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Combining Statistical Clustering with Hydraulic Modeling for Resilient Reduction of Water Losses in Water Distribution Networks: Large Scale Application Study in the City of Patras in Western Greece

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Abstract: Partitioning of water distribution networks (WDNs) into pressure management areas (PMAs) or district metered areas (DMAs) is the most widely applied method for the efficient management and reduction of real losses (leakages). Although PMA partitioning is a crucial task, most clustering methods are strongly affected by user-defined weighting factors that heavily affect the final outcome while being associated with heavy computational loads, leading to time-consuming applications. In this work, we use hierarchical clustering enriched with topological proximity constraints to develop an approach for the optimal sizing and allocation of PMAs (or DMAs) in water distribution networks that seeks to minimize water leakages while maintaining a sufficient level of hydraulic resilience. To quantify the latter, we introduce a resilience index that accounts for water leakages and nodal heads in pressure-driven and mixed pressure-demand ways, respectively. The strong points of the introduced approach are that (1) it uses the original pipeline grid as a connectivity matrix in order to avoid unrealistic clustering outcomes; (2) it is statistically rigorous and user unbiased as it is based solely on statistical metrics, thus not relying on and/or being affected by user-defined weighting factors; and (3) it is easy and fast to implement, requiring minimal processing power. The effectiveness of the developed methodology is tested in a large-scale application study in four PMAs (namely Boud, Kentro, Panahaiki, and Prosfygika) of the city of Patras in western Greece, which cover the entire city center and the most important part of the urban fabric of Patras, consisting of approximately 202 km of pipeline and serving approximately 58,000 consumers. Due to its simplicity, minimal computational requirements, and objective selection criteria, the suggested clustering approach for WDN partitioning can serve as an important step toward developing useful decision-making frameworks for water experts and officials, allowing for improved management and reduction of real water losses.

Keywords: statistical clustering; water networks partitioning; water distribution networks; water losses; leakage management; hydraulic resilience

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1. Introduction

Reduction of water losses in Water Distribution Networks (WDNs) is a crucial task for all water agencies and experts, as the lost water remains unbilled, undermining their environmental footprint and financial viability [1–7]. Water losses are the sums of apparent losses (i.e., unauthorized consumption and metering errors) and real losses (i.e., leaks and tank overflows) through the pipeline grid [8,9]. As the complete elimination of leakages is not technically achievable (see [9,10]), one of the most widely used methods for their reduction is that of WDN partitioning into district metered or pressure management areas (DMAs and PMAs, respectively) followed by the decrease of the inlet pressures to the lowest permissible limit that meets the needs of the consumption/demand [10–22].

Network partitioning into DMAs and PMAs was originally introduced in the United Kingdom in the 1980s (see [11,23]) and is one of the most widely applied methods for leakage reduction in WDNs, as real losses increase with increasing water pressure. The implementation of network partitioning has reportedly led to an 85% reduction in water losses in the United Kingdom, as described by Farley [23] and Kunkel [24]. Other benefits of network partitioning include (a) optimal sensor placement to promote effective areal monitoring, (b) fast detection and localization of bursts, (c) fast isolation of contaminated areas (malicious and/or accidental), (d) better overall water quality in cases of multiple water supplies, and (e) facilitation of transitioning from intermittent to continuous supply water systems [25–32].

A main concern regarding district metering is the water quality deterioration, relative to the original network, due to the increase of the residence time of fresh water introduced by the reduction of water flow paths within the partitioned area, in cases of a single water source [32,33]. However, many studies agree that the water reduction quality is not significant (see [25,34–37]), and thus, the water quality should not be used as the primary criterion for WDN partitioning (see [31,38]). The complexity of partitioning an existing WDN into individual PMAs becomes more apparent if one considers the large number of possible solutions and conflicting criteria, e.g., leakage reduction vs. hydraulic resilience. The latter is defined as the capability of a network system with a given topology to react and overcome stress conditions such as pipe breaks, control valve failures, abrupt changes in water consumption/demand and/or pressure heads, etc. [39].

Many current practices are based on semi-empirical criteria, such as setting the network's PMAs/DMAs by following natural (e.g., river banks), administrative (e.g., districts) or engineered boundaries (e.g., roads), taking into account the locations of reservoirs (tanks), the population density, and the altimetry of individual PMAs [25–28,40]. Although network partitioning into small DMAs (or PMAs) may lead to low leakage rates and fast detection of critical events, it increases both the delineation costs (see [41–43]) and the overall hydraulic vulnerability of the study area (i.e., low hydraulic resilience index values, see [44,45]). The optimal DMA/PMA size is usually set empirically so that service connections range between 500 and 5000 properties [46,47]. Karadirek et al. [48] have suggested that the optimal size of a DMA/PMA should not exceed 1000 connections.

Recent studies suggest application of heuristic approaches in water network partitioning is divided into clustering and sectorization phases [32–49]. The clustering phase includes the formation of DMAs based on the original network's connectivity and topology, while the sectorization phase optimizes the valves and meters placement for effective network performance and monitoring in order to minimize financial costs [32,50,51]. Perelman et al. [52], Di Nardo et al. [53], and Khoa Bui et al. [32] classified the developed clustering procedures into six groups based on their algorithmic structures: (a) graph theory methods, (b) community structure algorithms, (c) modularity-based algorithms, (d) multilevel graph partitioning methods, (e) spectral graph algorithms, and (f) the multi-agent approach.

