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Cyber physical system perspective for smart water management in a campus

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ABSTRACT

Smart water management in a large-scale campus is a good instance of cyber physical system (CPS). For realising this instantiation calls, a systematic framework together with the actual implementation of the associated modules needs to be devised. In this paper, the key issues of monitoring/sensing, networking, and computation parts put forward toward a deployable solution are proposed. Monitoring and Networking involving appropriate sensing and data transmission to monitor the water flow in the storage tanks at National Institute of Technology, Surathkal, Karnataka, India, are worked out to a mature stage. This paper captures essential details of these technical contributions, including necessary customisation and enhancement of the existing technologies. In the direction of addressing the data analytics of the computing part, the issue of imputing the missing values has been considered. An extensive set of results and comparisons obtained by applying different algorithms to the collected data are also presented. The technical contributions of this paper form a strong base toward the CPS realisation in the Campus, resulting in efficient water management when augmented with further analytics and modeling to address scalability.

Keywords: Cyber physical system; Water management; Data analytics; Imputing missing techniques; Computation

1. Introduction

Continuous supply of water to consumers has become a major challenge in water management research. Main objective of water supply management is to provide everyday supply of potable water at the pressure essential for the consumers. In recent years, water has become scarce resource in India, due to many reasons such as rapidly increasing population, pollution, lack of bulk water supply infrastructure, and frequent occurrences of natural calamities. The World Resources Institute and Columbia Water Centre show that there is an insufficient availability of water resources to satisfy the basic needs of the population of an area [1]. The continuous supply of water might be difficult in all seasons due to scarcity of potable water [2,3]. Thus, in this paper, a systematic approach toward some alteration over existing water pipeline infrastructure with the use of minimal wireless technology in order to monitor the usage of water in storage tanks is incorporated [4]. With the knowledge of these details, we can track the water distribution and amount of water being used by the consumer. The prime aim is to implement cyber physical system (CPS) perspective to reduce the water scarcity by using minimal wireless technology to monitor and control the water flow in a storage tank and extending to large area efficiently. CPSs are response reactive systems that are networked and/or distributed, adaptive and predictive intelligent, and real-time systems, possibly with wireless sensing, actuation systems, with humans and environment in the loop systems. CPS is about understanding the intersection between the physical and cyber processes, not their union as explained by Lee et al. [5]. The intersection combines the model and methods of the physical property system with the methods of computer science and engineering [6]. In ref. [7], authors have used the available simulation tools that provide the interaction of the cyber and physical systems that precisely reflect the operation of the CPS. In ref. [8,9], authors employed a CPS perceptive toward

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environmental decision support in the context of intelligent water distribution [10]. A game theory algorithm technique is used for decision support in an intelligent water distribution network [11,12]. A paper [13] presented the details of the construction of an ontology-based framework and also shows the benefits of ontology in terms of automatic reasoning. The test case has successfully proved the efficiency and the intelligence that the ontology-based model has to leverage the decision support in the agents. A general workflow of CPS can be categorized into four main steps [14]:

- Monitoring: Physical system monitoring is a primary basic step of CPS. In our experiment, we are monitoring the physical system by analysing the historical data collected which can be used by the CPS and ensure the operations in the future. The demerits observed in the physical system are to be corrected, which is the primary goal of CPS.
- Networking: This step deals with the data collection. There can be much more than one wireless devices, sensors, or radio frequency (RF) modules used in CPS. These RF modules or sensors generate data in real time. Later these data need to be aggregated together for further processing. Meanwhile, many other applications need to be interacted with the networking communication.
- Computing: This step deals with the analysis and summary of the data collected during monitoring to check the physical system conditions and perform certain predefined actions. The action to be executed should meet the conditions of the physical system. For example, data predictive model in our experiment is used to predict the control of the valve in storage tank according to the algorithm designed with respect to the historical data for future operation.
- Actuation: This step executes the actions determined during the computing phase. The actuation can actuate various forms of actions such as correcting the cyber behaviour of the CPS, controlling the physical process, etc. For instance, in our experiment, the action is to control the valve in storage tank according to the historical data.

The rest of this paper is structures as follows. Section II includes the working setup of monitoring unit installed in storage tanks. Section III presents a detailed discussion about the communication between RF modules, aggregator, data transfer unit (DTU), and web server. Section IV explains the computation part about prediction of random missing values using different imputation techniques. Results are included in Section V; prediction efficiencies of imputation techniques are compared using existing performance evaluation techniques. Section VI concludes the discussion on emphasising the future work.

2. Experimental setup for Monitoring Unit

Each storage water tank consisting of water monitoring system (Fig. 1) includes following components:

- METER INTERFACE UNIT: MIU includes water meter, reed switch, and RF module.
- AGGREGATOR: To aggregate data from different MIUs and communicate with DTU.
- DTU: To process water flow-related level related data and upload data to server.

The pictorial representation of three storage tanks installed at different places in national institute of technology, Surathkal campus, is shown in Fig. 2.

