Socio-economic characteristics are influencing the temporal and spatial variability of water demand – the biggest source of uncertainties within water distribution system modeling. Improving our knowledge on these influences can be utilized to decrease demand uncertainties. This paper aims to link smart water meter data to socio-economic user characteristics by applying a novel clustering algorithm that uses dynamic time warping on daily demand patterns. The approach is tested on simulated and measured single family home datasets. We show that the novel algorithm performs better compared to commonly used clustering methods, both, in finding the right number of clusters as well as assigning patterns correctly. Additionally, the methodology can be used to identify outliers within clusters of demand patterns. Furthermore, this study investigates which socio-economic characteristics (e.g., employment status, number of residents) are prevalent within single clusters and, consequently, can be linked to the shape of the cluster’s barycenters. In future, the proposed methods in combination with stochastic demand models can be used to fill data-gaps in hydraulic models.

**Keywords** Water demand · Water meters · Hydrologic data · Water supply systems · Hydraulic models · Social factors · Economic factors

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1 Introduction

Water utilities make use of hydraulic simulation software to design and operate their systems in a more effective way (Haestad Methods, 2003). However, models of Water Distribution Systems (WDSs) consist of thousands or tens of thousands of parameters (the length, diameter and roughness of every pipe or the water demand at every node). These parameters are mostly unknown, have to be estimated through model calibration (Zhou et al., 2018) and are fraught with uncertainties. Especially, water demand plays a crucial role in the dynamics of WDSs, since it fluctuates over a variety of temporal and spatial scales depending on the type of consumers (Hutton et al., 2014; Díaz and González, 2020). Additionally, due to the low density of metered consumers and the difficulty to obtain large amounts of demand data in real-time, the variability of water demand is the biggest source of uncertainty in WDS modeling.

Over the last decade, Smart Water Meters (SWMs) that measure and transmit water consumption data at single household level are available in high temporal resolution, from sub-second up to one hour (Boyle et al., 2013), potentially overcoming limitations of current metering practices. These devices have the potential to revolutionize WDS modeling (Gurung et al., 2014; Nguyen et al., 2018; Stewart et al., 2018). However, the large-scale roll-out of SWMs globally is yet to happen since technology adoption barriers—caused by financial, cyber security, privacy issues—hinder the wide-spread deployment of this new technology (Cominola et al., 2015). Furthermore, for water utilities adopting this new technology, the cost-benefit trade off has not yet been quantitatively justified (Cominola et al., 2018; Monks et al., 2019). Besides data management challenges associated with big data streams (Shahee et al., 2020), water companies are further challenged to generate relevant knowledge from the raw consumption data that has to be useful for their hydraulic computer models. However, a combination of system wide consumer information and data from a few SWMs represents a promising approach to reduce modeling uncertainties, by filling in data gaps at the unmeasured locations according to their consumers’ characteristics, without extensively measuring real-time water demand at every node in a WDS. The question is: Is it possible to link raw SWM data to rather general consumer information?

Deriving valuable information from SWMs is by far not trivial, since water use is stochastic by nature (Blokker et al., 2010); no one operates water end-use devices (shower, water tap, toilet, . . .) exactly at the same time each day and extracts precisely the same amount of water during each usage. Nevertheless, by building periodic means over a certain number of days, patterns in water usage behavior emerge. These patterns are called daily demand patterns. The patterns contain information about consumer’s daily routines, reveal irregular consumption behaviors and are shaped by their socio-economic characteristics, e.g., age, gender, economic situation, employment status or family composition. Hereinafter, we will refer to this information as the underlying high-level information. This paper will show that data mining techniques can be used to automatically distinguish daily demand patterns into groups according to their underlying high-level consumer information.

We aim to answer following two questions by applying a novel clustering algorithm on daily demand patterns generated from SWM data:

Q.1. How many distinct daily demand patterns are in a specific SWM dataset?

Q.2. Can we draw conclusions from these pattern shapes on the consumers’ underlying high-level information?

The proposed methods are tested on two artificial SWM datasets generated with the stochastic demand modeling software SIMDEUM (Blokker et al., 2010) and a real-world SWM dataset from Milford, Ohio (Buchberger et al., 2003).

