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Dynamic segment criticality analysis: A precursor to scheduling of maintenance routines in water distribution networks

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Abstract This study proposes a framework for dynamic segment criticality analysis and its implications on scheduling of some reactive maintenance routines in water distribution networks (WDNs). The framework harmonises multilayer networks which are capable of ascertaining the dynamics of WDNs in discrete time and a novel hybrid segment criticality measure (SCM) to achieve dynamic segment criticality analysis. The novel hybrid SCM utilises reachability theory from complex networks, which accounts for multiple sources, cyclic paths in WDNs, and demand shortfall attributed to segment isolation is computed using Pressure Driven Analysis (PDA) courtesy EPANET. Using a benchmark WDN, North Marin Water District Network, as a case study we have demonstrated the efficacy of the proposed framework and its ability to capture the dynamics of WDNs and evaluate the criticality of any segment given any temporal window. The results indicate the framework accurately evaluates the criticality of all segments within any temporal window and establishes the fact that segment criticality varies with time. Based on the results of this study reactive maintenance routines could be scheduled during temporal periods where the segment criticality measure is minimal to avoid excessive service disruption and customer displeasure. This study supports managers of water utilities with a decision support system to accurately schedule maintenance routines and evaluate segment criticality.

1. Introduction

Water Distribution Networks (WDNs) are critical infrastructure for the transport of water for domestic and industrial uses. WDNs are generally buried underground, and are subjected to intrinsic and extrinsic factors that make them susceptible to failures [1,2]. Failure of a single component of a WDN could affect the systems performance in delivering water at the right quality and quantity [3]. Practically, when a single component of a WDN (e.g., pipeline, pump, valve, etc) is out of service or damaged, a segment (small collection of nodes and pipes) of the WDN is isolated by closing appropriate isolation valves to implement the needed maintenance. Segment isolation could

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result in unintended cut-off of other segments downstream of the isolated segment [4,5], thereby depriving them of supply from the main source(s). This makes segment isolation in WDNs very critical and must be implemented carefully to limit its impact.

Due to the dynamic nature of WDNs, WDN assets (e.g., pumps, valves, and reservoirs) are not operational 24/7. Flow distribution on the network changes significantly depending on the operational status of these assets. Additionally, the demand and pressure at nodes also vary significantly with time. This implies that the cumulative demand shortfall created in the WDN due to the isolation of a segment for maintenance becomes a function of time. For instance, the impact of isolating segment i at time t might differ from isolating it at time $t + \delta t$. Thus, the time of isolating a segment for rehabilitation determines the severity of its impact on the WDN.

Reactive maintenance is one of the most dominant rehabilitation/maintenance regimes in WDNs [6]. These maintenance routines are carried out in response to component failure/deterioration in order to restore the WDN asset to its normal operating condition. These routines include pipe flushing to dislodge contaminants, repair of leakages and minor component replacements (e.g., pumps and valves). In order to carry out these activities, the affected segment has to be isolated during the entire repair/maintenance period. Ill-informed isolation of segments could also result in extensive pressure surge when implemented at the wrong time of the day or temporal window [7,8].

The identification and isolation of segments with minimal impact on downstream water delivery is done through segment criticality analysis. Segment criticality analysis used to study the criticality of segments in WDNs and ascertain their isolation impact on service delivery. Traditionally, segment criticality analysis has been carried out from a static point of view focusing exclusively on topological metrics. Abdel-Mottaleb and Walski [9] developed a topological theoretical graph approach based on reachability from water source(s) to segments to evaluate the criticality of segments in WDNs. A couple of studies [10,11] have applied the depth search segment identification algorithm proposed by Li and Kao [12] for criticality assessment of segments in WDNs. This depth search segment identification algorithm is based on articulation point identification method described by Horowits, et al. [13]. Another topological method based on segment degree distribution has also been proposed [14]. Even though the aforementioned topological methods provide a quick approximation and screening technique for segment criticality assessment, they utilised generic topological measures which do not capture some essential components of WDNs such as multiple sources and cyclic (looped) paths. Additionally, the hydraulics of the WDN which is mainly responsible for the amount of water delivered when a segment is isolated is completely ignored.

To address the hydraulic limitation of topological segment criticality methods, studies have proposed the integration of topological and hydraulic measures in segment criticality analysis. In this light, Gupta, et al. [15] presented a segment reliability analysis of WDNs based on a depth search algorithm and demand shortfall due to segment isolation. Other studies [16,17] have evaluated the criticality of segments using the modified depth search algorithm proposed by Li and Kao [12] and its variants [4,11] in conjunction with EPANET-simulated demand shortfall. Hernandez and Ormsbee [18] also presented a graphical method for segment criticality analysis based on loss of water supply due to loss of connectivity, loss of water resulting from pressure deficiency and increased water age as a result of segment isolation.

Previous studies in segment criticality analysis have abstracted WDNs as static networks and utilised generic topological metrics, which fail to account for multiple sources (such as tanks and reservoirs) and cyclic paths (loops). Additionally, the above-mentioned studies considered only daily averages or peak demands, which cannot realistically represent the criticality of segments in WDNs at all times. Single snapshot analysis of WDNs based on average or peak segment demand may underestimate or overestimate the vulnerability/criticality of segments.

This study presents a systematic framework for dynamic segment criticality/vulnerability assessment of WDNs and its implications for reactive maintenance scheduling. The framework is based on the idea of charactering the dynamics of the WDN via multilayer networks, where each layer depicts the state of the WDN within a temporal window (e.g., 1 h). The characterisation of the dynamics of WDNs and node vulnerability assessment via multilayer networks was recently introduced by the authors [19] to accurately characterise the dynamics of WDNs and ascertain the impacts of node failure in discrete time. In this study, the concept is extended to account for segments in WDNs. A novel dimensionless hybrid Segment Criticality Measure (SCM), which is based on reachability theory in complex networks and the cumulative demand shortfall created in the WDN as a result of segment isolation is proposed. Unlike previous studies that utilised generic topological measures (e.g., centrality measures) that are incapable of accounting for multiple sources and cyclic paths in the topology of WDNs, the proposed SCM utilises reachability theory in graphs to account for these essential components and features of WDNs.