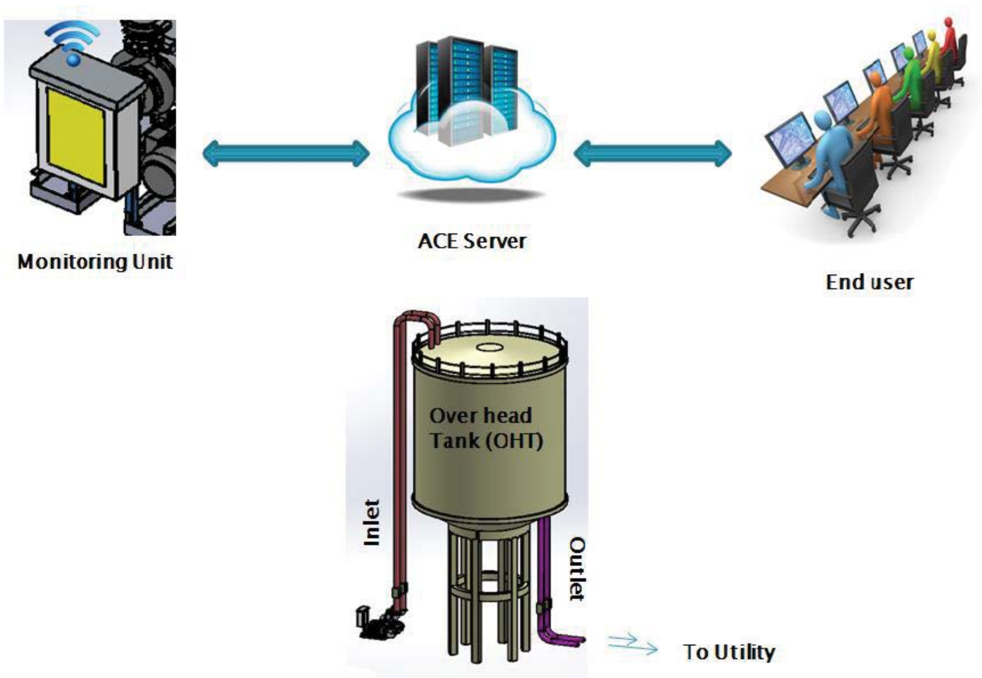

Fig. 1. System tank overview.

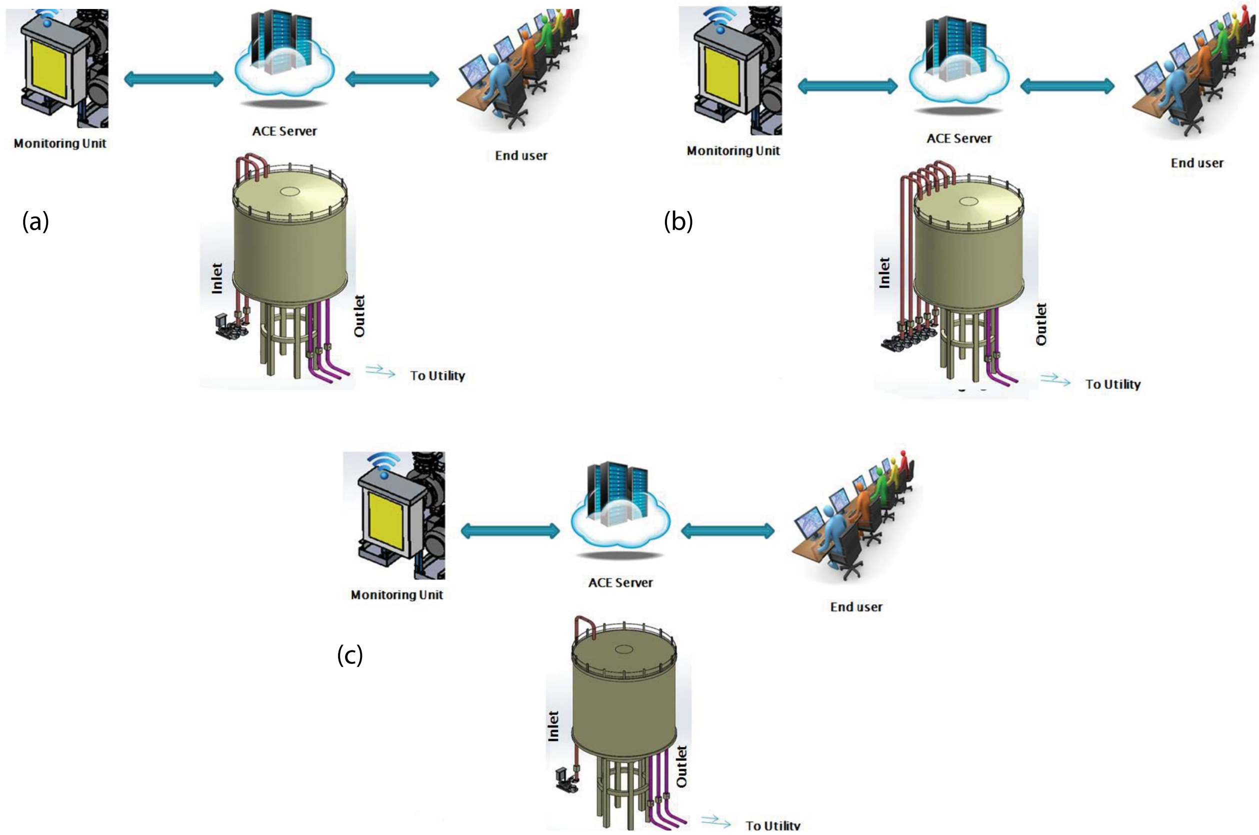

Fig. 2. Pictorial representation of three storage tanks.

The storage tank shown in Fig. 2(a) consists of two inlets and three outlets. Similarly, Figs. 2(b) and (c) show one inlet and three outlets, and five inlets and two outlets, respectively. Here, each inlet and outlet pipe has an RF module mounted on water meter. The RF module is used to count the number of pulses with the help of water meter and stores the counted pulses into flash memory. Then aggregator communicates with all RF modules of respective tanks and receives the counted pulses and shares it with the DTU.

3. Networking

3.1. Communication between RF module and aggregator

Each inlet and outlet pipe of a storage tank is connected to MIU as shown in Fig. 3. A water meter dias is connected to reed switch, and then RF module is interfaced with the reed switch. Whenever the rotating needle in the dias inside the water meter contacts the magnet of the reed switch, then reed switch will discharge the RF module pin. This is read out as count one, and it is stored in nonvolatile memory (RF flash memory). It keeps on storing the discharge count until aggregator sends the request query to the RF module for the inlet and outlet data. Once the aggregator receives all details from the RF module, the aggregator sends reset command to RF module to reset the count pulse to zero. The procedure has been repeated for every sampling period of 15 min.

Algorithm-1 shows basic steps of the operation for communication between RF module and aggregator.

Algorithm 1:

- Step 1: Storing the pulse count into nonvolatile memory.
- Step 2: Increment the counter value by one whenever reed switch discharges the RF module and stores into nonvolatile memory and go to Step 3.
- Step 3: Loading pulse count into nonvolatile memory and go to Step 4.
- Step 4: If aggregator read command is received, go to Step 5, else go to Step 2.
- Step 5: If aggregator pulse count reset command is received, reset the pulse count and go to Step 6, else send pulse count to aggregator.
- Step 6: Send acknowledgement to aggregator and go to Step 3.