1.1 Related work

Cluster analysis belongs to the family of unsupervised learning algorithms and is a technique to find groups in datasets (Lin et al., 2012). For SWM data analysis, clustering can be used to segment users into groups with similar water-use behaviour (Cominola et al., 2019), e.g., commercial vs. residential or single households vs. multi-family homes. While customer segmentation was mostly focusing in the past on smart meters that measure energy consumption (Espinoza et al., 2005; Nizar and Dong, 2009; Nambi et al., 2016; Kwac et al., 2014), only few studies applied customer segmentation on SWM data. Most research uses k-Means clustering (Lloyd, 2006) in combination with different distance measures. McKenna et al. (2014) clustered SWM data into commercial and residential patterns by applying k-Means on features extracted through fitting Gaussian mixture models. Mounce et al. (2016) used k-Means++ (Arthur and Vassilvitskii, 2007) with correlation distance to cluster data in residential and commercial groups. García et al. (2015) classified demand patterns using k-Means clustering. Cheifetz et al. (2017) made use of Fourier-based time series models for clustering demand patterns. The patterns were qualitatively interpreted as residential, commercial, office, industrial or noise. Cardell-Oliver et al. (2016) identified groups of similar households by features of their high-magnitude water use behaviours based on previous work (Cardell-Oliver, 2013b; Wang et al., 2015). Cominola et al. (2018) applied customer segmentation analysis simultaneously on water and electricity data by clustering extracted eigen-behaviors and
linked the clusters to a list of user psycho-graphic features. Recently, Cominola et al. (2019) coupled non-intrusive end-use disaggregation with customer segmentation to identify and cluster primary water use behaviors.

Clustering techniques are also used as a prior step to demand forecasting. For example, Aksela and Aksela (2011) constructed clusters with \( k \)-Means according to their average weekly consumption before forecasting future demand. Candelieri (2017) clustered SWM data using \( k \)-Means with cosine distance, first to split data into weekdays and weekends, then to split the data into residential, non-residential and mixed type clusters.

In contrast to the studies mentioned above, this paper employs Soft Dynamic Time Warping (SDTW) as time series clustering distance measure. This distance measure is capable of optimally aligning two sequences in time by non-linearly warping the time-axes of the sequences until their dissimilarity is minimized (Dürrenmatt et al., 2013). The time when people use water is highly variable among different users with otherwise similar socio-economic characteristics (Blokker et al., 2008). The SDTW distance measure can expose similarities in daily schedules of inhabitant’s water use that are shifted in time, which are not detectable by using linear time distance measure (Euclidean, correlation). Originally developed for speech recognition (Sakoe and Chiba, 1978), Dynamic Time Warping (DTW) has been applied in the field of water management in the past, but never in the context of time series clustering. Past applications of DTW in water management included burst detection (Huang et al., 2018), analysing residence times in waste water treatment plant reactors (Dürrenmatt, 2011), sewer flow monitoring (Dürrenmatt et al., 2013) or identifying water demand end-uses (Yang et al., 2018; Nguyen et al., 2014).

1.2 Contributions

Although clustering of SWM data has been done before, this paper’s approach is innovative in many aspects. First, a novel method is proposed to cluster SWM data that is capable of finding similarities in daily demand patterns even if they are shifted in the time domain. Hence, it should outperform clustering methods with fixed time distance measures (e.g. Euclidean (Mounce et al., 2016; Garcia et al., 2015)). Second, the proposed methods are tested on SWM datasets that were simulated with the stochastic demand modeling software SIMDEUM. Since the ground truth of these datasets are known, it enables measuring and comparing the performance of different clustering approaches. Third, while former work focused on identifying different types of consumer classes by mainly distinguishing between residential and commercial use, this work goes one step further by investigating which underlying high-level information of residential customers is prevalent in different clusters, e.g. by looking at work schedules or the number of household residents.

Furthermore, we want to highlight the simplicity of the proposed approach compared to other methods. While most of the discussed studies used clustering on burdensome obtained surrogate parameters (e.g., eigenbehaviours (Cominola et al., 2019), high-magnitude water use behaviors (Cardell-Oliver et al., 2016), parameters from fits from Gaussian distributions (McKenna et al., 2014) or Fourier regression mixture models (Cheifetz et al., 2017)), the SDTW clustering method is applied directly on the demand patterns and, hence, does not risk losing valuable information contained in the raw data. Additionally, SDTW enables user segmentation using water consumption data without the need for additional information as, for example, electricity (Cominola et al., 2018) or end-use disaggregated water consumption data (Cominola et al., 2019). Moreover, the SDTW clustering approach is an unsupervised algorithm with no need for prior information nor previous calibration of, for example, consumption threshold parameters.

