

Document downloaded from:

<http://hdl.handle.net/10251/120337>

This paper must be cited as:

Pastor-Jabaloyes, L.; Arregui De La Cruz, F.; Cobacho Jordán, R. (2018). A filtering algorithm for high-resolution flow traces to improve water end-use analysis. *Water Science & Technology: Water Supply*. 19(2):451-462. <https://doi.org/10.2166/ws.2018.090>



The final publication is available at

<http://doi.org/10.2166/ws.2018.090>

Copyright IWA Publishing

Additional Information

A filtering algorithm for high-resolution flow traces to improve water end-use analysis

L. Pastor-Jabaloyes*, F.J. Arregui* and R. Cobacho*

* ITA-Grupo de Ingeniería y Tecnología del Agua, Dpto. de Ingeniería del Agua y Medio Ambiente, Universitat Politècnica de València, Camino de Vera s/n, València 46022, Spain
(E-mail: laupasja@ita.upv.es; farregui@ita.upv.es; rcobacho@ita.upv.es)

Abstract

One of the main difficulties encountered when designing automatic tools for water end use identification is the inherent noise present in recorded flow traces. Noise is mainly caused by the inability of the monitoring equipment to accurately register water consumption and data-loggers to register, without distortion, the signal received from the water meter. A universal filtering algorithm has been developed to remove noise and simplify water consumption flow traces with the aim of improving future automatic end use identification algorithms. The performance of the proposed filtering methodology is assessed through the analysis of 21,647 events. Water consumption data were sourced from two different water end use studies, having consumers and monitoring equipment with dissimilar characteristics. The results obtained show that the algorithm is capable of removing an average of 70% of the data points that constitute the flow traces of the complex events examined. The simplified flow traces allow for faster and more accurate disaggregation and classification algorithms, without losing significant information or distorting the original signal. The ability of the proposed filtering algorithm to fit the original flow traces was benchmarked using the Kling-Gupta efficiency coefficient, obtaining an average value above 0.79.

Keywords

Filtering; water end use event; water micro-component; smart metering data; residential water flow trace disaggregation

INTRODUCTION

Sustainability in the use of water resources has been an international concern for many years. There is a clear need to promote efficient water usage in urban areas (UNEP, 2011) in order to face future challenges driven by an increasing population demand and a decreasing amount of water resources of the required quality. Demand side management strategies can be a useful instrument for reducing water consumption if they are properly designed and implemented.

A more accurate characterization of residential demand is a powerful tool that gives effective support to water demand modelling and management (Buchberger and Wells, 1996; Guercio et al., 2001; Alvisi et al., 2003; García et al., 2004; Blokker et al., 2010; Creaco et al., 2015, 2016). The development of high resolution smart meters facilitates a more accurate and detailed characterization of water consumption profiles (Cominola et al., 2015). Frequent readings of the meters, approximately every second, can even provide how water is used by the different appliances (end use identification) inside the house (DeOreo et al., 1996; Mayer et al., 1999; Cubillo et al., 2008; Beal and Stewart, 2011). This information can also be employed to develop more accurate forecasting models (Bennet et al., 2013; Makki et al., 2015) or even provide ad-hoc feedback to each customer and promote behavioural changes towards efficiency (Fielding et al., 2013). Unfortunately, with the available technology, these studies involve a considerable investment in human and capital resources. As a result, such an approach is not economically viable for large samples (Nguyen et al., 2013a) and it is necessary to develop automatic processing tools to disaggregate and categorize high resolution consumption data into individual (single-use) water end use events.

Filtering of water flow traces is the preliminary step to develop automatic water end use disaggregation and classification algorithms. The main objective of this first step is to simplify the flow traces and to accurately identify the start and end of each water consumption event (which can

be overlapped with other uses in the household) by means of changes in the flow rate gradient. Filtering of the flow signal is crucial because it decreases the complexity of the algorithms that will be needed to disaggregate overlapped into single-use events. The disaggregated single-use events define the consumption characteristics associated to the various end uses present in the household, and these particular characteristics of the disaggregated consumption events are the input data to train forthcoming classification algorithms.

Currently, there are three commercial software packages available for residential end use disaggregation and classification: Trace Wizard® (DeOreo et al., 1996), Identiflow® (Kowalski and Marshallsay, 2003) and BuntBrainForEndUses® (Arregui, 2015). These tools are not completely described in the scientific literature, and there is not detailed published information about the type of water flow trace processing algorithms employed. An alternative approach to end use identification was proposed by Larson et al. (2012). This unconventional approach relies on data collected through pressure sensors instead of water meters. Even though in this case the filtering strategies utilised are explained in detail, the type of signal - pressure instead of flow rate - is completely different and the filtering methodology cannot be directly applied to consumption flow traces. The development of the filter presented in this paper has taken the work conducted by Nguyen et al. (2013b) as a starting point: the approach known as *gradient vector filtering technique*. However, the direct application of the technique by Nguyen et al. (2013b) to the consumption data available in this study was not possible because: 1) the purpose of the gradient analysis conducted by the mentioned authors was to detect the start and end of an event and not to filter the flow trace 2) the available raw flow trace signals were too noisy to use Nguyen et al. (2013b) gradient filtering algorithms. The reason for these dissimilarities in noise levels can be found in the equipment employed to measure and register water consumption, which had quite different specifications to the one used by Nguyen et al. (2013b). Therefore, further development of the existing filtering algorithms was needed to make them applicable to noisier flow traces.

The new filter developed by the authors improves flow trace gradient analysis and enhances signal processing, accounting for volume and flow rate changes. The filter is structured in four stages: noise reduction, gradient analysis, identification of sequences of homogeneous gradients, and volume adjustment. R (R Core Team, 2013) was the programming language selected to write the algorithm code. The filter uses 10 configuration parameters that provide the flexibility to solve a wide variety of consumption events. An automatic calibration procedure that finds the best combination of configuration parameters of the filter was developed (Pastor-Jabaloyes et al., 2018). The applicability of the proposed algorithms was tested on two different sets of flow traces extracted from two different end use studies (in total, 21,647 sampled consumption events). The performance of the filter was assessed through four indicators: volume error, Kling-Gupta efficiency or KGE coefficient (Gupta et al., 2009), reduction in the number of points used to define the event, and savings in memory requirements. To gain a better understanding of the numerical performance indicators of the filter, an additional visual inspection of 52 events, selected according to three parameters of complexity, was conducted.

