Grey Wolf Optimization based Sensor Placement for Leakage Detection in Water Distribution System

Rejeesh Rayaroth, G. Sivaradje

Abstract--- ***Water Distribution System (WDS) are employed in everyday life either for domestic or for industrial purpose. WDS are large scale systems that need the design of better leak detection methods to avoid water waste. Recently, researchers concerned about WDS have focused their research on water leakage detection techniques. However, the different existing techniques failed to improve the performance of accuracy and time consumption during water leakage detection. In order to address the above mentioned issues, Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolf Optimization (BCSA-MHGWO) Technique is introduced. The main aim of the BCSA-MHGWO technique is to detect the water leakage with a minimal number of sensor placed nodes. Initially, WDS is represented in graph model comprising a set of vertices (i.e., nodes) and set of edges (i.e., pipes). The sensitivity and entropy value is calculated for all nodes based on the pressure and flow rate. After calculating the sensitivity value, the correlation value of all nodes is measured by using bivariate correlation coefficient based on the pressure series. Finally, grey wolf optimization process is carried out in BCSA-MHGWO technique to select the optimal nodes for sensor placement based on the sensitivity, entropy and correlation value for water leakage detection. In this way, water leakage detection accuracy and time performance get improved using BCSA-MHGWO technique. The performance of BCSA-MHGWO Technique is measured in terms of water leakage detection accuracy, water leakage detection time, and false positive rate. The simulation results show that BCSA-MHGWO Technique improves the performance of water leakage detection accuracy and also reduces water leakage detection time when compared to state-of-the-art works.***

Keywords--- ***Water Distribution Systems, Leak Detection, Bivariate Correlation, Sensitivity, Entropy, Meta-Heuristic, Grey Wolf Optimization.***

I. INTRODUCTION

In water-distribution systems, large quantity of water is lost during transportation from treatment plants to the consumers. The quantity of water lost is 20-30 percent of production. Water loss is mainly due to the leakage, errors, fire-fighting, pipe flushing, etc. Leakage is the main cause for the water loss. Leakage takes place in many components of distribution systems, namely transmission pipes, distribution pipes, service connection pipes, joints, valves, and fire hydrants. A fast and accurate water leakage detection system was introduced using one-dimensional convolutional neural network and support vector machine (1D-CNN-SVM) model in [1]. A graph-based localization algorithm was used to identify the leakage location. However, the water leakage detection accuracy was not improved using 1D-CNN-SVM model. Particle Filter (PF) based technique was introduced in [2] for leak detection in water pipelines and applied to real world network in Mandya. But, the water leakage detection time was not reduced using Particle Filter (PF) based technique.

A new water leakage detection method was introduced in [3] using pressure data. Kalman Filter was employed to eliminate the noise. Through evaluating the cumulative integral of pretreated data and relating floor function, the leakage was identified detected. Though the water leakage was detected correctly, the computational cost was not reduced. A new technique method was introduced in [4] for leak detection in WDN through repeated water balance and minimal use of additional off-line flow measurements. A multi-stage graph partitioning approach was designed to identify where the offline flow measurements were made for minimizing the cost. But, the false positive rate was not reduced using multi-stage graph partitioning approach.

An optimal sensor placement methodology was introduced in [5] using genetic algorithms for increasing isolability with reasonable number of sensors. The methodologies were used in Barcelona Network by PICCOLO simulator. The sensor placement and leakage detection and localization methodologies were used in district management areas (DMA). But, the number of sensor placement was not minimized using optimal sensor placement methodology. An integrated model-based monitoring framework was introduced in [6] for leakage localization in district-metered areas (DMA) of water distribution networks. The leakage localization methodology was introduced depending on flow and pressure sensors at DMA inlets. But, the detection accuracy level was not improved.

An integrated management system was introduced in [7] for water distribution networks combined analytical and neurofuzzy decision support systems, geographical information systems and wireless sensor networks. The designed methodology aimed on sustainable management of water pipe networks through real-time data acquisition and processing of sensor signals gathered from distributed adhoc wireless sensor network. But, the computational complexity was not reduced using integrated management system. A new algorithm structure was introduced in [8] with modularity of wavelet and neural network joined the capability of wavelet transform for examining leakage signals and classification ability of artificial neural networks.

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However, designed algorithm was not evident to identify the features concerning noisy leak signals.

A fully integrated network analysis model based pressure-dependent multi-species extension (EPANET-PMX) was introduced in [9] for addressing the sensitivity problems. But, the EPANET-PMX was less sensitive to the leaks. An uncontrolled leak locating method was introduced in [10] for water distribution networks. The main aim of method is based on discretization of water supply system for predefined areas and detecting approximate location where leakage happens. The location of leakage was identified through group of neuro-fuzzy classifiers. However, the leakage was not identified in accurate manner.

The certain drawbacks are identified from above mentioned existing methods like less water leakage detection accuracy, high false positive rate, high water leakage detection time and so on. In order to address above mentioned issues, Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolves Optimization (BCSA-MHGWO) Technique is developed.