2 Materials and Methods

2.1 Water demand pattern generation

SWM data (and demand patterns) are time series (Shumway and Stoffer, 2010). A time series \( x \) of length \( M \) is a sequence of data points in strict chronological order

\[
x = \{ x_t \} = (x_1, x_2, \ldots, x_M) \in \mathbb{R}^M.
\]

A water demand pattern \( \bar{x}_p \) is generated by building periodic means from a SWM time series \( x \)

\[
\bar{x}_j^p = \frac{1}{N_p} \sum_{i=1}^{N_p} x_{(i-1) + j} \quad \forall j = 1, 2, \ldots, P,
\]

where \( P \) is the period length and \( N_p = \left\lfloor \frac{M}{P} \right\rfloor \) is the number of full periods in \( x \). More specifically, we will deal throughout this paper with daily demand patterns (\( P = 24 \) hours).
2.2 Soft Dynamic Time Warping (SDTW)

Unlike Euclidean distance, SDTW is able to compare time series of variable size and is robust to shifts or dilations across the time dimension [Cuturi and Blondel (2017)]. The SDTW method computes the best possible alignment between time series. This is relevant for SWM data since the daily water use behaviours of different households might be similar, but shifted in the time domain due to different daily schedules, e.g. caused by different wake-up, working or commuting times.

2.2.1 Two time series

Let \( x \in \mathbb{R}^M \) and \( y \in \mathbb{R}^N \) be two time series. Note that \( x \) and \( y \) do not have to be equally long, nor do they have to have the same sampling rate. Since this publication focuses on clustering daily demand patterns, the time series are always of the same length and sampling rate introduced by the periodic mean in Eq. (2). First, the elements of a pairwise distance matrix \( D \in \mathbb{R}^{M \times N} \) are computed between the points of two time series \( x \) and \( y \):

\[
D_{mn} = \delta(x_m, y_n),
\]

where \( \delta \) is an arbitrary distance measure. A path connecting the upper left corner and the right bottom corner of \( D \) that only allows moves to the right (\( \rightarrow \)), diagonal (\( \downarrow \)) or down (\( \downarrow \)) is called a warping path \( p \). This path is used to align the two time series \( x \) and \( y \). The warping path \( p \) is linked to the binary alignment matrix \( A \in \mathbb{R}^{M \times N} \):

\[
p = (\rightarrow, \downarrow, \downarrow, \rightarrow, \ldots) \triangleq A = \begin{bmatrix}
1 & 1 & 0 & 0 & \cdots \\
0 & 0 & 1 & 0 & \\
0 & 0 & 1 & 1 & \\
\vdots & \ddots & & & \\
\end{bmatrix}.
\]

In the following, we will write \( \mathcal{A} \in \{0, 1\}^{M \times N} \) as the set of all possible (binary) alignment matrices \( A \). The warping distance \( d \) along a warping path \( p \) is defined through

\[
d(A, D) = \sum_{ij} A_{ij} D_{ij} = \text{Tr}(A^T D),
\]

where \( \text{Tr}(\cdot) \) is the trace of a matrix. The optimal warping path \( p^* \) with minimal distance \( d^* \) is computed with SDTW in the following way [Cuturi and Blondel (2017)]

\[
d^*(x, y) = \min_{A \in \mathcal{A}} (d(A, D)) = -\log \left( \sum_{A \in \mathcal{A}} e^{-d(A, D)} \right).
\]

The SDTW distance measure integrates over all possible alignments, is differentiable and leads to a robust smooth solution in an optimization framework [Cuturi and Blondel (2017)]. Although the set of all possible alignment matrices \( \mathcal{A} \) grows exponentially with \( M \) and \( N \), Eq. (6) can be recursively solved with computational complexity of order \( O(MN) \) starting from \( r_{0,0} = 0 \):

\[
r_{i,j} = \delta(x_i, y_j) + \min \{ r_{i-1,j-1}, r_{i-1,j}, r_{i,j-1} \}.
\]

2.2.2 Multiple time series

The optimal distance \( d^* \) can be used to average over multiple time series. The ability to build such averages is a necessary condition for time series clustering. Let \( \{y_l\} = (y_1, \ldots, y_L) \) be a family of \( L \) time series. To average \( \{y_l\} \) with SDTW, the following minimization problem has to be solved

\[
\min_{x^* \in \mathbb{R}^M} \sum_{i=1}^L d^*(x^*, y_i).
\]

This problem is solved using a quasi-Newton method, the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm [Nocedal and Wright (2006)]. The solution \( x^* \) is called the barycenter of \( \{y_l\} \).