3.2. Communication between DTU and Aggregator

Each storage tank will have one DTU, where DTU is used to collect the inlet and outlet water flow details of each pipe in a storage tank from the aggregator with the help of RS232 port through universal asynchronous receiver/transmitter configuration. We have designed DTU to request the data from different MIUs for every sampling time period of 15 min. So, DTU after every 15 min will query it through the aggregator. Then, aggregator communicates with different MIUs and collects the data from MIUs. Once the aggregator receives the information, it starts transmitting the

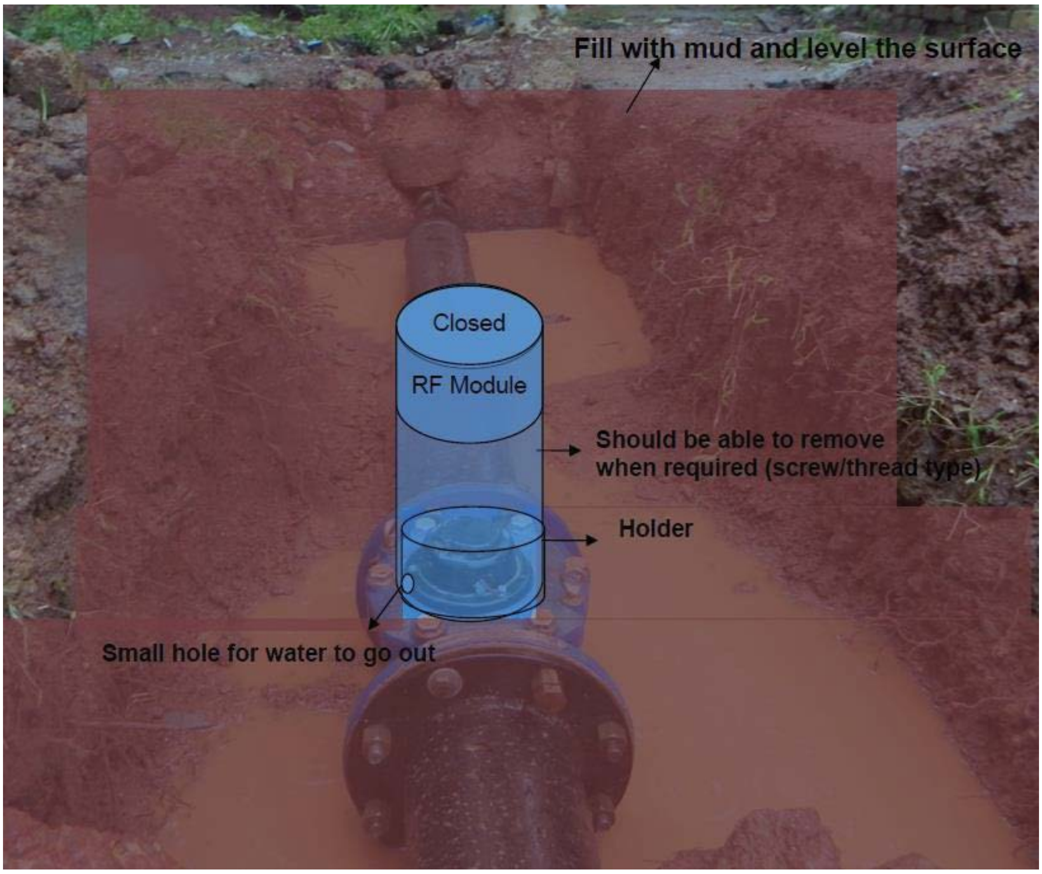

Fig. 3. Meter interface unit.

information to DTU through RS232 port. When the DTU receives the information based on inlet and outlet details of each tank, it will calculate the total volume of inlet, outlet, and finally the net volume in the tank. Inlet volume of water flow in a storage tank is calculated using Eq. (1).

$$\mathrm{IC}_j = I_j \times D_j \tag{1}$$

where IC_j = Inlet count, I_j = Count in the water meter dial, D_j = Discharge count, and j represents the tank number, i.e., 1, 2, 3, and so on. The outlet volume of a water flow in a storage tank is calculated using Eq. (2).

$$\mathrm{OC}_j = O_j \times D_j \tag{2}$$

where OC_j = Outlet count, O_j = Count in the water meter dial, D_j = Discharge count, and j represents the tank number, i.e., 1, 2, 3, and so on. The total inlet volume of water flow in a storage tank is calculated using Eqs. (3) and (4).

$$\mathrm{Inlet}_j = \left[\left(\text{Present Reading}\right) - \left(\text{Previous Reading}\right)\right] \times \mathrm{IC}_j \tag{3}$$

$$\text{Total Inlet} = \mathrm{Inlet}_j + \mathrm{Inlet}_j + 1 + \mathrm{Inlet}_j + 2 + \tag{4}$$

Total outlet volume of water flow in a storage tank is calculated using Eqs. (5) and (6).

$$\mathrm{Outlet}_j = \left[\left(\text{Present Reading}\right) - \left(\text{Previous Reading}\right)\right] \times \mathrm{OC}_j \tag{5}$$

$$\text{Total Outlet} = \mathrm{Outlet}_j + \mathrm{Outlet}_j + 1 + \mathrm{Outlet}_j + 2 + \tag{6}$$

Total volume of water flow in a storage tank is calculated using Eq. (7).

$$\text{Present Water Reading} = \text{Previous Water Reading} - \text{Total Outlet} + \text{Total Inlet} \tag{7}$$

Algorithm 2 shows the basic steps of the operation for communication between DTU and aggregator.

Algorithm 2:

- Step 1: Initializes the peripherals and retrieves the settings from memory.
- Step 2: If short messaging service (SMS) received, processing the SMS module block by checking device identification information and goes to step 3, else directly goes to step 4.
- Step 3: If web time periodicity is elapsed, then it reads the inlet and outlet parameters from each water meter, calculates the total volume of inlet, outlet, and net volume of total water flows in each tank. Else goes back to step 2 till web time periodicity is elapsed.