The graph theory algorithm is the most widely used concept for water network clustering. It seeks to divide the network nodes into a desired number of (ideally) equally sized clusters while minimizing the number of inter-connection edges between different clusters [52]. The depth-first and the breadth-first searches are the most well-known variants of the graph theory approach (see [30,33,54,55]) that obtains the number of independent groups through connectivity analysis, commonly based on a shortest-path search while weighting both pipe characteristics and mean nodal pressures (see [54,56–59]). The graph theory-based partitioning algorithms usually include a demanding computational load which leads to time-consuming applications. The multilevel graph partitioning approach, which has been introduced by Karypis and Kumar [60], uses parallel computing approaches in order to equally deliver the computational load to different processors (or processor's cores) in order to minimize the running time of an algorithm (see [37,51,61,62]).

The community structure algorithm is a bottom-up hierarchical approach (see [52]) that seeks to maximize the effectiveness of the partitioning operation using the modularity quality function introduced by Newman [63]. The algorithm combines the sub-clusters that result in the highest modularity (compared to an equally sized cluster of randomly selected nodes) until all computational nodes are grouped. It was first applied to water network clustering by Diao [36] who used an oriented dendrogram cutting approach in order to size clusters between 300–5000 properties. Campbell et al. [64] used the same approach but excluded from their analysis the main transmission pipes (in their study called trunk network), based on the assumption that the closure of these pipes would extensively affect the rest of the network when using the random walk approach to detect clusters. A similar approach was introduced by Ciaponi et al. [65] who first identified the main transmission pipes and then the related clusters by attaching the service pipes to the main network using the shortest-path approach. An analytical presentation of other variants of the modularity-based approach can be found in Khoa Bui et al. [32].

Spectral graph clustering is based on eigenvector and eigenvalue analyses of graph Laplacian matrices (see [53]), using both linear algebra and graph theory (see [66–69]). Application of the spectral clustering method to water networks partitioning combines an adjacency (or connectivity) matrix and a weight matrix for pipes, the latter taking into account the hydraulic parameters of the pipeline (e.g., diameter, length, flow, etc.; see [53]). It is mentioned that particular care should be taken during the selection of weight criteria, as they may lead to significantly different clustering results [32,53]. Liu and Han [70] expanded the spectral graph method to an automated DMA design approach which uses a multicriteria decision method to determine the optimal solution.

The multi-agent approach, which was first introduced to water network partitioning by Izquierdo et al. [71], assumes that the WDN pipes and nodes are autonomous but, also, interactable agents. Using the agents' hydraulic characteristics, the network is divided into homogenous clusters by linking the nearby nodes to water source points (reservoirs) of the corresponding WDN [71,72]. It is mentioned that the multi-agent concept can also be used to determine the homogeneity of an already partitioned network by a different clustering approach [73].

It follows from the discussion above that (a) most clustering methods are strongly affected by user-defined weighting factors that heavily affect the final outcome; (b) the nodes' connectivity usually follows the shortest path approach, which in the case of real complex networks may differ significantly from the original pipeline grid; and (c) the aforementioned clustering algorithms are associated with heavy computational loads leading to time-consuming applications. Under this setting, we conclude that there is no user-unbiased, rigorous approach for the statistical clustering of water distribution networks into district metered areas (DMAs), explicitly taking into account both the topographic variability and the original connectivity of the network. To bridge this gap, the next section focuses on the development of a state-of-the-art tool for the partitioning of WDNs into DMAs [74] using the hierarchical clustering approach introduced by Deidda et al. [75], which is based on Ward's method (see [76–79]) enriched with topological proximity constraints (e.g., nodes' altitude), in order to avoid excessive partitioning of the original water network. The strong points of the introduced approach are that (1) it uses the original pipeline grid as a connectivity matrix in order to avoid unrealistic clustering outcomes; (2) it is statistically rigorous and user unbiased, as it is based solely on statistical metrics, thus not relying on and/or being affected by user-defined weighting factors; and (3) it is easy and fast to implement, requiring minimal processing power, making it suitable for engineering applications.

The rest of the manuscript is organized as follows: Section 2 provides important information about the study area and the available data. The introduced methodology is described in

Section 3, while important results from its implementation are presented and discussed in Section 4. Conclusions and future research directions are summarized in Section 5.

2. Data and Study Area

In the analysis that follows, we use consumption (billed and unbilled), topographic, pipeline-related, and operational (flow-pressure) data which have been collected from the four largest pressure management areas (PMAs, namely Boud, Kentro, Panahaiki, and Prosfygika, see Figure 1) of the city of Patras in western Greece, with a continuous supply. The selected PMAs consist of approximately 202 km of pipeline (mainly HDPE and PVC pipes), cover an area of more than 4 km^2, which corresponds to the entire city center and the most important part of the urban fabric of Patras, and serve approximately 58,000 consumers (based on data from the Hellenic Statistical Authority and the Municipality of Patras), with more than 44,000 active hydrometers (see Table 1). An important point regarding the four PMAs is that they share similar characteristics regarding population and building densities, land uses (which are mostly commercial and residential), and topography, as they lie along the coastline of the gulf of Patras.

Figure 1. Map indicating the locations of the four largest PMAs of the city of Patras in western Greece. Numbers correspond to the entries in Table 1.

Table 1. Name, total area, length of the pipeline grid, population, and number of authorized active hydrometers of the four largest pressure management areas (PMAs) of the city of Patras. Numbers indicate the locations of PMAs in Figure 1.