Additionally, the proposed SCM accounts for the state of the WDN during different temporal windows via multilayer networks which is seldom considered by previous studies. Much attention has not been dedicated to the dynamic nature of segment criticality, which takes into consideration the essence of time, variations in demand, and the operational status of various components of the distribution network. Criticality estimates of segments accounting for time present an opportunity for managers of WDNs to optimally schedule reactive maintenance routines to avoid prolonged service downtime and minimise customer dissatisfaction. To the best of our knowledge no study has represented the dynamics of WDNs via multilayer networks and combined it with a segment criticality measure to derive the full benefit of both worlds in dynamic segment criticality analysis. And evaluate its implication on scheduling of reactive maintenance routines in WDNs.

The study is organised as follows; Section 1 presents the introduction, Section 2 details the methods and materials. Specifically, it presents multilayer networks, segmentation in WDNs and the proposed Segment Criticality Measure. Section 3 presents the case study. Sections 4 presents the results, detailed discussions, and implications of the study. Finally, Section 5 concludes the study.

2. Materials and methods

Dynamic segment criticality analysis in this study is implemented in two phases. In phase one, we characterise the dynamics of WDNs in discrete time (1-hour interval) using the concept of multilayer networks. Phase two focuses on the criticality estimation of each segment in each layer of the multilayer network using a Segment Criticality Measure (SCM). SCM is a hybrid measure that takes into consideration both topological (connectivity loss) and hydraulic (demand shortfall) metrics. These two phases are then synthesized to achieve dynamic segment vulnerability in WDNs.

2.1. Multi-layer networks

Multilayer networks have been used to study the dynamics of complex system's components interacting at comparable time scales [20]. The temporal structure of edge or link activations affect the dynamics of information flow in the network. As such, snapshots of the same network through time exhibit different interaction properties. These snapshots are referred to as the layers of the multilayer network. Multilayer networks are known to retain multi-dimensional information [21], and are able to reveal hidden structural properties not previously considered [22,23]. It has been widely used in literature to study the reliability and robustness of transportation networks [21,24], percolation in power grids [25,26], and information cascade [27,28]. WDNs under extended period simulation represent a temporal system whose characteristics such as demand, pressure and operational status of pumps & valves and flow directions change with time. Network science has shown that characterising such complex dynamic systems with multilayer networks is fundamental for the comprehension of these systems [29]. Generally, multilayer networks can be classified as either multiplex networks, network of networks or multi-slice networks. The most suitable form of multilayer networks for WDNs is the multi-slice networks.

2.1.1. Multi-slice networks

A multi-slice network is a special type of multilayer network in which there is one-to-one mapping of vertices in different layers [30]. Thus, the vertices replicate themselves across different layers and each layer is a snapshot of the temporal network. Each layer has the same set of vertices, but the interactions (edge activations) differ in different layers. In the context of WDNs under extended period simulation, these edge or link activations represent the flow direction of water in the pipes and operational status of the components (valves, pumps etc) in the network. The concept of multi-slice networks is illustrated in Fig. 1.

Fig. 1 represents snapshots of a real type WDN within different temporal windows. The interactions exhibited determine the criticality of the nodes in the WDN. Each layer corresponds to the state of the network within a temporal window δt. The interactions between nodes are the unique flow directions in each temporal window. The nodes replicate themselves across all snapshots, but the directional flow and operational status of the sources and pumps differ. Each node is weighted by its corresponding demand within a predefined temporal window. In the case of the segment valve topology, each segment is weighted by the corresponding cumulative demand within the predefined temporal window.

In the absence of connections/links between different layers, a multi-slice network is defined mathematically as:

$$M = \left(Y, \vec{G}\right) \tag{1}$$

where $\vec{G} = (G_1, G_2, \ldots, G_m)$ and $G_\alpha = (V_\alpha, E_\alpha)$ represents the interactions occurring in a time window δt and Y represents the layers. The interactions depicting each time window describes each layer in the network. Each layer is fully characterized by an $N \times N$ adjacency matrix, $A^{[\alpha]}$ wit h $\alpha = 1, 2, \ldots, m$. We restrict the interactions in each layer to be directed to suit WDNs. The adjacency matrix of any arbitrary layer α is defined as.

$$A_{ij}^{[\alpha]} = \begin{cases} 1, \textit{if node } i \textit{ connects to node } j \textit{ in the time} \\ \textit{window } [t + (\alpha - 1)\delta t, t + \alpha\delta t) \\ 0, \textit{otherwise} \end{cases}$$

2.2. Segmentation of WDNs

One of the fundamental requirements for segment criticality assessment is the optimal segmentation of WDNs to meet hydraulic conditions. Suboptimal segmentation results in astronomical nodal pressure, a scenario where nodal pressures are significantly higher than the maximum allowable pressure for service delivery, increasing the probability of pipe failure in the network [7]. Over the last decade, several studies have looked at cost-effective strategies of designing [31] and retrofitting WDNs with isolation valves to achieve robust segmentation in WDNs [7,8,32]. Recently, more effective methods based on modularity [33,34] have been proposed. A modularity-based method is available in the commercial software WaterGEMS. Another critical issue of relevance is the programmatic identification of segments in WDNs. Scalable algorithms [4,5,10,35] have been proposed in literature to rapidly identify segments in WDNs. In this study, we utilised an efficient depth search algorithm [14] for the identification of segments with minimal computational time.

To facilitate the use of graph theory in segment criticality analysis, segments are usually represented as vertices and isolation (ISO) valves as edges. This representation is generally referred to as the segment valve topology [36]. Segment valve topology is an alternate representation of WDNs which preserves the properties (state) of the WDN. Fig. 2 presents a real type WDN which is fitted with 9 ISO valves using the concept of modularity and delineated into 6 distinct segments via the aforementioned depth search algorithm. Each segment is then represented as a vertex graphically.

This study focused exclusively on dynamic segment criticality analysis with the assumption that majority of the WDNs in use have already been optimally segmented to meet prevailing hydraulic conditions. For detailed information on optimal segmentation and identification of segments see [33] and [14], respectively.