- Step 4: Sends the received data to server over general packet radio services (GPRS).

3.3. Communication between DTU and ACE web server

The DTU will communicate with affordable, convenient and efficient (ACE) server over GPRS and establish HTTP POST connection with the server to send data. If GPRS connection is not available, then DTU shall retry three times to connect. If it is not connected, then error connection will be sent. It will send three types of message packets to the web, namely,

- Device identification: Device identification message will be sent to server after successful configuration of the application ID or device type or DTU ID through SMS command from the configuration mobile.
- Water meter parameters: Water meter parameters shall be sent to server on expiration of web reporting period.
- Water meter communication failure: Water communication failure message shall be sent to server when DTU fails to read parameters from Aggregator or receives parameter value with error code.

3.4. Communication protocol

The water meter is interfaced with RF module (865–867 MHz) which is a low power RF module which provides immune condition for wireless communication [15]. The main influence for using this RF module is that, with the help of serial data interface, we can add wireless capability to any product. The use of wireless communication on water meter hugely cuts down the cost of maintenance and manual cabling. The gateway is used to communicate with the ACE web server over GPRS and establish HTTP POST connection to send data. The communication between the DTU and the web server is device-initiated communication, and hence, the DTU has to be pre-programmed with the server domain information. The web application is available for enterprise users through both Intranet and Internet as per the policy.

3.5. Methods for Computation of missing data analysis

The data analysis is carried out by using R software for computation. In our experimental setup, we have artificially omitted some missing values into the data sets for the purpose of finding omitted values in the data sets [16,17]. A series of 0%–60% of missingness is introduced in the data sets. Zero percentage missingness means no data are omitted in the data sets. When *X* percentage missingness is introduced in the data sets, each column (attribute) has *X*% chance of value being missed, regardless of its position. The values are deleted randomly. The data in the data sets are in accordance with the missing at random principle [18,19]. The performance of the algorithm on the full data set is used as a reference point for comparing with the algorithm for the missingness in the data sets. Fig. 4 shows the computation flow diagram.

- Combining and cleaning the data.
- Keeping the training set as reference, introducing missing value in the training data sets.
- Applying imputation methods to the missing value data sets.

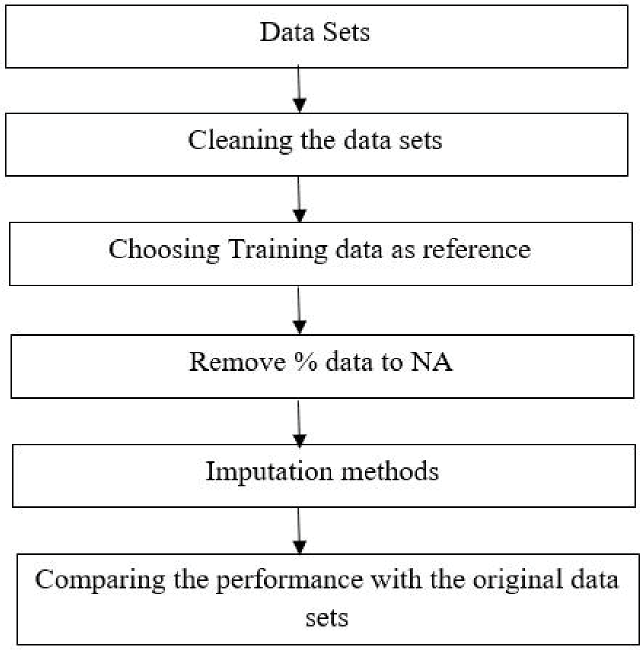

Fig. 4. Computation flow diagram.

- Testing the imputation methods using the training data sets.
- Record the resulting root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).
- Accuracy is measured with the use of MAPE.
- Comparing RMSE, MAE, MAPE, and accuracy of the imputation methods.

3.6. Imputation method techniques

- Mean: many functions are added implicitly in R programming tool to perform statistical analyses. A mean of a data value is a statistical analysis of the middle value of the data. It is calculated by the sum of the data values in the data set divided by the number of the data in the series. It is given in Eq. (8),

$$M = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{8}$$

where "x_i" is the input values, "n" is the number of values in the data series, and M is the mean.

- Median: A median of the data value is an integer measure of the middle value of the data. Median is calculated by sorting the data in ascending order and then finding the middle value of the data in the data sets.
- *K*-nearest neighbours (*K*-NN): In refs. [20–22], *K*-NN is defined for each missing value by finding the *K* value nearest neighbours and then replacing that value with the missing value for a given data set by averaging nonmissing values of its *K* neighbours. The distance computation for defining the nearest neighbours is based on an extension of the Gower distance [20].

- Expectation maximisation (EM): It is the method that uses alternative value to impute a value (expectation) and then analyse whether that is the most probable value (maximisation) [23]. If not, then it re-imputes the most probable value. This keeps repeating until reaches the most probable value.
- Matrix completion: Matrix completion uses low rank matrix approximation to fill the missing values in the data sets (matrix) via nuclear norm regularisation [24,25]. The algorithm works like EM, i.e., each iteration to fill the missing value in the data sets (matrix) is completed with the current estimate.

4. Results and discussion

The hardware setup to monitor water flow has been achieved successfully in the existing pipeline infrastructure. The methodology of this testing is as follows: each storage water tank consists of water monitoring system which includes MIU includes water meter, reed switch, and RF module, aggregator, and DTU. The data were collected for the interval of every 15 min. The communication between RF module and aggregator, DTU and aggregator, and DTU and web server is recorded accurately. At the last through web, the details of the amount of water flowing in each representative storage tanks can be observed. The observations showed that the model is highly efficient for prediction, and further it can also be used for systematic water distributions at large areas. These data sets (observations) help us understand the condition when there is shortage of water and excess of water supplied to different areas. With these details, we can make a decision when water is needed and when water should be pumped. Further research is needed to resolve the water scarcity issue.

