Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 119 (2015) 28 – 34

Procedia Engineering

www.elsevier.com/locate/procedia

13th Computer Control for Water Industry Conference, CCWI 2015

A particle filter based leak detection technique for water distribution systems

Anjana G R[1], Sheetal Kumar K R[1], M S Mohan Kumar[1*] and Bharadwaj Amrutur [2]

[1]*Department of Civil Engineering, and Robert Bosch Centre for Cyber Physical Systems,*
[2]*Department of Electrical Communication Engineering and Robert Bosch Centre for Cyber Physical Systems,*
Indian Institute of Science, Bangalore, Karnataka (India)

Abstract

Leak detection and localization plays an important role in the efficient management of Water Distribution Systems (WDS), as it will help in reducing water wastage. Automation of WDS (with water quantity and quality sensors) has helped the water authorities around the world to get near real time data of important system parameters. Various models developed on the basis of Extended Kalman Filter (EKF), Nonlinear Kalman Filter etc. have been widely used for leak detection in pipelines. These models are applied on flow, pressure and acoustic signals from the system. But the main disadvantage of most of these models is that, they require the non-linear pipeline model to be linearized. In this paper, we propose the use of a Particle Filter (PF) based technique for the detection of leaks in water pipelines, and the developed model is applied to a real world network in Mandya (Karnataka, India).

Peer-review under responsibility of the Scientific Committee of CCWI 2015

Keywords: Particle filter; leak detection; water distribution systems

* Corresponding author. Dr. M S Mohan Kumar.
E-mail address: msmk@civil.iisc.ernet.in

1. Introduction:

Water is one of the most important and life sustaining element of our ecosystem. Due to population growth, climate change etc. there developed a huge gap between the supply and demand of water. In developing countries like India,

Peer-review under responsibility of the Scientific Committee of CCWI 2015
doi:10.1016/j.proeng.2015.08.849

the gap in supply and demand of water is increasing and predominant. Hence, in these situations, conservation of water becomes extremely important. And for effective water conservation, minimization of water leakage in distribution systems also need to be addressed. Most of the cities in India, like Bangalore, experience 45-50% leakage in their water distribution networks. Since most of the Indian cities are distributing water based on the supply of water rather than the demand of water, the demand based algorithms developed in literature cannot be directly applied for system analysis. The main objective of this paper is to develop a Particle filter (PF) based leak detection technique for supply based water distribution systems. The methodology is applied to a real world network in Mandya, (Karnataka, India). The network under study is a tree network, and water is supplied under gravity in this system.

Automation of water distribution systems around the world had helped the water authorities to get real time data of key water quality and quantity parameters. Filters (Bayes filter, Kalman filter, Particle filter etc.) are mainly used for state estimation when online data is available and there is noise associated with it. But the main disadvantage of most of these techniques is that they require the non-linear system model to be linearized. In this paper, we propose the use of a Particle Filter (PF) based technique for the detection of leaks in water pipelines, which is essentially a non-linear system.

Application of filter technologies for leak detection is not new in water networks. Linear filters like Extended Kalman filters, Adaptive particle filters etc. have been widely used in leak detection in gas pipe lines [1&2]. Also, they were used for demand estimation in water systems as well [3, 4 &5]. But, there use for estimation of pipe flows and pressure in water systems is novel.

2. Methodology

The methodology adopted for this study and each step in the methodology is briefly explained in the following section.

2.1 Particle Filters:

The study involves the use of a particle filter based approach for state estimation (SE) using particle filters in a supply based water distribution system. Particle filtering is a sequential Monte Carlo method for estimating the posterior density of the state-space models where the state of the system evolves in time; and information about the state is obtained via noisy measurements (from sensors) at each time step. Generally, the state- space model of any system is represented as a function of the state at the previous time step and the process noise.

$$\boldsymbol{x_k} = \boldsymbol{f_k}(\boldsymbol{x_{k-1}}, \boldsymbol{v_{k-1}}) \qquad (1)$$