The major contribution of the paper is given as,

- Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolf Optimization (BCSA-MHGWO) Technique is introduced with high water leakage detection accuracy. BCSA-MHGWO technique used minimal number of sensor placed nodes to detect the water leak with minimal time consumption.
- The sensitivity and entropy value is calculated in BCSA-MHGWO technique for all nodes based on the pressure and flow rate. The bivariate correlation coefficient measures the correlation based on pressure series for sensor placement.
- Grey wolf optimization process in BCSA-MHGWO technique selects the optimal nodes for sensor placement based on sensitivity, entropy and correlation value for water leakage detection with higher accuracy and lesser time consumption.

II. RELATED WORKS

Branch and-cut-and-bound approach was introduced in [11] with an individual structure. A suitable stopping criterion was set where the approximations of excellent quality were attained. But, the water leakage detection accuracy was increased through branch and-cut-and-bound approach. A new methodology was introduced in [12] with uncertainties of many sources in optimal sensor placement issue for leak localization on potential pressure measurement points. For describing the relation between sensors and leak localization quality, a cost-benefit function was introduced depending on sensor placement performances and GoF statistics. Though cost was reduced, leak localization was not accurately detected in WDS.

A new technique was introduced in [13] to evaluate results of model-reduction plans with diagnostic method for leak detection in water distribution networks. The main aim is to identify the reduction approach for error-domain model falsification. However, the time consumption for leakage detection was not minimized using diagnostic method. An acoustic emission (AE) method was introduced in [14] on leak detection of water distribution system depending on socket joint failure. The acoustic features of leak signals in socket and spigot pipe segments were studied. The pipe leakage was controlled for water networks through fault detection and isolation mechanism with dictionary learning strategy in [15]. Sparse representation plan was introduced for sensor placement. But, the error rate during the leakage detection was not minimized using dictionary learning strategy.

Leakage detection and isolation in water distribution networks was identified in [16] through optimal sensor placement. An iterative methodology was introduced through detecting the essential sensors that resulted in increasing the optimal search efficiency. However, number of sensor placement in nodes was not reduced. Leak detection was carried out in [17] by vibration monitoring methods. But, the computational complexity was not reduced during the leak detection. The leakage was modeled as the function of pressure and pipe length, leakage coefficient by fixed pressure reducing valves (PRVs) in [18] for pressure fluctuation. Water CAD was employed to reduce the leakage through PRVs. But, the pressure and flow rate was not monitored in accurate manner.

An effective decision support system (DSS) was introduced in [19] for operational monitoring and control of water distribution systems depending on layer General Fuzzy Min–Max Neural Network (GFMMNN) and graph theory. However, the water leakage was not carried out in efficient manner using DSS. Leak detection method was introduced in [20] depending on Bayesian theory and Fisher's law in water distribution. A hydraulic model was linked with leak parameters. The uncertainty of parameter values was computed through probability density function and renewed with Bayesian theory. However, the leakage detection performance was not improved using Leak detection method.

III. METHODOLOGY

3.1 Problem Formulation

Water is an essential one for our lives. Water is an inadequate resource and it is essential for agriculture, industry and living thing survival on earth including human beings. A large quantity of water is wasted in an uncontrolled manner because of poor water allocation, inefficient utilization and integrated water management. Leakage detection in water distribution systems is the critical problem in water conservation. The key reason for leakage of distribution water pipelines is pressure on pipelines when it goes beyond the maximum pressure rated by the manufacturer while designing pipelines. In addition, it causes the deformation of pipes that result in an explosion during water flowing through them. After the explosion, the water leaves the main track and causes leakage. Several works have been developed for leakage detection but, the location of water leak was not accurately detected.

Based on this motivation, Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolves Optimization (BCSA-MHGWO) Technique is introduced for water leakage detection by placing the sensor in optimal nodes. The following system model is employed to enhance the quality of water leakage detection with minimum time.

3.2 System Model of BCSA-MHGWO technique

In BCSA-MHGWO technique, a water distribution network (WDN) is signified as a graph $G = (V, E)$ where 'E' represents the set of edges (i.e., pipes) and 'V' denotes the set of vertices (i.e., nodes) where the pipes meet. Vertices include the source node like reservoirs or tanks where water is collected or sink node where the water gets consumed. Each pipe links two vertices v_i and v_j which is represented as 'v_{ij}'. Every decision variable 'D_v' is linked to node 'v_i' of network to produce the result as 1 or -1. The result '1' denotes the sensor get installed in the node. The result '-1' denotes the sensor not get installed in the node. Sensor location optimization is to identify the nodes where the sensors are installed to attain acquisition of data for leak detection. The input for the sensor location optimization is given from the epanet tool kit and number of nodes chosen for sensor placement is given as output.

3.3 Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolves Optimization (BCSA-MHGWO) Technique

The main objective of BCSA-MHGWO technique is to place the minimal number sensors at optimal nodes for water leakage detection in the WDN. BCSA-MHGWO technique performs the correlation and sensitivity analysis for pressure and flow rate in nodes. After finding the correlation and sensitivity value of nodes, the optimization process is carried out to select the optimal node for sensor placement in the water distribution network. The overall flow diagram of BCSA-MHGWO technique is shown in figure 1.

