Impact Analysis of Contamination and Sensor Placement in Water Distribution Network in Kochi, India

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***Abstract*—The contamination in the Urban water distribution networks (WDNs) is a spontaneous event, and it can occur anytime and anywhere in a water distribution network. The contamination causes severe health impacts to an urban population. Therefore, an IoT-based water quality sensors are used as the resilience tool for water distribution networks. Resilience includes contamination detection and localization. The placement of the water quality sensors in the water distribution network must be optimally planned as distribution networks are sensitive to invasive sensors, the infrastructure's aging, and the sensor deployment's robustness. The proposed methodology identifies the sensor placement locations as the critical points in a particular water distribution network and analyzes the contamination scenarios for each critical point. The proposed method was applied to the benchmark water distribution system Net3 and the live network in Edakochi, Kerala (India). The results demonstrate the significant detection efficiency of the defined water quality sensor placement framework.**

***Index Terms*—Water distribution network, critical nodes, WNTR, Optimal sensor placement**

I. Introduction

Water is considered one of the primary necessities of all living beings. As per UNO, quality, quantity, availability, and accessibility of water are each human's primary rights worldwide [1]. Hence, the water distribution networks (WDN) are essential and considered one of the critical infrastructures of any city. The WDN comprises reservoirs, treatment plants, distribution mains, and consumer points. The water quality of the WDN is compromised due to the accidental intrusion of the contaminants significantly at the distribution lines, infrastructure attack, line burst, crack, and leakage, which deliberates the release of the contaminants. The quality of the water is essential as it causes a direct health impact on the city population. An IoT-based monitoring network with water quality sensors upgrades the WDN into a smart-self-resilient system regarding water quality [2], [3]. Water contamination spread can be mitigated, as well as monitor the real-time events of the WDN. The major event in the urban WDNs temporary malfunctions was the chemical pollutant intrusion in Elk River, USA, on January 2014, which affected 300,000 people in around one week. Grey water intrusion into the WDN due to a faulty pipe connection in Beijing and lead intrusion in drinking water in Hong Kong happened in May 2016. Contamination intrusion scenarios for such events have always been unpredictable and fatal and can happen in any future. Since the rate of contamination spread is high, it is necessary to identify the source of contamination and stop the spread quickly [4].

The WDN consists of various uncertainties and constraints such as the system parameters, the stochastic demands, computational feasibilities of the solution frameworks, inaccuracies of the sensors, the impact metrics and the risk objectives selection, the contamination scenario selection, and the placement of sensors [5]. The contamination location identification is a tedious task. The gray water intrusion scenarios in the real world are prevalent nowadays; they can cause health problems such as diarrhea, fever, vomiting, and allergies. The economic feasibility of the engineering solutions to cover the entire WDN in terms of the sensors is difficult [6]. The optimal number of locations in which the sensor can be deployed will reduce the equipment cost as well as increase the resilience of the risk of contamination.

A critical node in WDN can be considered the most influential WDN junction. In this research paper, we introduce a comprehensive framework designed to effectively identify the critical nodes in any WDN and analyze the impact of the critical nodes in the network in the context of contamination spread. EPANET-Python-WNTR tools combination can detect the critical nodes, analyze the contamination effects on the critical nodes, and the health impact on the community concerning the NET3 benchmark network and the live network of Edakochi, Kochi, India.

The paper is organized as follows: Section II describes similar work in this area. Section III presents the framework for optimal sensor placement in a WDN network, and Section IV illustrates the case studies and results using the framework. Finally, Section V presents the conclusion and future work.

II. Related Work

The WDN deals with various sensor location and placement problems. Here are some of the problems and solutions below: An algorithm for Early Warning System for Contamination in WDN proposes closing off selected network segments to minimize the impact of contamination. It discusses how to use the WNTR tool to help shape subsequent replies in the event of the kind of incident. Early warning systems are designed to identify contamination occurrences promptly enough to reduce any negative consequences on the network population. In this way, the algorithm presented in this study might be included in EWS to forecast contamination occurrences in water networks and propose operational actions to alert people exposed to those events. The results of this study highlight WDN operation uncertainty in the localization of contaminant events and network connectivity structure. It also presents the algorithm as an excellent development base for early warning systems [7].

