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Big Data analytics and IoT in Operation safety management in Under Water Management

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ABSTRACT

The smart city is described as the place where citizens live well-organized urban lives, ensure their sustainability, and cause the least damage to the environment through information and communication technology (ICTs). Big data and the internet of things sensors and applications collect data that allows effective technology solutions. In water management, smart water meters reporting water quality and use, alerting leaks to the water company, or potential contamination. In this paper, the Supervisory controller and data acquirement (SCADA) Approach for sustainable water management in the smart city based on IoT and Big Data Analytics. Big data analysis is a new technical term for the collection from deployed IoT sensors of huge amounts of relevant data to track the physical state, use and quality of the device. The Internet of Things (IoT) software can be extended to the entire water supply system and to device product use to carry out this principle of big data analysis. The experimental results demonstrate that the implementation aims to proactively control the usage of water by both companies and customers and to achieve higher levels of sustainable water supply.

1. Introduction

Water management is defined as the operation to plan, create, distribute and manage water resources optimally. This influences several key human life issues such as food production, water usage, sewage treatment, irrigation, sanitation, energy generation, and use, etc [1]. As water solution providers, smart water management and monitoring systems can assist. The conservation of water is a key aspect of water management, especially in urban areas where it is extremely challenging to keep a record of water consumption [2]. This issue can be overcome by Big data and IoT, which keeps records of water users on a certain day. We can analyze the data and conditions of the day to determine how much water people consume in a specific city. The water authorities will certainly be more efficient in managing the runoff of the water [3].

In an industry like manufacturing, power, and other sectors, the Internet of things can be used for measuring and tracking the data collected and to draw on real-time water testing [4]. IoT and Big data may also be used in the field for public utility firms. Water testing meters and sensor systems provide the readings to end-users [5]. The end-user can get information, such as TDS, Chlorine, Electrical conductivity, etc. The end-user can get information. This will help to obtain the reliable, efficient evaluation of outcomes in real-time and also helps the problem areas to be defined [6]. The sensors and equipment which are specifically designed to show the water level are important for reservoirs and overhead water tanks. Such devices can be used to calculate the amount of water used everyday in the reservoir or the overhead tank to the database at the regular time. The entire water level cycle in the dam is certainly to help preserve the water and then show it on the main server. Fig. 1 shows the smart water management operations [7–10].

Apparently, during the irrigation process, a large amount of water is being wasted. This is because, irrespective of the weather conditions and moisture in the soil, the irrigation is scheduled automatically at a certain time [11]. The use of IoT and Big Data will address this problem of water waste. To get the right amount of water to the desired location, IoT sensors can determinate the weather conditions and soil humidity [12–15]. The main challenge in the management of water is monitoring water levels, leaks, water quality, and water flow through

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Fig. 1. Smart water management.

various channels. In all these places, IoT can come to our rescue. The water system can detect temperature changes, water leakage, chemical leakage and pressure level from sensors located at various locations within the water system [16,17]. The sensors then collect and send information to the main server. This means that service engineers can easily solve problems. The benefit of IoT and big data in water is that the amount of chemical residue found in the water can be detected and measured. IoT and Big Data can enhance water management in several ways, including water leak identification, structural water management, water quality monitoring, and security, water resources quality control, consistency in use, infrastructure maintenance. Infrastructure prescriptive maintenance [18–20].

The main contribution of this paper is,

- To provide a Mathematical model of the proposed Supervisory Control and Data Acquisition (SCADA) method.
- The Internet of Things and Big Data Analytics in Smart water management framework using SCADA has been demonstrated.
- Environmental monitoring was carried out remotely via the internet in Raspberry Pi microprocessor using python language by an interfacing sensor for data collection from the environment

The remainder of the article decorated as follows: In Sections 1 and 2 discussed the underwater management related experiments. In Section 3 we proposed the mathematical model of the SCADA method. In Section 4 discussed experimental results. Finally, Section 5 concludes the research paper.

2. Literature review

Pinki Saha et al. [21] introduced the Intelligent underwater monitoring system that uses big data storage by IoUT. They used turbidity, physical and substantive qualities of water are measured via an Arduino based temperature-sensor interface device, pH level sensor, turbidity sensor, and store in big data. For correspondence between client and server, the webserver will use the HyperText Transfer Protocol to set the customer and server to remote calling procedures. Intelligent underwater interrelated objects describe the importance and extent of reliable underwater communication using IoT.

Jianping Wang et al. [22] proposed a Software-defined Network (SDN) for designing underwater acoustic sensor communication. They utilized the detailed description of the design procedures of a data plane and control plane. In the data plane, research is carried out including the hardware development of the OpenFlow-based Virtual Switch and software-based design of the physical layer. Hierarchical clustering technology and techniques for the node approach are well introduced to the design of media access control layers. The controller hardware is also used in the control unit and the main controller module is installed.

