UNet-WD: Deep Learning for Multi-Appliance Water Disaggregation

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***Abstract*—Water usage in residential buildings highly impacts the overall urban demand. Following the release of the first public high-resolution smart meter data at the fixture level, we envision that extending non-intrusive load monitoring to water disaggregation will avoid installing one smart meter per appliance while still providing users with insights into their consumption habits, which eventually promote water savings. The interest in deep learning in the energy sector has increased over the years, motivated by superior accuracy in real-world settings with many appliances. In light of this, the work aims to explore the effectiveness of deep neural networks in disaggregating water usage data by proposing a UNet architecture for near real-time multi-appliance water disaggregation. Experiments on various time resolutions show interesting results. Further qualitative analysis highlights the challenge posed by data sparsity in water end-use datasets and suggests possible research directions.**

***Index Terms*—water, nonintrusive load monitoring, machine learning, deep learning, smart grid**

I. Introduction

With global warming, increasing population and industrialization, the stress on available water resources is rising. Ensuring water sustainability has become a global priority that requires innovative approaches for efficient management. According to the Environmental Protection Agency (EPA), the average American household accounts daily for more than 1135 liters of water.

The recent advancements of the Internet of Things (IoT) and Low-Power Wide-Area Network (LPWAN) technology are pushing the widespread deployment of smart meters in the infrastructure and residential buildings, transforming the water distribution system into a smart water grid. Gathering an unprecedented amount of water usage data on sub-minute intervals enables deriving fine-grained insights into consumption patterns, paving the way to new opportunities for conservation.

In this context, we envision the extension of non-intrusive load monitoring (NILM) - originally formulated for energy - to water analysis for disaggregating household-level aggregated water consumption to be a promising approach toward sustainable residential usage. Specifically, water disaggregation separates the overall consumption measured by one single meter into its fixture usage components, hence bypassing the cost, time and complexity of installing a sensor for each device in domestic environments.

A research study [1] demonstrated that providing households with real-time feedback on the power consumption of each appliance can result in significant savings as informed users start to limit their energy usage. Relevant efforts have been therefore directed at empowering NILM in residential buildings, leading to many research proposals. Among them, data-driven methods based on machine and deep learning have emerged as prominent solutions for addressing the challenges caused by large-scale high-resolution power meter datasets.

However, while energy disaggregation has been investigated for decades, water data analytics is still in its infancy. The lack of public datasets comprising aggregated and disaggregated device water consumption data has posed a severe obstacle to testing solutions for water disaggregation, thus stopping the emergence of a proper state of the art. Indeed, water utilities usually provide researchers with household-level data under non-disclosure agreements to preserve critical information about the water infrastructure and consumers' privacy. This limited amount of data eventually explains the low number of works addressing water disaggregation compared to energy.

Recently, in 2022, Di Mauro et al. [2] presented a pilot study site of water end-use demand monitoring in a residential apartment in Italy. The high-resolution measurements from an ultrasonic water meter based on LoRa wireless transmission technology have been collected to build the first open dataset for water disaggregation. Fig. 1 shows the water flows monitored over 600 timesteps on a 6-second resolution for display purposes. The release

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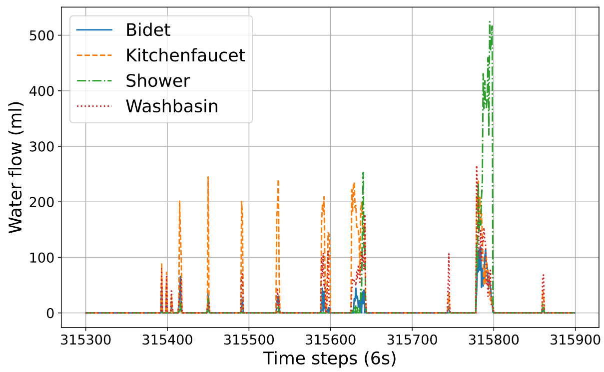


Fig. 1: Bidet, kitchen faucet, shower and washbasin 6s-resolution water flows (ml) from WEUSEDTO dataset.

of the WEUSEDTO dataset marks an important milestone, offering the first tangible opportunity to advance the research in the field.

Therefore, in this work, we aim to explore the potentiality of deep learning for water disaggregation by proposing UNet-WD, a deep neural network for multi-appliance water consumption estimation. The study discusses the data sparsity issues that are proper for water consumption time series and concludes by highlighting future research directions.

II. Related works

Non-Intrusive Load Monitoring (NILM) has garnered significant attention since Hart proposed a combinatorial optimization to disaggregate residential loads [3]. Early studies primarily rely on Hidden Markov Models (HMMs). However, to overcome the computational issues of HMMs when applied to a large number of appliances, researchers explored new classification techniques such as Support Vector Machines (SVMs) and decision trees. Dynamic time warping (DTW) comes from time series analysis, while graph signal processing embeds the inherent spatiotemporal correlations between time points into a graph.