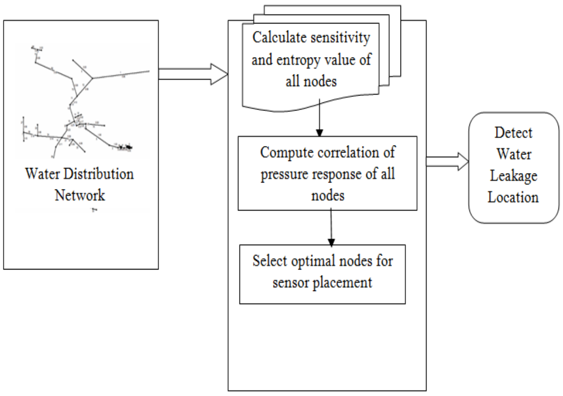

Figure 1: Overall Flow Process of BCSA-MHGWO Technique

Figure 1 describes the overall flow process of BCSA-MHGWO technique to detect the water leakage with minimum time. As illustrated in the figure, the BCSA-MHGWO technique comprises three processes, namely sensitivity analysis, correlation analysis and optimization. The sensitivity analysis is used to find the pressure or flow sensitivity according to the pipeline roughness. Correlation analysis is used to find the correlation between the pressure values of all sensor location nodes with minimal time. Optimization is carried out to select the optimal nodes for sensor placement based on the sensitivity and correlation value. Consequently, the water leakage is correctly detected through placing the sensor at correct node location with minimum time. The brief description about BCSA-MHGWO technique is described in subsections.

3.3.1 Sensitivity and Entropy Analysis

Based on the physical nature of water distribution network, some nodes have equivalent pressure performance in both operations (i.e., normal and leak onset). The pressure and demand flow in nodes where a sensor installed are obtained from extended-period hydraulic simulation using EPANET software in BCSA-MHGWO technique. The simulations are carried out for two case scenarios: with and without leak. In without leak cases, information of consumption and border conditions of the standard day is taken. In with leak cases, additional node pressure-dependent flow is taken. Leaks in the simulation with nodal emitters whose flow value 'V_f' is given by,

$$V_f = cP_n{}^{\alpha} \qquad (1)$$

From (1), 'c' denotes the coefficient dependent of network conditions. 'P_n' represents the nodal pressure and 'α' symbolizes exponent dependent on pipe and leak type. The simulation is carried out repeatedly to attain the pressures and flows for all nodes for each condition. Flow rate and pressure vectors are collected for without leaks case is denoted as 'F_W' and 'P_W'. Besides, for leak cases in each node flows and pressures vectors are represented as 'F_L' and 'P_L'. The elements of 'F_W' and 'P_W' vectors are symbolizes the network nodes in which the sensor are installed (n). 'F_L' and 'P_L' symbolizes the nodes where the leak occurs (l). The leak locations lie in the range of $l \in \{1,2\ldots N\}$ and sensor locations lies in the range of $n \in \{1,2\ldots N\}$. The vector length is represented as 'N' and matrixes size is symbolized as $N\ x\ N$. The simulation is repeated for every hour per day. The pressure and flow rate are essential one for sensitivity and entropy analysis. The pressure or flow sensitivity according to the pipe roughness variation is given as,

$$S_{n,l} = \sum_{h=1}^{24} \left| \frac{P_{W_n} - P_{L_{n,l}}}{F_{W_l} - F_{L_{l,l}}} \right|^h \qquad (2)$$

From (2), '$S_{n,l}$' denote the sensitivity of node 'n' facing leak in the node 'l'. 'F_{W_l}' represent the normal flow in node 'l'. '$F_{L_{l,l}}$' denote the flow with leak in node a 'l'. 'P_{W_n}' and '$P_{L_{n,l}}$' are pressure in node 'n' when flow in node 'l' is 'F_{W_l}' and '$F_{L_{l,l}}$' respectively.

'h' symbol denotes the hour of day. Entropy is defined as the measure for information quantity based on probability distribution. Entropy is used as an indicator for sensitivity allocation in all possible leaks. When sensitivity is distributed consistently, the entropy value is higher.

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3.3.2 Correlation Analysis

In BCSA-MHGWO technique, when node pressure varies due to leakage, the node is said to be sensitive and it is easy to detect the leak. When the node pressure remains same in case of a leak, the node is said to be less sensitive. The information collected is useless duplication. For addressing this problem, the correlation between nodes pressure series is calculated using Bivariate Correlation Coefficient. The matrix 'P_L' is employed to construct the Bivariate Correlation Matrix 'BCM' by,

$$BCM_{x,y} = \sum_{h=1}^{24} \left(\frac{\sum_{l=1}^{N} \left(P_{Lx,l} - \overline{P_{Lx}}\right)\left(P_{Ly,l} - \overline{P_{Ly}}\right)}{\sqrt{\sum_{l=1}^{N} \left(P_{Lx,l} - \overline{P_{Lx}}\right)^2} \sqrt{\sum_{l=1}^{N} \left(P_{Ly,l} - \overline{P_{Ly}}\right)^2}} \right)^h \quad (3)$$

From (3), '$BCM_{x,y}$' denotes the correlation between pressure response of every nodes duple $\{x, y\}$, '$\forall\, x, y \in \{1, 2 \ldots \mathrm{N}\}$'. Based on the sensitivity analysis and correlation analysis, optimization process is carried out in next subsection.