Muhammad Herwindra Berlian et al. [23] suggested the Hadoop distributed file system (HDFS) for designing smart environment monitoring and analysis in real-time systems based on the internet of Underwater things and big data. They utilizing the integral IOUT based intelligent environment system and Big Data framework consisting of an open-platform data-processing system that collects and stores the oxidation-reducing potential, pH, electrical conductivity, total solid dissolution, salinity, dissolved oxygen and t data on a remotely operated vehicle (ROV). The coral reef monitoring system that is used to prevent coral bleaching with a subsequent underwater camera to take photos sent to and then analyzed by the data center is used to monitor the ROVs' network in a wide river.

Jun-Hong Cui et al. [24] initialized the Underwater wireless sensor Network(UWSN) for aquatic applications. The characteristics of mobile UWSNs are significantly different from ground-based wireless entries, including low transmission capacity, broad distribution, floating node flexibility, and a high error probability. They switch from a top application layer to the lower physical layer along with the layered protocol stack. A collection of new design problems is studied at each surface. The creation of scalable mobile UWSNs must be met by interdisciplinary efforts in acoustical communications, signal processing and the development of mobile acoustic networks.

Maruthi H V et al. [25] introduced the Object Linking and Embedding for Process Control Unified Architecture (OPC-UA). OPC-UA is a personalized platform for the management of logistics and industrial processes. An Arduino micro-control device's Word, which is accessible from computation to the tide meter, is approved by the Raspberry Pi by a mini personal Digital Assistant. It also uploads a message on an overweight network where its set up. As mineral deposits are a core necessity and with massive population growth, water management has become an important component in human lives and scenarios, such as cities, natural areas and so on.

To overcome these issues, in this paper, we propose the Supervisory Control and Data Acquisition (SCADA) method for monitoring and controlling the underwater management using IoT and Big Data. Big data development is extended beyond IoT to increase software use. Big data management improves efficiency and security to preserve the data gathered in Big Data Analysis in IoT settings, and their implementation was examined. The SCADA system is a computer-based industrial control system, which collects and analyzes in-time information on industrial devices across different industries to track, monitor and control. SCADA modules are easier to integrate and provide better capacity and functionality to help react more quickly in real-time processes.

3. Supervisory controller and data acquirement (SCADA) method

In distribution systems as well as in wastewater treatment SCADA system is applicable. The PC-based workstation in plants is situated in a control room that allows operators to monitor and execute control actions. SCADA is used in water tank grades, water system tension, plant temp, sedimentation, filtration, chemical treatment, and so on in distribution plants. SCADA also leads to the integration of enterprise systems, cost efficiency and safety of systems in water control systems and plants.Computer-controlled systems comprising a variety of communication systems that allow the monitoring and monitoring of water treatment, distribution, and wastewater collection, and treatment (SCADA) are integrated into water management systems. The platform allows data acquisition and administration management and is capable of receiving and transmitting commands within the network. It can be wireless, wired link or telemetry in the communication system. Together, SCADA systems also helped reduce service operating costs and increased the supply of water to homes, businesses, and industries. The functionalities of SCADA monitoring and control will enable the businesses to protect and prevent major deterioration of their infrastructure. Data has been collected from the individual SCADA systems