2.3. Segment criticality measure

Segment Criticality Measure (SCM) is a hybrid segment criticality metric that is based on the connectivity loss of the seg-

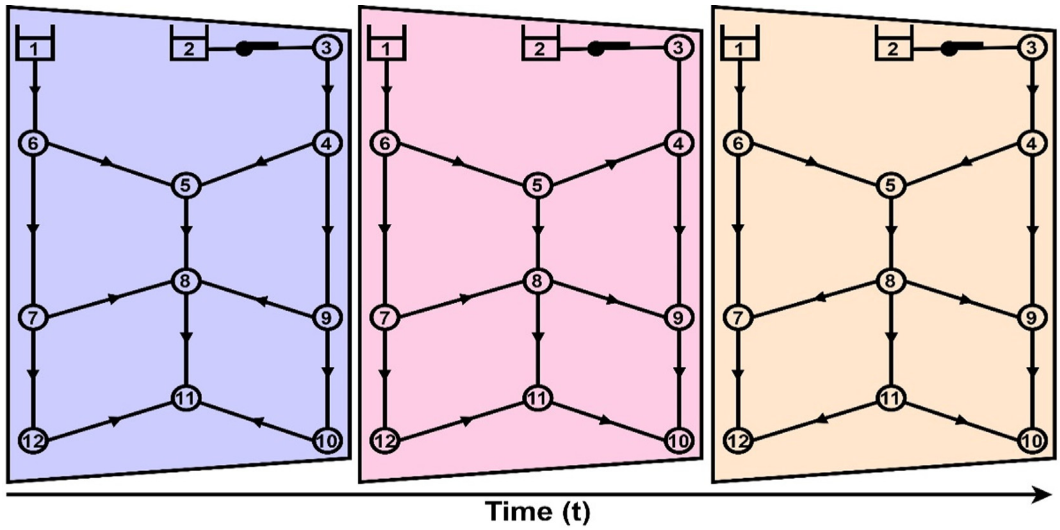

Fig. 1 Real type WDN represented as a multi-slice network.

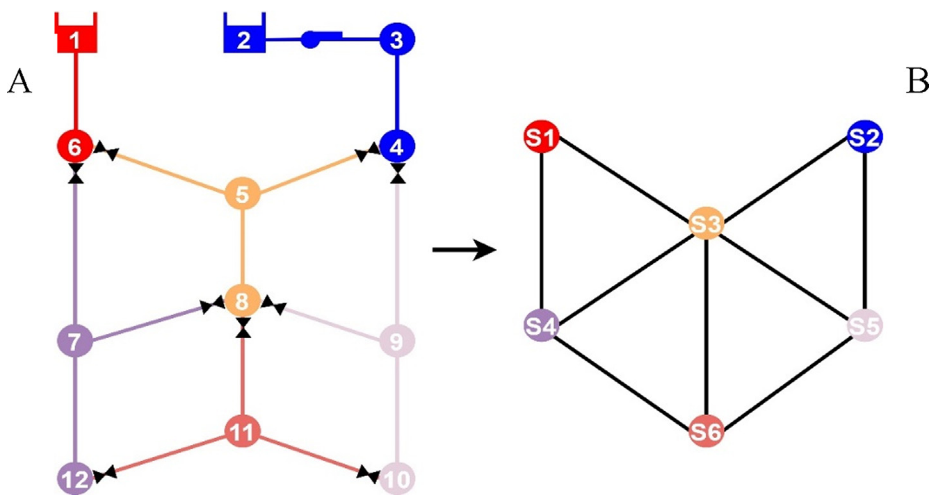

Fig. 2 **A:** Real type WDN with 9 ISO valves. **B:** Segment valve topology of the network.

ment valve topology and the cumulative demand shortfall created in the WDN as a result of segment isolation. In segment criticality analysis, WDNs are represented using segment valve topology. When a segment is isolated for maintenance, its isolation does not sequentially impact all segments directly connected to it but rather all paths from the source(s) that contain this segment become invalid. As such, computing the number of segments impacted by the isolation of a single segment is complex. Using tools from graph theory, a novel algorithm is presented in this study to compute the number of impacted segments due to the isolation of any arbitrary segment.

Given a graph $G(V, E)$ representing the segment valve topology, all segments connected directly or indirectly to any arbitrary segment k can be retrieved. Let $N(k) = R_G(k)$ represent the set of all segments reachable from segment k in G. To find the number of segments affected, n, due to the isolation of segment k, we iterate through $N(k)$ to see if there is/are path(s) from the source(s) to these segments that do not traverse segment k. Here, source(s) refers to segment(s) that have a source (reservoir). Segments with tanks cannot be considered as true sources in WDNs since they have limited capability in terms of service delivery [9]. If there is/are path(s) from the source (s) to segment i in $N(k)$ that do not traverse segment k, then segment i is not affected by the isolation of segment k. This implies that there are no unintended isolation events due to the isolation of segment k for maintenance purposes. If there is no path from the source(s) to segment i in $N(k)$, then the isolation of segment k will result in unintended isolation of segment i.

In order to circumvent unintended isolations, WDNs are generally designed to have alternate paths and loops (cyclic paths). These loops introduce significant bottlenecks in path computations in WDNs. To the best of our knowledge, segment criticality measures presented in literature seldom consider looped segment valve topology architecture with multiple sources. A modified Dijkstra Algorithm [37] with the ability to handle loops is utilised in the computation of water paths in the segment valve topology representation of the WDN. Algorithm 1 outlines the pseudocode for computing the number of affected segments due to the isolation of any arbitrary segment for maintenance. For WDNs with multiple sources, Line 9 of Algorithm 1 can be modified to compute the paths from these individual sources. The algorithm takes the segment valve topology of the WDN as input and outputs the number of segments impacted due to the isolation of each segment in the WDN.

Algorithm 1: Number of Affected Segments

Inputs: Segment Valve Topology denoted$G(v, e)$, MaxPaths, Source
Outputs: Number of segments affected
1. $n = |v|$
2. **for** $k = 1 : n$
3. $A \leftarrow$ neighbors(G,k, ∞) //All neighbours of segment i
4. A ← [A k] // Concatenate segment to its neighbors
5. $m = |A|$, $C = []$
6. **for** $j = 2 : m$
7. path{j} ← kShortestPath(G,$source$,$A(j)$, $MaxPaths$) // paths in G
8. pth = $|path|$
9. **for** $i = 1 : pth$
10. $B \leftarrow$ find(path{i} = = k) // Index B if segment i is in path k
11. **if** $B = []$
12. $C \leftarrow [CA(j)]$ //Concatenate non affected segments
13. break
14. **end**
15. **end**
16. **end**
17. **if** $C = []$
18. $D \leftarrow A$ // All neighbors are impacted
19. **else**
20. $D \leftarrow$ setdiff(A, C) // Remove non impacted segments from neighbors of segment i
21. **end**
22. $E = |D|$ // Number of affected segments
23. **End**

Connectivity Loss (CL) in the context of segment criticality analysis is defined as the fraction of the segment valve topology invalidated due to the isolation of a segment. The CL of a segment k is mathematically defined on the segment valve topology represented by graph $G(V, E)$ as:.

$$CL(k) = \frac{n}{N_T} \forall k \in V \tag{2}$$

where, n is the number of segments impacted due to the isolation of segment k using algorithm 1 and $N_T = |V|$ is the total number of segments in the WDN.