METHODS

Filter architecture

Essentially, the filtering algorithm has to emulate the mental simplifications carried out by a human analyst. For example, when overlapped events are manually disaggregated, a human analyst does not confuse the flow rate changes due to signal noise with those related to the start or the end of a single event. Ignoring the first type of changes - caused by noise in the flow signal - while maintaining the second type - caused by overlapped uses of water - involves a simplification of the flow trace that the

filtering algorithm has to overcome. To successfully achieve this objective, the first stage of the filter calculates the physical characteristics of the water flow trace (e.g. gradient change or flow rate change magnitude). Then, these characteristics are compared with predefined thresholds. Finally, a simplification of the flow trace will be applied provided that certain conditions on the established thresholds are satisfied. In total, 10 thresholds have been defined, which are the input parameters of the filtering algorithm.

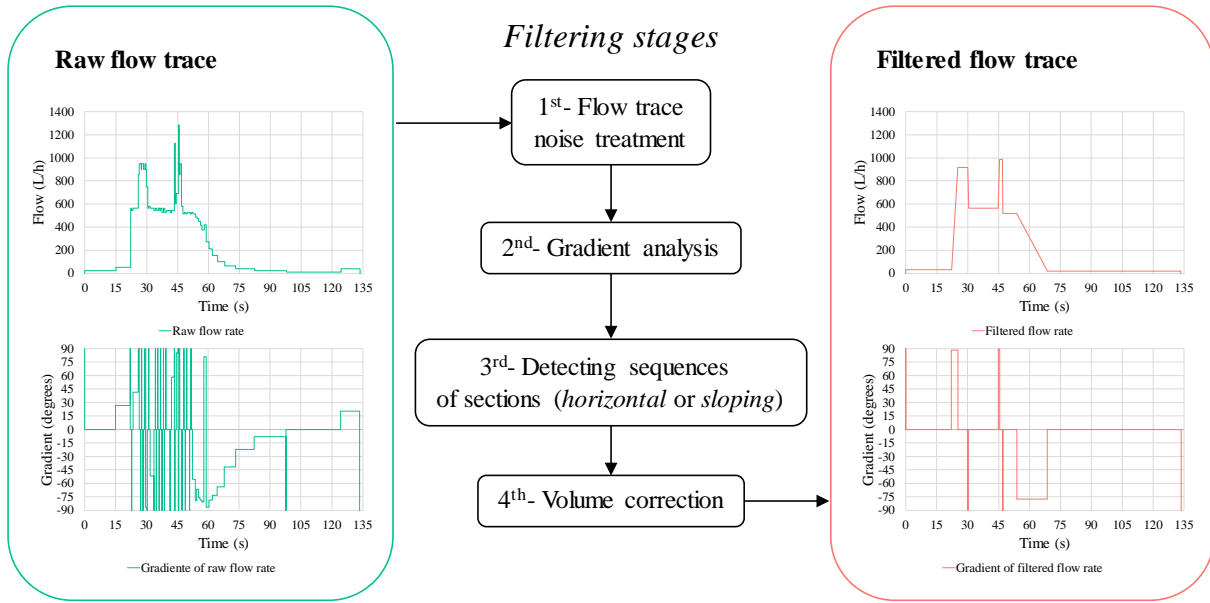


Figure 1. General structure of the filtering process.

The general filtering process has been implemented in a four-stage structure, as shown in Figure 1. The first filtering stage aims at removing the flow rate changes that are caused by the flow trace noise. Three general types of noise have been identified (Figure 2): (i) *pure noise*, which is defined as the volume below a threshold that is enclosed by two consecutive flow rate changes whose signs are opposite; (ii) *fissure noise*, which is conceptually similar to the previous one, but the changes define a gap (i.e. the first flow rate change is negative and the second one is positive); (iii) noise that is present at the start and/or the end of a sloping section. Therefore, the volume and gradient associated to a flow rate change need to be determined to characterise these types of noise. Given a water flow trace expressed as a vector $\mathbf{fr}=(fr_1,fr_2,\dots,fr_i,\dots,fr_m)$ in litres per hour (L/h), and recorded at time t_i in milliseconds (ms), a vector of flow rate change \mathbf{a} and a vector of time window \mathbf{tw} are defined as:

$$a_j = fr_{j+1} - fr_j, \quad 1 \leq j < m \quad (1)$$

$$tw_j = t_{j+1} - t_j, \quad 1 \leq j < m \quad (2)$$

Where index j refers to those points of \mathbf{fr} that satisfy:

$$fr_{i+1} - fr_i \neq 0, \quad 1 \leq i \leq m \quad (3)$$

Based on vectors \mathbf{a} and \mathbf{tw} , the volume vector \mathbf{v} is defined as:

$$\begin{cases} v_j = |a_j| * tw_j, & \text{if } a_j > 0 \\ v_j = |a_j| * tw_{j-1}, & \text{if } a_j < 0 \end{cases}, \quad 1 \leq j < m \quad (4)$$

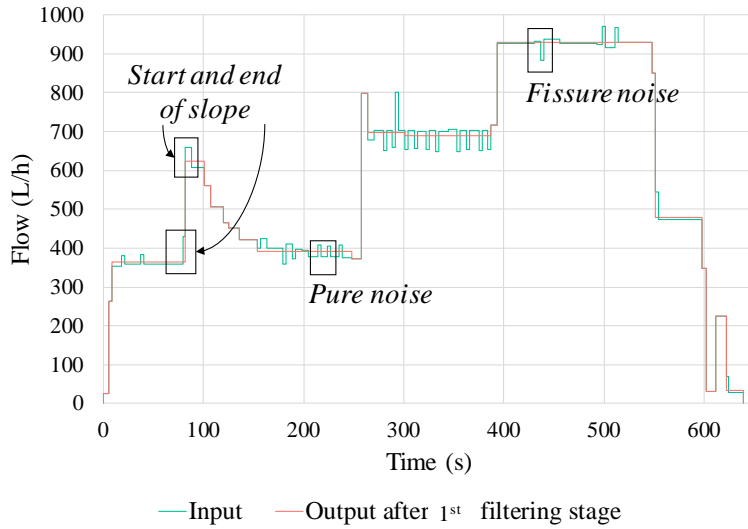


Figure 2. Examples of different types of noise on a raw flow trace (*Input*). Water flow trace resulting from the first filtering stage (*Output after 1st filtering stage*).