In this paper, the author presented the objectives for defining the sensor placement problem, standard optimization algorithms, and toolkits available to help with algorithm testing and comparison. The main aim of this work is to give an overview of sensor placement focusing on contaminant detection for WDS. The authors identified the objectives for defining an early warning system in the first section. The authors overviewed the optimization algorithms and methods used to solve different design problems in the second section. The authors listed the toolkits for the sensor placement problem in the third section. This paper's final remark is that the water network's size, topography, time, and sensor costs determine the problem definition and posterior-solving strategies [8].

In this paper, the authors present the capability of the WNTR platform as freeware dedicated to WDN and sewer utilities. This paper presents selected possibilities, such as the context of emergency terrorist attacks, as an early warning system. This paper discusses the oldest IT application that enables simulations of threats and assessment of their impact on the water network's integrity. This article also addresses potential difficulties, especially for newbies in water networks' modeling in EPANET. This work exemplifies the effective use of software interfaced with EPANET [9].

This article overviews nature-inspired optimization techniques for optimal sensor placement in a WDN. It discusses case studies, an overview of nature-inspired optimization techniques, and their applications. Solution methods advanced from linear and non-linear programming to nature-based optimization techniques. The paper discusses different nature-based or nature-inspired optimization techniques that have existed. The authors point out that the choice of algorithm is often dictated by the number of objectives to be optimized, the number and complexity of decision variables and constraints, and the computational complexity of the objective function, [10].

This paper aims to provide the best sensor placement based on network data. The SPSO method performs sensor-placement strategy (SPS) optimization using particle swarm optimization (PSO) as an optimization algorithm. When fitness, blind spot, consumed contamination, and localization are performed in Teva spot, SPSO and SPSO perform better than Teva-Spot. The number of pipes increases, and the performance of SPSO improves. The SPSO was first demonstrated by comparing the configuration result with the TEVA-SPOT example SPS on the well-known benchmark network by applying the same number of sensors [11].

This paper explains the monitoring of water quality in real life. The methodology is based on the optimization objectives approach, which detects water contamination after the initial injection. The paper also explains how to find out The expected contaminated population, expected population contaminated before the contamination detection, expected water volume consumed before the contamination detection, total water demand with a contaminant concentration higher than a determined value, $\delta(k,i)$ is a variable taking into consideration the contamination status at the node i during the time step k, The contaminant mass ingested at a specific node, The contaminant mass consumed by the consumers. The multi-objective function can be calculated using all the above parameters [12].

III. Framework for WDN sensor placement

A WDN consists of reservoirs, overhead tanks (OHT), junctions, pipes, pumps, and valves. The contamination events in a distribution network can adversely affect a community, such as health impact on the community people [13]. The IoT systems can aid the deteriorated real-life scenarios by continuously monitoring the WDN fatalities such as leakage, contamination, infrastructure aging, cracks, and so on [14]–[16]. Since IoT system realization for the WDN is costlier and vulnerable to the infrastructure [17], identifying the optimal locations for the sensors is a critical and daunting task. This section presents the framework to identify the critical nodes in a water distribution network and the contamination impact on these nodes as shown in Fig.1. Placement of the water quality sensors in the critical nodes improves the scalability of the IoT monitoring systems in WDN, reduces the risk of contaminants spreading, and hence improves the resilience of the WDN. The framework includes WDN live network modeling using geographic information system (GIS) and EPANET, identifying the critical node locations and the impact of critical node analysis using the Python-Water Network Tool for Resilience (WNTR) toolbox. The framework identifies the most optimal sensor placement location for benchmark and live networks.

A. WDN Live Network Modeling

A real live WDN is modeled in a Geographic Information System (GIS) platform with plug-ins backed by EPANET (a WDN simulation tool) [18]. The portable document format (PDF) is georeferenced in the QGIS using the plug-in QGISRed and can create the WDN network base model. The parameters and attributes are incorporated for all the WDN components, such for 'pipes,' diameter, length, and roughness coefficients and for 'junctions' elevation, base demand, and demand pattern and for 'reservoirs' the head, and for pumps, the pump curves and so on. The stakeholder, Kerala Water Authority (KWA) provides the pilot area's demand pattern. Each consumer average base demand is calculated from the field data collected using the random sampling techniques of 10% samples, around 400 houses. The two-month consumption data fitted to a normal distribution curve to estimate each household's average daily base demand. Each household average member is considered 4.4 per Central Public Health & Environmental Engineering Organisation (CPHEEO) [19]. Hence, the average daily demand is estimated as 142 LPCD. The Voronoi polygon and nearest neighboring algorithms combined to estimate the base demand for each node in the Edakochi network [20], [21].