2.3 Clustering

The \( k \)-Means clustering method [Lloyd (2006)] is used to identify different demand patterns in the SWM data. The principle behind \( k \)-Means algorithm is to separate the data into a preset number of \( k \) clusters \( C = \{C_1, \ldots, C_k\} \) that

minimize intra-cluster variability and maximize inter-cluster differences [McKenna et al. (2014)]. Let \( \{y_l\} \) be again a family of \( L \) time series. Then \( k \)-Means clustering in the Euclidean metric equals minimizing the following nested sums

\[
\min_C \sum_{j=1}^k \sum_{y \in C_j} ||y - \mu_j||_2, 
\]

(9)

where \( \mu_j \) is the within-cluster mean of \( C_j \). Note that the Euclidean norm \( || \cdot ||_2 \) is only valid when the time series are of equal length \( (M=N) \). Analogously, clustering using the SDTW distance measure is defined as

\[
\min_C \sum_{j=1}^k \sum_{y \in C_j} d^*(x^*_j, y), 
\]

(10)

where \( x^*_j \) is the barycenter of the \( j \)-th cluster.

Furthermore, we introduce a simplified version of the \( k \)-Means clustering algorithm. Instead of investigating the whole daily demand time series \( y \), this algorithm uses only the mean \( (E[y]) \) and the standard deviation \( (\sqrt{E[y^2] - (E[y])^2}) \) of the daily pattern during work hours (10:00-16:00). Hence, the feature space is reduced to a two-dimensional space through following transformation

\[
y \Rightarrow \left( \frac{E[y]}{\sqrt{E[y^2] - (E[y])^2}} \right). 
\]

(11)

Within this work the problem defined in Eq.(9) will be called Euclidean clustering, Eq.(11) Simple clustering, and Eq.(10) SDTW clustering. The latter is capable of finding more general similarities in patterns by allowing more freedom in the time domain and will be benchmarked against Simple and Euclidean clustering. The initial cluster centers are seeded according to the \( k \)-Means++ algorithm [Arthur and Vassilvitskii (2007)] to increase the method’s robustness. Prior to clustering, the time series \( y \) can be normalized:

\[
y'_i = \frac{y_i - \min(y_i)}{\max(y_i) - \min(y_i)}. 
\]

(12)

### 2.4 Performance Measures

Success and error rates are used to validate the clustering results based on the ground truth [Witten et al. (2011)], whereas Silhouette coefficients are used to validate the clusters based on the (dis)similarities of their members [Rousseeuw (1987)]. Two cases have to be distinguished for validating clustering results: (i) if the ground truth is known; (ii) if there exist no information about the true nature of the outcomes. For the first case, the correct allocation of distinct patterns is known and one can compute a success respectively an error rate [Witten et al. (2011)]. In the second case, the allocation and the number of distinct patterns is unknown. For datasets with unknown ground truth, the clustering results can still be validated based on Silhouette coefficients.

#### 2.4.1 Success and error rate

True Positive (TP) is the case if a pattern is assigned to the correct cluster. False Positive (FP) means that a pattern belonging to another cluster is wrongly assigned to the current cluster. A True Negative (TN) is the case when a pattern from another cluster is correctly assigned to the other cluster. Finally, a False Negative (FN) is the case when a pattern belonging to the cluster is wrongly assigned to another cluster. One can define an overall Success Rate (SR) with all above mentioned cases through following equation [Witten et al. (2011)]

\[
SR = \frac{TP + TN}{TP + TN + FP + FN}. 
\]

(13)

The Error Rate (ER) is the complement of SR:

\[
ER = 1 - SR. 
\]

(14)

#### 2.4.2 Silhouette Coefficients

Silhouette coefficients \( S_j \) are properties of a single time series \( y_j \) [Rousseeuw (1987)]. They can be used to determine the quality of clusters when the ground truth is unknown. The \( S_j \) values are computed as a combination of two scores: (i) the mean intra-cluster distance and (ii) the distance between a sample and the nearest cluster that \( y_j \) is not part of.
The mean intra-cluster distance is defined as the average distance of time series \( y_i \) to all other time series \( y_j \) that are members of the same cluster \( C_i \). Let \( y_i \) be the \( i \)th member of the time series belonging to cluster \( C_i \), then its intra-cluster distance (the mean distance between all members \( y_j \) of cluster \( C_i \)) \( a(y_i) \) is defined as

\[
a(y_i) = \frac{1}{|C_i| - 1} \sum_{j \neq i} d(y_j, y_i).
\]

