Framework of WSN based human centric cyber physical in-pipe water monitoring system

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***Abstract*—We present a human centric cyber physical framework architecture of our in-pipe water monitoring and feedback system. This system comprises of the physical water distribution infrastructure, together with the hardware and software supported intelligent agents for water allotment, leak detection and contamination spread control. An agent-based approach for connecting the cyber and physical layers is selected, where the agents get information from sensors monitoring the physical components and provide this information to the cyber system. The Hidden Markov Models (HMM) are briefly discussed to determine water consumption patterns and make decisions for cyber and physical systems.**

Keywords*— Cyber physical systems (CPS), Wireless Sensor Networks, Water distribution system, In-pipe monitoring.

I. Introduction

The treated fresh water called drinking water attains the water quality standards required for human consumption. After treatment, chlorine is added to the water and it is distributed by the water supply network. Pressure provided by the pumps and high rising tanks is needed to deliver water to the consumers. Water distribution systems are planned to take care of factors, such as location, future and current demand, population growth, leakage, flow, pressure and pipe sizes etc. Water quality exacerbates as the water passes through the distribution network through chemical reactions and biological processes. Quality of water thus distributed has a direct effect on the general public health [1].

The authorities regulate the chemistry of the potable water before distributing to the customers in order to control the inclusion of poisonous chemicals. This regulation involves close pH monitoring and control. Corrosion inhibitors like phosphates and silicates are added to reduce release of metals from the metal pipes into the water [1]. To sanitize water, chlorine based disinfectant such as sodium hypochlorite or monochloramine is added to the water when it leaves the treatment plant.

Cyber physical systems (CPS) for water distribution comprises of physical components, like valves, pipes, and reservoirs which are coupled with the hardware and software that supports intelligent water distribution and maintenance. We are interested in the information (such as water demand patterns, and water quality (contaminants)) which are critical for public health and provides basic services to masses by directing maintenance efforts and identifying weak areas to repair or monitor. RFID-based sensors embedded in the pipe infrastructure collect this information and send it through the access points to internet where they are made available to the cyber data server. This information is then fed to the algorithms running on the cyber system. These algorithms provide decision support to hardware controllers that are used to manage the quantity and quality of the water. Our research includes both cyber and physical aspects of water distribution system.

We have developed PipeSense [2] which is an RFID-based in-pipe water monitoring system. Our system is implemented through sensors that measure the volume, pressure, and chemical composition of water at various locations in the area. The available information such as demand and usage, pressure, level of contaminations and their patterns assist in real-time control of the water distribution system, which can increase system utilization and its efficiency.

The remainder of this paper articulates our proposed framework, discusses some models helpful in making decisions and recognizing patterns in the data. Section 2 presents a review of related literature. The human centric CPS framework for PipeSense is discussed in Section 3. Section 4 discusses in brief the HMM proposed model that can be applied in our approach to predict the contamination spread and give patterns for water demands based on the data received. In section 5, some of the future works related to the research are discussed and section 6 concludes the paper.

II. Literature Review and Background

The growing demand for water in the current century lays a challenge to researchers from numerous fields to plan more efficient water distribution system designs, including control devices, techniques to optimize the existing network, and also information systems. Previous work like PipeNet [3] used noise vulnerable acoustic signals to detect leaks in the piping structures with fewer nodes. This made their system very complex with high probability of false alarms. Moreover, the humans have no control over the system. In [4] a middle ware

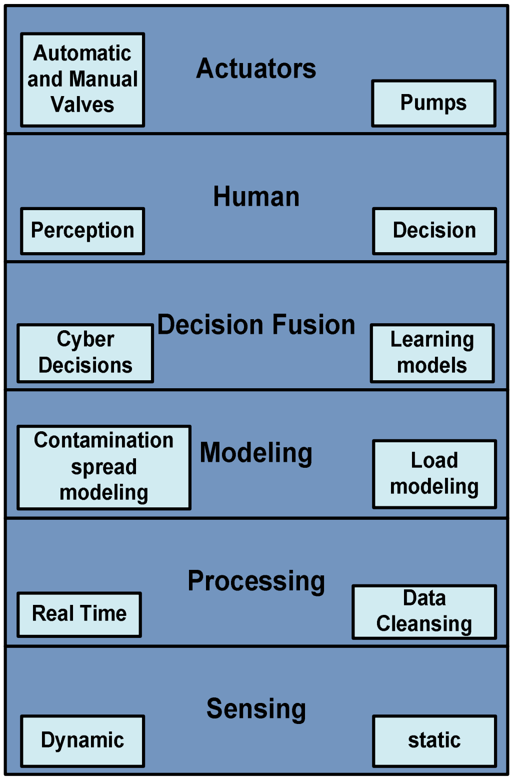

Fig.1: Framework for cyber physical PipeSense System.

framework for cyber physical water distribution system was presented for eight complex nodes based on single-board computer deployed in Singapore. This framework is used to

detect the pattern of the leaks using the principles of Algebraic Hierarchical Equations for System Design (AHEAD) [5]. However, this framework is unable to predict the future water consumption and leak patterns. Pressure and acoustic data both are utilized to detect the leaks in the water distribution system. Again the accuracy of the leak detection process is not very efficient due to the use of acoustic signals.