B. Critical Points for Live and Benchmark WDN

Critical points are identified using the following algorithms: betweenness centrality, closeness centrality, and degree centrality. Critical Points for WDN live and benchmark network and the contamination impact of the WDN dependent on the critical nodes of the network. Critical nodes in a network can cause the highest impact on the WDN. A critical node in a network is a node whose removal would result in a significant change to the connectivity. Degree centrality, betweenness centrality, and closeness centrality are three approaches for centrality measures, which are mathematical methods for identifying the most critical nodes in a network. Methods to identify the critical points:

- Degree centrality: the number of connections a node has
- Betweenness centrality: the number of shortest paths that pass through a node.
- Closeness centrality: the average distance from a node to all other nodes.

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C. Tools and platforms

The software platform Python with libraries NetworkX and WNTR can be utilized to identify critical nodes within a water network model. The water network model is imported using the built-in function provided by the WNTR library. Subsequently, various centrality measures such as degree centrality, betweenness centrality, and closeness centrality can be calculated using the respective functions in the NetworkX library. Nodes with the highest values for these measures are considered critical nodes. These critical nodes can be visualized using the matplotlib library in Python. This methodology is applied to benchmark and live networks to identify critical nodes. The NetworkX library does not have a built-in method for directly importing a .inp file, a format typically used for storing input data for finite element analysis (FEA) simulations. However, Python libraries to parse the .inp file and extract the necessary information to create a graph object that can be used with NetworkX. Moreover, another method is to use the pandas library to read the .inp file as a CSV file and subsequently create the graph using the extracted data.

The WNTR platform evaluated the effect of contamination spread and its impact on the population of critical nodes. The platform is intended for visualizing and analyzing networks, such as social networks, transportation networks, and so on. Identifying the critical nodes in a network depends on the specific characteristics of the network. Hydraulic and water quality simulations are conducted for each scenario, where the result of each scenario is saved to a database, and the pre-analysis based on the data is conducted to identify the eligible locations for sensor placement and average contamination volume. Eligible locations can be determined based on the contamination effect analysis. The average contamination volume is the value used for evaluating critical nodes.

IV. Case Studies and Results

A. Study area

The real live network of Edakochi, Kerala, and the benchmark network Net3 were considered for testing the framework. Edakochi consists of two municipal divisions of the Kochi municipal corporation in Kerala, India, as shown in Fig 2. Kochi is one of the smart cities of India and is known as the queen of the Arabian Sea. The total population in Edakochi is around 20000 and consists of more than 4000 consumer water connections. Extensive field surveys and various participatory rural appraisal (PRA) tools such as self-help group discussion, transcent walk, and so on were conducted for the study area to identify the challenges for community members on WDN (see Fig 3). The survey revealed that one of their significant challenges is the quality of the water, which is often turbid and foul smell. Since the hydraulic model is unavailable for the study, the authors build the network as explained in section III.

The EPANET Net3 system was modeled on the North Marin Water District in Novato, CA, 1994 as part of a water quality study. The system has one reservoir, three tanks, two pumps, 6.8 miles of pipelines, and a total demand of 2.11 MGD [22]. The five critical nodes in both the Net3 network and the live network identified using the framework are shown in Fig 4 and Fig 5. The critical nodes for betweenness centrality, closeness centrality, and degree centrality are three sets of 5 nodes for the benchmark and real networks.

B. Results and Discussion

This section discusses the impact analysis of the critical nodes estimated from three centrality methods. Water security