On the other hand, to calculate the gradient vector \mathbf{g} (Equation 5), it is necessary to apply a *scale parameter* ($p1$, ranging from 130 h·ms/L to 170 h·ms/L; default value equal to 150 h·ms/L) to ensure that the gradient growth, as a function of the flow rate change, is slow enough for large time windows ($tw_i > 6000$ ms).

$$g_j = p1 * a_j / tw_j, \quad 1 \leq j < m \quad (5)$$

Note that Equation 3 implies that the points in the original flow trace for which $tw_k = t_i - t_{i-1} = 1$ ms ($1 < k < m$) are not considered in the calculation of \mathbf{a} , \mathbf{tw} , \mathbf{v} y \mathbf{g} . Besides $p1$, four more parameters are used in the first filtering stage: a) *maximum volume* ($p2$) enclosed by *pure* and *fissure noise* (ranging from 0.1 L to 0.18 L; default value equal to 0.16 L); b) *maximum flow rate change* ($p3$) to take into account the appearance of *fissure noise* (ranging from 40 L/h to 120 L/h; default value equal to 80 L/h); c) *maximum gradient difference* ($p4$) expressed in degrees, to identify the start or end of a sloping section (ranging from 30° to 75°; default value equal to 40°); and d) *percentage of a stepped section with slope* ($p5$) that belongs to the first or last flow rate change, which is necessary to avoid removing the first or last flow rate change when $p5$ is exceeded and *fissure noise* conditions are satisfied simultaneously (ranging from 0.001% to 10%; default value equal to 5%). Figure 2 shows the output after the first filtering stage.

The second filtering stage carries out a gradient analysis. The gradients obtained after the first filtering stage do not allow for a proper identification of the start or end of certain sloping sections. For example, in Figure 3-a1 there are two different sloping sections that are identified as a single one (discontinuous lines), since the gradients from both sections are high and have the same sign (Figure 3-a1). The solution adopted to overcome this problem is to consider an auxiliary point in the gradient calculation when the flow rate change and time window are both above certain thresholds. If a gradient sign change occurs, an extra point is also created. Consequently, four more parameters have been defined: a) *minimum flow rate change* ($p6$, ranging from 40 L/h to 120 L/h; default value equal to 100 L/h); b) *minimum time window* ($p7$, ranging from 5000 ms to 14000 ms; default value equal to 10000 ms); and c) two parameters related to the time window to process short events (duration < 5 min): *minimum time window* ($p8$, ranging from 3000 ms to 11000 ms; default value equal to 6000 ms) and its *percentage of total duration* ($p9$, ranging from 0.001% to 10%; default value equal to 5%). The results obtained after this second filtering stage can be examined in Figure 3-b1. Once the

gradient is corrected, each section is classified as *horizontal* or *sloping*. To conduct this classification the last parameter of the filter is defined: *maximum gradient (p10)*. Horizontal sections have been defined as having slopes below *p10*, which can range between 3° and 30° (default value equal to 10°).

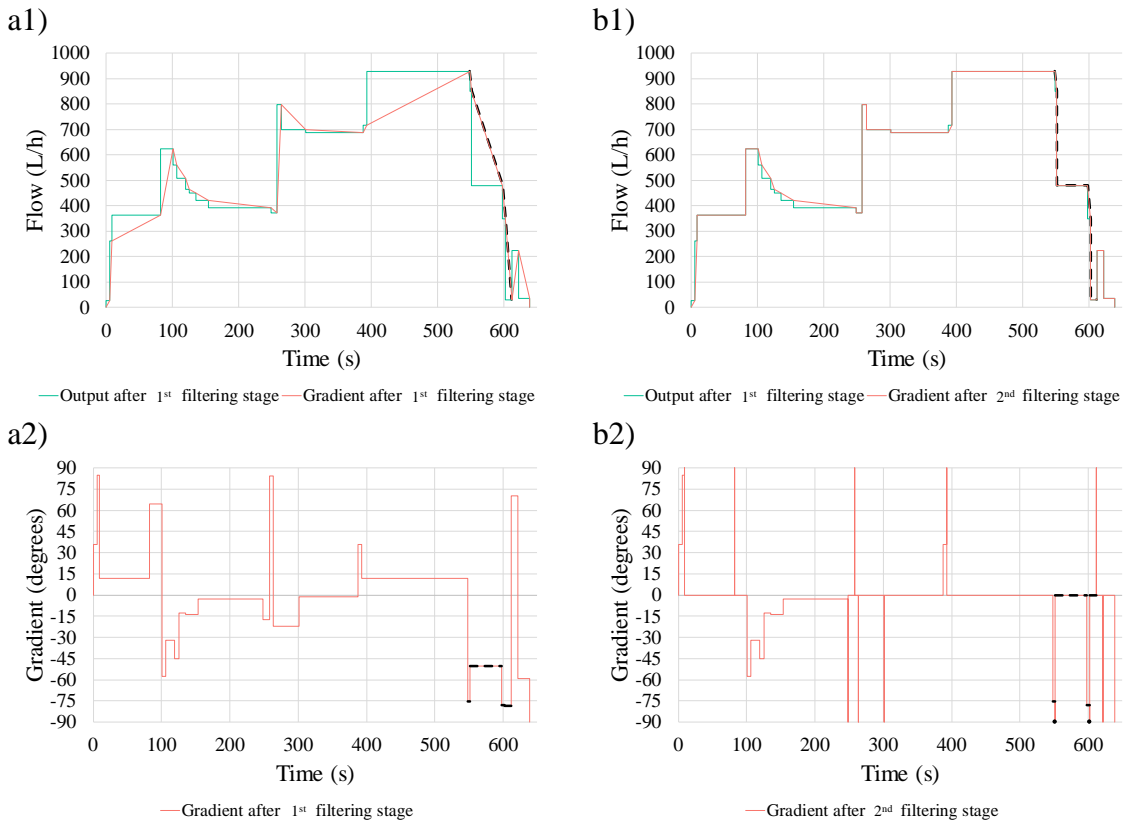


Figure 3. *a1)* and *a2)* illustrate the flow trace and gradients after the 1st filtering stage applied to the raw flow trace used as an example in Figure 2; *b1)* and *b2)* show the flow trace and gradients after the 2nd filtering stage.