\(|C_i| \) is the number of samples in cluster \( C_i \) and \( d \) is an arbitrary distance measure. The second score \( b(y_i) \) is the distance \( d \) between the time series \( y_i \) of \( C_i \) and its nearest cluster \( C_j \):

\[
b(y_i) := \min_{i \neq j} \frac{1}{|C_j|} \sum_{y_k \in C_j} d(y_k, y_i) = \frac{1}{|C_j|} \sum_{y_k \in C_j} d(y_k, y_i),
\]

where \( y_k \in C_j \) represents the members of the cluster \( C_j \). The two scores are combined in following way to obtain the Silhouette coefficient of a time series \( y_i \) \cite{rousseeuw1987silhouettes}:

\[
S(y_i) = \frac{b(y_i) - a(y_i)}{\max(a(y_i), b(y_i))}.
\]

By definition, the Silhouette coefficient is between \(-1 \leq S_i \leq 1\). Higher \( S_i \) values relate to a model with better defined clusters, i.e., each time series is closer to its own cluster members than to the nearest cluster.

The specific number of clusters \( k \) is required as an input parameter for the \( k \)-Means algorithm. Average Silhouette coefficient for all \( L \) time series can be used to compare clustering results for different \( k \) to decide on the number of clusters that are in the data

\[
\overline{S} = \frac{1}{L} \sum_{i=1}^{L} S(y_i).
\]

Investigating the behavior of \( \overline{S} \) as a function of \( k \) is subsequently called cluster analysis.

### 2.5 Datasets

The SDTW methodology is tested on three datasets of water use at single family homes: (i) an artificial SWM dataset generated with SIMDEUM \cite{blokker2010simdeum} consisting of single-person households, (ii) another SIMDEUM dataset with multiple-person homes, and (iii) a measured SWM dataset from Milford, Ohio \cite{buchberger2003smart}. Daily demand patterns with a time resolution of 30 minutes are generated and smoothed with a two-hour moving average. A more detailed description of the datasets can be found in the supplemental materials.

#### 2.5.1 SIMDEUM single-person households

SIMDEUM is a water demand end-use model that is capable of simulating water usage at household level with a time resolution of down to one second \cite{blokker2010simdeum}. The model generates randomly water end-use events based on statistical information of users and end-use devices. The information includes census data for the number of residents in a household, their age distribution, the average number of appliances, their daily routines, as well as frequency, duration and intensity for different end-uses such as kitchen tap uses, toilet flushes, number of showers taken per day, washing machine or dishwasher uses, etc.

To generate the first simulated dataset, we simulated 100 single-person households with different daily routines. For each household, the water consumption of its residents for a period of 100 days was simulated. The dataset consists of adult inhabitants with (50) and without (50) jobs away from home. Consequently, the employment status of the occupants is the underlying high-level information responsible for the different pattern shapes. Throughout this paper, we will refer to the first half of the household demand patterns as work patterns and to the second half as home patterns.

#### 2.5.2 SIMDEUM multiple-person households

The second simulated dataset was produced by generating SIMDEUM simulations for 200 multi-person homes with one to five residents according to the household statistics in The Netherlands (see Table 2 in \cite{blokker2010simdeum}); again simulated for 100 days for each household. The high-level information consists of the type of the household (one-person, two-person, family), the number of residents, their age distribution, their daily schedules, their profession (employed, unemployed, retired, kid, teenager).
2.5.3 Measured SWM data from Milford (Ohio)

The measured SWM dataset contains data from SWM installed at 21 single-family houses in Milford (Ohio, USA) recorded between the 1st of April and 31st of October 1997 [Buchberger et al., 2003]. Since user behaviour and, hence, daily demand patterns can differ significantly between weekends and weekdays [Alvisi et al., 2007], patterns were generated separately for weekdays and weekends. The underlying high-level information contains the number of residents and the pattern type (home, work).