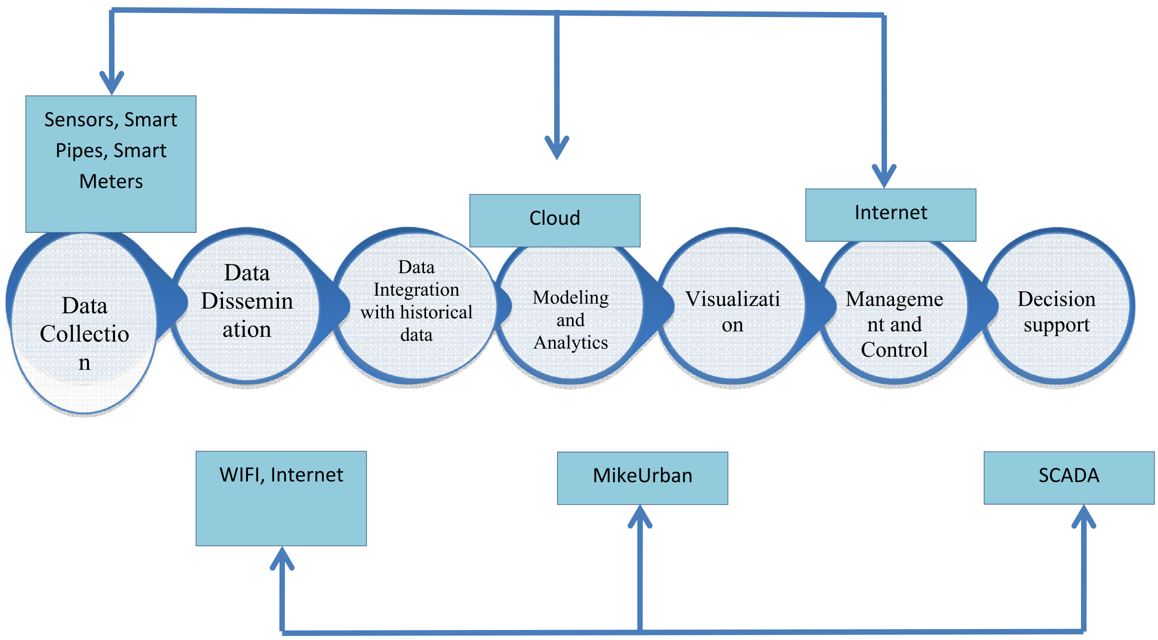

Fig. 2. Smart water management technology and tools scheme representation.

and fed to determine optimal pump settings for real-time control (RTC). Fig. 2 shows the proposed SCADA method for smart water management.

Mathematical Model of Supervisory Control and Data Acquisition (SCADA) approach:

Mathematical models are used in the water distribution network to define and simulate network activity or responses and to approximate network statements and parameters for certain operating and loading conditions. This section discusses some of the outstanding mathematical models used to help solve water supply system management problems.

Proposition 1 (*Dynamic Hydraulic Model and Steady State*). *In a particular instant, the hydraulic steady-state model computes the hydraulic network variables. A snapshot of the water distribution network is provided. The first law for the conservation of the flow at nodes in a pipe system (mass conservation) is used by Kirchhoff.*

$$\sum_j p_{j,i} = P_i \quad i = 1, \ldots, I \text{ (junction nodes)} \tag{1}$$

As shown in Eq. (1) where $p_{j,i}$ is flow in link connecting nodes j and i, I is the number of nodes, P_i is the demand at the node i.

The second Kirchhoff conservation law is also referred to as the energy conservation law. The total head loss around any network loop is 0.

$$\sum_{j,i\in n} g_{j,i} = 0 \quad n = 1, \ldots, N \text{ (loops)} \tag{2}$$

As shown in Eq. (2) where g_n is the head loss of the pipe (j, i) and N is the number of loops. For simplicity's sake, we assume that only one tank is available so that pseudo loops between fixed heads are not necessary. This is pervasive later.

The third equation required to model the network shows the flow-to-head loss relationship. This connection is in the form of a law of Ohm. The phrase is represented in a simplified form,

$$g_{j,i} = T_{j,i} \left|p_{j,i}\right|^{m-1} p_{j,i} \tag{3}$$

As shown in Eq. (3) where $T_{j,i}$ is the resistance of the pipe associated nodes j and i and m is fixed head loss exponent. This is also the situation for valves with a coefficient of resistance depending on certain local coefficients of the head loss and valve diameter.

A pump usually has a characteristic curve that describes how the head gain and flow are linked. A parabolic function can approximate this,

$$g_{j,i} = b_l p_{j,i}^2 + a_l p_{j,i} + c_l \tag{4}$$

As shown in Eq. (4) where b_l, a_l, and c_l are the pump supplier coefficients of the characteristics.

The combination of (1)–(4) constitutes a series of non-linear equations which describe the constant status of water distribution networks. Solutions of these equations are the flows and heads within these water distribution networks, where all piping resistances, characteristic turns (piping and pumping parameters), node specifications, reservoir rates, working pump numbers and speeds as well as valve opening degrees (operating conditions) are known.

The dynamic hydraulic model or EPS explains the hydraulic behavior of water distribution networks with time changes. The law on mass preservation for a node with tanks or storage components has been usually designed to include the following:

$$\sum_j p_{j,i} - P_i - \frac{dU_i}{dt} = 0 \tag{5}$$

As shown in Eq. (5) where U_i is the volume of the tank at the node i and t is the time. F_i and B_i are represented respectively for each head (summing of tank level and height) and cross-section area of the tank. The tank can be dynamically represented as,

$$B_i \frac{dF_i}{dt} = P_i^J = \sum_j p_{j,i} - P_i \tag{6}$$

Extend the (6) to a multi-tank network. A series of differential equations can express a dynamic network model.

$$B \frac{dF}{dt} = P^J \tag{7}$$

As shown in Eq. (7) where B is the vector of the cross-sectional regions, F is the vector of tank heads, and P^J is the vector of net tanks inflows. The Tank Differential Equation (7), can be properly solved using numerical means (forward Euler, enhanced Euler), hybrid transitional and explicit methods of integration. In general, water demands by the users are assumed to be combined in the nodes in which the pressure heads are determined. However, water requirements are irregularly distributed over pipes.