3.3.3 Grey Wolf Optimization (GWO)

Grey Wolf Optimization (GWO) is a new meta-heuristic algorithm that mimics the social hierarchy and hunting method of grey wolves. Grey wolves are initial predators as they are at top of the food chain. Grey wolf lives in a group with 5–12 grey wolves on average. GWO comprises three essential processes, namely encircling prey, hunting and attacking prey. In GWO, initially the number of grey wolves (i.e., nodes) is initialized. After initialization, the fitness value of each node for sensor placement is based on three objective functions, namely sensitivity, entropy and correlation.

$$Fitness\ Value = maximum\ \text{sensitivity} + maximum\ entrophy + minimum\ correlation \quad (4)$$

After evaluating the fitness value, best solution considered in hierarchical order are alpha, beta and delta. The remaining candidate solutions are taken as omega as shown in figure 2.

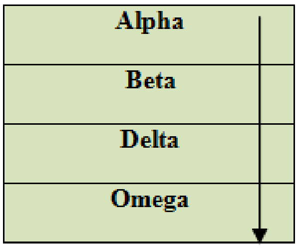

Figure 2: Social Dominant Hierarchy of Grey Wolves

The first level in social dominant hierarchy of grey wolves is an alpha. The male and female leaders are termed as alpha. The alpha makes the decisions for the group. The group acknowledges alpha by holding the tails down. The alpha wolf is termed as a dominant wolf because his/her orders are followed by the group. The alpha is not essentially a strongest member of the group but best in administrating the group. The next level in social dominant hierarchy is termed as beta. The betas are secondary wolves that facilitate the alpha during decision-making. The beta wolf is male or female. Beta wolves are probably the best wolves to become the alpha wolves when alpha wolves pass away or get very old. The beta wolf respects the alpha and orders the lower-level wolves. The beta emphasizes the alpha command to group and provides better feedback to the alpha.

The third level in social dominant hierarchy is delta. Delta wolves submit to alphas and betas but control the omega. Scouts, sentinels, elders, hunters, and caretakers are in delta wolf category.

Scouts are employed for watching boundaries of territory and notifying the pack in danger situation. Sentinels preserve and guarantee the safety of the group. Elders are termed as the experienced wolves. Hunter facilitates the alpha and beta when hunting the prey and providing food for group. Care taker cares the weak, ill, and wounded wolves in the group.

The lowest grey wolf hierarchy is termed as omega. Omega wolves submit themselves to all other dominant wolves. They are the final wolves that are allowed to eat the food source. It shows that the omega is not an essential wolf in the group. The whole group experiences the face internal fighting and issues when losing the omega.

Encircling Prey Process

A grey wolf has the capability to identify the location of prey (i.e., water leak in the pipeline) and encircle them. Grey wolves encircle prey in hunting process. The encircling behavior of grey wolves are given by,

$$\vec{W} = \left|\vec{Z}.\vec{P_p}(t) - \vec{P_g}(t)\right| \quad (5)$$

$$\vec{P_g}(t+1) = \vec{P_p}(t) - \vec{X}.\vec{W} \quad (6)$$

From (5) and (6), 't' represent the current iteration of GWO. '$\vec{X}$' and '$\vec{Z}$' are coefficient vectors, '$\vec{P_p}(t)$' denotes the position vector of prey, and '$\vec{P_g}(t)$'is the position vector of a grey wolf (i.e., node). The vectors '$\vec{X}$' and '$\vec{Z}$' are computed by,

$$\vec{X} = 2\vec{x}\,.\vec{v_1} - \vec{x} \quad (7)$$

$$\vec{Z} = 2\vec{v_2} \quad (8)$$

From (7) and (8), '$\vec{x}$' gets linearly decreased from 2 to 0 over number of iterations and 'v_1' and 'v_2' denotes the random vectors in interval of [0, 1].

Hunting Process

In GWO, the hunting (i.e., optimization) is guided by alpha, beta, and delta. The omega wolves follow three wolves. In many cases, the hunting process is guided by alpha. The beta and delta wolves contribute in hunting intermittently. In search space, the location of prey is not identified.

For hunting performance of grey wolves, the alpha, beta, and delta know the location of prey.

In order to identify the location of prey (i.e., leak), three best solutions attained are taken and force the other search agents to update positions in accordance with the position of best search agents (i.e., location of water leak). The position update of grey wolves is shown in Figure 3.