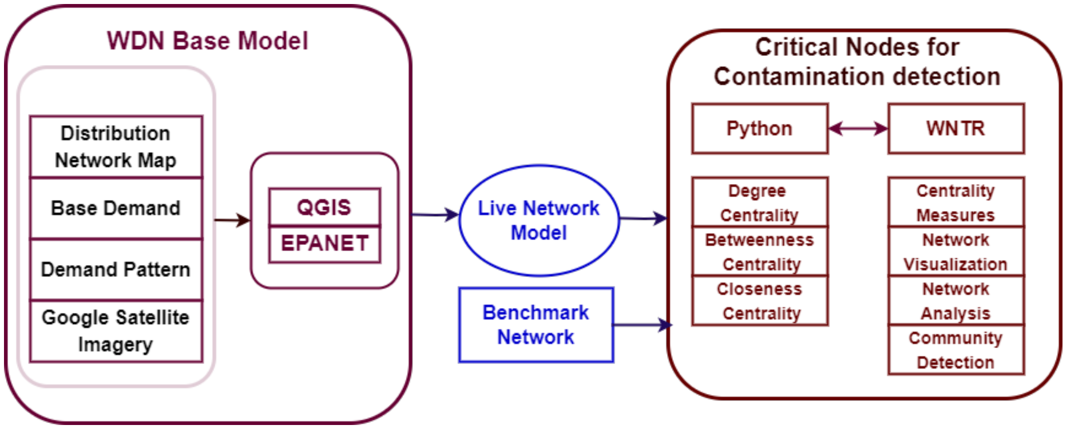


Fig. 1: Framework for WDN sensor placement

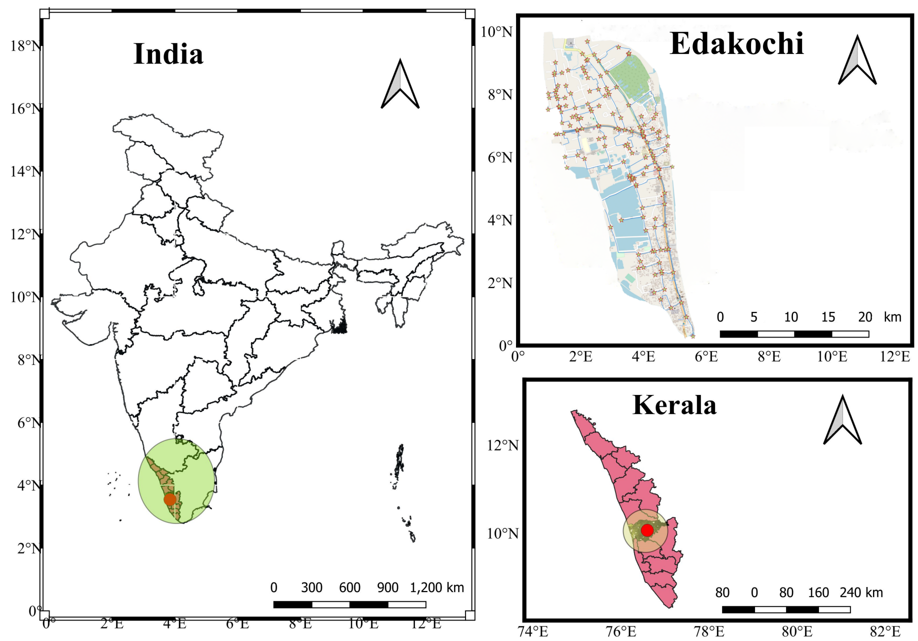


Fig. 2: Study area

metrics are utilized to quantify the potential consequences of contamination scenarios. One such metric, "Population Impacted," is derived from another metric, Mass Consumed. Mass Consumed refers to the mass of a contaminant that exits the network via node demand at each node-time pair. These metrics can be calculated using the WNTR. The population impact is calculated using the in-built function metrics. In the degree centrality graph for the benchmark network, node 119 has the highest population impact, and node 120 has the lowest. In the betweenness centrality graph, node 207 has the highest population impact, and node 209 has the lowest. In the closeness centrality graph, node 207 has the highest population impact, and node 184 has the lowest impact. The degree centrality graph shows that node 119 is more critical than node 120 regarding its impact on the population. The betweenness centrality graph shows that node 207 is more critical than node 209 regarding its impact on the population. The closeness centrality graph shows that node 207 is more critical than node 184 regarding its impact on the population, as shown in Fig. 6.

In the degree centrality graph for the live network, node J398 has the highest population impact, and node J103 has the lowest population impact. In the betweenness centrality graph, node J398 has the highest population impact, and node J97 has the lowest. In the closeness centrality graph, node J523 has the highest population impact, and node J176 has the lowest. The degree centrality graph shows that node J398 is more critical than node J103 regarding its impact on the population. The betweenness centrality graph shows that node J398 is more critical than node J97 regarding its impact on the population. The closeness centrality graph shows that node J523 is more critical than node J176 regarding its impact on the population

Fig. 3: Water logs, public tap, collected water and survey team for Edakochi

TABLE I: Impact analysis for Critical nodes of Betweenness Centrality

Node	Injection node	Max concentration	Max individual Dose	Number of estimated Infected	Nodes for 90% fatalities	Nodes with Fatalities
207	0-1	90.6322	16.049	1101	4	4
208	0-1	112.095	14.072	1101	4	4
209	0-1	112.095	8.755	1101	4	4
206	0-1	112.095	17.139	1101	4	4
211	0-1	112.095	14.08	607	2	2

shown in Fig. 7.