Proposition 2 (*Graphic Models Connect*). *Connected graphs comprising a limited amount of interconnected elements can describe a water distribution network. An oriented edge and its two distinct endpoints or vertexes are a graph element. The length, diameter, and roughness of each edge are defined. Bands may consist of pumps, valves, components, bends, pipes, or other hydraulic elements with a known relationship of head loss/flow. The endpoints are called intersection points (jointing nodes) or connection points to tanks or sources of water (data nodes). For a connected graph with edges, e, junction nodes, n, and date nodes, s, the general mathematical expressions can be formulated with the guiding principles of mass and energy conservation. The rule of continuity is as,*

$$\sum_{j=1}^{e} \lambda_{i,j} p_j + P_i = 0;\ \lambda_{i,j} \in \{-1, 0, 1\}\ and\ i = 1, \ldots, m \tag{8}$$

In compact form,

$$[\wedge]\{p\} + \{P\} = \{0\} \tag{9}$$

This shows that the sum of inflow ($\lambda_{i,j} = -1$) or outflows ($\lambda_{i,j} = 1$) should be zero in each junction node. $\wedge$ is the matrix incidence reduced to junction nodes, p is the edge rate and P is the external demand for the junction.

The Energy Balance Law indicates that for closed loops the algebraic sum of head loss h must equal none, or that for non-closed loops the difference between the endpoint heads is equal to. It is classified as,

$$\sum_{j=1}^{e} \delta_{n,j} g_j + \Phi_{\mathrm{n}} = 0;\ \delta_{n,j} \in \{-1, 0, 1\}\ and\ n = 1, \ldots, N + w - 1 \tag{10}$$

In compact form,

$$[\Gamma]\{g\} + \{\Phi\} = \{0\} \tag{11}$$

As shown in Eq. (11) where Φ components are zero for fundamental circuits. Γ is the loop matrix.

As described above, edges may be different hydraulic elements having a known relationship between head loss and flow. The head loss variable, h, is a non-linear function of the flow rate expressed as follows as,

$$g = T\,|p|^{m-1}\ por bp^2 + ap + c \tag{12}$$

Proposition 3 (*Hydraulic Models for Microscopy and Macroscopy*). *The first principles governing water distribution networks described in Eqs. (1)–(7) are used to develop microscopic models. These are complete or reference simulation models with exact connection parameters (diameter, size, roughness), nodes, network topologies are defined, and nodal demands must be calculated before use to resolve water distribution networkproblems.*

In contrast, macroscopic modeling is based on techniques of empirical modeling. The data, especially large flows, and heads related to tanks and pumps in the networks, are developed and updated. For the solution of optimum control and functional problems in water distribution networks, macroscopic models are suitable. These can be in the form of models for regression, neural artificial networks, and other data-based models. While these models differ in-depth, a macroscopic model of a water supply network can be conceptually represented in discrete time.

$$y(l+1) = h(y(l), v(l), r(l), \varepsilon(l)) \tag{13}$$

As shown in Eq. (13) where y(l) is the vector of the state variable. Nodal pressure, pipe flow, and tank depth are the status variables. The status variables l + 1 are defined by the state variables l and the further amounts. v(l) is a vector control variable. The control parameters include outlet and pumping station pressure and discharge via the flow control valves. r(l) is a vector of the network nodal demand distributed in a network. The stochastic disturbance is represented by $\varepsilon(l)$ and network function is not linear. Fig. 3 shows the mathematical model flow chart of water management.

Proposition 4 (*Transient Hydraulic Models*). *The transient flow of water distribution networks can be represented as water-hammer equations by the following terms,*

$$sB\frac{\partial F}{\partial y} + \frac{\partial p}{\partial t} + \frac{h}{2RB} p\,|p| = 0 \tag{14}$$

$$\frac{\partial F}{\partial y} + \frac{b^2}{sB}\frac{\partial p}{\partial y} = 0 \tag{15}$$

As shown in Eqs. (14) and (15) *where s is the gravity acceleration, R is pipe diameter, F is the hydraulic head, p is the flow in the pipe, y is distance, t is time, h is the friction factor, B is the pipe cross-sectional region, and b is wave speed.*

Eqs. (15) and (16) can be converted into a set of ordinary differential equations along characteristic lines by using the method of characteristics $\frac{dy}{dt} = \pm b$.

$$C^+ : \begin{cases} \frac{\partial F}{\partial y} + \frac{b}{sB}\frac{dp}{dt} + \frac{hb}{2sRB^2} p\,|p| = 0 \\ \frac{dy}{dt} = +b \end{cases} \tag{16}$$

$$C^- : \begin{cases} -\frac{\partial F}{\partial y} + \frac{b}{sB}\frac{dp}{dt} + \frac{hb}{2sRB^2} p\,|p| = 0 \\ \frac{dy}{dt} = -b \end{cases} \tag{17}$$

As shown in the above equation where dy is the distance differential and dt is the time differential.