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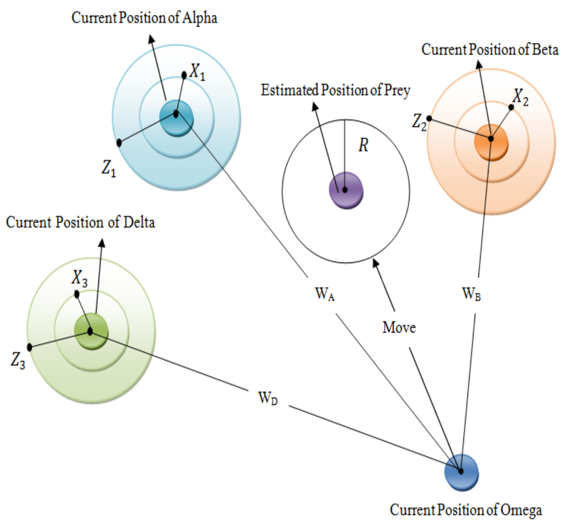

Figure 3: Position Update of Grey Wolves

From figure 3, the process how the search agent updates their position in proportion to alpha, beta and delta position in search space is explained. The position of the grey wolves (i.e., alpha, beta and delta) are updated by,

$$\left.\begin{aligned} \vec{W_A} &= |\vec{Z_1}.\vec{P_A} - \vec{P}| \\ \vec{W_B} &= |\vec{Z_2}.\vec{P_B} - \vec{P}| \\ \vec{W_D} &= |\vec{Z_3}.\vec{P_D} - \vec{P}| \end{aligned}\right\} \quad (9)$$

$$\left.\begin{aligned} \vec{P_1} &= \vec{P_A} - \vec{X_1}.\vec{W_A} \\ \vec{P_2} &= \vec{P_B} - \vec{X_2}.\vec{W_B} \\ \vec{P_3} &= \vec{P_D} - \vec{X_3}.\vec{W_D} \end{aligned}\right\} \quad (10)$$

In addition, it is examined that final position is in random place within a circle that is described by positions of alpha, beta, and delta in search space.

$$\vec{P}(t+1) = \frac{\vec{P_1}+\vec{P_2}+\vec{P_3}}{3} \quad (11)$$

From (11), the final updated position is described. After hunting process, attacking prey process is described.

Attacking and Searching Prey Process

The grey wolves complete the hunting process through attacking the prey when it is standstill position. For attacking the prey, value of '$\vec{x}$' gets reduced. The variation of 'X' is minimized by '$\vec{x}$'. '$\vec{X}$' denotes the random value in interval $[-2x, 2x]$ where 'x' gets reduced from 2 to 0 based on iteration count. When the random values of '$\vec{X}$' are in [-1, 1], the next position of search agent lies in any position between the current position and position of prey. '$|X| < 1$' allows the wolves to attack towards prey. Grey wolves search consistent with position of alpha, beta, and delta. While searching for prey they move away from each other and meet together to attack prey. The search process initiates with random population of grey wolves (i.e., nodes). After calculating the fitness value, alpha, beta, and delta wolves identify the probable position of prey (i.e., leak). Every wolf updates their distance from prey. The parameter 'x' gets reduced from '2 to 0' to highlight the exploration and exploitation respectively. The grey wolf gets diverge from prey when $|\vec{X}| > 1$and join towards the prey when $|\vec{X}| < 1$. After meeting an end criterion, GWO gets terminated. The algorithmic description of Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolf Optimization is explained as follows,

Algorithm 1 Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolf Optimization Algorithm

Input: Number of nodes '$W_i = W_1, W_2, W_3, W_4 \ldots., W_n$', Number of pipelines
Output: Minimum Number of Nodes for Sensor Placement

1. **Begin**
2. Initialize number of nodes, x, X *and* Z
3. **for** each node
4. Calculate sensitivity value '$S_{n,l}$'
5. Measure correlation value of all nodes pressure '$BCM_{x,y}$'
6. Calculate fitness value
7. Select $W_A, W_B,$ *and* W_D based on fitness value
8. **while** ($t <$ *maximum iteration count*)
9. Update position of 'W_i'
10. Update x, X *and* Z
11. Calculate fitness value
12. Update $W_A, W_B,$ *and* W_D
13. $t = t + 1$
14. **end while**
15. Find optimal node for sensor placement
16. **end for**
17. **end**

Algorithm 1 explains Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolf Optimization Algorithm to select the optimal node for sensor placement. Initially, the fitness value is calculated for all nodes based on the sensitivity and correlation value. After calculating the fitness value, alpha, beta and delta wolves are selected. Based on the alpha, beta and delta wolves, the position gets updated. For update position of wolves, the fitness value is calculated and the process gets repeated until the maximum criterion is met. Finally, the minimal number of optimal nodes is selected for sensor placement to detect the water leakage in water distribution network

IV. SIMULATION SETTINGS

Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolf Optimization (BCSA-MHGW) Technique is implemented in MATLAB Simulink with 3.4 GHz Intel Core i3 processor, 4GB RAM, and windows 7 platform for leak detection in water distribution system. The nodes pressure and demand flow in water pipeline networks are collected from extended-period hydraulic simulation using EPANET software. BCSA-MHGWO technique is applied for District Metered Areas (DMA) in Barcelona water distribution network. Total length of DMA is approximately 17.4 km of pipelines.