PMA Number and Name	Area (km^2)	Pipeline Length (km)	Population (cap.)	Number of Active Hydrometers
(1) Boud	0.953	44,954	15,362	10,586
(2) Kentro	1.207	62,174	13,992	16,454
(3) Panachaiki	1.184	51,703	18,003	11,983
(4) Prosfygika	0.802	43,246	10,657	5206

Users' consumption and flow-pressure data, for each of the four PMAs, were acquired from the Municipal Enterprise of Water Supply and Sewerage of the City of Patras (DEYAP) for the eight-month-long high consumption period of 2019, which for the case of Greece spans from 1 March to 31 October [80–83]. It is important to note that all four PMAs did not exhibit any prolonged periods of malfunctioning and/or pressure regulation issues. Data were, first, quality assessed in order to remove any errors related to communication malfunctions of the 3G transmission system [4].

As outlined in the Introduction, in order to manage and reduce leakages in water distribution networks, one needs to first estimate their volume as a percentage of the System Input Volume (SIV). To do so, we used the results obtained by Serafeim et al. [20]. The latter study compared the water loss estimates obtained by applying the water balance (or top-down) approach, and the bottom-up approach based on the MNF estimation method from Serafeim et al. [4], to the aforementioned four PMAs (i.e., Boud, Kentro, Panahaiki and Prosfygika). Table 2 summarizes the allocation of the SIV into revenue water (RW, also referred to as billed authorized consumption, BAC) and non-revenue water (NRW) and their sub-components, for the four PMAs. NRW consists of the unbilled authorized consumption (UAC) and the water losses (WL) component, with the latter being equal to the sum of apparent losses (AL) and real losses (RL, mainly due to leakages).

Table 2. Allocation of the system input volume (SIV) into BAC (billed authorized consumption), UAC (unbilled authorized consumption), AL (apparent losses), and RL (real losses) for the four largest pressure management areas (PMAs) of the city of Patras, for the eight-month long high consumption period from 1 March 2019 to 31 October 2019. Numbers indicate the locations of PMAs in Figure 1.

PMA Number and Name	SIV (m^3/d)	BAC (%)	UAC (%)	AL (%)	RL (%)
(1) Boud	3456	44.36	10.00	4.44	41.20
(2) Kentro	9216	39.23	10.00	3.92	46.85
(3) Panachaiki	6912	54.87	10.00	5.49	29.64
(4) Prosfygika	4032	28.27	10.00	2.83	58.90

3. Methodology

In what follows, we detail the algorithmic steps of the developed approach for the optimal sizing and allocation of pressure management areas. In doing so, we use the EPANET solver (see [84,85]) for hydraulic modeling of water distribution and resilience estimation, and hierarchical clustering enriched with topological proximity constraints (see [75]) for the delineation of PMAs. Before proceeding with the implementation of the algorithm, it is essential to estimate the water equilibrium of the analyzed water system (see Section 2 and Table 2) using, e.g., the recently developed probabilistic minimum night flow (MNF) estimation methodology introduced by Serafeim et al. [4,20]. Figure 2 presents a flow chart of the developed algorithmic steps that were applied to the four largest PMAs of the water distribution network of the city of Patras (see Figure 1), as detailed in Sections 3.1–3.4 below.