4.1. Performance evaluation of an Imputation technique

The performance of the model for imputation technique is measured with respect to prediction efficiency by using R software. The imputation technique efficiency is represented by mean, median, *K*-NN, EM, and matrix completion using RMSE, MAE, and MAPE [26–28]. In this work, we have developed overall model, month model, and day wise model for each imputation technique. For each model, random missing values are generated which range between 0% and 60%. The comparative performance analysis with respect to RMSE, MAE, and MAPE for each model is as shown in Figs. 5–13.

- RMSE: RMSE is an approach of verifying the model with the imputed value from the model with the existing missing value [29]. In ref. [30], if the RMSE value is high, then the imputed value is far away from the actual value. If the RMSE value is low, then the imputed value is near to the actual value. If RMSE value is zero, then both imputed and actual values are same. RMSE can be measured using Eq. (9).

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{T}\left(Y_i - \hat{Y}_i\right)^2}{n-1}} \tag{9}$$

where Y_i = Approximation from data value model from forecasting, $\hat{Y}_i$ = Actual value of actual data obtained from calculation, n = Number of sample size using in model estimation.

- MAE: MAE is an approach of verifying the model by measuring the difference between the imputed value and the actual value [29]. In ref. [30], if MAE value is low, then the imputed value is near the actual value and if high then the imputed value is far away from the actual value; if MAE value is zero, then the imputed value is equal to actual value. The MAE is measured using Eq. (10).

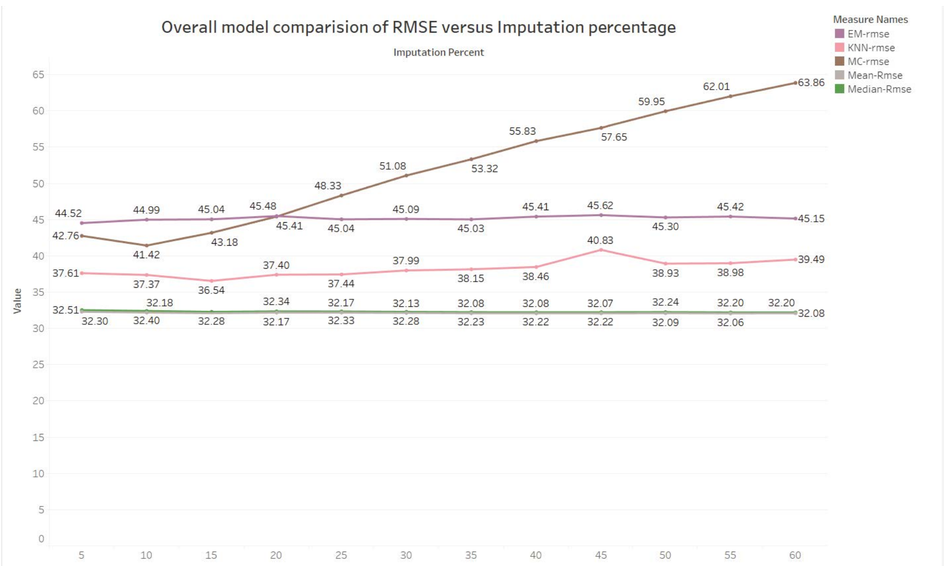

Fig. 5. Overall model comparison of RMSE vs. percentage missing data.

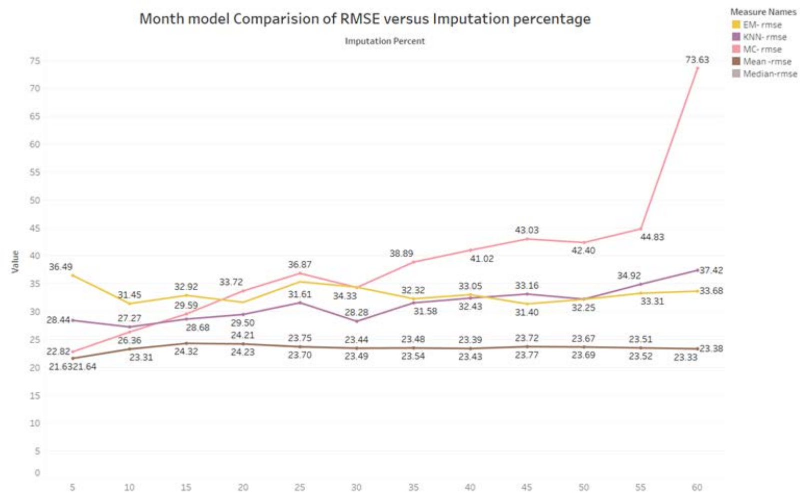

Fig. 6. Month model comparison of RMSE vs. percentage missing data.

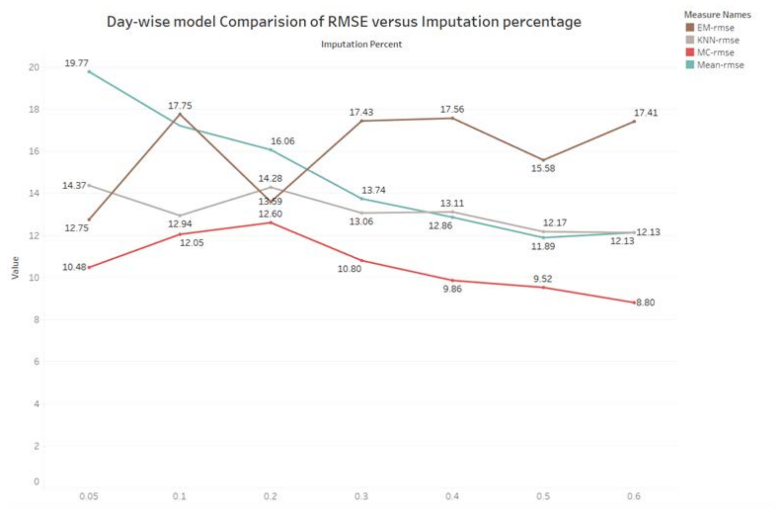

Fig. 7. Day wise model comparison of flow rate RMSE vs. percentage missing data.