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It comprises 883 nodes, 927 pipes and distributes the water to 639 consumers. The pipe diameters changes from 70 to 400 mm. The pressure at night flow varies between 29.31m and 43.46 m. Flow and pressure are determined at inflow and outflow point. The hydraulic model was calibrated in terms of pipe roughness several years ago. DMA comprises 311 nodes with demand (RM), 60l nodes without demand (EC), 48 hydrant nodes without demand (HI type), 14 dummy valve nodes without demand (VT) and 448 dummy nodes without demand (XX type). The water pipeline has two inflow inputs (i.e., reservoir nodes).

Leak detection is depending on the damage (leaks) in many locations of piping network includes the liquid outflow at leak location that varies the flow features (pressure heads, flow rates, acoustics signals, etc.) at monitoring locations of piping network. It is imagined that leaks occur at XX type nodes in which 448 potential leaks are detected. Leaks happen at any network node or pipe. Leak locations are limited to some type of node to avoid complexity issues. Pressure sensors at RM type nodes are employed as network monitoring points. Flow rate are employed for leak detection and gathering pressure data.

V. RESULT ANALYSIS

Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolf Optimization (BCSA-MHGW) Technique is introduced for water leakage detection in water distribution system and compared with existing one-dimensional convolutional neural network and support vector machine (1D-CNN-SVM) model [1] and Particle Filter (PF) based technique [2]. The efficiency of BCSA-MHGW technique is evaluated along with the metrics such as water leakage detection accuracy, water leakage detection time, and false positive rate.

5.1 Water Leakage Detection Accuracy (WLDA)

Water leakage detection accuracy is defined as the process of detecting the leak in accurate manner with minimum number of sensor placement at the nodes. It is measured in terms of percentage (%). It is formulated as,

$$WLDA = \frac{\text{Leaks accurately detected by sensor nodes}}{\text{Number of sensor placement nodes}} \quad (12)$$

When the water level detection accuracy is higher, the method is said to be more efficient.

Table 1 Tabulation for Water Leakage Detection Accuracy

Number of Sensor Placement Nodes (Number)	Water Leakage Detection Accuracy (%)		
	1D-CNN-SVM model	PF based Technique	BCSA-MHGW Technique
10	65	68	79
20	67	71	81
30	69	73	83
40	72	76	85
50	74	79	87
60	77	83	89
70	80	86	91
80	82	88	93
90	84	90	95
100	87	91	97

Table 1 describes the water level detection accuracy of three methods, namely 1D-CNN-SVM model, PF based Technique and BCSA-MHGW Technique for different number of sensor placement nodes. The pressure value is sensed by the nodes at each hour in a day. From the table value, it is clear that the water level detection accuracy using proposed BCSA-MHGW Technique is higher when compared to existing one-dimensional convolutional neural network and support vector machine (1D-CNN-SVM) model [1] and Particle Filter (PF) based technique [2]. The graphical representation of water level detection accuracy is shown in figure 4.

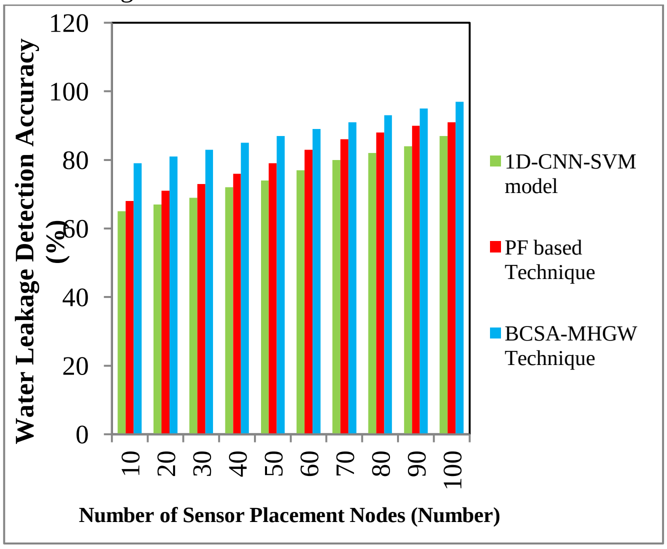

Figure 4: Measurement of Water Leakage Detection Accuracy

Figure 4 describes the performance results of water leakage detection accuracy for different number of sensor placement nodes. In above mentioned graph, different number of sensor placement nodes is taken in the 'X' axis and the water leakage detection accuracy is taken in the 'Y' axis. From above mentioned figure, the green color line denotes the water leakage detection accuracy of 1D-CNN-SVM model where red color and blue color represents the water leakage detection accuracy of PF based technique and BCSA-MHGW Technique. From above mentioned graph, it is clear that the water leakage detection accuracy using BCSA-MHGW Technique is comparatively higher than the existing 1D-CNN-SVM model [1] and PF based technique [2].