The third filtering stage detects sequences of sections that have been classified in the same category (*horizontal* or *sloping*). If the flow rate change of a new sloping section is below *p3*, it cannot be considered the start or end of a single event, then that section is removed.

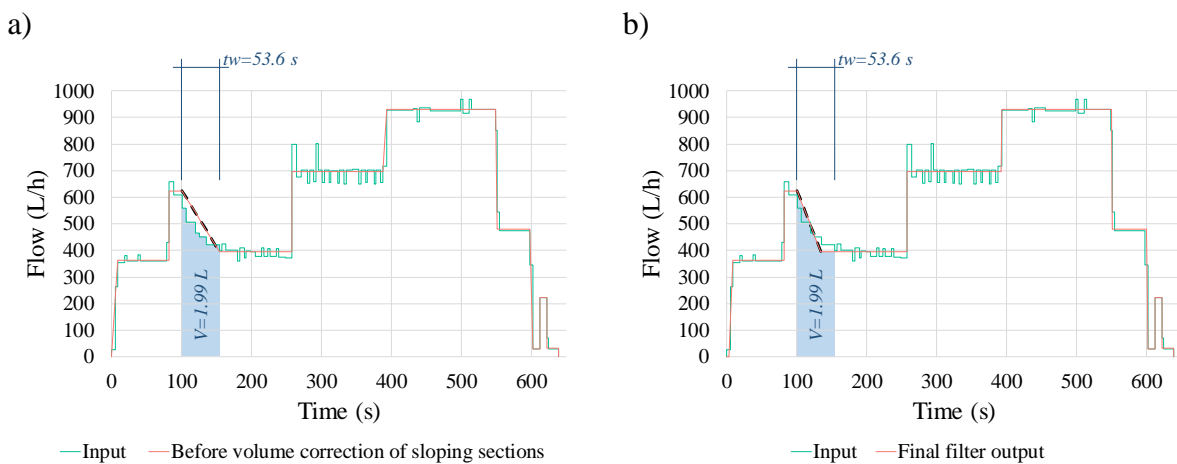


Figure 4. Correction of a sloping section to adjust volume differences between the original and the filtered flow trace.

The fourth filtering stage corrects the filtered events to match the current volume (area under the flow trace) with the volume defined by the original flow trace. Given a time window, the algorithm equates the average flow rate of the horizontal sections with the average flow rate of the original flow trace. For the sloping sections, the slope is adjusted to balance out the volume differences. Figure 4 illustrates an example, in which a volume excess of a filtered event (Figure 4-a) is corrected by modifying the gradient of a sloping section (Figure 4-b, discontinuous line). The final result of the complete filtering is shown in Figure 4-b (*Final filter output*).

Validation of the filtering process

Data from two water end used studies, in geographically distant regions, has been used to test the filtering algorithm. Besides the demographic and physical characteristics of the households, another significant difference between these studies is the type of monitoring equipment installed. In study 1 (R1), the smart meters were ELSTER Y250 single-jet (maximum flow rate of 5 m³/h) or ELSTER Y250M multi-jet (maximum flow rate of 7 m³/h) depending on the type of residential household monitored. These meters produce a pulse every 0.04 L and 0.06 L consumed, respectively. Newly designed data loggers (Watchmeter, IoTsens) calculated the average consumption flow rate every 3 s. This recording mode was chosen to optimize the files size and the transmission to the server via GPRS/GSM. On the other hand, in study 2 (R2), a piston type volumetric water meter was used (Aquadis+, ITRON), which generates a pulse every 0.1 L. The data logger (Cosmos, SENSUS) recorded the occurrence time of each pulse with a resolution of 0.02 s. The significant differences between the monitoring equipment and their settings directly affects the water flow traces obtained. Flow traces from R1 present a soft noise and stepped flow rate changes. On the contrary, flow traces from R2, show rapid flow rate changes and significant signal noise (Figure 5). In order to verify the filtering algorithm ability to suit a heterogeneous variety of events, the samples used for validation include cases from these two studies.

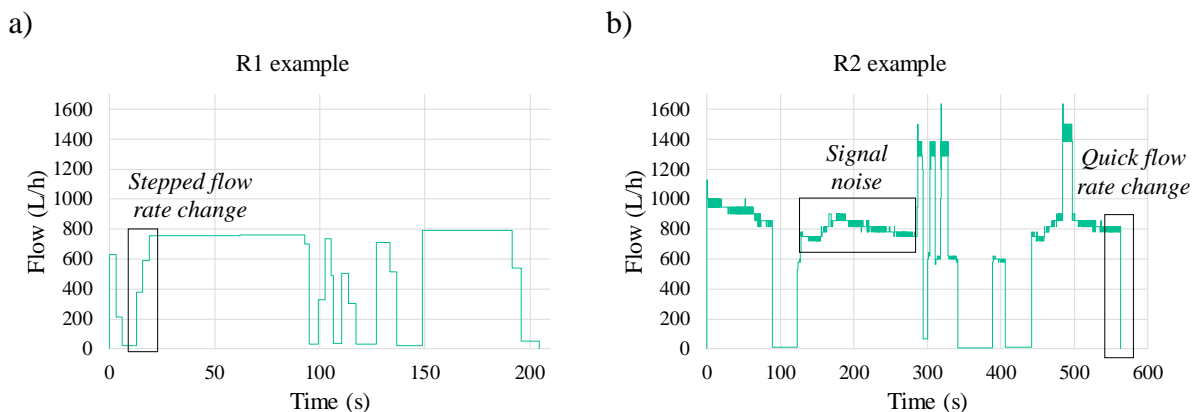


Figure 5. a) example of a stepped flow rate change from R1; b) example of a noisy signal and quick flow rate changes from R2.