The computation of the cumulative demand shortfall in the entire WDN due to segment isolation is partially based on the computation of the number of affected segments in Algorithm 1. The demand shortfall created in the network as a result of isolating segment k,$DS(k)$, is defined as the demand not satisfied due to the isolation of n number of segments (affected segments). Under demand driven hydraulic simulation, this demand shortfall represents just the cumulative sum of only the demand not supplied to the affected segments. However, studies [7,38] have shown that isolation of segments induce pressure variations in other segments of the WDN and the actual amount of water delivered to customers becomes a function of prevailing pressure. As such, demand driven hydraulic simulation which does not account for these induced pressure variations underestimates the actual demand supplied in the network. Pressure dependent hydraulic simulation resolves this issue by accounting for prevailing pressure in the hydraulic simulation and provides a reliable estimate for the actual amount of water delivered to customers [39]. The pressure dependent formulation proposed by Wagner et al. [40] to evaluate the water delivered at any arbitrary node i in a WDN is given as;.

$$D_i^{act} = \begin{cases} 0 & P_i \le P_i^{min} \\ D_i^{req} \sqrt{\frac{P_i - P_i^{min}}{P_i^{ser} - P_i^{min}}} & P_i^{min} < P_i < P_i^{ser} \\ D_i^{req} & P_i^{ser} \le P_i \end{cases} \tag{3}$$

where D_i^{act} = actual demand at node i, D_i^{req} = required demand at node$i$, P_i^{min} = minimum pressure required to deliver any amount of demand at node$i$, P_i^{ser} = service pressure required to supply demand at node i, P_i = pressure computed via hydraulic simulation at node$i$. This cumulative demand shortfall created in the WDN is estimated using pressure dependent simulation in EPANET 2.2 [41].

Mathematically, $DS(k)$ can be expressed as the sum of the difference between the nominal segment demands and the actual delivered segment demands at time t when a segment k isolated.

$$DS(k) = \sum_{i=1}^{N_T} (D_n(i) - D_{act}(i)) \tag{4}$$

where$D_n(i)$ = nominal demand on segment i under normal working conditions (no isolation incident). $D_{act}(i)$ = actual delivered demand at segment i due to isolation of segment k. N_T = total number of segments in the WDN. When segment k is isolated, the actual demand delivered at this segment and all segments affected (topological point of view as computed in algorithm 1) are set to zero. Pressure dependent simulation helps to ascertain the service delivery impact of isolating segment k on other segments that are not impacted topologically. Thus, segments that are not cut off from the reservoir(s) due to the isolation of segment$k$.

Finally, the SCM which weighs the connectivity loss of the segment valve topology as a result of isolating segment k, $CL(k)$, with its cumulative demand shortfall, $DS(k)$, is given as:.

$$SCM(k) = \frac{CL(k) * DS(k)}{\sum_{i=1}^{N_T} D_n(i)} \tag{5}$$

The SCM defined above is a local dimensionless metric for segment criticality assessment. In defining SCM, both the connectivity loss of the segment valve topology and cumulative demand shortfall created in the WDN due to the isolation of each segment is normalized by the number of segments and the overall nominal demand respectively. Coupling connectivity loss with cumulative demand shortfall ensures that the criticality of segments with the same connectivity loss are differentiated based on cumulative demand shortfall in the WDN. The isolation of any two arbitrary segments in a WDN could result in the same connectivity loss of the segment valve topology structure but their respective demand shortfall might not be the same. In the event of unintended isolation, both the topological impact (connectivity loss) and hydraulic impact (cumulative demand shortfall) increase significantly. Since SCM combines connectivity loss and cumulative demand shortfall, the SCM for a segment whose isolation results in unintended isolation might have a significantly higher criticality measure/ranking than segments whose isolation do not result in unintended isolation. In a scenario where the resulting cumulative demand shortfall is minimal, the SCM will be moderate.

2.4. Ranking of segment criticality

Kendall's rank correlation coefficient is used to measure similarities in the criticality ranking of segments in different layers of the multilayer representation of the segment valve topology. Mathematically, Kendall's rank correlation coefficient, τ, determining the strength of ordinal association between the criticality ranking of segments in layers X and Y accounting for ties is given as:.

$$\tau = \frac{n_c - n_d}{\sqrt{\left(\frac{n(n-1)}{2} - T\right)\left(\frac{n(n-1)}{2} - U\right)}} \tag{6}$$

where n_c = number of concordant pairs, n_d = number of discordant pairs, n = number of segments, $T = \sum_i t_i(t_i - 1)/2, U = \sum_j u_j(u_j - 1)/2, t_i$ = number of X values that are tied at a given rank and u_j = number of Y values that are tied at a given rank. Kendall's rank correlation coefficient assumes values between the closed interval$[-11]$. $\tau = -1$ implies the criticality rankings are opposite (reversed order), $\tau = 0$ indicates the criticality rankings are independent (no relationship) and $\tau = +1$ implies the ranking are exactly the same. Generally, as τ values approach $+1$ we say the criticality rankings are similar. On the other hand, as τ values approach -1, we say the criticality rankings are dissimilar (approaching reversed order).

3. Case study

A benchmark WDN, North Marin Water District Network, California-USA [42] is used as a case study to demonstrate the proposed methodology. This network has been segmented into 20 distinct segments based on the concept of modularity [33]. Fig. 3 shows the network and its alternate segment valve topology representation. Segments 1 and 2 are demarcated as sources in Fig. 3. This implies that these segments have reservoirs and are capable of supplying water to the entire fleet of segments in the network either independently or simultaneously. Using flows in the links (pipes with ISO valves) between adjoining segments, their functional status within any temporal window can be ascertained.

Using the EPANET MATLAB toolkit [43], a pressure dependent extended period simulation is carried out for 24 h so that the criticality of each segment is captured for any given temporal period within the day. The WDN is then characterised as a multi-slice network with 24 layers. Each layer represents the state of the WDN within a 1-hour temporal window. This ensures that we can study the criticality of segments (impact of segment isolation) in discrete time and ascertain their impact on the entire network in terms of disruption and service delivery on hourly basis. To speed up the computational time, the parallelization toolbox in MATLAB R2019b [44] was extensively used to speed up the computational time required to evaluate every segment isolation scenario in each layer of the segment valve topology representation. To ensure thorough analysis of segment criticality, the isolation impact of each segment in each layer of the WDN in terms of connectivity loss and demand shortfall is evaluated.