Here, $\mathbf{x_k}$ represents the state vector of the system at the k^{th} time step, which is assumed to be latent or unobservable and $\mathbf{v_{k-1}}$ is the process noise vector for the $k\text{-}1^{th}$ time step [6]. f_k is the state transformation equation for the system, which is non-linear and time dependent function for water distribution networks. The information about $\mathbf{x_k}$ can be found out using noisy measurements from the field like pressure and flow measurements.

$$\boldsymbol{z_k} = \boldsymbol{h_k}(\boldsymbol{x_k}, \boldsymbol{n_k}) \qquad (2)$$

In the above equation, z_k represents the noisy measurements from the field sensors; h_k is the measurement transformation equation and n_k is the measurement noise [7]. Particle filters are a form of recursive Bayesian filters, in which the distribution $p\ (x_k \mid z_{1:k})$ is obtained in two steps. First, is the prediction step,

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1} \quad (3)$$

The second step is the update step, where in the prior estimate from the prediction step, $p(x_k \mid z_{1:k-1})$ is updated with new measurements z_k:

$$p(x_k|z_{1:k}) \propto p(z_k|x_k)p(x_k|z_{1:k-1}) \quad (4)$$

The core idea of particle filter theory is to represent the posterior probability distribution function of the states ($p(x_k \mid z_{1:k})$) by approximating it by an ensemble of particles (n_p) obtained from Monte Carlo Simulation, each designates a particular weight $\mathbf{w}_k^i$, such that:

$$x_k = \sum_{i=1}^{n_p} w_i x_k^i \quad (5)$$

Here, x_k^i denotes the state of the ith particle at kth time step. If the particle size is sufficiently large, then it approximates the posterior distribution [5]:

$$p(x_k|z_k) \approx \sum_{i=1}^{n_p} w_i \delta(x_k - x_k^i) \quad (6)$$

where, δ is the Dirac delta function at x_k. Also, the weights of the particles at the time step k, w_k^i can be expressed recursively as a function of w_{k-1}^i as follows [7]:

$$w_t^i = w_{t-1}^i \frac{p(z_k|x_k^i)p(x_k^i|x_{k-1}^i)}{p(x_k^i|x_{t-1}^i, z_k)} \quad (7)$$

In the present study, a regularized particle filter is used for state estimation. Regularized particle filter is effective in counteracting the degeneracy problem and the sample impoverishment problem that arise during particle re-sampling [7]. According to it,

$$p(x_k|z_{1:k}) \approx \sum_{i=1}^{n_p} w_k^i K(x_k - x_k^i) \quad (8)$$

where, $K(x_k - x_k^i)$ is a kernel function (Epanechnikov kernel) centred at x_k^i.

2.2 Hydraulic Modelling:

The basic process variables that are used to describe the behaviour of the elements and nodes of a whole water supply network are the flows and the pressures in the system. Along a pipe section, head drop is related to the flow characteristics in a non-linear fashion. Consider a pipe section of length l_p (m), area A_p (m^2). If the head difference between the two ends of a pipe, Δh is considered, the non-linear differential equation, which describe the dynamic behaviour of the fluid in the non-elastic pipeline is:

$$\frac{dQ(t)}{dt} = \frac{gA_p}{l_p}(\Delta h - h_{loss}(t)) \quad (9)$$

Here, h_{loss} is the total loss in the pipe section and is given by,

$$h_{loss(t)} = h_{loss-fp}(t) + h_{loss-l}(t) \quad (10)$$

where, $h_{loss-fp}$ denotes the friction loss and h_{loss-l} denotes the local head loss. In this study, Hazen-Williams equation for head loss is being used to calculate the head loss due to pipe friction.

$$h_{loss-fp}(t) = \frac{10.71 l_p}{C^{1.852} D_p^{4.87}} Q_t^{1.852} \quad (11)$$

Here D_p (m) is the diameter of the pipe, Q (m^3/s) is the flow through the pipe and C is the Hazen Williams roughness coefficient. Also, for network solution, at the junctions the continuity equation should be satisfied:

$$\sum \boldsymbol{Q}_{in(i)} - \sum \boldsymbol{Q}_{out(i)} = \boldsymbol{q}_i \quad \boldsymbol{for\ i = 1, 2 \ldots NJ} \tag{12}$$