3 Results

3.1 Simulated dataset with single-person households

The dataset consists of work and home patterns. We will refer to a cluster consisting predominantly of work patterns as work cluster, and to a cluster whose majority patterns are home patterns as home cluster. The intention of this numerical experiment is to see (i) if the SDTW clustering approach is able to extract the employment status of the residents; (ii) if we are able to identify the correct number of distinct patterns in the dataset with cluster analysis; and (iii) how SDTW clustering performs compared to the benchmark algorithms (Simple and Euclidean clustering). Figure 1 presents the SIMDEUM dataset. Figure 1(a) shows the daily demand pattern of a single-person household where the occupant is staying at home throughout the day. Additionally, the standard deviation $\sigma$ is shown. Figure 1(b) provides the 100 days water usage data of this household. Figure 1(c) presents the demand patterns of the whole SIMDEUM dataset (100 households). The work patterns are shown as dotted purple lines, the home patterns are shown as solid green lines. Furthermore, the mean over all patterns is shown as a dashed black line. Variations of the patterns from the mean are clearly visible, both, in time and in magnitude. First, SDTW clustering is applied on the dataset. The patterns are normalized prior to clustering to suppress the influence of different average consumption, so that the algorithm focuses only on pattern shapes and not on magnitudes. Figure 2 (a) and (b) present the clustering results for $k=2$ and the performance measures; the home cluster on the left side (a) and the work cluster on the right side (b). Demand patterns classified correctly (TP) are shown as solid green lines, FP are depicted as dashed purple lines. The work cluster is a pure cluster consisting only of work patterns. The SR is 82% and ER is 18% (see the doughnut chart in Figure 2(b)).

![Figure 1: Representation of the SIMDEUM single-person household dataset. (a): Daily demand pattern constructed from 100 days of SWM data and its standard deviation $\sigma$ of an example household. (b): The example household’s water consumption over 100 days. (c): Demand patterns (mean over 100 days) of the whole dataset showing 50 work patterns, 50 home patterns and the mean over all demand patterns $\mu$.](image-url)
Furthermore, Figure 2(a) and (b) show the barycenters $\mathbf{x}^\star$. Additionally, the within-cluster mean $\mathbf{\mu}$ is shown to illustrate the difference of $\mathbf{x}^\star$ and $\mathbf{\mu}$. It can be seen that the SDTW clustering approach is capable of segmenting the daily demand patterns according to the employment status of the inhabitants. Furthermore, the barycenters show the expected water use behavior of the user groups. The users within the home cluster use water over the whole day, while users in the work cluster have almost zero consumption while their residents are at work. Second, we perform a cluster analysis to see if we can identify the correct number of patterns. Note that the distinct number of patterns is two (work, home), since there is no other high-level information contained in the data. The results of the cluster analysis with the SDTW method are presented in Figure 3(a) and compared with the benchmark algorithms. Additionally, the individual Silhouette coefficients $S(y_i)$ are shown for the correct number of clusters $k=2$ (Figure 3(b)). The maximum $\bar{S}$ value indicates the most probable number of clusters in the dataset. The SDTW and the Euclidean clustering approach are capable of finding the correct number of clusters (maximum at $k=2$), whereas the simple algorithm overestimates the number of clusters. Figure 3(c) shows a comparison of the three clustering algorithms with respect to the SRs, where the SDTW algorithm clearly performs best.
3.2 Simulated dataset with multiple-person households

The purpose of this experiment is to apply the SDTW algorithm on a more complex dataset. Figure 4 shows the dataset. On average, the consumption grows linearly with the household size or the type of household (one-person, two-person, family). Hence, this high-level information (the type of households, the number of users) is supposed to be influential on the pattern shape. Furthermore, the growing variance in the data leads to a lot of consumption overlaps between households of different resident numbers, making it difficult to segment the data by consumption only. First, we will perform a cluster analysis to identify the number of distinct patterns in the dataset, followed by a closer look on the cluster’s barycenters. Second, we will try to identify the most influential high-level information. Again, the performance of the SDTW method is compared with Simple and Euclidean clustering.

The cluster analysis is shown in Figure 5 (d) together with the individual silhouette coefficients for SDTW clustering for $k = 2$ (e). The average silhouette value is $S = 0.61$. All clustering algorithms identified two distinct clusters. Clustering results for $k = 2$ are depicted in Figure 5. Cluster $C_1$ contains mostly family households, $C_2$ one- and two-person homes. It is assumed that the algorithm segments the daily patterns into family and non-family homes (one-person and two-person households). This consideration is taken into account to compute the success rate, which equals SR = 97% (Figure 5 (f)). A comparison with the benchmark algorithms shows again that SDTW clustering has the highest SRs (see Figure 5 (f)). Figure 5 (c) shows a histogram of the cluster members in dependency on the resident numbers. The clusters are well separated for one and two persons as well as for four and more persons. Three-person households are present in both clusters with a much higher probability of being a member of $C_1$ (family households).

3.3 Measured dataset (Milford)

The same technique are now applied to the Milford dataset. Subsequently, a closer look at the clustering results and individual Silhouette coefficients is used to identify possible outliers within the clusters. Figure 6 shows the dataset. The increase in consumption by household size is not as prominent as for the SIMDEUM simulations (see Figure 4). Furthermore, the variance is high leading to overlaps between households of all different resident numbers. Hence, the number of residents will not play a big role in segmenting the patterns as other information, e.g., the work schedules.