4. Results and discussion

This section presents the results of the study, discussions, and the general implications. First, segment criticality analysis for different temporal periods is presented and the correlations between these temporal periods are evaluated. Then, we present the implications of dynamic segment criticality on scheduling of reactive maintenance routines.

4.1. Multilayer segment criticality analysis

The SCM results of the segments for three temporal windows of the case study WDN are presented in Fig. 4, where the colour bar represents the degree of criticality (0 – least critical and 1 – most critical). The higher the criticality ranking of a segment, the higher its impact on the entire network in terms of service delivery when it is isolated within a particular temporal period. The absence of a link between two adjacent segments implies a non-interaction (no water flow) between them within the temporal period considered.

Layer 0 in Fig. 4 presents the SCM of each segment within the temporal period 00:00am – 0:59am. Within this temporal period, source segment 1 (S1) is dormant, an indication that it does not supply water. As such, segment 1 is the least vulnerable. Source segment 2 (S2) has the sole responsibility to supply the entire fleet of segments. Isolation of this source segment will invalidate the entire WDN and therefore is ranked as the most critical segment. The successor of S2 in the connectivity structure of the segment valve topology, S4, is the 2nd most critical segment. S20, which is a sink/terminal segment is among the least ranked segments as a result of low demand shortfall created in the network due to its isolation. In layer 7 of Fig. 4, both source segments, S1 and S2, are functioning simultaneously. The isolation of S2 has a significant impact on service delivery compared to S1 due to the huge demand shortfall created in the entire network as a result of its isolation. Therefore, S2 is ranked the most critical segment within this temporal period. S4 ranks the second most critical segment. The isolation of this segment will cut off majority of the downstream segments from the source segment S2.

Furthermore, the isolation of S16 in layer 13 of Fig. 4 will result in the unintended isolation of S17, S18, S19 & S20. From a connectivity loss point of view, the impact of isolating S16 is enormous. However, considering only connectivity loss as a criticality measure would significantly exaggerate the criticality of S16. This is due to the fact that the cumulative demand shortfall created in the network within this temporal period is very small. The demand shortfall created in the network due to the isolation of S13, which does not result in unintended isolation is significantly higher than that of S16 in this temporal window. As such, the proposed SCM, which weights connectivity loss with relative demand shortfall, ranks the

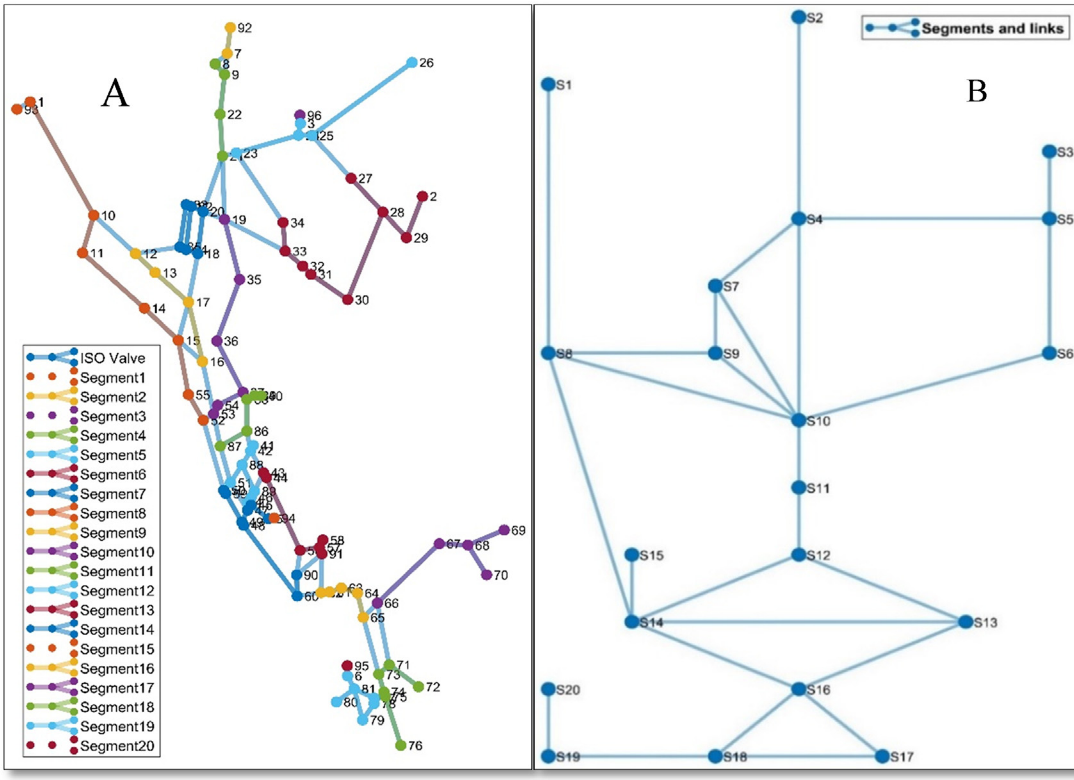

Fig. 3 **A:** North Marin Water District WDN. **B:** Segment valve topology representation.