Q_{in} is the inflow to the junction i, Q_{out} is the outflow from the junction i and q_i is the demand at the junction i. And NJ is the total number of junctions in the water distribution system. Using these hydraulic relationships, the state space model for the water network is derived. The state vector, $X(t)$ is denoted as,

$$\boldsymbol{X(t)} = [\boldsymbol{x}_1^t\ \boldsymbol{x}_2^t \ldots\ldots \boldsymbol{x}_n^t]'$$

$$= [\boldsymbol{q}_1^t\ \boldsymbol{q}_2^t \ldots\ldots \boldsymbol{q}_{np}^t\ \boldsymbol{p}_1^t\ \boldsymbol{p}_2^t \ldots\ldots \boldsymbol{p}_{nn}^t]' \tag{13}$$

Here, $\boldsymbol{x}_i^t$ is the state variable at time t, where i range from 1 to number of states n. The state variables are the flow, $\boldsymbol{q}_j^t$of the pipe j at time t and pressure, $\boldsymbol{p}_k^t$ of the node k at time t; j varies from 1 to number of pipes in the network, np and k varies from 1 to number of nodes in the network, *nn*.

2.3 Anomaly Indicator:

Statistical process control (SPC) methods are used for burst detection in this study. For burst detection, Jung et al.(2013) found out that the univariate CUmulative SUMmation(CUSUM) are effective than other SPC methods. According to SPC-CUSUM, [4]

$$\boldsymbol{z}_i = \frac{x_i - \overline{x_i}}{\sigma_i} \tag{14}$$

where, $\boldsymbol{z}_i$ is the normalized state value (standard score) at the i^{th} time step, $\boldsymbol{x}_i$ is the state value at the i^{th} time period, $\overline{\boldsymbol{x}_i}$ and $\boldsymbol{\sigma}_i$ are the mean and standard deviation of the quantity at the i^{th} time period.

The methodology adopted in this study is graphically explained in Figure 1.

2.4 Application:

The system in study is a real world network in Mandya, (Karnataka, India), (Figure 2). Since the system is a supply based system, the water demand factors for each hour is found out from the water supply statistics. The system supplies 25-28 MLD of water to a population of about 137,735 in Mandya [8]. Water is supplied into the network from a reservoir, and the system works under gravity. The network is a reduced model of the real world system and it is mainly a tree network, hence the system reduction will not greatly affect the accuracy of the model. The developed model has 43 pipes and 23 junctions and one reservoir. 23 flow measurements are obtained from the system, and the flow meters are assumed to be located near to the consumer ends in the system.