The Eqs. (17) and (18) approximate solutions simultaneously give the temporary heads and flow to the network's grid points. With the selection of correct initial and boundary conditions (based on known heads and flows in the network), you can obtain solutions with the finite difference method. According to the Darcy–Weisbach equation, pipeline's friction factor h is calculated with parameters pipeline length K, pipe diameter R, head loss g and flow velocity u, obtained from the simulation of a static network, like:

$$g_{ji} = h_{ji}\frac{K_{ji} u_{ji} \left|u_{ji}\right|}{R_{ji} 2s} \tag{18}$$

Proposition 5 (*Models for Water Quality*). *Models for tracer studies (travel times and flow path) in water distribution networks are found to be suitable for water quality studies; location and operating optimization for the disinfectant booster stations; and position of the source contaminants and location for tracer studies; contaminant/disinfectant concentrations analysis; and simulation of the age of the water, water operational quality optimization. Systems of water quality and hydraulic systems are used to address water distribution network problems of water quality. These models are important instruments for predicting the transport and destiny of water quality in water distribution networks.*

The propagation of chemicals or substances in water distribution networks involves piped advection; kinetic reaction mechanism; and node mixing. A one-dimensional mass conservation differential equation in the form will describe the continuously flowing contaminants in the tube.

$$\frac{\partial C}{\partial t} = -\frac{p}{B}\frac{\partial C}{\partial y} + \theta(C) \tag{19}$$

As shown in Eq. (19) where C is the pipe-wide contaminant concentration, p the pipe-wide volumetric flow rate, B is the transversal pipe area, y the positively flowed pipe distance and $\theta(C)$ is the pipeline reaction rate.

A first-order kinetic rate equation can be used to express changes in the contaminant concentration in the pipe:

$$\theta(C) = lC \tag{20}$$

As shown in Eq. (20) where l is the coefficient of the first-order reaction rate and C is the bulk flow of contaminants. The coefficient is positive

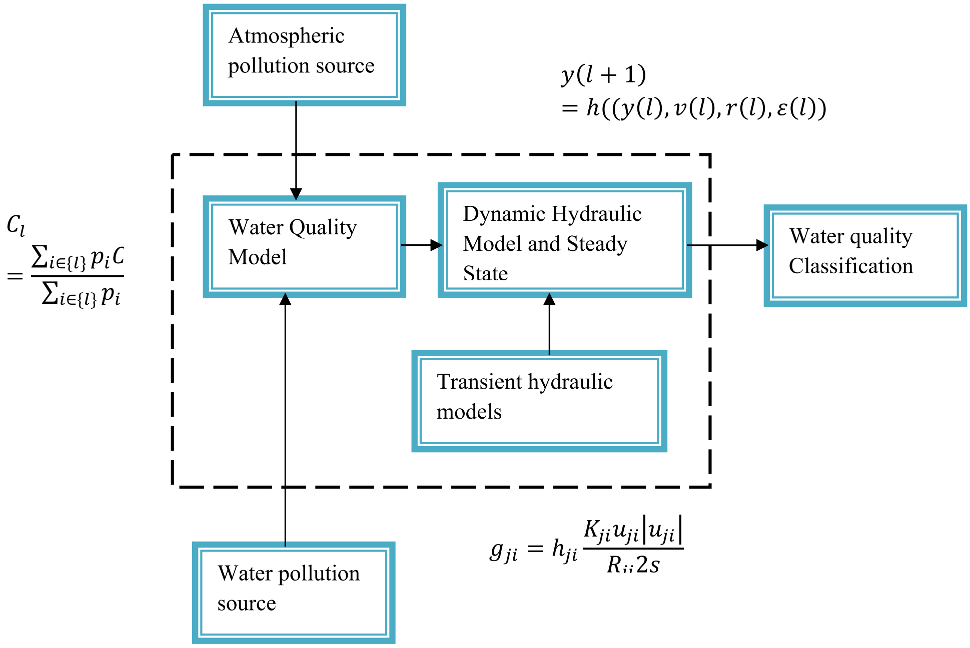

Fig. 3. Flow chart of water management.

for processes involving the growth of contaminants while it is negative for processes leading to the decline.

The node mixing can be derived from the following mass balance principle:

$$C_l = \frac{\sum_{i\in\{l\}} p_i C_i}{\sum_{i\in\{l\}} p_i} \tag{21}$$

As shown in Eq. (21) where C_l refers to the contaminant node l, l is a series of pipes entering.