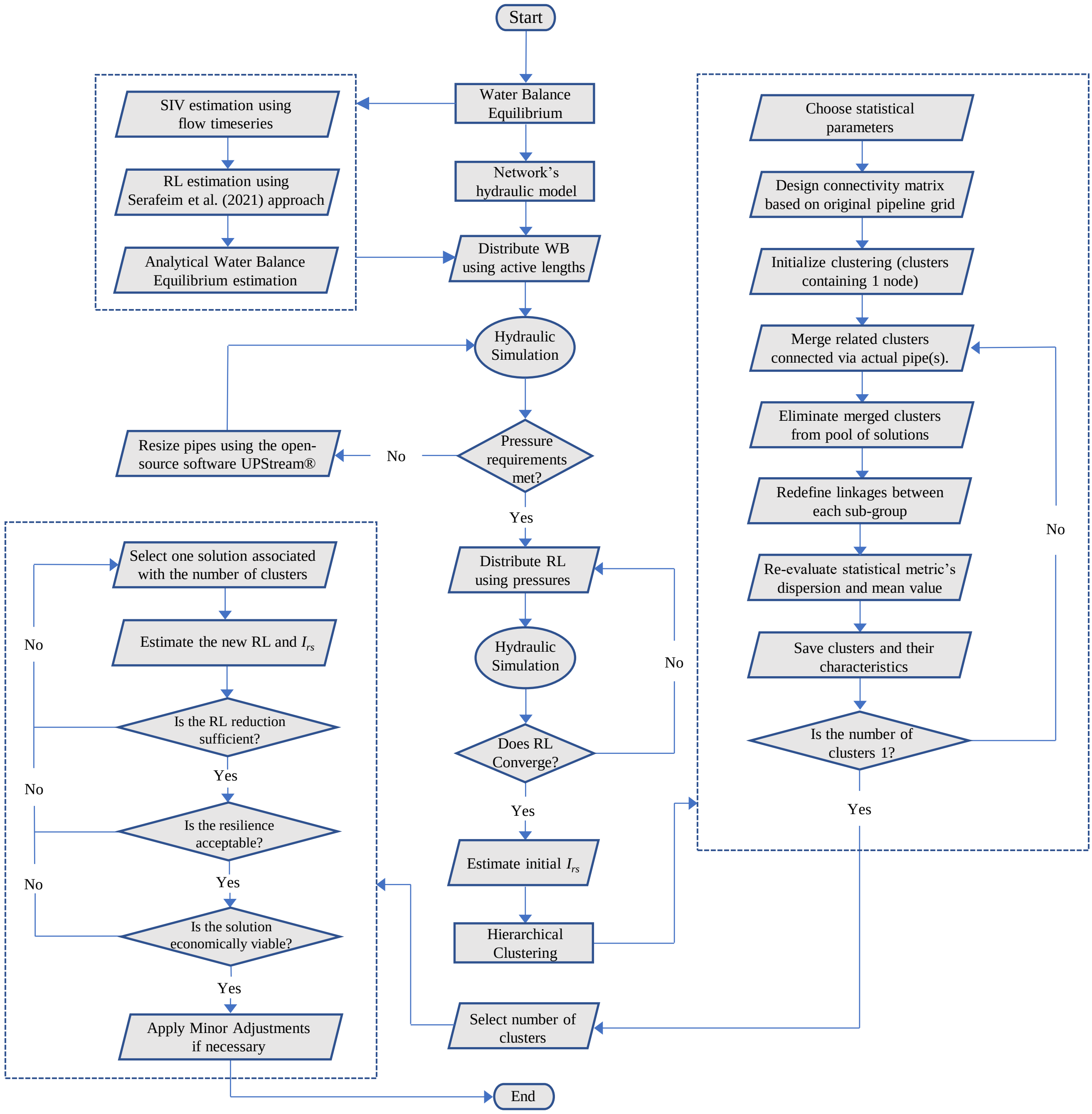

Figure 2. Flow chart of the algorithmic steps of the developed approach.

3.1. *Real Losses (RL, Leakages) Allocation*

To conduct the first/initial set of hydraulic simulations, one needs to define the total water demand at each computational node of the network, as the sum of a demand-driven and a pressure-driven component. The demand-driven component (i.e., the sum of AL, BAC, and UAC) depends on the flow time pattern, as users' consumption varies during the day, and it is distributed to the computational nodes of the network proportionally to the active lengths of its pipe members [86] here defined as the half-sums of the pipe lengths that start (or end) at each node.

The pressure-driven component reflects the network's real losses (RL), which are an increasing function of the applied pressure [87–89]. Since the pressure heads at the computational nodes are not known prior to conducting the first set of hydraulic simulations, we approximate (and later, correct; see below) the pressure-driven component of the demand at each computational node by distributing the total real losses (RL) of the network proportionally to the active lengths of its pipe members.

As nodal pressures directly affect the leakage flow rates (see [21,90,91]), as well as the crack expansion rates (see [10]), we use the zero-order estimates of nodal pressures obtained from the first set of hydraulic simulations (see above) to re-distribute the total leakages (RL) to the computational nodes of the network. We do so by borrowing concepts from Torricelli's Law, assuming that the distribution of RL to computational nodes is proportional to the square root of the excesses of the simulated nodal pressures above the minimum pressure required to meet the consumption standards. This can be accomplished by multiplying the initial RL at each node of the network by the dimensionless parameter:

$$c_i = \frac{(h_i - h_i^*)^{0.5}}{\sum_{i=1}^{n} (h_i - h_i^*)^{0.5}}\text{ , for } h_i > h_i^* \tag{1}$$

where h_i is the simulated total head at node $i = 1, \ldots, n$ (i.e., the sum of the nodal elevation and the pressure head), and h_i^* is the minimum threshold head at node i (i.e., the sum of the nodal elevation and the minimum required pressure head). The hydraulic simulation is repeated until the desired water losses converge.

3.2. Minimum Night Flow (Bottom-Up) Approach

To minimize water losses and the associated financial cost (as the lost water remains unbilled), while maintaining an acceptable level of hydraulic resilience, a proper metric is needed. The resilience indicator relates the water discharges delivered to consumers to the associated demand, during critical operational conditions (such as pipe breaks, pump failures, power outages, control valve failures, abrupt changes in the water consumption/demand and/or the pressure heads, etc.), under a given network topology (operating pressures, topographic variability, length of the pipeline grid, pipe diameters, materials, age, the density of connections, etc.; see [39,92,93]). Under Todini's [94] concept, the resilience index (I_r, see Equation (2)) corresponds to the ratio of the surplus of the available power delivered to the consumers to the maximum power that can be delivered by the designed network under the current topology:

$$I_r = \frac{\sum_{i=1}^{n} q_i^* (h_i - h_i^*)}{\sum_{r=1}^{R} Q_r H_r - \sum_{i=1}^{n} q_i^* h_i^*} \tag{2}$$

where n is the number of computational nodes, q_i^* is the demand (sum of user's consumption, apparent losses, and real losses) at node i, and Q_r and H_r are the total flows (i.e., including users' consumption, apparent losses, and real losses) and heads, respectively, at the inlets $r = 1, \ldots, R$ of the study area (i.e., PMA). Although Todini's index has been applied by many researchers to a number of water distribution systems (see [50,95–101]), some authors proposed different variants (see [87,93,102,103]) primarily due to the fact that, according to Equation (2), real losses contribute positively to the resilience of the network [93].