Water leakage detection process is carried out to detect the water leakage location with help of sensor placed nodes. The sensitivity and correlation analysis is carried out for pressure and water flow rate at the sensor nodes. Bivariate correlation process is carried out to find the correlation based on pressure series. Then, Grey Wolf Optimization process is performed to identify the optimal nodes for sensor placement. After identifying the optimal nodes, the sensor are placed in that particular node for accurately detecting the water leakage at pipelines, nodes, etc. By this way, the water leakage is detected in water distribution system with higher accuracy.

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Let us consider ten instances at different number of sensor placement nodes for water leakage detection. At every instance, the number of sensor placement nodes gets changed. When the sensor is placed in optimal location, water leakage detection accuracy gets increased. When number of sensor placement node is 60, the water leakage detection accuracy of 1D-CNN-SVM model, PF based technique and BCSA-MHGW Technique is 77%, 83% and 89% respectively. The water leakage detection accuracy of BCSA-MHGW Technique is increased by 13% and 9% compared to existing 1D-CNN-SVM model [1] and Fault PF based technique [2] respectively.

5.2 *Water Leakage Detection Time (WLDT)*

Water leakage detection time is defined as amount of time consumed for detecting the leak by placing minimum number of sensor in nodes. It is measured in terms of milliseconds (ms). It is given by,

$$WLDT = Ending\ time - starting\ time\ of\ detecting\ water\ leak \quad (13)$$

When the water level detection time is lesser, the method is said to be more efficient.

Table 2: Tabulation for Water Leakage Detection Time

Number of Sensor Placement Nodes (Number)	Water Leakage Detection Time (ms)		
	1D-CNN-SVM Model	PF based Technique	BCSA-MHGW Technique
10	75	68	62
20	73	65	60
30	71	61	57
40	68	58	54
50	65	56	51
60	62	53	48
70	60	51	45
80	57	48	43
90	53	46	39
100	51	44	36

Table 2 illustrates the water level detection time of three methods, namely 1D-CNN-SVM model, PF based Technique and BCSA-MHGW Technique for different number of sensor placement nodes.

The pressure of the pipes is sensed by sensor placed nodes at each hour in day.

From table value, it is observed that the water level detection time using proposed BCSA-MHGW Technique is lesser when compared to existing one-dimensional convolutional neural network and support vector machine (1D-CNN-SVM) model [1] and Particle Filter (PF) based technique [2]. The graphical representation of water level detection time is shown in figure 5.

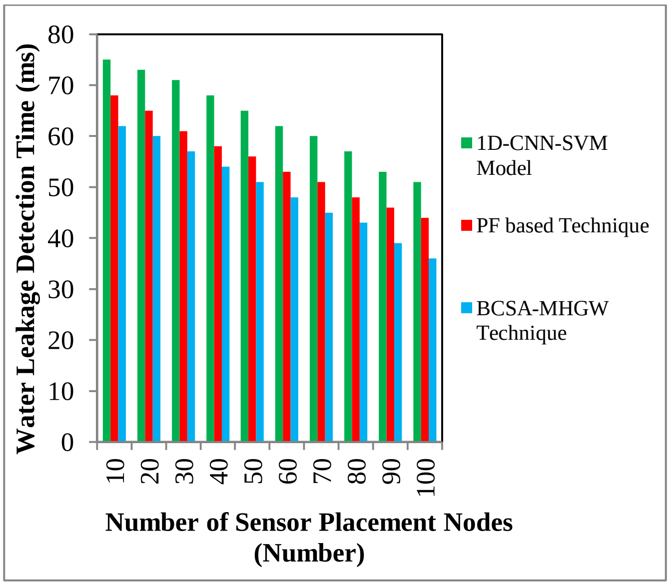

Figure 5: Measurement of Water Leakage Detection Time

Figure 5 illustrates the performance results of water leakage detection time for different number of sensor placement nodes. In above graph, different number of sensor placement nodes is taken in the 'X' axis and the water leakage detection time is taken in 'Y' axis. From figure, the green color line symbolizes the water leakage detection time of 1D-CNN-SVM model where red color and blue color denotes the water leakage detection time of PF based technique and BCSA-MHGW Technique. From above mentioned graph, it is clear that the water leakage detection time using BCSA-MHGW Technique is comparatively lesser than the existing 1D-CNN-SVM model [1] and PF based technique [2].

Water leakage detection process is carried out to detect the water leakage location with help of sensor placed at nodes. The sensitivity and correlation analysis is carried out for pressure and water flow rate at the sensor nodes to find pipeline roughness at particular nodes for water leakage identification. Grey Wolf Optimization process is carried out to find the optimal nodes for sensor placement to minimize the water leakage. As the sensor is located in that optimal node, water leakage is detected with minimal time consumption.

Let us consider ten iterations for different number of sensor placement nodes. The different number of sensor placement nodes is taken. By using the optimization process, optimal node is selected for sensor placement to detect water leakage in WDS. When the number of sensor placement gets increased, water leakage detection time gets reduced correspondingly. When number of sensor placement node is 40, the water leakage detection accuracy of 1D-CNN-SVM model, PF based technique and BCSA-MHGW Technique is 68ms, 58ms and 54ms respectively. The water leakage detection time of BCSA-MHGW Technique is reduced by 22% and 10% compared to existing 1D-CNN-SVM model [1] and Fault PF based technique [2] respectively.