The impact of the critical nodes for the benchmark and live network and the optimality of the selected sensor placement are analyzed in WNTR. The nodes are injected with contamination and observe the water flow and contamination in the networks. The nodes at the network's end mostly had low contamination rates, and nodes with high contamination were observed to have high centrality scores.

Table III presents the concentration, maximum Individual dose, and fatality rates of each critical node for the contamination spread for one hour. It shows the most optimized placement strategy as the Degree centrality.

V. Conclusion and Future work

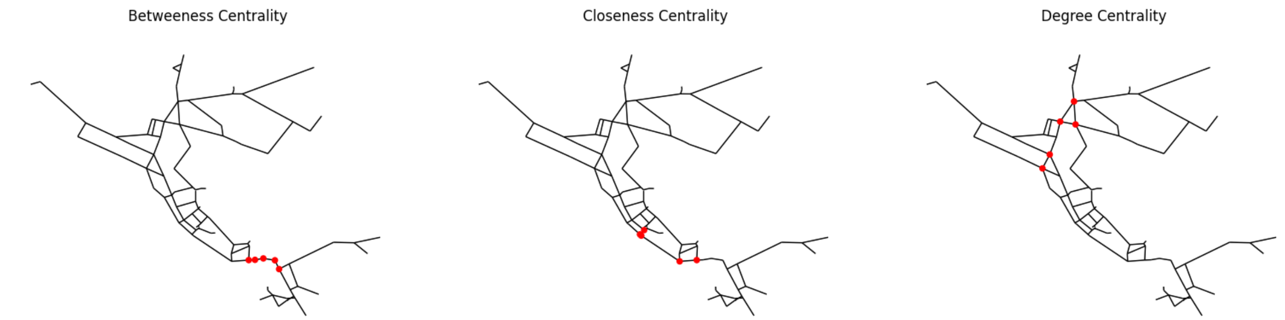
A water distribution network is one of the critical infrastructures of a city or an urban water system (UWS), and continuous monitoring of the WDN for water quality is unavoidable. This work presented a simulation study of water quality sensor placement for benchmark and real live water distribution networks. The WDN for the real network was modeled from scratch using the GIS-EPANET platform. A WDN optimal placement of water quality sensor framework introduced with betweenness centrality, closeness centrality, and degree centrality, critical node estimation algorithms for provides insights for the best sensor placement nodes of the network. The impact of the identified three sets of five critical nodes is analyzed in WNTR. The results showed the impact of each set of critical nodes and, hence, the significance of the algorithm for the benchmark network. The quantitative and qualitative analysis of each algorithm and sensor placement

TABLE II: Impact analysis for Critical nodes of closeness Centrality

Node	Injection node	Max concentration	Max individual Dose	Number of estimated Infected	Nodes for 90% fatalities	Nodes with Fatalities
185	0-1	76.84	7.062	1762	4	5
183	0-1	146.299	6.329	1705	3	4
205	0-1	81.288	7.283	1101	4	4
184	0-1	81.288	0.885	1938	5	6
207	0-1	90.632	16.052	1101	4	4

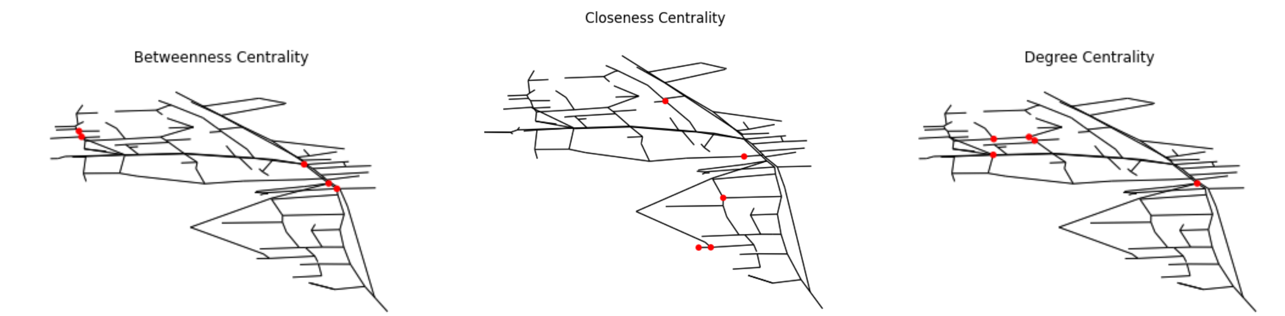
TABLE III: Impact analysis for Critical nodes of Degree Centrality