More specifically, Prasad et al. [102] combined Todini's index with the uniformity of pipe diameters, as minimal diameter changes result in more reliable water circulation. Raad et al. [103] proposed a mixed reliability index where the resilience index is multiplied by the normalized flow entropy (a measure for the uniformity of water flow in pipe members), which has the advantage of addressing the uniformity of both flows (via flow entropy) and power (via the resilience index). Saldarriaga et al. [87] proposed and tested the unitary power measure, which leads to very similar results as Todini's index, defined as the product of the flow rate in each pipe and the piezometric head difference between the pipe's initial and terminal nodes. Baños et al. [104] compared Todini's [94], Prasad et al. [102], and Saldarriaga et al. [87] approaches mentioning that the obtained results are relatively similar. Creaco et al. [93] proposed a generalized resilience index, which uses both demand and pressure-driven modeling approaches in order to account for network leakages. It should be noted that the Creaco et al. [93] approach models leakages (i.e., real losses) as a fraction of the nodal demand, and, as a result, they are not approached as pressure driven.

Herein, we introduce the variant $I_{r,s}$ (see Equation (3)) of the original resilience index in Equation (2), which accounts for the leakages and nodal heads in pressure-driven and mixed pressure-demand ways, respectively, and apply it using the iterative procedure described in Section 3.1:

$$I_{r,s} = \frac{\sum_{i=1}^{n} q_i \left(h_i - h_i^*\right)}{\sum_{r=1}^{R} Q_r H_r - \sum_{i=1}^{n} q_i h_i^*} \quad (3)$$

where Q_r and H_r are defined identically to Equation (2), corresponding to the total flows (i.e., including users' consumption, apparent losses, and real losses) and heads, respectively, at the inlets $r = 1, \ldots, R$ of the study area (i.e., PMA), and q_i denotes the sum of the users' consumption and apparent losses at node i (i.e., contrary to q_i^* in Equation (2), q_i in Equation (3) does not include real losses or leakages). Apparent losses are introduced by unauthorized consumption, illegal connections on the main WDN, metering errors at the inlets of district metered areas or pressure management areas, and incorrect estimates of billed users' consumptions.

3.3. Hierarchical Clustering Approach Based on Ward's Method

As outlined in the Introduction, to partition the original four pressure management areas into smaller ones we use the hierarchical clustering approach enriched with topological proximity constraints as proposed by Deidda et al. [75]. In their study, regarding spatial frequency analysis of rainfall extremes, Deidda et al. [75] embedded a condition of geographic proximity constraints into a hierarchical clustering approach based on Ward's method to identify homogenous and contiguous ensembles of nodes. More specifically, according to Ward's method, one estimates and minimizes the groups' variance of specific statistical characteristics starting from clusters containing a single instance and gradually combining clusters based on Delaunay's triangulation of rain gauge locations in the area of the analysis (for more details, see [75]).

For the purposes of our work (i.e., WDN clustering), we test as characteristic variables for statistical clustering the nodal altitudes and EPANET-calculated pressure heads and use the network's connectivity matrix (i.e., obtained by the original pipeline grid, where each pipe connects two nodes, instead of Delaunay's triangulation) to establish the connectivity between neighboring clusters. Under this setting, starting from clusters containing a single node, we hierarchically merge clusters based on a pool of candidates that are directly connected via actual pipes. More precisely, after each merge, we eliminate the associated clusters from the pool of possible candidates and redefine the linkages between each sub-group while re-evaluating the statistical metric's dispersion and mean value. The aforementioned procedure is repeated until all nodes are grouped into a single cluster (initial network). To exemplify how the selection of characteristic variables affects the clustering procedure, Figure 3 illustrates the partitioning of PMA "Kentro" into two clusters, using as statistical quantities the nodal altitudes (Figure 3a) and the simulated pressures (Figure 3b). One sees that the clustering results obtained for the two variables are very similar (compare Figure 3a,b) and, therefore, at least for the WDN of the city of Patras, one can use the altimetry of the network as the dominant variable, thus avoiding prior hydraulic simulation of pressure heads.

Figure 3. Partitioning of PMA "Kentro" into two clusters based on (**a**) nodal altitudes, and (**b**) simulated pressures.

3.4. Selection of the proper clustering solution

Application of the hierarchical clustering approach described in Section 3.3 to a PMA, results in a pool of possible partitioning alternatives, each one having a different number of clusters: from one (that encompasses the whole network maximizing both the real losses and the resilience index) to the total number of nodes (a solution that minimizes both the real losses and the resilience index). The selection of a proper solution is case-specific, providing an optimal balance between RL reduction and the resulting hydraulic resilience level of the entire network. Thus, for each application, one should set the desired RL reduction rate, as well as the acceptable level of hydraulic resilience reduction, with respect to the available budget. It is noted that, in order to implement the clustering/partitioning strategy described previously and the corresponding hydraulic simulations, some minor adjustments (i.e., the introduction of new and/or the removal of existing pipe members) may be needed to hydraulically isolate the identified clusters and connect them to the main inlet of the study area.

4. Results

In what follows, we apply the methodology developed in Section 3 to the four largest Pressure Management Areas of the city of Patras, and partition them into smaller and easily manageable PMAs, based solely on topographic characteristics (i.e., nodal elevations), as clustering based on calculated pressure heads led to very similar results; see Figure 3 and Section 3.3.

Table 3 presents the inlet point elevation (z_r), applied pressure (P_r), and hourly maximum water consumption (Q_r), for each of the four PMAs studied. The hourly maximum water consumption (Q_r) has been obtained using the flow-pressure time series at the PMA inlets, during the eight-month-long high consumption period of the year from 1 March to 31 October 2019. During the partitioning phase, particular care was taken when selecting the inlet pressures applied to each cluster, so that water supply disruptions at critical points of the network induced by low-pressure heads were avoided, as well as possible pipeline failures induced by high pressures. This was done by connecting the inlet of each delineated cluster to a main distribution pipe and setting its inlet pressure equal to the nodal pressure head calculated for the original PMA configuration (i.e., prior to partitioning).