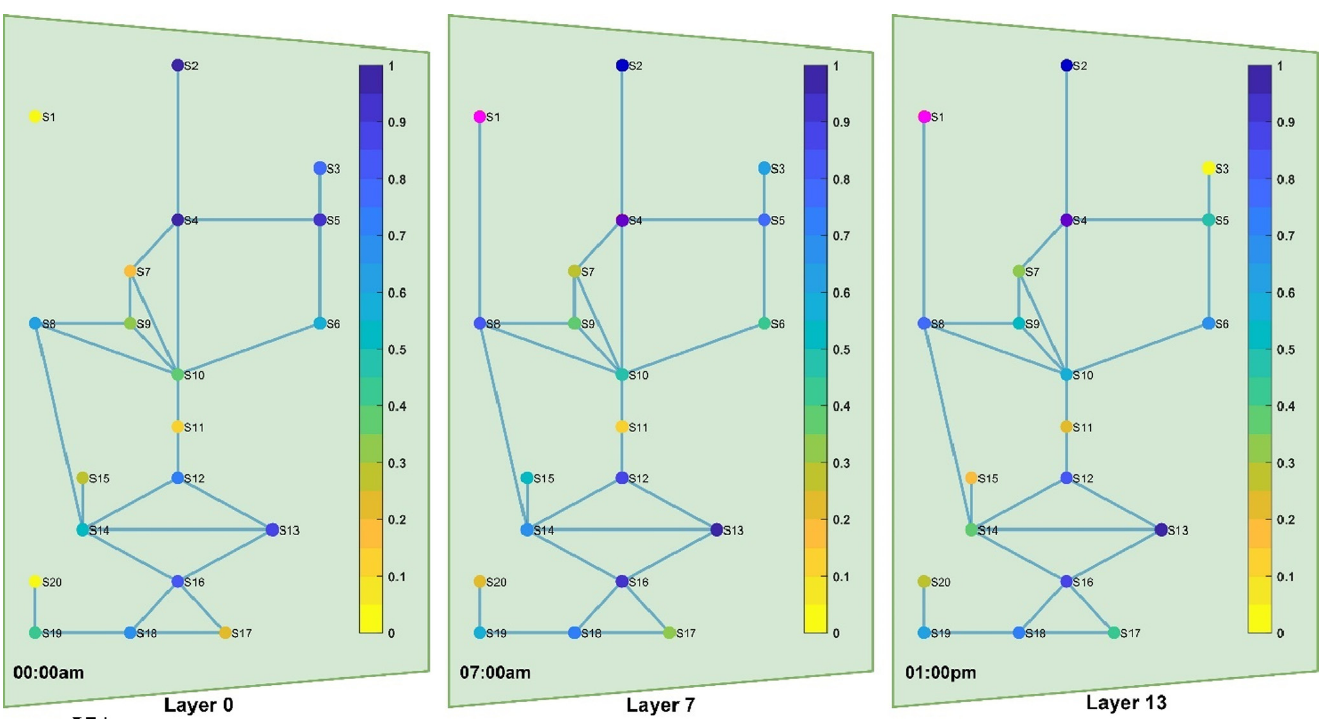

Fig. 4 Layers 0 and 7 of the segment valve topology multilayer representation.

criticality of S13 higher. It is important to highlight the fact that generally, the higher the connectivity loss the higher the cumulative demand shortfall created in the network. However, the isolation of S16 within this temporal period presents itself as an exception since the segment demands of S17, S18, S19 and S20 are very minimal within this temporal period. The

Table 1 Kendall's rank correlation coefficient of segment criticality rankings in Layers 0 to 23 of the real-life WDN.

	L_0	L_1	L_2	L_3	L_4	L_5	L_6	L_7	L_8	L_9	L_{10}	L_{11}	L_{12}	L_{13}	L_{14}	L_{15}	L_{16}	L_{17}	L_{18}	L_{19}	L_{20}	L_{21}	L_{22}	L_{23}
L_0	1	0.56	0.50	0.49	0.45	0.44	0.45	0.47	0.25	0.51	0.48	0.51	0.51	0.46	0.50	0.70	0.67	0.67	0.66	0.67	0.67	0.67	0.70	0.86
L_1		1.00	0.95	0.94	0.84	0.46	0.75	0.79	0.54	0.48	0.44	0.44	0.44	0.41	0.44	0.24	0.22	0.22	0.21	0.22	0.22	0.22	0.24	0.43
L_2			1.00	0.99	0.88	0.46	0.80	0.82	0.59	0.44	0.43	0.39	0.39	0.40	0.43	0.19	0.17	0.17	0.17	0.17	0.17	0.17	0.19	0.38
L_3				1.00	0.89	0.47	0.81	0.81	0.60	0.43	0.42	0.38	0.38	0.39	0.42	0.18	0.16	0.16	0.16	0.16	0.16	0.16	0.18	0.37
L_4					1.00	0.47	0.83	0.77	0.62	0.39	0.38	0.31	0.31	0.32	0.36	0.14	0.14	0.14	0.13	0.14	0.14	0.14	0.14	0.33
L_5						1.00	0.64	0.62	0.81	0.87	0.86	0.76	0.76	0.79	0.84	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.40
L_6							1.00	0.92	0.77	0.56	0.55	0.49	0.49	0.50	0.53	0.31	0.31	0.31	0.30	0.31	0.31	0.31	0.31	0.41
L_7								1.00	0.73	0.62	0.61	0.53	0.53	0.54	0.57	0.33	0.36	0.36	0.35	0.36	0.36	0.36	0.33	0.43
L_8									1.00	0.70	0.69	0.57	0.57	0.59	0.65	0.40	0.42	0.42	0.42	0.42	0.42	0.42	0.40	0.21
L_9										1.00	0.97	0.87	0.87	0.87	0.93	0.68	0.70	0.70	0.70	0.70	0.70	0.70	0.68	0.49
L_{10}											1.00	0.88	0.88	0.90	0.96	0.69	0.71	0.71	0.71	0.71	0.71	0.71	0.69	0.50
L_{11}												1.00	1.00	0.97	0.92	0.81	0.79	0.79	0.78	0.79	0.79	0.79	0.81	0.63
L_{12}													1.00	0.97	0.92	0.81	0.79	0.79	0.78	0.79	0.79	0.79	0.81	0.63
L_{13}														1.00	0.95	0.77	0.75	0.75	0.76	0.75	0.75	0.75	0.77	0.58
L_{14}															1.00	0.72	0.70	0.70	0.71	0.70	0.70	0.70	0.72	0.53
L_{15}																1.00	0.98	0.98	0.97	0.98	0.98	0.98	1.00	0.82
L_{16}																	1.00	1.00	0.99	1.00	1.00	1.00	0.98	0.80
L_{17}																		1.00	0.99	1.00	1.00	1.00	0.98	0.80
L_{18}																			1.00	0.99	0.99	0.99	0.97	0.79
L_{19}																				1.00	1.00	1.00	0.98	0.80
L_{20}																					1.00	1.00	0.98	0.80
L_{21}																						1.00	0.98	0.80
L_{22}																							1.00	0.82
L_{23}																								1.00

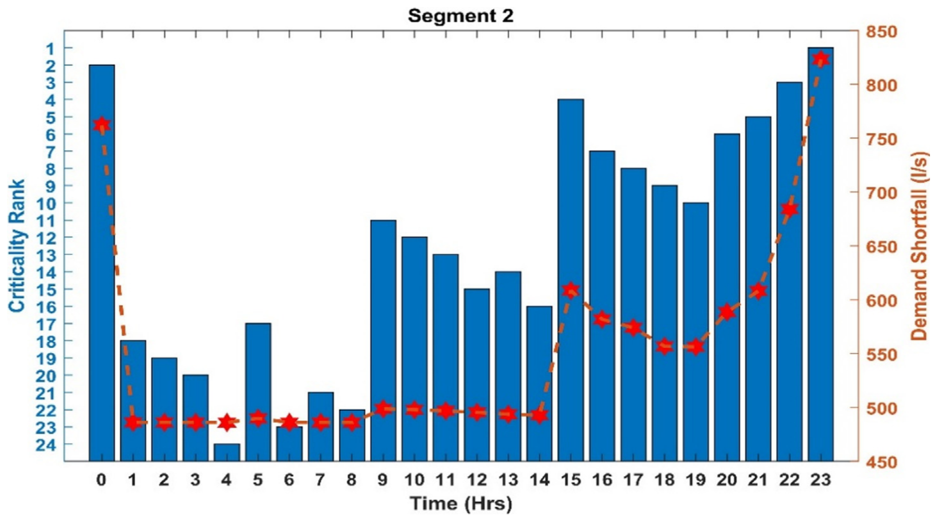

Fig. 5 Criticality rankings of Segment 2.