We have begun to see the growing demand of water due to increasing populations and improvements in living standards of the general public. Water allocation is the allotment of water quantity to areas according to population and demand. The increase is population also means the old water distribution system infrastructure cannot maintain the pressure and supply thus it is bound to develop faults and wear and tear. The second threat to the water distribution systems is the spread of poisonous contaminations in water. Contamination spread in a water distribution system is relatively quick and unpredictable, therefore, quick identification and spread prevention is important to take contaminant control. This may risk the lives and health of the consumers and should be dealt promptly. In order to solve these problems, two complementary measures may be taken. First, improving the management system through feedback and control using recent development in the areas of communication and secondly the information technology.

As water distribution systems can hold thousands of independent, intelligent entities that need to be simulated and controlled, these system settings are extraordinarily tempting for multi-agent technology. Multi-agent system (MAS) is a system composed of multiple interacting intelligent agents which are seen in the likes of cyber physical systems [6]. Multi-agent systems are used to solve problems which are difficult for an individual agent to solve. Examples of problems which are appropriate to multi-agent systems research include online trading, disaster response, and modeling social structures. Typically multi-agent systems research refers to software agents. However, the agents in a multi-agent system could equally well be robots, humans or human teams. Multi-agent techniques have been used for modeling and simulation of the effects in similar technologies. With the current developments in communication and hardware, computer-based control is now a reality. The main goals of our human centric CPS framework are to improve the quality for public safety and maximize the overall efficiency of the network and to determine future water consumption targets and the need for infrastructure enhancements.

We intend to develop models based on the real state water quality and demand to analyze the effect of real water demand patterns on the current distribution network. We have developed a human centric CPS framework architecture to integrate the human as an agent in the water monitoring and distribution application. Some examples of the work close to our endeavor such as the modeling of the leaks using genetic algorithms [7] and distribution network optimization in [8]. Contamination spread and its determination which is helpful in emergency situations are discussed in [9] and [10].

In our work, we have designed a human centric framework with the goal to develop an event-driven, CPS for efficient water monitoring system. Our system comprises of greater number of inexpensive nodes who can communicate with each other, resulting in a more efficient sensing and fewer false alarms. The data thus collected will be integrated and assimilated into Markovian models for predicting/updating the state of the system, which will in turn be fed into the physical network to optimize pumping operations for water conservation and allocation and also cater for spread prevention and removal of contaminations from the system. The same system will also include features to evaluate events such as leaks and pipe bursts that involve multiple geographically distributed sensor nodes.

III. HUMAN CENTRIC CPS FRAMEWORK

Fig.1. shows our human centric CPS framework architecture, which comprises of six tiers connected to each other. A brief explanation of each tier is given below:

Sensing Tier – This tier comprises of flow, pressure, pH and pollution or contamination sensors. These sensors can also be divided into static sensors, sensors that monitor ambient temperatures as well as valves and pumps proper functioning and dynamic sensors that continuously monitor the in-pipe system as well as give geographical location of the nodes. The information from the sensor is partially cleansed at the node level and is then transmitted to the server where the data is fully processed.

Processing Tier – After getting the partially cleansed data from the sensors, the processing tier performs extensive data cleansing in real-time and can also store the data for historical referencing.

Modeling Tier – The processed data is then fed to the modeling tier. This tier comprises of Hidden Markov models for demand pattern predictions and for determining contamination spread.

Decision Fusion Tier – The outcomes from the demand and contamination spread models are then fed to the decision fusion tier. Here, the cyber decisions are made according to the standard artificial intelligent models and these decisions are learned by the cyber systems through the learning and training models for accurate decisions in the future.

Human Tier – The decisions from cyber models are not imposed on the system instantly but further evaluation of the decision is done in this all important human tier where humans are present in the feedback of the framework. This human feedback along with the human agents responsible for the manual maintenance of the system, makes the framework human centric. The humans may overrule the cyber decisions if it is perceived by the humans as a false alarm. The outcome of the human decision is monitored by the system and used in the learning models to train the system.

Actuator tier – The actuators can be valves and pumps either manual or automatic that can be used to stop, open, increase pressure and isolate a section of pipes in case of leakages, pipe bursts or to stop contamination spread. The final decisions are sent to human operators and automatic systems to perform the specified tasks.