To validate the methodology, a sample of households from both studies was selected. Average daily consumption and presence of continuous leakage were two factors considered. The final sample included 20 households - 10 from R1 and 10 from R2. Due to the specific characteristics of the households in each study, cases with high average daily consumption and presence of internal leaks are more common in R1 (Figure 6). Normally, these two features are correlated with long events and a high number of simultaneous water uses; and, in turn, with more complex flow traces. Therefore, consumption data from R1 presented more difficulties for the filtering algorithm.



Figure 6. Daily consumption for the sample of households taken from studies R1 and R2.

A two week period of analysis has been chosen for each household, which corresponds to readings obtained in Autumn 2015 for R1 and in Autumn 2016 for R2. A total of 21,647 water consumption events were recorded. The calibration methodology of the filtering algorithm described in Pastor-Jabaloyes et al. (2018), which is based on the Elitist Non-Dominated Sorting Genetic Algorithm NSGA-II, allows for an automatic selection of the configuration parameters of the filter for each event. Numerical indicators of the filter performance were calculated for the 21,647 events analysed. To gain a better understanding of the indicators interpretation, a sub-sample of 52 events was selected for detailed and visual inspection. In order to include as much diversity of events as possible, three parameters were established to quantify the filtering complexity of the events: a) event *duration* ($i1$), a long duration of an event usually implies overlapping of several water uses; b) *number of points* ($i2$) that defines the event in the water flow trace, which is higher in those events defined by a noisier flow trace; c) *maximum flow rate* ($i3$), which is normally higher for overlapped events.

Table 1. Summary of the event characteristics used as input data for the validation process. Size and distribution of the sub-sample analysed.

Group	Duration (min)	Original sample of events	Sub-sample of events					
		% Total volume	Number of points	Maximum flow (L/h)	Complex events		Number of events final sample	
					R1	R2	R1	R2
Gr1	<0.5	1.2%	>6	>603.8	149	46	2	2
Gr2	>=0.5 & <1.7	4.8%	>10	>729.0	156	107	3	3
Gr3	>=1.7 & <4.7	13.1%	>18	>782.6	190	141	6	6
Gr4	>4.7	80.9%	>52	>1018.0	232	96	15	15

The first quartile, median and third quartile of duration from the original sample (21,647 events) are shown in Table 1. As a result, four groups were considered (Gr1, Gr2, Gr3 and Gr4). For each group, the third quartile of the number of points was determined. Then, the events of each group with a number of points below their respective third quartile were sifted out. Finally, the third quartile of the maximum flow rate was computed for the remaining sample. The events taken into account to select the final sub-sample have a maximum flow rate above the third quartile calculated for each group. From all the events that satisfy the conditions previously defined, 26 events per study (52

events in total) have been randomly chosen. Their distribution for each group is based on the fact that 75% of the events from the original sample (event duration less than 4.7 min) represent just 19.1% of the total volume (Table 1). Therefore, the three first groups have less weight in the size of sub-sample analysed.

RESULTS AND DISCUSSION

The use of a 10 parameter filter ensures the applicability of the filter to almost any type of flow trace and water consumption event. For the case study presented, a combination for the 10 parameters was found automatically for each one of the 21,647 events. This was done by applying the calibration methodology of the filter described in Pastor-Jabaloyes et al. (2018) that is based on the use of the Elitist Non-Dominated Sorting Genetic Algorithm NSGA-II. This methodology automatically finds, depending on the specific characteristics of each event, the values of the parameters that need to be used by the filter. Therefore, the consideration of 10 parameters does not become a drawback of the filter but an advantage as it can be applied to simplify almost any flow trace signal.

The performance of the filter for the 21,647 events was assessed by means of four numerical indicators. The first one was the total volume error expressed as a percentage of the volume in the original water flow trace. The second indicator was the Kling-Gupta efficiency or KGE (Gupta et al., 2009). This indicator is a dimensionless index that can range from $-\infty$ to 1, 1 being the best value, obtained when a perfect fitting of the original flow trace is reached. It evaluates the ability of the filtering algorithm to fit the original water flow trace. R package *hydroGOF* was used to calculate the KGE index. The other two indicators measure the memory savings achieved by filtering the signal: the reduction in the number of points (expressed as a percentage), and the reduction in the memory requirements (expressed in bytes).

Table 2. Average values of performance indicators per duration group and research by applying the filtering algorithm to the 21,647 sampled events.

	R1				R2			
	Gr-1	Gr-2	Gr-3	Gr-4	Gr-1	Gr-2	Gr-3	Gr-4
Number of events	4612	3787	5732	2306	1308	1118	1644	1140
Avg. Duration (min)	0.31	1.02	11.03	20.00	0.18	1.05	3.10	38.80
Avg. Volume (L)	0.5	2.3	25.2	36.8	1.08	4.9	6.4	31.5
Avg. volume error (%)	0.007%	0.03%	0.07%	0.13%	0.011%	0.02%	0.12%	0.17%
KGE	0.86	0.82	0.79	0.80	0.93	0.84	0.909	0.87
Number of points reduction (%)	17.5%	33.8%	55.8%	63.7%	52.6%	78.2%	63.3%	85.1%
Memory requirements reduction (bytes)	27	123	1089	1679	230	1283	1711	9552
Memory requirements reduction (%)	8.5%	24.3%	46.9%	56.5%	35.3%	70.9%	61.2%	81.9%

Table 2 summarizes the average values obtained for the four performance indicators in each duration group. As shown, for all four groups, the average volume error of the filtered events is less than 0.17%. In relation to the goodness of fit, the average KGE values are typically above 0.8 in all groups. The performance achieved indicates that the filtering algorithm simplifies water flow traces following accurately the shapes defined by the original trace. However, it should be highlighted that the objective is not to exactly reproduce the original trace, since imperfections caused by noise in the signal must be removed. Thus, reaching a value 1 for the KGE index is not a desirable performance of the filter. On the other hand, memory saving indicators show that filter improves as events become longer. Results show that, for the most complex events in group Gr4, the percentage of point reduction can be as high as 63.7% in R1 and 85.1% in R2. Indicators related to memory requirement savings follow a similar trend. Therefore, this filter enables a much more efficient storage, with no

information losses, of the huge amount of data recorded in water end uses studies. In addition, simplified water flow traces can be more easily displayed in a web viewer while minimizing slowdown problems, as they are faster to upload and process.