The results of the cluster analysis can be found in Figure 7 (d). The average silhouette coefficients $S$ show a very distinct maximum for $k = 2$ for all clustering approaches; resulting in the assumption that two distinct patterns are present in the dataset. Figure 7 (a) to (c) present clustering results for SDTW for $k = 2$. The clusters are not connected to the number of residents as for the SIMDEUM multi-person homes, but show to be dependent on the residents work schedules. The barycenters $\mathbf{x}^*$ clearly show that cluster $C_1$ (Figure 7 (a)) is the work cluster, $C_2$ represents the home cluster (Figure 7 (b)). Thus, the work schedules are identified as the most influential high-level information with a SR=95 %. SDTW clustering results again in the highest SRs (see Figure 7 (f)). Additionally, Figure 7 (c) shows a histogram of the cluster members in dependency of their work schedules. The clusters are well separated in the work and home cluster. Only two patterns are misclassified. These special cases are depicted in Figure 8. The weekday pattern of Home 11 has a
Figure 5: Clustering results for SIMDEUM multi-person households obtained with SDTW clustering. SDTW: (a) Family household cluster and (b) one- and two-person home cluster, all shown with barycenters $x^*$, cluster means $\mu$ and colors according to the resident number. Additionally, doughnut charts are shown in (b) depicting the SR and ER in segmenting the daily patterns in one- and two-person homes vs. family homes. Histograms for the resident distribution within the clusters are depicted in (c), including translucent black bars for the total number of homes. Additionally, results with negative Silhouette coefficients ($S(y_l) < 0$) are highlighted. (d) Cluster analysis plots and (e) silhouette plots for $k = 2$ for SDTW clustering. (f) Comparison of clustering performance with respect to SRs.
different shape than all other patterns with three peaks. It is marked as a work pattern through expert opinion, but is a cluster member of the home cluster. The weekend pattern of Home 15 is the other way around: classified as work pattern, but marked as home pattern (Note that all weekend patterns are supposed to be home patterns). A closer look reveals a shape that is between the shape of work and home patterns, showing distinct morning and evening peaks but no prominent valley during the day. Furthermore, by looking at the negative Silhouette coefficients, two dissimilar patterns are identified (weekend patterns of Home 3 and 6). These patterns have a pre-eminent morning peak, while missing a peak in the evening.

Figure 6: Representation of the Milford dataset consisting of 21 households and divided into weekday and weekends. (a): Daily weekday and weekend demand pattern of the households colored according to the number of residents. The mean $\mu$ is depicted as a dashed black line. (b): Violin plots for the average daily consumption as a function of the resident number.

Additionally to the results presented in this section, further numerical studies on the same datasets can be found in the supplemental materials accompanying this paper. The additional results contain comparisons between SDTW algorithm with a clustering based on the original DTW score, and time invariance robustness tests of Euclidean clustering compared to the SDTW algorithm. Both tests were performed on the first dataset. In both cases, the SDTW algorithm showed to be superior compared to DTW and Euclidean clustering. Moreover, the supplemental material contains more details on the benchmark tests comparing the performance of SDTW clustering with the Simple as well as the Euclidean clustering algorithm.

4 Discussion

As outlined in the Introduction, the first question this study sought to determine was the number of distinct demand patterns in a specific SWM dataset. Cluster analysis was used to answer this question. The SDTW clustering method was able to identify the correct number of clusters ($k = 2$) for the simulated single-person households (Figure 3), which correspond to the work schedules of the residents. Cluster analysis on the SIMDEUM multiple-person clearly revealed the presence of two different demand pattern types (Figure 5(d) and 7(d)). The clusters of the SIMDEUM multi-person household are connected to the type of houses (family vs. one- and two person houses) or to the number of residents, respectively. Although the number of residents ranges from one to five, we assume that the household’s average consumption and its variance leads to substantial overlaps of patterns with different resident numbers, making it difficult for clustering algorithms to disaggregate the dataset in five separated groups. It has to be noted that none of the benchmarking algorithm was able to identify more than two clusters in this dataset, as well. For the Milford dataset, two different clusters have been found, which are linked to the residents’ work schedules. By looking at the individual Silhouette coefficients in the Milford dataset, additional outlier patterns were identified with different shapes (e.g., a missing evening peak) (Figure 8, Home 3 and 6). Note that the identification of outlier patterns can be done in an automatic way. Benchmark tests with other clustering algorithms clearly showed a better performance of the SDTW algorithm with respect to success rates over all datasets (see supplemental material for further details). However, the better clustering performance of the SDTW method comes with higher computational times introduced by DTW distance computations. Nonetheless, the computation time grows only linearly with the length of the time series. For
Figure 7: Clustering results for Milford dataset showing (a) the work cluster and (b) the home cluster, all shown with barycenters $x^*$, cluster means $\mu$ and colors according to the resident number. (c) Histograms for the resident distribution within the clusters are depicted in (c), including translucent black bars for the total number of homes. Results with negative Silhouette coefficients ($S(y_l) < 0$) are highlighted. Additionally, doughnut charts are shown depicting the SR and ER in segmenting the daily patterns in work and home patterns. (d) Cluster analysis plots and (e) silhouette plots for $k = 2$ for SDTW clustering. (f) Comparison of clustering performance with respect to SRs.
The data analyzed in the manuscript the clustering analysis took less than a minute on a common personal computer. Therefore, computational complexity does not state a problem for real world applications.