This system is then monitored again by the sensing tier to determine the result of a particular decision. This whole process is shown in a form of a flow diagram in Fig.2. Let us consider an example situation, for instance sensors picked up high contamination levels of a certain poisonous element at a certain location. This sensed information is then processed and cleansed in real-time and provided to the modeling tier which has contamination spread models to isolate that pipe section and prevent water distributing from this section. The models put the data in different scenarios and send the outcomes to the decision fusion where the HMM models take an appropriate decision. These decisions are sent to human decision makers who then decide/ judge the decision as per their perception and they may overrule the cyber decision and send their decision to the physical actuators in the form of warning messages. Cyber system will learn from the outcome of the human decision through a learning model.

Certain events causing leakages and pipe bursts can be very efficiently handled through the human centric cyber physical system. The system will determine the best possible routes for the water in case of the said events. The same system can also inform authorities to send maintainers and engineers to the concerned areas to monitor and control. In short, the decisions taken are sent to the authorities, warning consumers of a potential threat and the administrators to control any unwanted event.

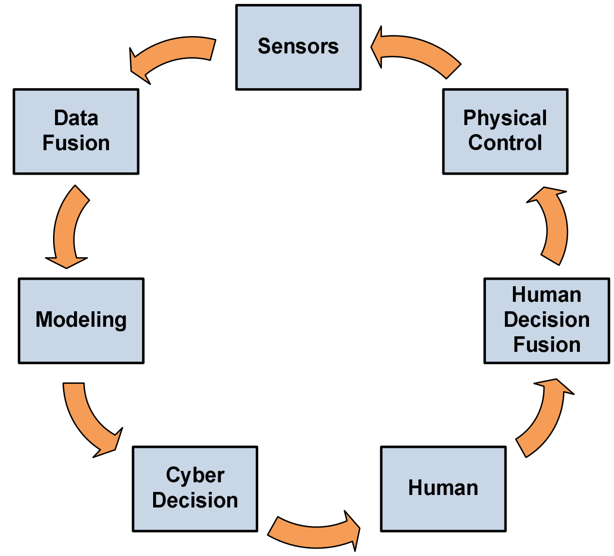

Fig. 2: Flow diagram of the cyber physical PipeSense system.

IV. PROPOSED MODEL FOR CYBER SYSTEM

We have selected agent-based modeling due to the distributed nature of our system. Moreover, we have explored some of the simulation platforms appropriate for our system, for physical layer simulation, we found EPANET 2.0 [11] which is open-source software by Environment Protection Agency (EPA) fitting due to its ability to touch a wide range of water distribution attributes. A realistic model for CPS will consider the randomness of the system's environment where the sensors were deployed and the system components which are in fact intelligent agents.

In multi-agent systems, there are numerous techniques which can be used to describe how each agent makes decisions such as Genetic Programming, Reinforced Learning, Rules Based Reasoning, Game Theory and Neural Network [12]. However, we are interested in using Bayesian models using Hidden Markov Model (HMM) which is one of the best tools to recognize and predict demand patterns and contamination spread within the data collected.

HMM is a statistical model in which the system being modeled is assumed to be a Markov process with unobserved state [13]. An HMM is a stochastic process generated by interrelated underlying probabilistic mechanisms called Markov Chain with a finite number of states and a set of random functions associated with the states in which the states are not directly visible, only output dependent on the state is visible. Every state is associated with a probability distribution over the possible output symbols. HMM generate the sequence of symbols that gives information about the sequence of states [14]. One of the models to solve and predict the demand patterns and contamination spread to some known events

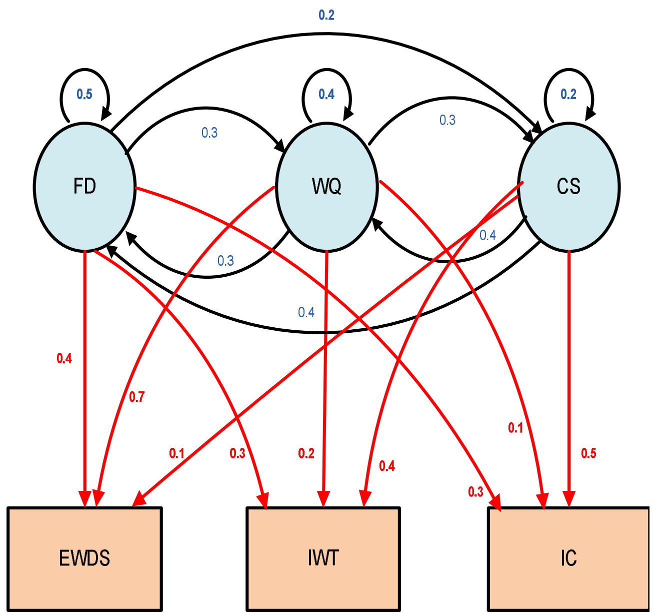

Fig. 3: HMM to determine patterns and probabilities of future water demand, water quality and contamination spread for the water distribution system.

using Hidden Markov Model with Bayesian Inference is shown in the Fig. 3.