Table 3. Inlet point elevation (z_r), applied pressure (P_r), and hourly maximum water consumption (Q_r) for each of the four PMAs studied. The corresponding Q_r estimates have been obtained using the available flow-pressure time series at the PMA inlets, during the eight-month-long high consumption period of the year from 1 March 2019 to 31 October 2019. Numbers indicate the locations of PMAs in Figure 1.

PMA Number and Name	z_r (m)	P_r (m)	Q_r (l/s)
(1) Boud	24.32	30.00	60.00
(2) Kentro	21.54	44.00	160.00
(3) Panachaiki	39.85	68.90	120.00
(4) Prosfygika	40.90	40.00	70.00

As noted in Section 3.4, the proposed methodology generates a pool of possible clustering scenarios, each being associated with a different number of clusters. In the current study, the selection of the most proper solution was done solely by contrasting the reduction rate of real losses and the reduction rate of the hydraulic resilience index, with an increasing number of clusters. Please note that this can be considered a viable approach in the absence of financial data, as delineation costs increase with increasing number of clusters. However, in engineering practice, the final decision should be made in view of both the network's specific characteristics and the available budget.

For each of the four study areas in Figure 1 and clustering outcome (i.e., the total number of clusters; one cluster corresponds to the original PMA configuration prior to partitioning), Table 4 summarizes the estimated flow rate of real losses (RL) and resilience index, as well as their percentage reduction (in square brackets) relative to the initial PMA configuration.

One sees that when partitioning the original PMA "Kentro" (i.e., number of clusters equal to one), to two clusters (i.e., sub-PMAs; see Figure 4b), there is a 13.73% reduction of the RL flow rate and a 13.53% reduction of the resilience index of the network. When shifting from two to three clusters, the reduction of RL is minimal (i.e., 0.30%), followed by a 27% reduction (i.e., 0.181/0.262 - 1) of the resilience index. Consequently, it becomes obvious that partitioning the initial network into two PMAs (see Figure 4b) is the most preferable solution in terms of balancing real losses reduction and hydraulic resilience of the final configuration of the network.

Similarly to the case of "Kentro", we divide "Boud" and "Panachaiki" into three sub-PMAs, as there is minimal reduction in the RL rates when moving from three to four sub-PMAs, followed by approximately 9.5% (i.e., 0.202/0.223 - 1) and 6% (i.e., 0.440/0.469 - 1) decrease of the resilience index, respectively (see Figure 4a,c).

Finally, for PMA "Prosfygika", when shifting from three to four clusters, the reduction of RL is minimal (i.e., 1.8%) and possibly incommensurate to the additional delineation costs. Thus, partitioning PMA "Prosfygika" into three sub-PMAs (see Figure 4d) seems the most promising option.

To illustrate the effectiveness of the developed approach, Figure 5 shows 3D plots of the simulated nodal pressure heads of the original and final network configurations for the four PMAs studied. One sees that the pressure heads in the original network of PMA "Boud" (Figure 5a) gradually increase with decreasing elevation (grey surface) along the pipeline grid (yellow color denotes pressure heads above 50 m), leading to increased leakage rates (see Section 3.1). Concerning the clustered network (Figure 5b), at most nodes the pressure heights do not exceed the 40 m threshold (blue color), resulting in reduced leakage rates. This becomes particularly apparent in the lower area of the network (see arrows) where the largest pressure values are met in the original configuration (Figure 5a).

