. During the measurement period, Figure 5 illustrates water consumption per zone around 13.07% residential, 34.68% industrial and 52.25% agricultural. This value is in line with the Jordanian Water consumption by sector according to the report of the Jordanian Ministry of Water and Irrigation. In the pilot zones, the residential zone contains 175 house units with 720 residents and infrequent overlay of house fixture usage (dishwasher, washer, shower, kitchen, to mention a few). This may seem a representative sample; instead, it is elastic and could make it possible to categorise usage behaviours into the different water end-use classes. The agricultural zone contains a set of olive trees, two greenhouse and water tanks with a capacity of more than 4 metres that are filled periodically. Tanks are connected with IoT component of SWDM system; they are used in a semi-regular pattern for irrigating crops (tomatoes, cucumbers, eggplant, etc.) as shown in Figure 3. The industrial zone represents the university's service area, which includes two dining canteens, the model school, three kiosks, one health centre, 15 faculties, four centres, the cleaning and services department on campus. This experiment was conducted before COVID-19. During the pandemic, the lockdown has made a lot of people change their behaviour. This will be measured and studied in the future. It is very evident that, due to capacity reduction, industrial water usage is reduced to 50% even on campus.

Figure 5 Percentage of data usage for each zone (see online version for colours)



Determining final water consumption is critical to SWDM's application of the mean K-means algorithm in order to find out the correlation between consumers and water usage and to identify patterns of behavioural usage. Figure 6 shows the subscriber dashboard. At any time, the user can check the consumption amount of a certain period and make a comment to the water supplier and the administrator who can also send a warning message to the subscribers' group. It is difficult to obtain any accurate predictions from the initial clustering keys. The model was trained in the SWDM system environment and areas based on BIP-design-based behaviour, which uses the cloud-based SWDM application to analyse and modify user's behaviour patterns. To do so, flexible IoT sensors and dashboard monitoring devices are installed to sense water levels, flow, and its distributed manner. These sensors can automatically detect, collect and store water consumption data in high resolution over shared cloud storage at the end of water usage. The stored data is composed of a subscriber profile, which includes location, device type, service plan, access gateway, region, and/or other information. These properties can be used to act and enforce policies to enhance the subscribers' experience to monitor the water consumption delivered to the subscribers. Figure 7 show real water consumption data; the highlighted period shows that total usage is configured to detect behaviour by looking at the readings they can access and using the methods we described. These figures illustrate a dataset comprising of hourly water consumption profile which was built, for an entire year, for the purpose of being used as experimental data. The subscriber profiles were built based on the defined zones usage scenario. The water usage profile can be used as it is for each zone or as a total for consumption purposes. It models the water consumption of a zone inhabited by families in Jordan.

Figure 6 Customer service dashboard (see online version for colours)