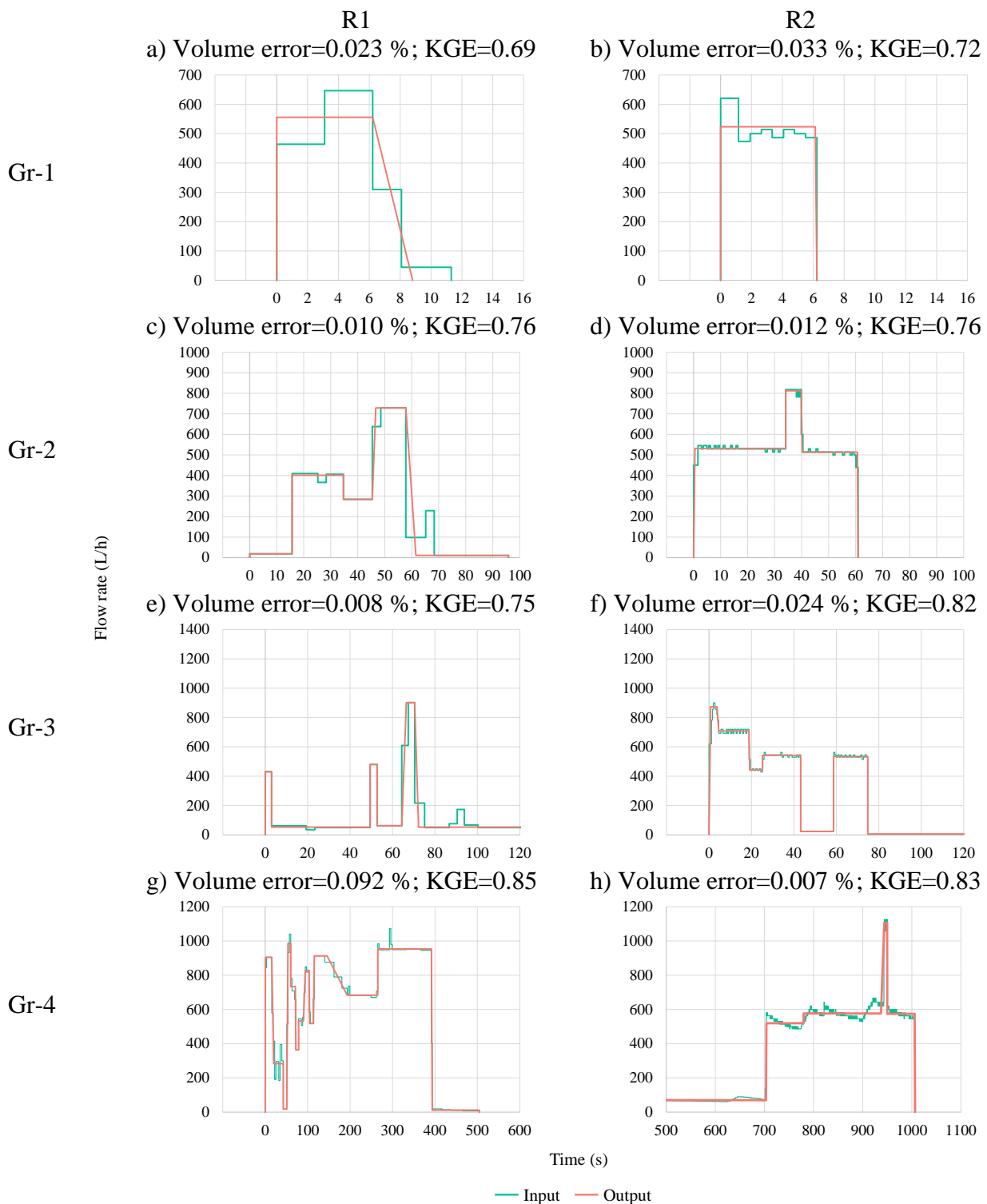


Figure 7. Analysed events per study and duration group that produced lower values of KGE indicator.

Since numerical indicators of the performance of the filter, especially those related to the goodness of fit, are difficult to interpret, a more detailed analysis that includes a visual inspection was conducted in a sub-sample of 52 events. These events were selected according to three parameters of complexity

as previously explained. Table 3 summarizes the average values of the numerical performance indicators of the filter for these 52 events.

Table 3. Average values of performance indicators per group that are reached by applying the filtering algorithm to the 52 analysed events.

	Gr1	Gr2	Gr3	Gr4
Average volume error (%)	0.02%	0.01%	0.20%	0.05%
KGE	0.807	0.809	0.85	0.93
Number of points reduction (%)	55.3%	73.8%	77.3%	81.0%
Memory requirements reduction (bytes)	114.0	1346.7	1904.7	12326.4
Memory requirements reduction (%)	32.0%	67.7%	71.8%	78.7%

Figure 7 shows examples of eight events from the sub-sample analysed - one per study and duration group - presenting lower values of KGE index, which means worse fitting to the original flow trace. In all cases, and considering the time scale, the differences between the original and the filtered flow traces are negligible. The filtering algorithm is even capable of ignoring small flow rate changes due to pressure variations (Figure 7-h) and it does not recognize these changes as the start or end of an event.