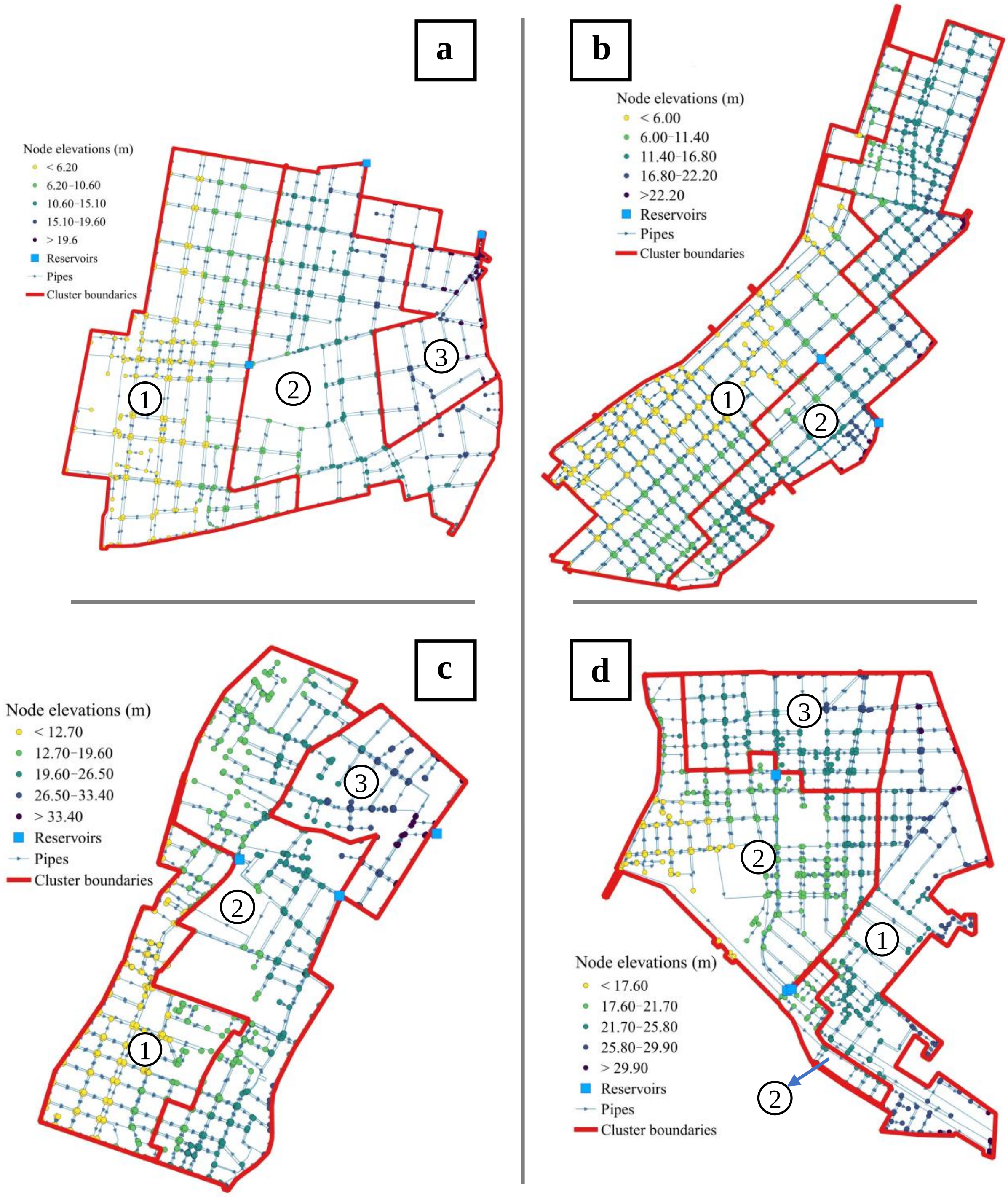

Figure 4. Clustering of original PMAs based on nodal altitudes: (**a**) Boud (three clusters), (**b**) Kentro (two clusters), (**c**) Panachaiki (three clusters), and (**d**) Prosfygika (three clusters). PMA locations are illustrated in Figure 1.

Similarly to "Boud", we observe significant nodal pressure reductions in PMAs "Kentro" (compare Figure 5c,d), "Panachaiki" (compare Figure 5e,f), and "Prosfygika" (compare Figure 5g,h), leading to a significant reduction of leakage rates. It is important to note that all nodal pressures in the original and clustered areas do not fall below the 30 m lowest threshold limit (i.e., $h_i^* = 30$ m; see Equations (2) and (3)) set by the competent Authority (i.e., DEYAP) for the city center of Patras.