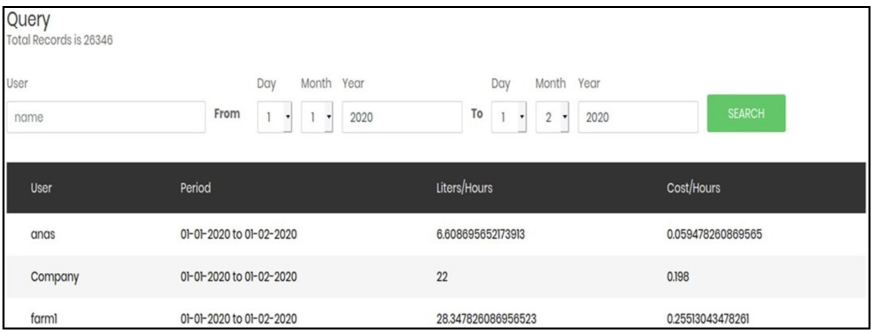
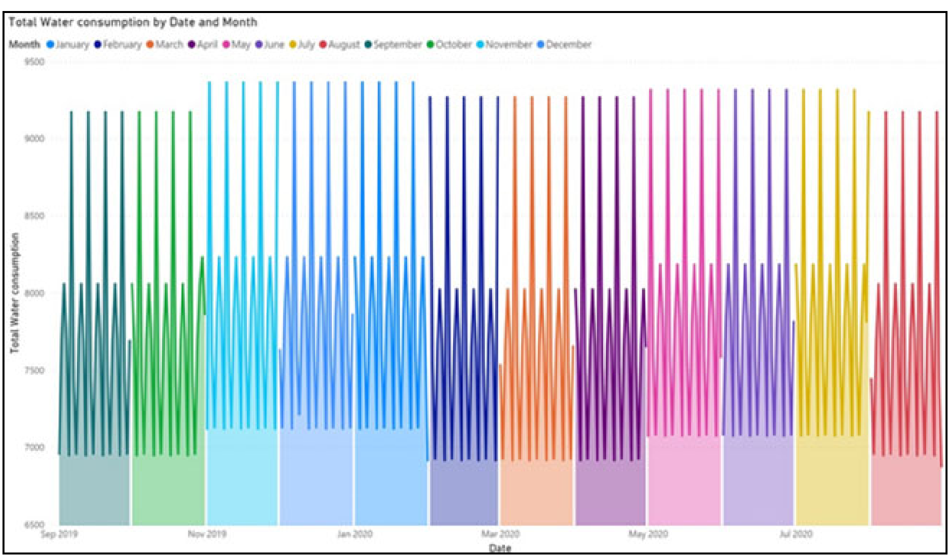


Figure 7 Real total water consumption data for three zones for a year (see online version for colours)



The prediction process was implemented as a separate service and operates a K-means procedure and customised for our purposes. Since first round of the K-mean analysis results (six months) is collected, the results are stored as a cloud-based structure and the time aspect id added to the compilation to improve the analysis process. The clustering result fluctuates with observation duration. This is crucial to predict potential SWDM application in a time frame. As the first pass analysis, the threshold value and K-value are modified to train the second pass (i.e., six months) duration analysis. From the subscriber perspective, the proposed system will help in rationalising water usage because the user will be aware of his consumption pattern and could predict bill value. The subscriber monitoring structure can provide analysis behaviours exploitation and exploration. Upon authentication, the subscriber's/customer's device is associated with the SWDM's user profile, which includes the subscriber's properties for policy enforcement rules and analytical purposes. This approach can be used in Water field areas to monitor the information that can be managed by WSN's IoT sensors and is required as a logical entity in the regions. This type of configuration will be used in intelligent, smart and mobile computing environments where mobile devices will be able to query local users and compare recent usage that enables them to manage their behaviour. To validate the approach, we develop a semi real-world model in situated water zones as an experimental testbed of distributed IoT sensors on which the ideas were implemented. This can be useful in habitat monitoring applications where user's data can be gathered in a specific zone. Also, this approach can be used in agriculture to define users' groups distributed across the ranch. This testbed will allow us to validate the results of the implementation and show that the approach is applicable to a variety of zones. To aggregate data from multiple distributed sensors at the same zone by computing the weighted sum of the read data, the following equation is presented:

$$result[n] = \sum_{i=1}^{N} w_i[J] d_i[n-1] \tag{3}$$

where w is the data from, i^{th} is IoT sensor, d is the weighting for reading data from the i^{th} IoT sensor, and N is the number of IoT sensors as shown in Figure 7. This equation has the good characteristic of being able to specify the weight reading data to satisfy optimisation requirements, for instance reducing the sensor noise ratio (Zhao et al., 2015). For certain applications, the weighted sum of the data may not be helpful (Teh et al., 2020). Therefore, SWDM application can find representative read data by summarising the number of reading data associated with a K-means. Through associating each read data point with its nearest cluster level point, the desired number of representatives are created. The centroids, of these K-means clusters become the predictor of the behaviour of water intake. Moreover, the number of IoT sensors that have reached a threshold and the total number of sensors used that are correlated with the K-means point will be used. For SWDM application process, an aggregation of the read data can be used as described in equation (3). This fact illustrates why the K-means is a suitable collection method for our designed IoT-based water sensor data.