The input and outgoing contaminant levels for these elements are expected to be the same for pumps and valves that are active elements (instant contaminant advection). The improvement in contaminant levels can be reflected in the variable-level tank,

$$\frac{d(C_Z U_Z)}{dt} = p_{in}C_{in} - p_{out}C_Z + \theta'\left(C_Z\right) \tag{22}$$

As shown in Eq. (22) Where C_Z and U_Z are the entirely mixed tank concentration and tank volume, C_{in} shall be the input pipe contaminant level, and $\theta'\left(C_Z\right)$ shall be that of the reaction rate within the tank. Analysis of the water quality model should be made easier by the supposed complete mixing of the nodes and tanks. There are other forms of mixing that can help develop more accurate water quality models using computational fluid dynamics.

The mathematical model of the SCADA method provides an accurate prediction of demands for peak water benefits from the need to boost or maximize water distribution network operations. Forecasting water demand is an important instrument for developing, operating and managing water distribution networks. It is based on the past use of water, the socio-economic and climate parameters related to past water consumption. The parameters include precipitation, temperature, season and evapotranspiration, water quality, wages, the size of the family and related factors.

Algorithm: Hybrid Algorithm

Input: j,i, l

Output: $p_{j,i}$, g_{ji}

For (i=0)

$$\sum_j p_{j,i} = P_i$$

For (j-0)

$$g_{j,i} = T_{j,i}\left|p_{j,i}\right|^{m-1} p_{j,i}$$

For (l=0)

$$g_{j,i} = b_l p_{j,i}^2 + a_l p_{j,i} + c_l$$

If (p=0)

$$\sum_{j=1}^{e} \lambda_{i,j} p_j + P_i = 0;$$

Else

$$\frac{d(C_Z U_Z)}{dt} = p_{in}C_{in} - p_{out}C_Z + \theta'(C_Z)$$

End for

End for

End for

End if

End

Return

In this paper, the Supervisory Control and Data Acquisition (SCADA) method has been proposed using Big data analytics and IoT for smart water management. To refine software-computerized simulation functions concerning management issues for water distribution networks, hybrid algorithms based on substitute models are proposed. Hybrid algorithms require fewer function assessments to provide optimal global solutions both for single and multi-objective optimization issues. With a single cycle, the study is taken into consideration a hybrid algorithm to

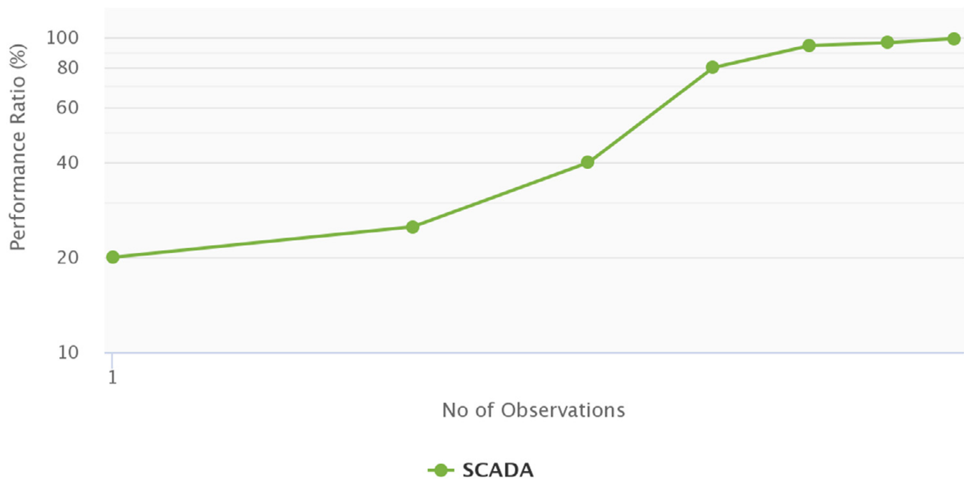

Fig. 4. Performance ratio.