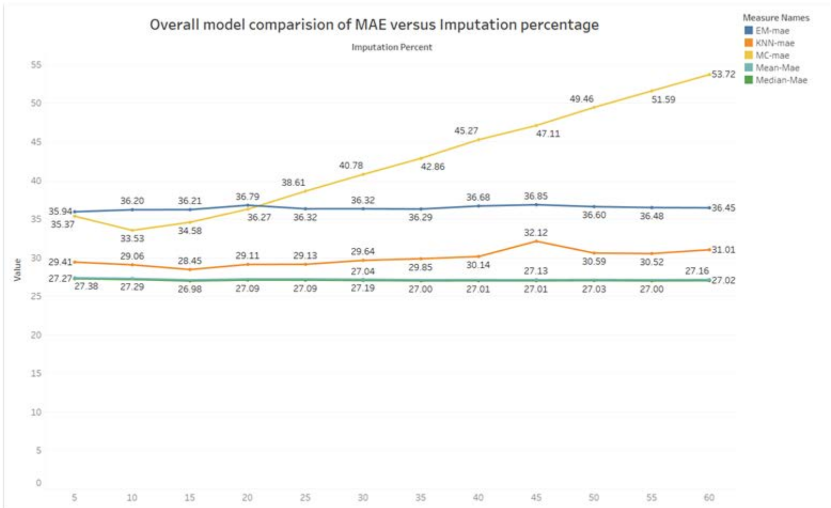

Fig. 8. Overall model comparison of MAE vs. percentage missing data.

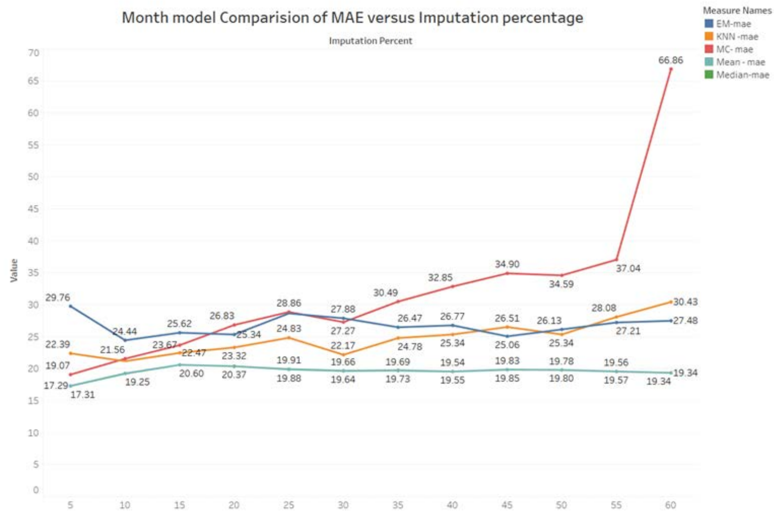

Fig. 9. Month model comparison of MAE vs. percentage missing data.

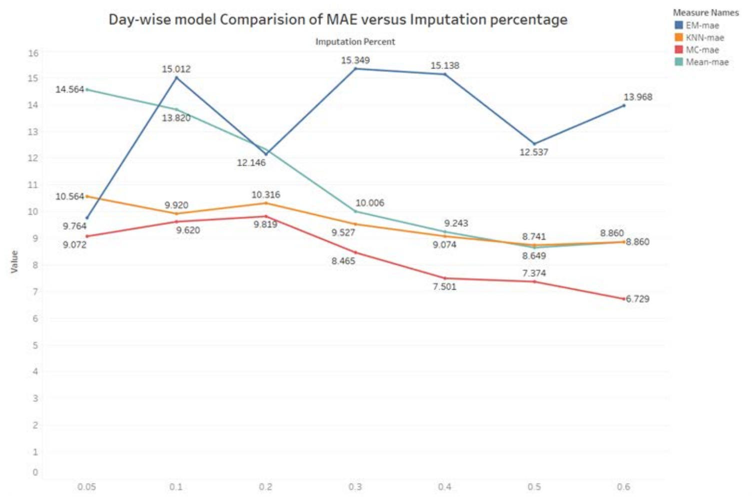

Fig. 10. Day wise model comparison of water flow rate MAE vs. percentage missing data.

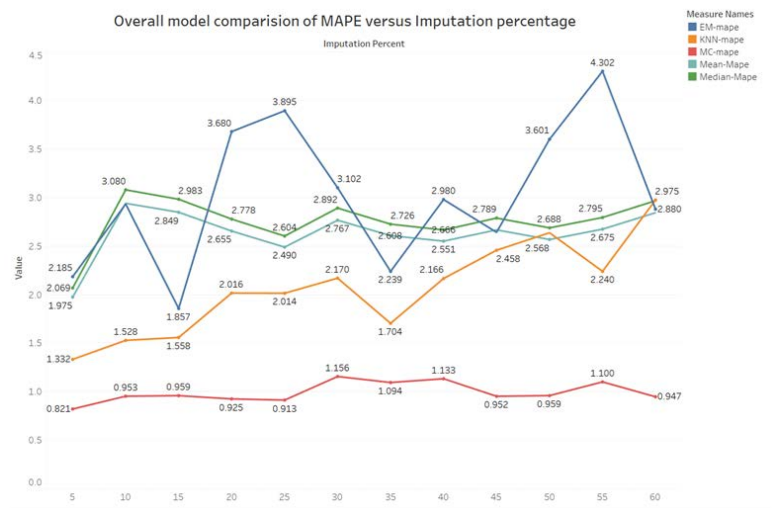

Fig. 11. Overall model comparison of MAPE vs. percentage missing data.

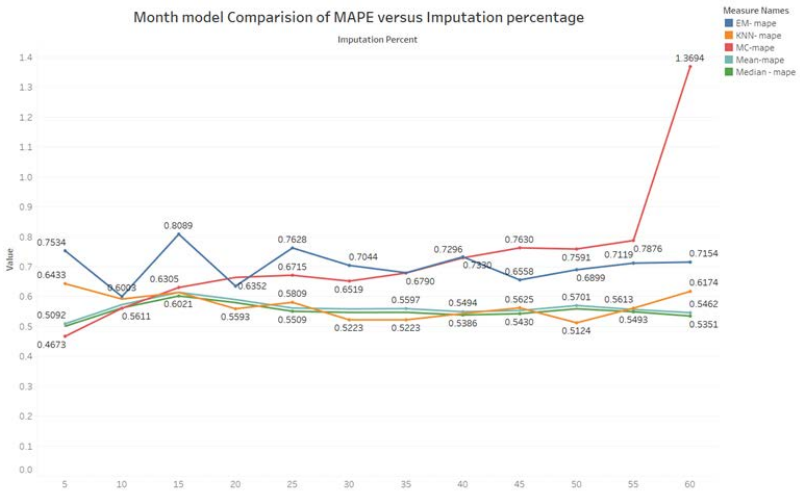

Fig. 12. Month model comparison of MAPE vs. percentage missing data.