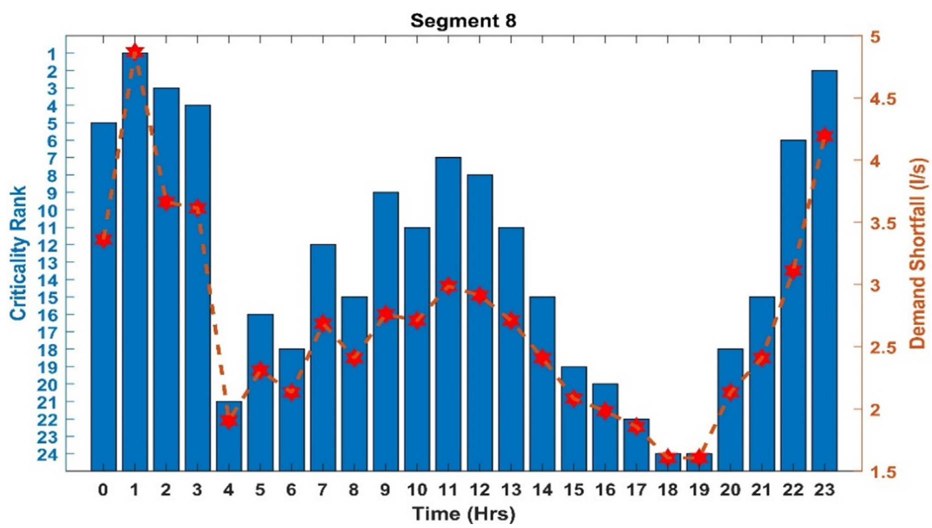

Fig. 6 Criticality rankings of Segment 8.

general dynamics of the network is similar to layer 7 & 13. However, the criticality ranking of the segments differ. This is due to the differences in segments demands and total demand shortfall within these separate temporal windows.

Table 1 presents the Kendall's correlation coefficient between the criticality ranking of segments in each of the 24 layers. A perfect correlation, correlation coefficient of one, implies the criticality ranking of segments between any pair of layers is similar. Perfect correlation is evident between layers 19, 20 & 21. This implies that the criticality ranking of these segments are identical despite the variation in cumulative segment demand. However, the criticality ranking in majority of the layers (temporal windows), are very much distinct. Extremely low correlation could be seen between layers 4 & 18, layers 3 & 21, etc. On average, majority of the entries in Table 1 have values less than 0.5, which give an indication of how the criticality rankings of segments vary from one temporal period to another. Adjacent temporal periods (layers) seem to exhibit much similarity as indicated by their relatively high correlation coefficients. This is expected as the dynamics of the network in terms of demand patterns and the operational status of valves and pumps do not differ significantly between adjacent temporal periods. The results presented in Fig. 4 and Table 1 lend credence to the fact that static networks fail to account for the variabilities exhibited from one temporal period to another. They rather focus on peak or average estimations which are not realistic for the different temporal windows within the day.

4.2. Segment criticality ranking and scheduling of maintenance routines

To facilitate maintenance scheduling, bar plots of the criticality ranking of each segment are presented considering all time periods in the pressure dependent extended period simulation. These plots enable us to identify precisely which temporal periods are most favourable for maintenance routines to be carried

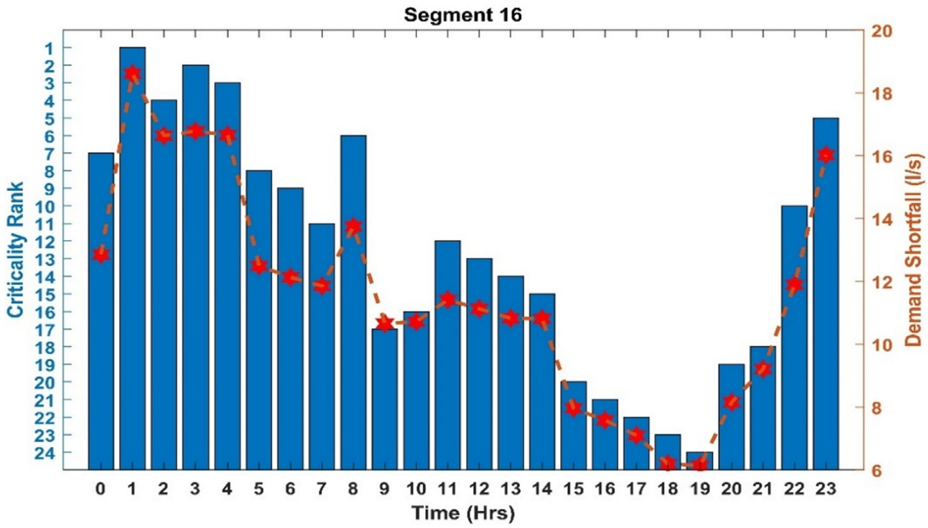

Fig. 7 Criticality rankings of segment 16.

out on components of each segment such as pipes, valves, and pumps etc.

Fig. 5 presents the SCM ranking of one of the source segments, S2. Between the temporal window 1:00 am to 2:59 pm both source segments, S1 & S2, are functional. This is evident in the demand shortfall created in the entire network. It is significantly less than the demand shortfall when only S2 is operational (3:00 pm to 00:59 am). According to the bar chart, the optimal period for isolating S2 for maintenance is between 4:00 am and 4:59 am. Isolating S2 within any other temporal period will result in higher service disruption. In circumstances where it is impossible to schedule maintenance routines within this temporal period, a compromise can be reached by opting for other temporal periods in which the criticality ranking is low, and the overall demand shortfall is minimal.