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5.3 False Positive Rate

False positive rate is defined as the leak that is incorrectly detected by the sensor placed nodes. It is measured in terms of percentage (%). False positive rate is formulated as,

$$False\ Positive\ Rate = \frac{Number\ of\ leaks\ incorrectly\ identified\ by\ sensor}{Number\ of\ sensor\ placement\ nodes} \quad (14)$$

When the false positive rate is lesser, the method is said to be more efficient.

Table 3: Tabulation for False Positive Rate

Number of Sensor Placement Nodes (Number)	False Positive Rate (%)		
	1D-CNN-SVM Model	PF based Technique	BCSA-MHGW Technique
10	62	54	49
20	60	52	47
30	58	50	45
40	55	47	43
50	52	44	40
60	51	41	37
70	48	38	33
80	45	35	31
90	42	32	29
100	39	30	26

Table 1 describes the false positive rate of three methods, namely 1D-CNN-SVM model, PF based Technique and BCSA-MHGW Technique for diverse number of sensor placement nodes. From table value, it is clear that the false positive rate using proposed BCSA-MHGW Technique is lesser when compared to existing one-dimensional convolutional neural network and support vector machine (1D-CNN-SVM) model [1] and Particle Filter (PF) based technique [2]. The graphical representation of false positive rate is described in figure 6.

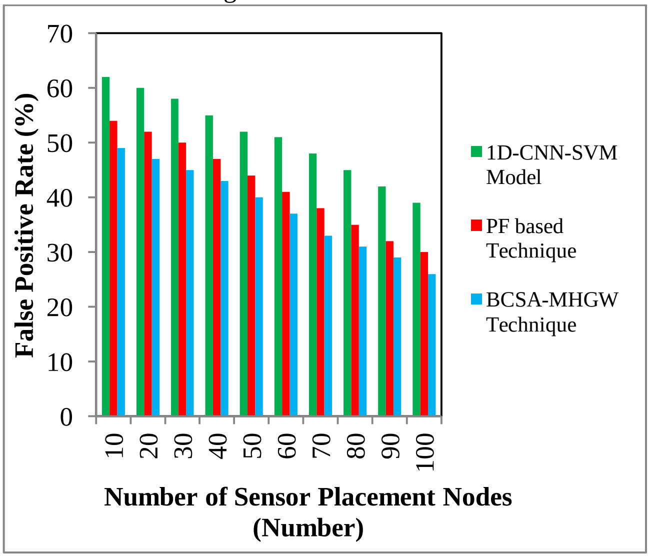

Figure 6: Measurement of False Positive Rate

Figure 6 describes the performance results of false positive rate for number of sensor placement nodes. In above mentioned graph, number of sensor placement nodes is taken in 'X' axis and the false positive rate is taken in 'Y' axis. From the figure, the green color line represents the false positive rate of 1D-CNN-SVM model where red color and blue color denotes the false positive rate of PF based technique and BCSA-MHGW Technique. In above graph, it is clear that the false positive rate using BCSA-MHGW Technique is comparatively lesser than existing 1D-CNN-SVM model [1] and PF based technique [2].

Water leakage detection process identifies the leak in WDS by using the sensors. Sensitivity analysis is carried out for detecting leak when node pressure and water flow rate gets varied. Bivariate correlation process is performed to correlate between the pipeline pressure and pressure in without leakage condition. Grey Wolf Optimization process identifies the optimal nodes for sensor localization to reduce the water leakage. When the sensor is positioned in optimal node, water leakage is identified in accurate manner without any error. For evaluating the performance of false positive rate, ten simulations are conducted for different number of sensor placement nodes. With optimization process, optimal node is chosen for sensor placement to accurately detect the water leakage. When the number of sensor placement gets increased, water leakage detection time gets increased correspondingly. When the number of sensor placement node is 80, the false positive rate of 1D-CNN-SVM model, PF based technique and BCSA-MHGW Technique is 45%, 35% and 31% respectively. The false positive rate of BCSA-MHGW Technique is reduced by 26% and 10% compared to existing 1D-CNN-SVM model [1] and Fault PF based technique [2] respectively.

VI. CONCLUSION

An efficient Bivariate Correlation and Sensitivity Analysis based Meta-Heuristic Grey Wolf Optimization (BCSA-MHGWO) Technique is introduced for detecting the water leakage with higher detection accuracy and lesser time consumption. BCSA-MHGWO technique detects the water leakage with minimal number of sensor placed nodes. The sensitivity and entropy value is calculated based on nodes pressure and flow rate in the water leak case. Bivariate correlation coefficient measures the correlation value of all nodes based on the pressure series. Grey wolf optimization process selects the optimal nodes for sensor placement with help of fitness value to detect the water leakage with lesser time consumption. The simulation is performed with different metrics such as water leakage detection accuracy, water leakage detection time and false positive rate. The performance result demonstrates that the BCSA-MHGWO technique enhances the water leakage detection accuracy with minimum detection time as well as false positive rate than the state-of-art methods.

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