The second question addressed the underlying high-level information responsible for the different pattern shapes. For the SIMDEUM single-person household dataset, the differences in the patterns were caused by the residents’ employment status (work, home). In this case, the shapes of the SDTW barycenters can be intuitively linked with the employment characteristics, resembling qualitatively better the expected behavior (e.g., work patterns have low valleys in consumption while the residents are at work). For the SIMDEUM multi-person households, the clustering approach resulted in clusters based on household type (one- and two-person versus family) with a high accuracy of 97 %. For the Milford dataset, barycenters were linked to the residents’ work schedules. Application of the clustering algorithms resulted in barycenters of a home cluster with high consumption during the day and a work cluster in which the consumption is low during work hours. Reasons for the low but non-zero consumption of the work cluster could be (i) that the households are multiple-person households in contrast to single-person households in the first SIMDEUM dataset and, hence, some of the inhabitants stay at home during the day, or (ii) that the inhabitants have different daily schedules on different days of the week, e.g., four-day jobs. In summary, it can be said that the out-of-home activities (work, school, . . .) and the number of household residents are the most important high-level information revealed by the automatic clustering algorithm.

In future, we plan to focus on analyzing more complex datasets (i) with other important high-level information of (e.g., household income, age, and gender distribution), (ii) from different countries, (iii) with different end-use devices or (iv) disaggregated by end-uses. Besides the clustering of consumption patterns, the proposed method is additionally valuable for (i) finding outlier patterns between different customers (e.g., unusual high water consumption) or (ii) identifying changes in patterns over time (e.g., changing daily routines caused by illness or unemployment). The next research steps will concentrate on parameterizing stochastic end-use models based on this approach to provide more realistic demand simulation tools.

5 Conclusion

Since water demand is shaped by socio-economic characteristics, knowledge on these characteristics and how they are connected with the dynamics of water consumption is highly valuable for WDS modeling. This work shows how data science algorithms can be used to link SWM data to high-level information. The novel SDTW clustering technique is capable of finding similarities in daily demand patterns even when they have similar features shifted in time. In this manuscript, the technique is tested on simulated and measured SWM datasets. It is shown for the dataset where the
ground truth is known that SDTW clustering is able to classify patterns accurately as well as to identify the correct number of patterns. It is shown that SDTW clustering outperforms commonly used clustering algorithms (e.g. Euclidean clustering). Furthermore, the shape of the cluster’s barycenters can be linked to user characteristics. The employment status and the number of household residents is identified as the most important underlying high-level information. Additionally, the methodology presented in this work can be used to identify outlier within demand patterns.

Generally, the findings of this study clearly demonstrated that socio-economic characteristics manifest themselves in the shapes of water usage patterns and, hence, these characteristics can be identified from the datasets through the proposed clustering approaches. Since demand patterns can be linked to high-level information, this information can be used to infer and simulate water consumption at unmeasured points in a WDS, either by using directly the daily demand patterns in hydraulic simulation software, or by using a SIMDEUM model parameterized by customers’ socio-economic data. For example, in the Netherlands, socio-economic data are freely available at a neighborhood (post-code) level from the national statistical agency. This offers the opportunity of complementing data-gaps in hydraulic models and, hence, the possibility of reducing model uncertainties.

A Data Availability Statement

Some or all data, models, or code generated or used during the study are available in a repository or online in accordance with funder data retention policies. (https://github.com/steffelbauer/swm_sdtw)

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