In Fig. 6, we present the criticality ranking of segment 8. All the nodes in S8 have the same demand pattern and its isolation does not result in unintended isolation of downstream segments. S8 have the least SCM between the temporal period 6:00 pm-7:59 pm. Maintenance routines involving components of segment 8 ought to be carried out within this temporal period. Since all the nodes in S8 have the same demand pattern and its isolation does not result in any unintended isolation, its SCM over the 24-hour period should agree with the diurnal demand pattern. A strong similitude is evident between the SCM of S8, demand shortfall and the default demand pattern (see Appendix A for default demand pattern). It is important to highlight the fact that in instances where nodes in a particular segment have different demand patterns and unintended isolation is possible, it is impossible to identify the temporal period in which its isolation will have minimal impact based on intuition or experience alone. This aforementioned scenario is illustrated in the segment criticality analysis of S16 presented in Fig. 7.

The isolation of S16 results in the unintended isolation of downstream segments S17, S18, S19 and S20. Some of these downstream segments have nodes that exhibit different demand patterns. The hourly cumulative demand shortfall created in the network due to the isolation of S16 will differ significantly from one temporal window to another in the network. This phenomenon demands that a robust SCM that considers the time varying component of WDNs as the one proposed in this study be implemented to capture these variabilities. The optimal temporal window for scheduling maintenance routines on components of S16 is 7:00 pm to 7:59 pm. As mentioned earlier, if it is impossible to schedule maintenance within this optimal temporal window a compromise can be reached. Since the SCM for the entire 24 hrs of each layer is considered, it is easy to evaluate alternate temporal windows that are suitable operationally albeit suboptimal per SCM.

The following practical implications can be drawn from this study. The proposed framework for dynamic segment criticality analysis could be used as a decision support system to optimally schedule maintenance in WDNs. It is important to highlight the fact that not all maintenance routines have to be scheduled, some must be implemented immediately to ensure the smooth functioning of the WDNs. This study presents stakeholders with a method to evaluate the criticality of segments within different temporal periods in a day in order to either prioritize the maintenance of a particular component or schedule its maintenance to limit service disruptions.

The framework could also be used to study the criticality of segments in general, simulate disaster scenarios, predict the resulting service delivery loss, and design disaster impact mitigating strategies. System reliability and diagnosis is another avenue to utilize the proposed SCM. The SCM introduced in this study could be utilized for emergency planning and response in near real-time to limit the catastrophic consequences of component failure in WDNs. Whenever there is a component failure, the proposed framework could be utilised by water engineers in near real-time to assess the impact of isolating the affected segment and evaluate the optimum temporal window to fix the damage.

5. Conclusions

A systematic framework for dynamic segment criticality analysis of WDNs have been proposed and validated on a real-life WDN in this study. The proposed Segment Criticality Measure (SCM) presents a hybrid approach that combines both topological and hydraulic metrics for segment criticality analysis. Based on the results of this study we have demonstrated that relying exclusively on topological metrics for segment criticality can be misleading at times. Collectively, we have demonstrated how the criticality of segments of WDNs under pressure dependent extended period simulation vary with time (different temporal windows) using multilayer networks. It is impossible to capture these variabilities using single period simulation and static networks. The consideration of time, thus varying segment demands, is crucial in the identification of the optimum window to implement scheduled maintenance routines. The following key points are highlighted from this study.

- A robust decision support framework to optimally schedule reactive maintenance routines in WDNs has been established. This framework identifies the most suitable time to carry out reactive maintenance routines or suggest alternative periods with less impact on service delivery. It alleviates the problems associated with guess work of engineers in segment isolation or over reliance on intuition which can be catastrophic at times.
- The SCM introduced in this study is primed for system diagnosis and reliability analysis. Segment isolations that result in colossal amount of demand deficit and unintended cut-off of other segments downstream could be identified and additional pipes added (or rings formed) to alleviate the burden of unintended segment isolation. This will go a long way to ensure reliable and consistent water delivery even in the event of segment isolation for reactive maintenance routines.
- The design and implementation of flushing regimes in WDNs to dislodge intruded contaminants or routine flushing to improve water quality could benefit immensely from the results of this study. The connectivity loss based on reachability theory in complex network introduced in this study could easily be used for contaminant zoning analysis. It can evaluate the impact of different zoning strategies by the closure of appropriate isolation valves to cut off contaminated segments and limit the impact of possible contamination scenarios.
- Disaster scenario analysis and impact mitigation strategies can be evaluated using the proposed segment criticality measure. Different disaster mitigation strategies to combat natural disasters such as earthquakes could be simulated as isolation of single or multiple segments to assess their impact on service delivery. Pipes are buried underground and could suffer from landslides and earthquakes in regions/areas with fault lines. Therefore, frameworks to analyse disaster scenarios are very crucial to water utilities to help them come up with rapid and timely interventions to limit the impact.

Segment criticality largely depends on the topology and hydraulics of the WDNs. Even though the SCM presented in this study is generally applicable to all WDNs, the results may vary significantly depending on the topology, hydraulics, and location of ISO valves. Additionally, the SCM is confined to a predetermined temporal window. Future studies could evaluate the impact of ISO valve failure on segment criticality analysis. Since this will result in the inability to properly isolate segments thereby increasing the number of segments to be isolated for the implementation of reactive maintenance routines.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. See Fig. 8.

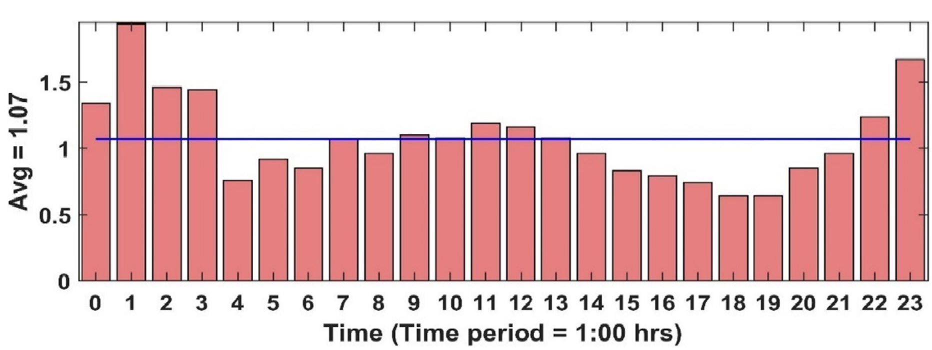

Fig. 8 Default demand pattern of real-life WDN.

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