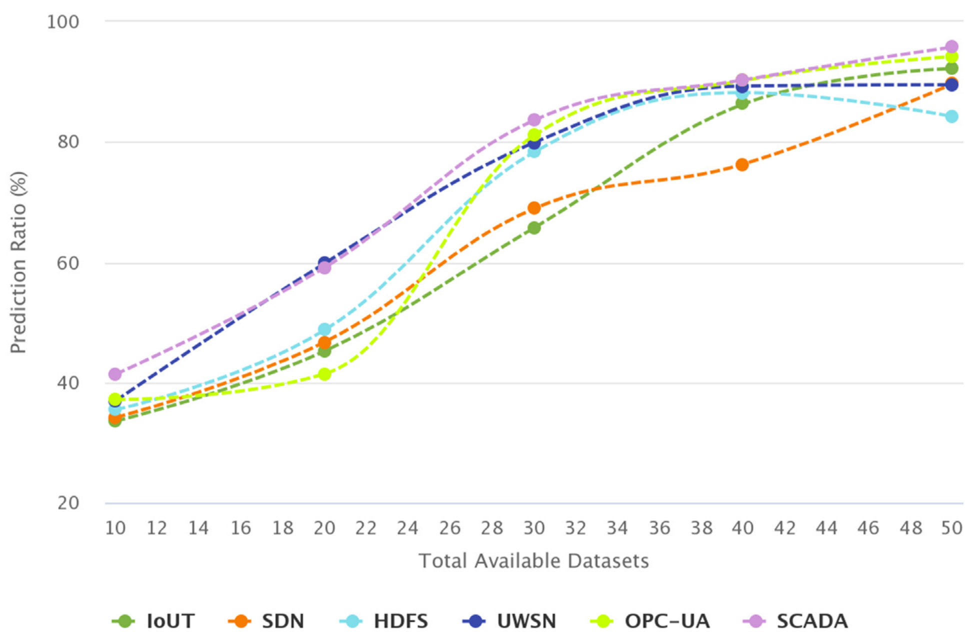

Fig. 5. Prediction ratio.

find critical pipes for higher background leakage flow. A multi-periodic leakage stream analysis will, therefore, give an enhanced result.

4. Experimental results

(i) Performance Ratio

The Big Data analytics with IoT and decision-making framework may guide water utilization to optimal performance. An efficient infrastructure can be created to improve its performance through big data analysis. Through analyzing big data and generating documents, the quality of the proposed SCADA has been enhanced. Big data were applied in water supply data was systemized and the existing information confusion was turned into effective solutions. It is becoming more important to exchange data from various sources, for example, GIS or SCADA. Security of information has also been improved: data access is configured automatically and made available for management purposes. Fig. 4 shows the performance ratio of the proposed SCADA approach.

(ii) Prediction Ratio

Combining current operating information, historical process data, machine data, chemicals, and site data to analyze the client from similar locations, advanced analytics will give you a very accurate prediction of sludge properties. Big Data technology is a tool that allows water service providers to turn the whole data stream into analysis and insights that enhance water supply and sanitation systems quality. Extended analysis based on big data analysis can be used to forecast water consumers' behavior and the prediction of demographic variables. Fig. 5 shows the prediction ratio of the proposed SCADA method and achieves a high prediction ratio.

Table 1 shows the prediction ratio of the proposed SCADA system. These components are considered to be input variables for the design of a predictive water consumption rate prediction model. It can also be used in the design of water shortage prediction systems and methods.

(iii) Accuracy Ratio

The optimum control system includes an optimization model, which works together with a good hydraulic calibration and accurate demand forecasting models. Accurate prediction of peak water demands results from the necessity of improving and optimizing water distribution operation and management. The proposed SCADA method achieves

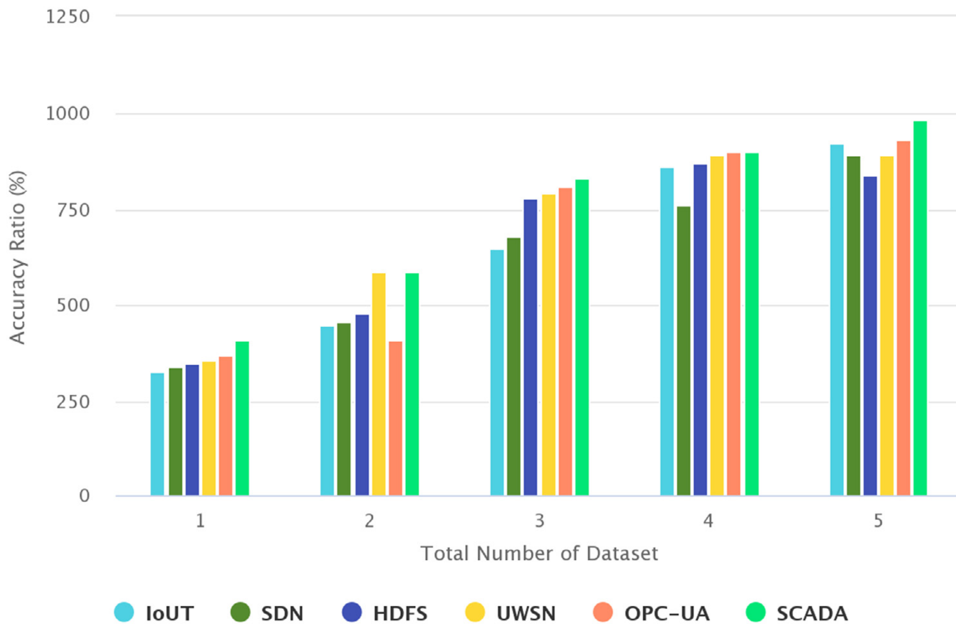

Fig. 6. Accuracy ratio.