Node	Injection node	Max concentration	Max individual Dose	Number of estimated Infected	Nodes for 90% fatalities	Nodes with Fatalities
111	0-1	76.014	1.859	1814	5	5
115	0-1	60.005	1.883	1814	5	5
119	0-1	4.481	0.197	2929	8	9
120	0-1	28.813	0.885	3996	9	12
193	0-1	129.69	4.926	2308	6	7



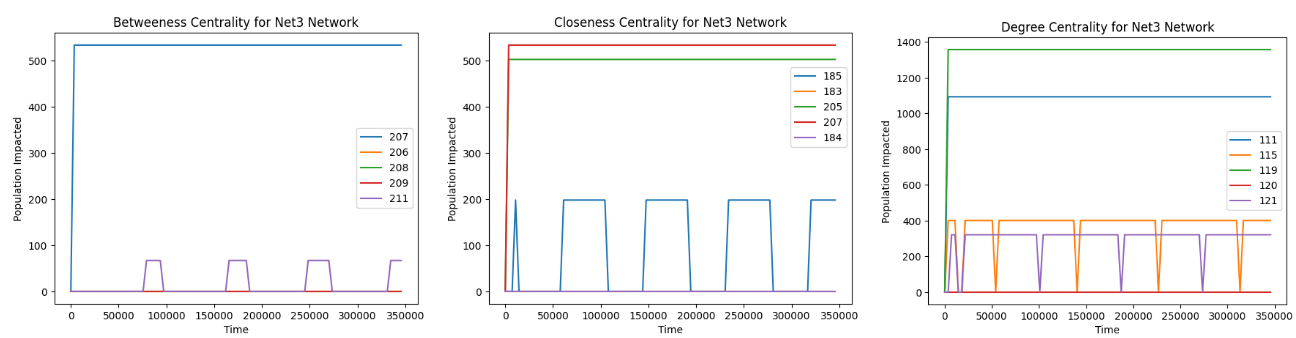
(a) Benchmark Betweenness Centrality. (b) Benchmark Closeness Centrality. (c) Benchmark Degree Centrality

Fig. 4: Critical nodes in benchmark network



(a) Live network Betweenness Centrality. (b) Live network Closeness Centrality. (c) Live network Degree Centrality

Fig. 5: Critical nodes in real-live network



(a) Benchmark Betweenness Centrality. (b) Benchmark Closeness Centrality. (c) Benchmark Degree Centrality

Fig. 6: Contamination impact analysis for critical nodes in bemchmark network

strategy will be performed to continue this work.

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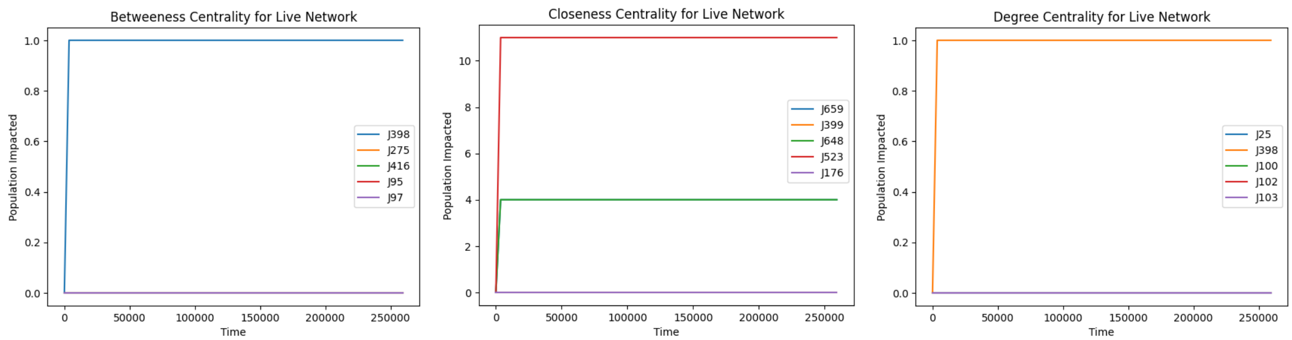

(a) Live network Betweenness Centrality. (b) Live network Closeness Centrality. (c) Live network Degree Centrality

Fig. 7: Contamination impact analysis for critical nodes in real live network

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