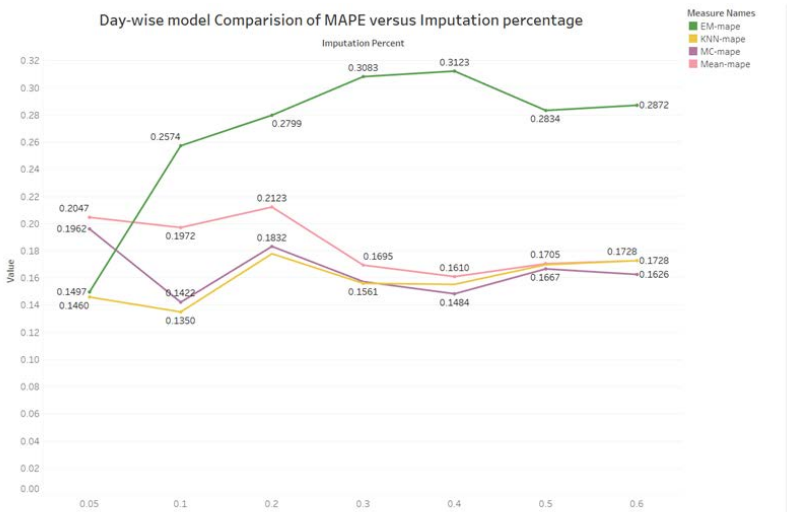

Fig. 13. Day wise model comparison of water flow rate MAPE vs. percentage missing data.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|f_i - y_i\right| \tag{10}$$

where, f_i = Approximation from data value model from forecasting, y_i = Actual value of actual data obtained from calculation, n = Number of sample size using model estimation.

- MAPE: MAPE is a method to check the accuracy of a prediction of a forecasting method in statistics [29]. It is usually calculated using Eq. (11) as the absolute value for every difference between the actual value and forecasted value and divided by the actual value with respect to time. Multiplying by hundred and dividing it by the number of values in the data makes it a percentage error.

$$\mathrm{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\frac{\left|A_t - f_t\right|}{A_t} \tag{11}$$

where A_t = Actual value, f_t = Forecast value, n = Number of values in the data sets.

The graphical results are shown in Figs. 5–13, which represent the performance evaluation of imputation techniques (RMSE, MAE, and MAPE) for overall year, month, and day wise models. These graphs portray the collective data for different values of EM, K-NN, matrix completion, and mean for every percentage missing value with reference to RMSE, MAE, and MAPE. The x-axis and y-axis represent the values for missing percentages and values of EM, K-NN, matrix completion, and mean, respectively. The missing values are to be considered between 5% and 60%. In the graph, for overall and month models, we observe that RMSE, MAE, and MAPE are high for all imputation techniques, which means the imputed value is far away from the actual value. In the case of day wise model, we observe that the parameters RMSE, MAE, and MAPE are low for all imputation techniques. The overall and month models does not suit our requirements as the RMSE, MAE, and MAPE variations are more dominant over forecast. Hence, in this work, we have considered day wise model in which variations in RMSE, MAE, and MAPE are observed to be less.

4.2. CPS in smart water management

The monitoring unit of storage tanks provides data regarding usage of water in regular time intervals. These data can be helpful to schedule the pump and detect the leakage using various methods. Following results were obtained from the study:

Fig. 14 shows the average daily pattern of water flow rate in storage tanks. The average trend analysis of daily pattern can be observed in the monitoring unit. The monitoring unit helps to analyse the trend to handle activities like scheduling the pump, leakage detection, or wastage of water detection. From Fig. 14, we can analyse a regular trend of additive increase and decrease in the average water flow rate in the storage tank between approximately 5 am and 4 pm and between 5 pm and midnight. A particular threshold can be set based on trend, and analysed whenever the water flow rate level rises/falls this threshold. The monitoring unit automatically triggers an alarm to the user based on the threshold to indicate the status of water flow rate in the storage tank, thus smartly managing the water flow rate in the storage tank.

In Fig. 15, we observe that the tank became empty in midday when water is needed the most, and it took 5 h to power on. To resolve this issue, water pumping scheduling is important. Therefore, in our experiment, the monitoring unit will analyse the trend and optimum threshold is set to the trend for every hour. Every time after crossing the threshold, it will power on the pump or communicates with the other tanks depending on their trend. Similarly, with the help of this trend, we can assume water wastage due to either water leaking in the pipe or the tap being left open accidentally. Similarly for every hour, we set a maximum threshold to the trend. Whenever it increases to more than the threshold, we can assume that there is wastage of water either from the tap

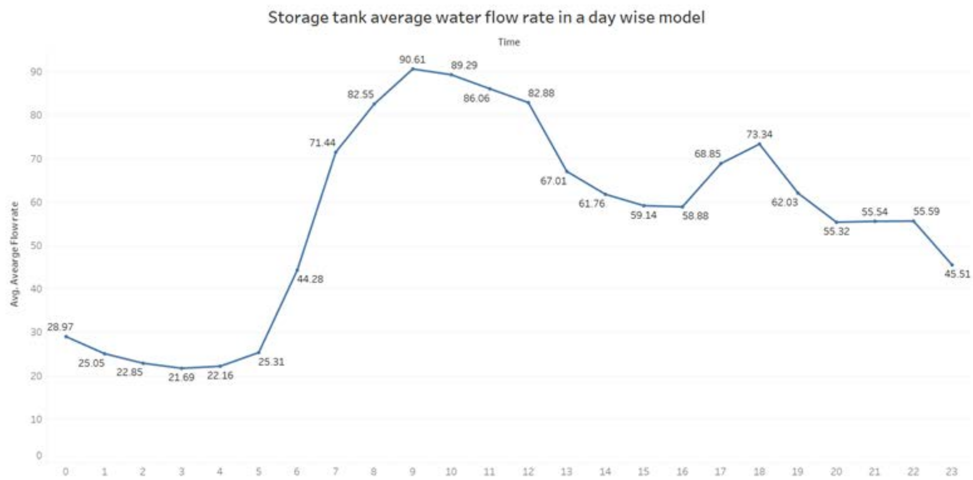

Fig. 14. Average water flow rate in a storage tank in a day wise model.