Fig. 7. Reliability ratio.

Table 1
Prediction ratio.

Total available datasets	IoUT	SDN	HDFS	UWSN	OPC-UA	SCADA
10	34	35	36	37	38	40
20	49	54	39	61	67	70
30	69	74	76	81	79	83
40	84	88	79	75	89	84
50	79	88	85	93	91	99

a high accuracy ratio when compared to IoUT, SDN, HDFS, UWSN, and OPC-UA. Fig. 6 shows the accuracy ratio of the proposed SCADA method.

Table 2 explains the accuracy ratio of the proposed SCADA method. It should be recommended an accurate forecast of the pipe failure model degradation speed, service life, and correct costing structure and discount rate for pipe failure.

(iv) Reliability Ratio

A proposal was made for long-term analysis and a reliable estimate of the SCADA for WDNs taking into account the quantity and quality of

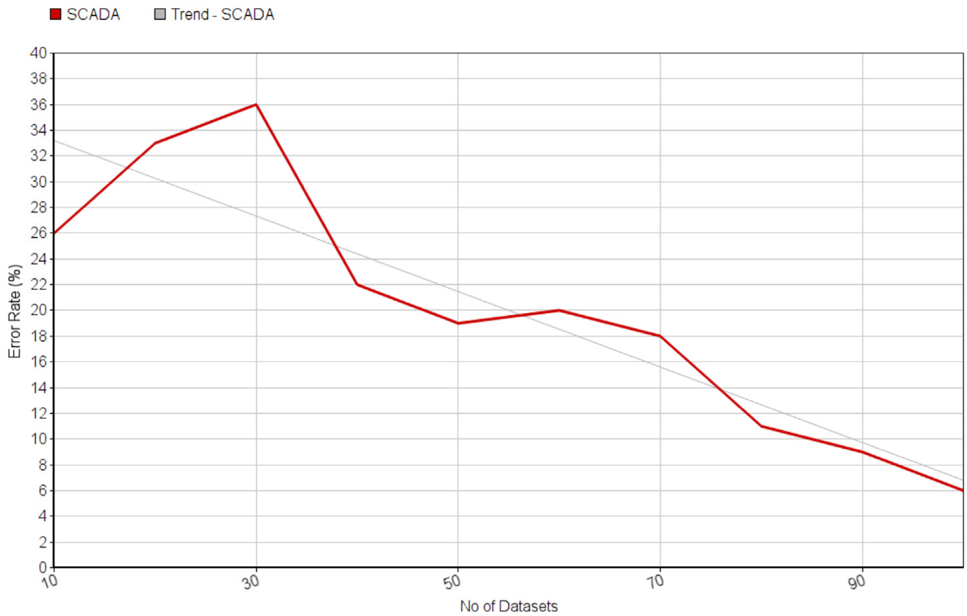

Fig. 8. Error rate.

Table 2
Accuracy ratio.

Total available datasets	IoUT	SDN	HDFS	UWSN	OPC-UA	SCADA
1	330	340	350	360	370	400
2	490	540	390	610	670	700
3	690	740	760	810	790	830
4	840	880	790	750	890	840
5	890	880	850	920	900	987

water and the stochastic nature of demand. Current analyzes on the performance of WDNs subject to natural and man-made disasters should be expanded, e.g. earthquakes, thefts, and terrorism. The architecture for a dynamic hydraulic model in real-time as an effective approach to deploying reliable, stable and responsive networks, to replace current hydraulic steady-state models with inherent reliability and efficiency limits. Fig. 7 shows the reliability ratio of the proposed approach.

(v) Error Rate

An optimization system is one of the flexible methods for solving management problems in WDNs. The secret to optimization is to reduce the total cost of solving a specific problem, reduce errors among the calculated and simulated values or optimize quality indices. In particular, water quality models are useful to explain the transportation processes for contaminants, while minimum models are used to optimize system errors or costs for operation, network rehabilitation or design, among other reasons. Fig. 8 shows the error rate of the proposed system.

5. Conclusion

In our research, we analyzed the modern storage and systemization options for IoT, Big Data and methods to analyze and visualize it. The SCADA, IoT and Big data have also been reviewed. In this study, we concluded that there is a great deal of information in the water supply and wastewater. This means that technical resources are increasingly needed, which allows these data to be processed quickly and economically. Big data software needs to be implemented. The advantage of Big Data and IoT is that a large number of models can be built for many segments based on the available information. These models are important instruments to evaluate, run and schedule current water distribution networks for the long term. This helps to predict using an appropriate model. We calculated the highest frequency of water loss cycles using the spectral analysis of big data. Water distribution includes the collection, storage, analysis and visualization of Big data and IoT sensors to improve and manage their development processes and strategies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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