Figure 7 shows the pattern of measured data over a predefined period and sends this information to the cluster key. K-means shows patterns from zones and selects critical patterns that describe some of the usage peaks. These patterns of water usage can be managed. In other words, sensor SWDM application is installed to forecast water in a ranch field. Each sensor monitors water flow and collects data on the cloud repository. Periodically, an IoT water sensor finds the pattern of changing water usage which would be the best match for gathered data. Patterns for variations changes are seen in Figure 7.

Information that is sent periodically to K-means is concise. For example, we can send Figure 7 to indicate the change pattern of Figure 4. The dips, spikes, and fluctuations in the water consumption pattern are categorised as major patterns that predict water usage. Each key cluster determines the patterns that predict consumption and submits them to the virtual analytics instance. The instance collects and analyses water consumption patterns. The main purpose of the SWDM application is to control, reduce, and manage water flow and consumption in different areas. Therefore, opting to aggregate cloud repository data depends not only on domain criteria, but also on the relative data collected in real-time using this approach to optimise throughput of the data processing while still satisfying the integrity of the data. Data integrity against unintended errors involves using the error detection and correction facilities of the communication and MQTT protocol. Contrastingly, the vulnerabilities point of the SWDM system results from their capabilities to install piracy water sensors or take over water sensors. Therefore, to detect intrusions, data integrity and continuity procedures need to be used, particularly in situations where an attacker tries to corrupt data. For example, an adversary who wants to kill crops in the field of precision agriculture could trigger sensors to report appropriate levels of water flow, when water is overflowing in the environment. The protection auditor detects poor data and the resource is mistakenly informed. Finally, in worst-case scenarios, the attacker has control over the data sources. This is handled by WSN means, including vendor intrusion detection mechanisms. This well-considered aspect is beyond the scope of this paper, given that we focus on imposing security at IoT sensor points.

The building of this small model is realised to be able to simulate a real model but, building such a model at the country level will be costly, because the water grid infrastructure needs to be replaced by ICT components, it needs trained teams of multidisciplinary with different specialties.

6 Conclusions

This paper introduced a SWDM, starting from the lower technologies inter-connectivity level up to the higher application level that include the sophisticated functionalists and offer several services to consumers. The model is a cloud-based IoT infrastructure that provides meaningful information across IoT devices. This model involves applying knowledge from various insights of the heterogeneous sensors by using BIP components. BIP enables the interpretation of context-awareness behaviours and interactions activities. This work is a part of a funded project; it aims to illuminate the designing of a smart water distribution that enables people to control water systems at different zones using different types of applications such as web cloud-based IoT application. Therefore, this project claimed that SWDM demonstrates the use of intelligent behaviour system and IoT components. It can compute the compositions of IoT-based devices automatically and dynamically. The model specifically targets web-based IoT service applications of the MQTT protocol and the BIP component framework. This paper addresses the challenges of managing large amounts of shared information and describes a scalable framework that maintains a balance in water usage characteristics. We present a prototype cloud-based implementation of our proposed architectural framework. In addition, this project aims to illuminate the designing of a smart water distribution that enables the people to control water systems at home and city using different types of applications such as web pages and cloud-based IoT applications. To this end, we integrate a composition aspect into the architecture that utilises domain-independent intelligence preparation to monitor execution. In the future, as a long term, the project could be applied on a limited area such as in a small city, this may need a deep study to gather data before mounting such a system, then a great fund needs to be agreed upon from the local enterprises to build the system. This system is not easy to build in reality therefore; a great number of multidisciplinary researchers need to share their knowledge and experiences, In the short term, over the limited model that is built on the university campus, the experiment may be conducted to gather big data and an AI algorithm may be used to analyse this data, new materials may be added enlarge the model and get more semi-real results, and parameters may be taken into consideration to control the process of water distribution. Then the user/subscriber security and privacy and data confidentiality must be handled and examined.

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