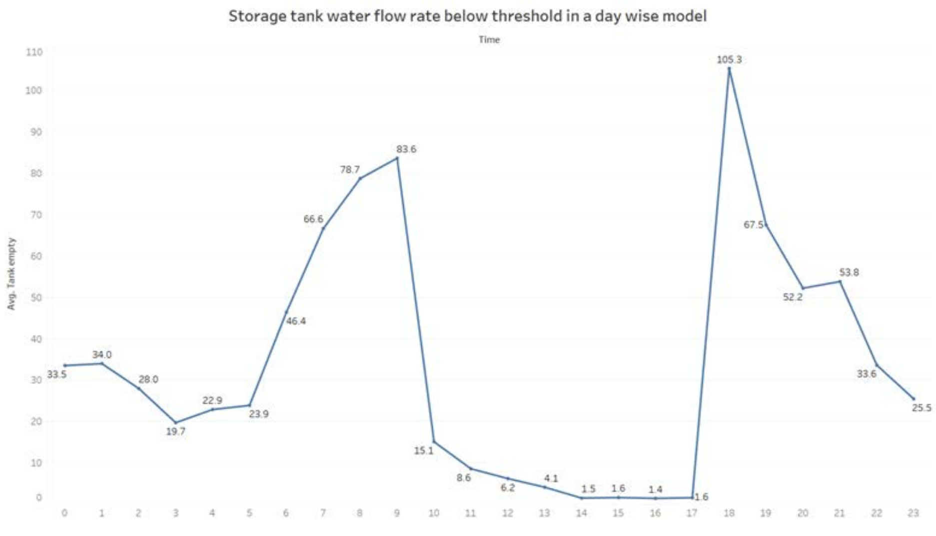

Fig. 15. Storage tank average water flow rate falling below threshold.

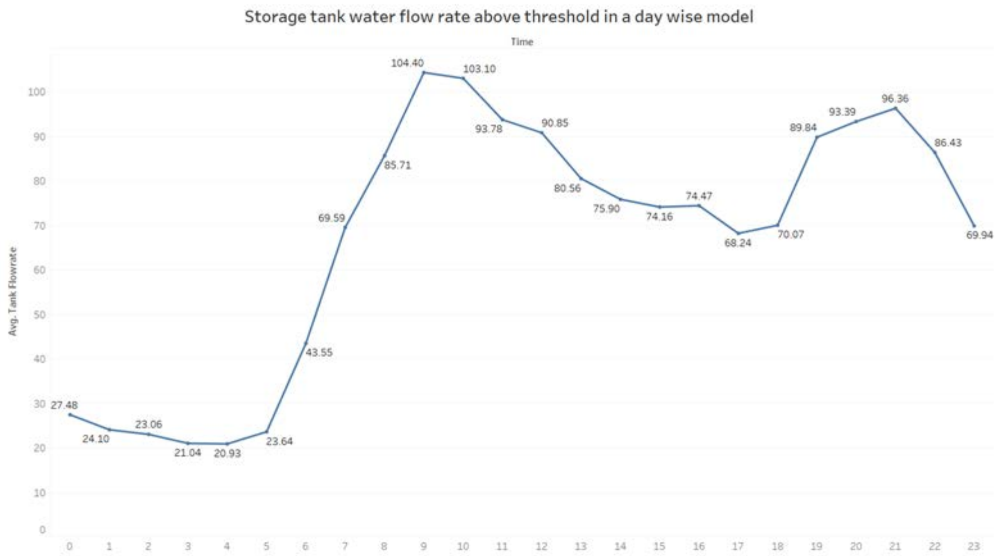

Fig. 16. Storage tank average flow rate rising above threshold.

or leakage in the pipe. In Fig. 16, we can observe that there is an increase in the trend with respect to average flow rate pattern in Fig. 14. So, the monitoring unit will trigger an alarm to the user through SMS [31]. Since there is a similar pattern in daily water flow rate usage like that in weekly and monthly, the water flow data for few consecutive days can be used to detect the change in water flow rate. Whenever this change crosses a certain threshold, an alarm is raised indicating possible defect in tank or taps causing leakage of water. The water monitoring team can then use these data to detect possible location of leakage, thus help in reducing water leakage and also scheduling of pump.

5. Conclusion

The proposed framework is ideal to monitor the water flowing in storage tanks and integrate into CPS that can motivate the control based on historical real-time water flow information data. At this juncture, the issue of handling missing data has been studied through simulations. In India, power failures is common, and it will take time to repair. So it is necessary for us to schedule the pumps when water is needed the most. Previously, the monitoring was done manually, which was the very tedious task. With the help of minimum wireless technology, the monitoring unit automatically schedules the pumping of water to the tanks according to the trend. The monitoring unit can be further automated using the actuation part in which the valve is controlled with respect to the decision made by the monitoring unit. The implementation of forecasting and actuation unit is our ongoing research work. Different techniques are tried to impute the values, by randomly introducing missing values. The performance is assessed based on the popular measures available in the literature, and it is found through elaborate studies that existing techniques are reasonably good toward handling the missing data. In the next phase, experimentation would be carried out to provide results for the burst-natured missing data, for different burst lengths. This is closer to real-life scenario, which opens up the possibility to explore new techniques/methods. The future work is planned toward CPS simulation by building predictive model which can handle missing data, actuate control, and later provide interaction between storage tanks to transfer sufficient quantity of water for distribution.

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