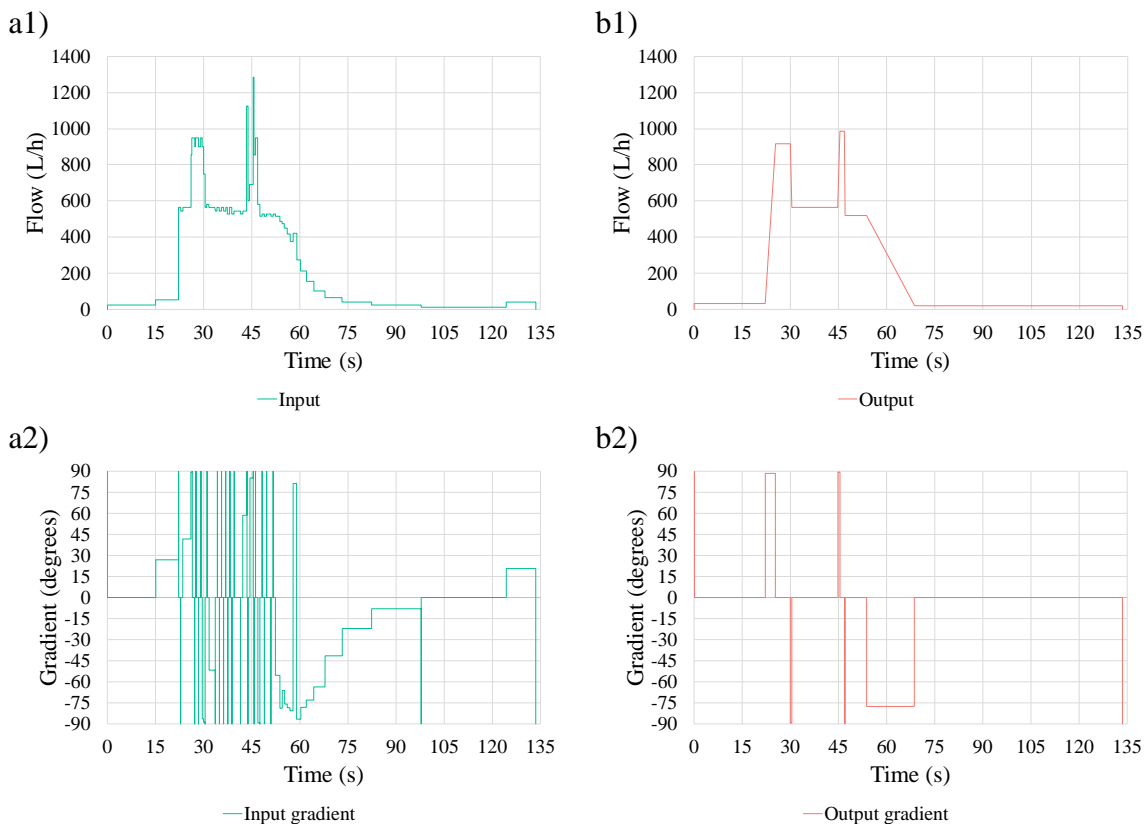


Figure 8. Water flow traces and gradients before (*a1* and *a2*) and after (*b1* and *b2*) filtering.

Filtering the flow signal and smoothing the gradient will also improve the overall performance of future disaggregation and classification algorithms that can be developed. This can be seen in Figure 8 showing a toilet flush (ballcock type) overlapped with two faucets. The gradient calculated on the basis of the original water flow trace is extremely erratic (Figure 8-a2): gradient changes due to noise are similar to the gradient changes caused by the start or end of a water consumption event. This is because the small flow rate changes associated with the noise in the signal occur in a very short time

window. Furthermore, the distortion that takes place around time equal 58 s (Figure 8-a1) divides the sloping section in two parts. However, in the filtered flow trace (Figure 8-b1), the start or end of a new single event can be easily identified, as signal distortions were removed. However, the shape of the original flow trace is maintained regardless of the filtering applied. In other words, the filtered flow trace keeps the relevant characteristics of the water consumption appliance, and can be used more efficiently by future disaggregation and classification algorithms without compromising their effectiveness.

CONCLUSIONS

Water end use analysis is today a powerful tool in urban water management. However, with the metering technologies currently available, any end use study requires a considerable investment in capital and human resources. This is the reason behind the efforts for developing automatic tools with the objective of disaggregating water flow traces and classifying single-use events. Within this research, filtering of flow trace signals is a fundamental preliminary step to improve the efficiency and effectiveness of these automatic tools. This paper presents a new universal filtering algorithm that can be applied to virtually any flow trace obtained with a variety of metering equipment. The performance and adaptability of the methodology has been tested by analysing 21,647 events sampled from two different end use studies. The results obtained show that for the most complex events, 63.7% for R1 and 85.1% for R2 of the points that define the original water flow trace are removed, saving a significant amount of memory and simplifying the following disaggregation and classification processes. Shapes and volumes of the original flow traces are maintained, as demonstrated by an average KGE values greater than 0.79 and the volume error indicators. Finally, to gain a good interpretation of this numerical indicator that measures the goodness of fit, a visual inspection of 52 events selected according to three parameters of complexity was conducted.

The filtering algorithm presented facilitates the identification of the start and end of overlapped water consumption events and, hence, the disaggregation of complex events. As a consequence, more effective and efficient strategies based on the simplified filtered water flow traces can be developed. Furthermore, the already established strategies can also benefit from this new tool, as the resulting flow traces maintain most of the characteristics of the original ones.

ACKNOWLEDGEMENTS

This study has received funding by the IMPADAPT project /CGL2013-48424-C2-1-R from the Spanish ministry MINECO with European FEDER funds and from the European Union's Seventh Framework Programme (FP7/2007e2013) under grant agreement no. 619172 (SmartH2O: an ICT Platform to leverage on Social Computing for the efficient management of Water Consumption).