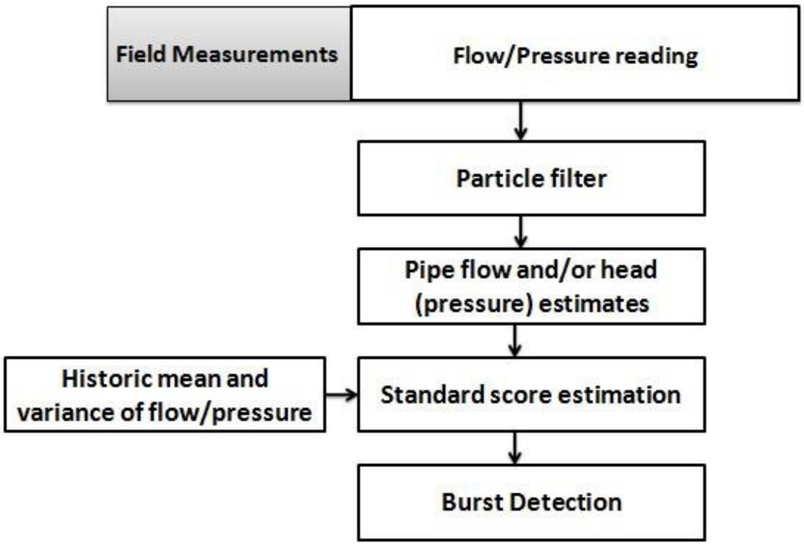
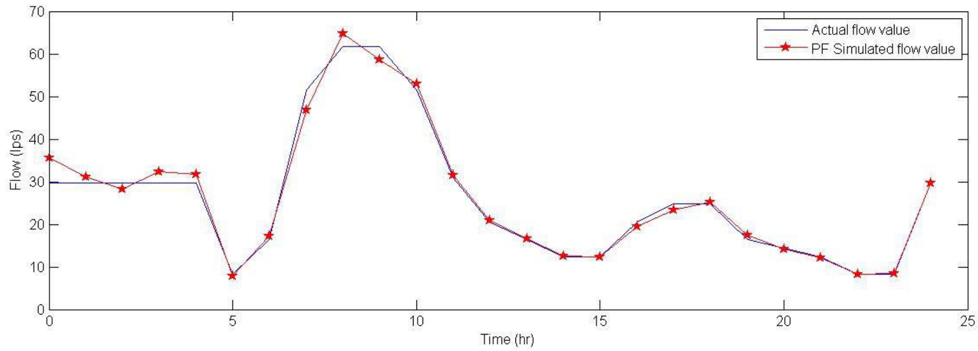


Figure 1: Methodology for leak detection using Particle Filter (PF)

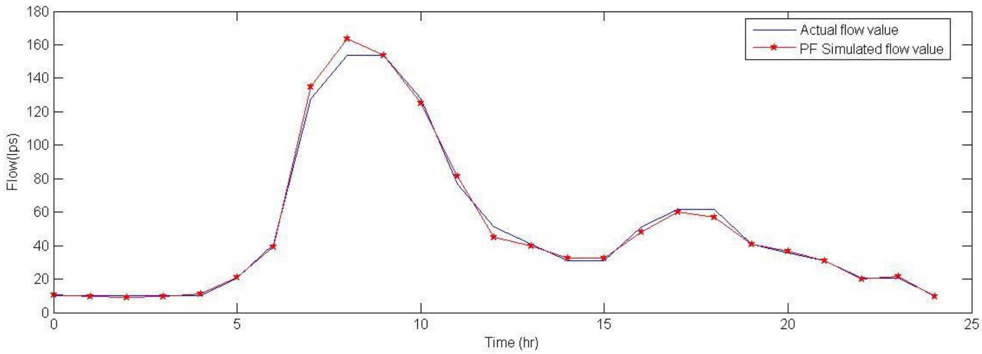
Figure 2: Schematic and water flow direction in Mandya water distribution network

3. Results and Discussions:

It was observed that the particle filter algorithm was able to simulate the flow values in all the pipes of the network, but the pressure readings simulated by the particle filter (PF) were oscillating and are not shown in this work. Comparison between the actual flows and the simulated flows in two different pipes of the network are given in the Figure 3 (a & b). Once the flow values were simulated using PF, it was used for anomaly detection in the system. And standard SPC-CUSUM chart was able to detect anomalies in the system; a break was simulated in the EPANET model of the network (10% of the actual pipe flow) and it was reflected in the standard score graph of flow measurements. (Figure 4).

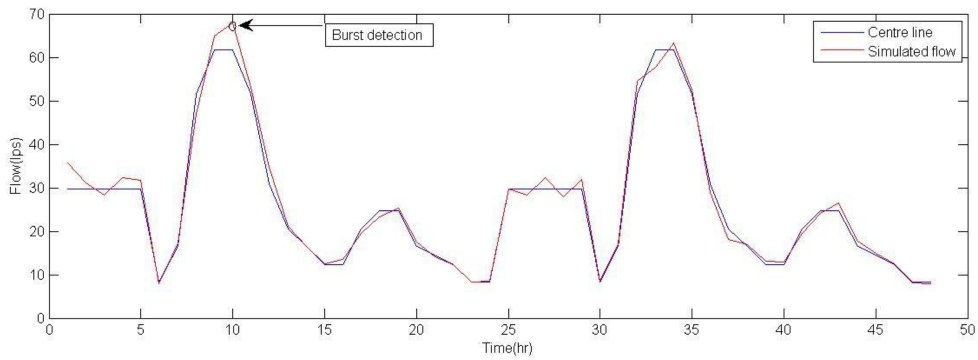


(a)