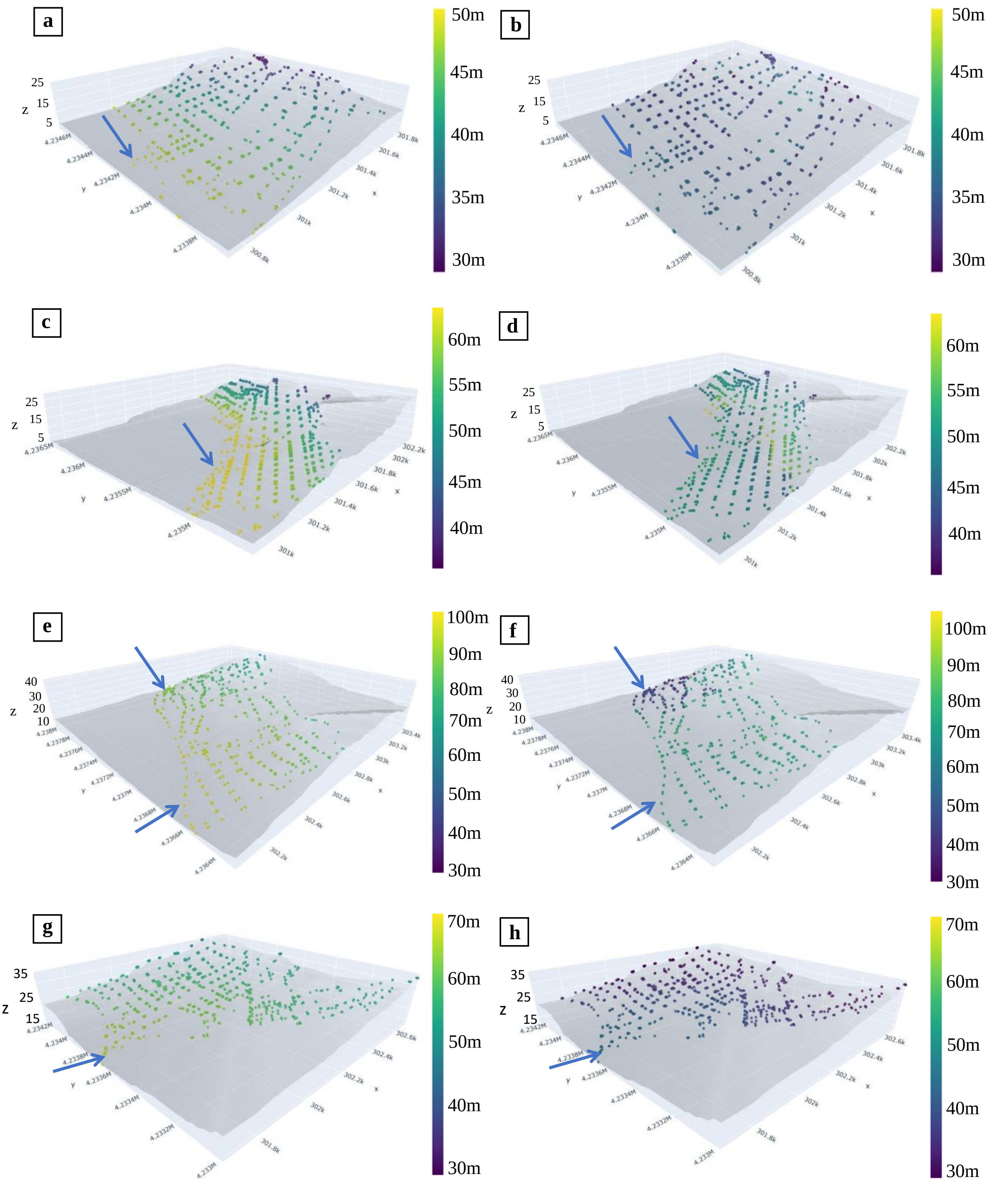

Figure 5. Three-dimensional plots of the location and simulated pressure heads of the original (i.e., one cluster; left column), and final network configurations (right column) of the four PMAs: (**a**,**b**) Boud; (**c**,**d**) Kentro; (**e**,**f**) Panachaiki, and (**g**,**h**) Prosfygika. Ground surface is shown in grey, while arrows indicate regions with a significant decrease of the pressure heads relative to the original network configuration (left column). PMA locations are illustrated in Figure 1.

Table 4. Total number of clusters (one cluster corresponds to the original PMA configuration prior to partitioning), calculated flow rates of real losses (RL), and resilience index estimates for the four PMAs of the WDN of the city of Patras. Values in square brackets indicate percentage reduction relative to the original PMA configuration. Numbers indicate PMA locations in Figure 1.

PMA Number and Name	Number of Clusters	RL (l/s) [% Reduction]	$I_{r,s}$ [% Reduction]
(1) Boud	1 (original PMA)	24.720 [0.00]	0.293 [0.00]
	2	20.573 [−16.78]	0.271 [−7.51]
	3	**17.645 [−28.62]**	**0.223 [−23.89]**
	4	17.365 [−29.75]	0.202 [−31.06]
(2) Kentro	1 (original PMA)	74.960 [0.00]	0.303 [0.00]
	2	**64.668 [−13.73]**	**0.262 [−13.53]**
	3	64.445 [−14.03]	0.181 [−40.26]
	4	63.986 [−14,64]	0.170 [−43.99]
(3) Panachaiki	1 (original PMA)	35.568 [0.00]	0.565 [0.00]
	2	31.811 [−10.56]	0.505 [−10.62]
	3	**28.721 [−19.25]**	**0.469 [−16.99]**
	4	28.493 [−19.89]	0.440 [−22.12]
(4) Prosfygika	1 (original PMA)	41.230 [0.00]	0.225 [0.00]
	2	28.651 [−30.51]	0.142 [−36.66]
	3	**24.367 [−40.90]**	**0.121 [−46.10]**
	4	23.924 [−41.97]	0.120 [−46.55]

5. Conclusions

While the partitioning of water distribution networks (WDNs) into pressure management areas (PMAs) and/or district metered areas (DMAs) is a crucial task for all water experts, no rigorous methodology currently exists that (a) is user-unbiased, avoiding subjective weighting factor selections; (b) uses the original pipeline grid as a connectivity matrix in order to avoid unrealistic delineation outcomes; and (c) is easy and fast to implement, requiring minimal processing power.

To bridge this gap, in the present work, we developed an approach for WDN partitioning into PMAs, which seeks to minimize real losses (leakages) while maintaining a sufficient level of hydraulic resilience in the network. In doing so, we used the EPANET solver for hydraulic modeling of water distribution and resilience estimation and hierarchical clustering enriched with topological proximity constraints (see [75]) for the delineation of PMAs. Regarding the latter, we introduced a variant (see Equation (3)) of the original resilience index which accounts for the leakages and nodal heads in a pressure-driven and mixed pressure-demand ways, respectively, while using, as connectivity matrix, the original pipeline grid of the network, avoiding unrealistic clustering outcomes.

The effectiveness of the developed methodology was tested through a large-scale application study in the four largest PMAs of the water distribution network of the city of Patras, leading to a significant reduction in leakages (see discussion in Section 4 and Table 4) while maintaining an acceptable hydraulic resilience level compared to the original configuration of the PMAs.

Following the discussion above, we conclude that, due to its easiness, minimal computational requirements, and objective selection criteria, the suggested approach can serve as an important step towards developing useful decision-making frameworks for water experts and officials, allowing for improved management and the reduction of real water losses. Future communications will focus on (a) the implementation of the algorithm to other underperforming PMAs of the WDN of the city of Patras, aiming at the reduction of the network's operating costs and environmental footprint; (b) the enrichment of the algorithm as to incorporate structural and/or physical constraints (e.g., streets, rivers, railroads; see [26]) during PMA partitioning based on GIS datasets; and (c) extensions of the algorithm for optimal selection of pressure reducing valve (PRV) locations for the resulting clustering outcomes. The latter task regards the sectorization phase of networks (see Introduction) and has not been addressed in the present communication.

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