REFERENCES

- Alvisi, S., Franchini, M., Marinelli, A. (2003). A stochastic model for representing drinking water demand at residential level. *Water Resources Management* **17**(3), 197-222, <https://doi.org/10.1023/A:1024100518186>.
- Arregui, F. (2015). *New software tool for water End-Uses studies*. Presentation of 8th IWA International Conference on Water Efficiency and Performance Assessment of Water Services, Cincinnati, USA.
- Beal, C.D. and Stewart, R.A. (2011). *South East Queensland Residential End Use Study: Final Report*. Urban Water Security Research Alliance, Technical Report No. 47.
- Bennet, C., Stewart, R.A., Beal, C.D (2013). ANN-Based residential water end-use demand forecasting model. *Expert Syst. Appl.* **40**, 1014–1023, doi:10.1016/j.eswa.2012.08.012.
- Blokker, E. J. M., Vreeburg, J. H. G., Van Dijk, J. C. (2010). Simulating residential water demand with a stochastic end-use model. *J. Water Resour. Plann. Manage.* **136**(1), 19–26, doi:

10.1061/(ASCE)WR.1943-5452.00000002.

- Buchberger, S. G. and Wells, G. J. (1996). Intensity, duration and frequency of residential water demands. *J. Water Resour. Plann. Manage.* **122** (1), 11-19, doi: 10.1061/(ASCE)0733-9496(1996)122:1(11).
- Cominola, A., Giuliani, M., Piga, D., Castelletti, A., Rizzoli, A.E. (2015). Benefits and challenges of using smart meters for advancing residential water demand modeling and management: A review. *Environmental Modelling & Software* **72**, 198-214, <https://doi.org/10.1016/j.envsoft.2015.07.012>.
- Creaco, E., Farmani, R., Kapelan, Z., Vamvakeridou-Lyroudia, L., Savic, D. (2015). Considering the mutual dependence of pulse duration and intensity in models for generating residential water demand. *J. Water Resour. Plann. Manage.* **141**(11), 04015031, doi: 10.1061/(ASCE)WR.1943-5452.0000557.
- Creaco, E., Alvisi, S., Raziye, F., Vamvakeridou-Lyroudia, L., Franchini, M., Kapelan, Z., Savic, D. (2016). Methods for preserving duration–intensity correlation on synthetically generated water-demand pulses. *J. Water Resour. Plann. Manage.* **142**(2), 06015002, doi: 10.1061/(ASCE)WR.1943-5452.0000613.
- Cubillo, F., Moreno, T., Ortega, S. (2008). *Microcomponentes y factores explicativos del consumo doméstico de agua en la Comunidad de Madrid*. Cuadernos de I+D+I, Canal de Isabel II, Madrid.
- DeOreo, W.B., Heaney, J.P., Mayer, P.W. (1996). Flow trace analysis to assess water use. *AWWA* **88**, 79-90.
- DeOreo, W.B., Mayer, P., Dziegielewski, B., Kiefer, J. (2016). *Residential End Uses of Water, Version 2. Executive report*. Water Research Foundation, ISBN 978-1-60573-236-7.
- Fielding, K.S., Spinks, A., Russell, S., McCrea, R., Stewart, R.A., Gardner, J. (2013). An experimental test of voluntary strategies to promote urban water demand management. *Journal of Environmental Management* **114**, 343-351, doi: 10.1016/j.jenvman.2012.10.027.
- Garcia, V. J., Garcia-Bartual, R., Cabrera, E., Arregui, F., Garcia-Serra, J. (2004). Stochastic model to evaluate residential water demands. *J. Water Resour. Plann. Manage.* **130**(5), 386-394, doi: 10.1061/(ASCE)0733-9496(2004)130:5(386).
- Guercio, R., Magini, R., Pallavicini, I. (2001). Instantaneous residential water demand as stochastic point process. *WIT Trans. Ecol. Environ.* **48**, 129-138, doi:10.2495/WRM010121.
- Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, G.F. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology* **377**, 80-91, <https://doi.org/10.1016/j.jhydrol.2009.08.003>.
- Kowalski, M., Marshallsay, D. (2003). *A System for Improved Assessment of Domestic Water Use Components*. II International Conference Efficient Use and Management of Urban Water Supply, International Water Association, Tenerife, Spain.
- Larson, E., Froehlich, J., Campbell, T., Haggerty, C., Atlas, L., Fogarty, J., Patel, S.N. (2012). Disaggregated water sensing from a single, pressure-based sensor: An extended analysis of HydroSense using staged experiments. *Pervasive and Mobile Computing* **8**, 82-102, <https://doi.org/10.1016/j.pmcj.2010.08.008>.
- Makki, A.A., Stewart, R.A., Beal, C.D., Panuwatwanich, K. (2015). Novel bottom-up urban water demand forecasting model: Revealing the determinants, drivers and predictors of residential indoor end-use consumption. *Resour. Conserv. Recycl.* **95**, 15-37, doi:10.1016/j.resconrec.2014.11.009.
- Mayer, P.W., DeOreo, W. B., Opitz, E.M., Kiefer, J.C., Davis, W.Y., Dziegielewski, B., Nelson, J.O. (1999). *Residential End Uses of Water*. AWWA, Research Foundation and American Water Works Association, Denver.
- Nguyen, K.A., Zhang, H., Stewart, R.A. (2013a). Development of an intelligent model to categorise residential water end use events. *Journal of Hydro-environment Research* **7**, 182-201,

<https://doi.org/10.1016/j.jher.2013.02.004>.

- Nguyen, K.A., Stewart, R.A., Zhang, H. (2013b). An intelligent pattern recognition model to automate the categorisation of residential water end-use events. *Environmental Modelling & Software* **47**, 108-127, <https://doi.org/10.1016/j.envsoft.2013.05.002>.
- Pastor-Jabaloyes, L., Arregui, F.J., Cobacho, R. (2018). Water end use disaggregation based on soft computing techniques. *Water* **10**(1), 46, doi: 10.3390/w10010046.
- R Core Team (2013). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. URL <http://www.R-project.org/>.
- UNEP (2011). *Water: Investing in Natural Capital*. UNEP, Towards a Green Economy: Pathways to Sustainable Development and Poverty Eradication, Nairobi.