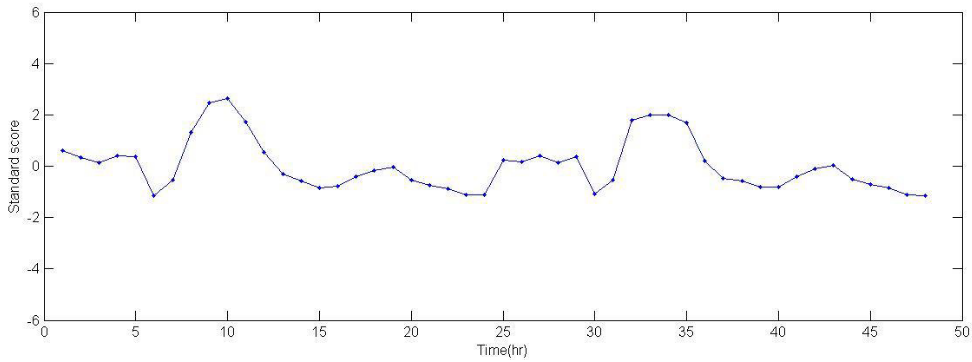


(b)

Figure 3(a & b): Comparison of actual flow in two pipes with corresponding value simulated using Particle Filter algorithm.



(a)



(b)

Figure 4: (a) Represent simulated flow for a pipe line using PF, and model output, assuming a burst in the system at 10hrs (10% of flow as leakage); The simulated flow lies well beyond the 4σ bound (σ of the historic values) generating an alarm. (b) Representative of the standard score for flow values; during the burst event, the value lies beyond the assumed normal threshold of -2 to +2.

4. Conclusions:

In this study, a particle filter based technique is proposed for state estimation in a supply based water distribution system. The method is applied to a real world network and the results are discussed in this paper. From this study, it is clear that PF algorithms can be used for state estimation (flow estimation) in supply based tree water distribution networks. But further study is required to assess its applicability in a looped network. Also, further study is required to optimize the ratio of flow measurements to pressure measurements required for any system, since use of many flow measurements will increase the cost of system instrumentation, as flow meters are generally more expensive than pressure sensors.

References

[1] A. Benkherouf, and A. Y. Allidina, "Leak detection and location in gas pipelines," *IEE Proceedings (Control Theory and Applications)*, vol. 135, no. 2, March, 1988, pp. 142-148.
[2] M. Liu, S.Zang, and D. Zhou, "Fast leak detection and location of gas pipelines based on an adaptive particle filter," *International Journal of Applied Mathematics and Computer Science*, vol.15, no.4, pp.541-550, 2005.
[3] D.Kang and K. Lansey, "Real-time demand estimation and confidence limit analysis for water distribution systems", *Journal of Water Resources Planning and Management,* vol.86, no.135,pp.825-835,2009.
[4] D. Jung, and K. Lansey, "Water distribution system burst detection using a nonlinear Kalman filter," *Journal of Water Resources Planning and Management*, 2014.
[5] C.J.Hutton, Z. Kapelan, Lyroudia-Vamvakeridou, and D.A.Savic, "Real-time demand estimation in water distribution systems under uncertainity", *12th CCWI Conference*, 2014.
[6] N.J.Gordon, D.J. Salmon, and A. F.M. Smith, "Novel approach to nonlinear/non Gaussian Bayesian state estimation", *IEEE Proceeding*, vol.140, no.2, pp. 107-113, 1993.
[7] M.S. Arulampalam, S.Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for online nonlinear/non Gaussian Bayesian tracking", *IEEE Transactions on Signal Processing*, vol.50, no.2, pp.174-188, 2002.
[8] https:\\www.census2011.com