We consider a system which may be described at any time as being in one of a set of 3 distinct regularly spaced time states,

State 1: Future Demand (FD).
State 2: Water Quality (WQ).
State 3: Contamination Spread (CS).

These states are the result of one or all of the three output possibilities like data showing expansions made in the water distribution system, 'Expand Water Distribution System (EWDS)', improvements made in the treatment system, 'Improve Water Treatment (IWT)', and the number of times a particular section of water distribution system is isolated in a given month, 'Isolate Contaminations (IC)'.

The system undergoes a change of state (possibly back to the same state) according to a set of probabilities associated with the state. We denote the time instants associated with the state changes as t = 1, 2 and 3. The above stochastic process could be called an observable Markov model since the output of the process is the set of states at each instant of time, where each state corresponds to a physical (observable) event. We have made some educated guesses for the start probabilities in eq. (1) since we lack proper data, however, this will serve well for evaluating our model. After validating our model with this dummy data, we can easily provide it with the real data for analysis.

Start Probabilities:

$$\{FD = 0.5, WQ = 0.3, CS = 0.2\} \quad (1)$$

Transition probabilities represent the change of the water distribution properties in the underlying Markov Chain. We postulate that the events on a particular month are characterized by a single one of the three states above, and we create matrixes 'A' and 'B' of state transition probabilities and emission probabilities respectively. These probabilities will be determined after several test runs in the real scenario. However, here we have provided the dummy readings for model evaluation.

Transition Probabilities:

$$A_{i,j} = \begin{array}{c} \begin{bmatrix} 0.5 & 0.3 & 0.2 \\ 0.3 & 0.4 & 0.3 \\ 0.4 & 0.4 & 0.2 \end{bmatrix} \end{array} \begin{array}{l} FD \\ WQ \\ CS \end{array} \quad (2)$$

Emission Probabilities:

$$B_{j,k} = \begin{array}{c} \begin{bmatrix} 0.4 & 0.3 & 0.3 \\ 0.7 & 0.2 & 0.1 \\ 0.1 & 0.4 & 0.5 \end{bmatrix} \end{array} \begin{array}{l} FD \\ WQ \\ CS \end{array} \quad (3)$$

We have arranged the emission matrix on the following assumptions; if FD increases then there is a 40% chance of the need to expand the water distribution system. If WQ increases then there is a 30% chance we need to improve the water treatment system. If CS increases then there is a 50% chance that we need to isolate the contamination. We can utilize this HMM to ask ourselves the possibility of the need to expand our existing water distribution network in the future, improve the water quality through treatment and the need to isolate the contaminations per effected region in the future.

For an observation sequence in equation (4), we can determine the probability of the following properties for the period of 6 months.

$$O = \{IWT, EWDS, EWDS, IC, IWT, EWDS\} \quad (4)$$

We have utilized Viterbi forward algorithm [15] widely used in HMMs to obtain the observation sequence probability. We can optimize the above observation sequence to get a meaningful sense in other words we can find a state sequence that would have most probably generated this output sequence. This Viterbi forward algorithm reveals the probability of eq.(4) to be 0.0019 and the optimum path of states for this observation sequence is {FD, WQ, WQ, CS, FD, FD, FD} with probability 1.59exp-5. The Viterbi path contains seven states as the seventh state was generated by the sixth state and a transition to the seventh state. We can also adjust the model parameters such as transition, emission and initial probabilities to maximize the probability of an observable sequence. This model is just a simple example; more complex situations can also be handled efficiently through the same model after some modifications. Learning and decision models for the proposed framework was not discussed due to limited space in this paper.

V. FUTURE WORK

We intend to enhance PipeSense with a multi-interface data service for administrative functions and a map service for the normal users. PipeSense can also utilize existing sensor modules and feed their data to the users' handheld computing devices for processing and analysis. We are exploring the use of communication methods such as Wi-Fi, Bluetooth etc. These provide a wide choice of data transfer speeds and flexibility in building a network. We have initially used a simple 802.11 based protocol. At the later stage of the research an improved energy efficient event driven MAC protocol for PipeSense will be introduced. Some of the application where this system can also be applied may be sewage monitoring, oil and gas installations and industrial gases leak detections and quality management.

VI. CONCLUSION

To sense various aspects of water distribution system and share this information to control, preserve and improve water quality are of major interest. This paper presents a CPS framework for PipeSense an in-pipe water monitoring system based on near field RFID WSNs. The CPS framework architecture and a proposed model for demand pattern and contamination spread for water has been described. In addition, directions for further research and development and its impact were presented.

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