NILM has been developed extensively over the last decade, due to the effectiveness of data-driven approaches like machine learning and deep learning on massive datasets. Most studies since 2016 have been based on convolutional neural networks (CNNs) [4]. [5], [6] propose a CNN architecture for sequence-to-point disaggregation, while 2D convolutions have also been used to transform power consumption time series into images, thus enabling the application of computer vision methods [7]. CNNs are more popular for NILM than recurrent neural networks (RNNs) [8]. Hybrid architectures like the CNN-LSTM [9] and attention-based models like Transformers [10] have also been designed.

Regarding water demand monitoring, [11] presented in 2015 the first work in which the appliance water consumption is non-intrusively disaggregated using an algorithm over 1-minute metering observations from a household. However, despite the growing deployment of smart meters, the lack of public datasets for water disaggregation represented a hurdle in advancing the research. Consequently, to bypass the issue, [12] explored the application of transfer learning to leverage pre-trained models from the energy domain to extract features for the water separation problem. This strategy proves beneficial when the domain of interest lacks sufficient data. Among the few other works, we mention [13] disaggregating high-resolution smart water meter data into appliances' end uses with unsupervised machine learning in a four-person household and [14] comparing several learning-based algorithms (SVM, random forest, feed-forward neural networks) in capturing the aspects of 1s-resolution synthetic data.

III. Problem formulation

Water disaggregation is formulated as the task of estimating the water consumption at the device level by observing the aggregated measurements of one sensor, within a fixed-length time window. Formally, for a set of M devices of interest, the objective is to determine every individual consumption time series $y_m(t) \in \mathbb{R}$ with $1 \leq m \leq M$ given the aggregate water consumption $x(t) \in \mathbb{R}$ s.t. the following Eq. 1 holds.

$$x(t) = \sum_{m=1}^{M} y_m(t) + \epsilon(t) \tag{1}$$

The ghost power $\epsilon(t) \in \mathbb{R}$ sums up the contributions into $x(t)$ from not accounted appliances.

IV. Proposed method

While single-appliance solutions fit one model for each appliance separately to get the corresponding $y_m(t)$, multi-appliance regressors output directly the vector $\mathbf{y}(t) = \{y_1(t), ..., y_M(t)\}$, offering notable advantages as they save considerable computation and time that would otherwise be spent on training and tuning a separate neural network for every appliance.

A. UNet-WD architecture

The UNet architecture [15] is commonly used in tasks like speech recognition, time series analysis and any sequential data analysis where the goal is identifying patterns in the data. In this work, the 1D-UNet NILM architecture by Faustine et al. [16] has been repurposed for the multi-appliance water disaggregation task.

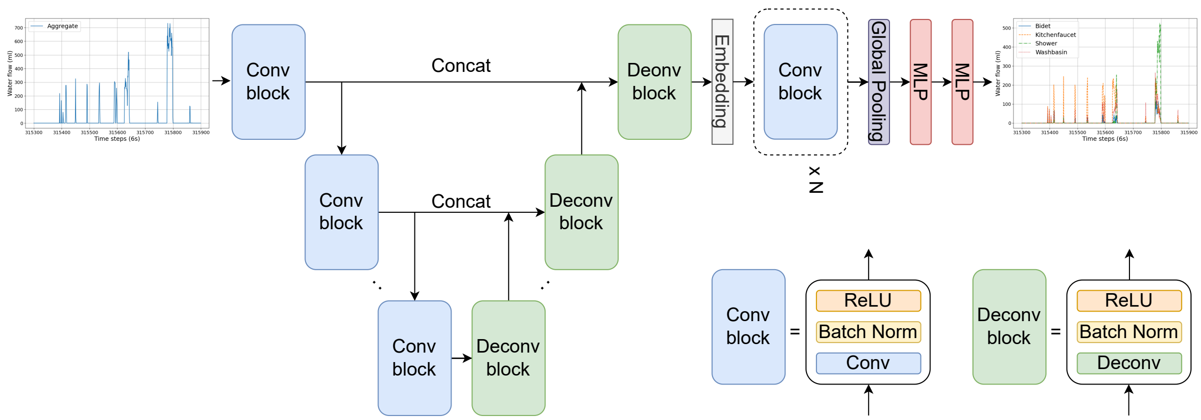


Fig. 2: UNet-WD architecture.

The encoder of the resulting UNet-WD consists of a sequence of downsampling blocks, each made by a 1D-convolution followed by batch normalization and non-linear activation function ReLU. The number of kernels (or filters) increases as we go deeper into the encoder, thus capturing more granular features in the data.

The decoder is symmetric to the encoder as it consists of a sequence of upsampling blocks, specifically an upsampling layer followed by a convolutional layer, batch normalization and the ReLU activation function. Skip connections from the corresponding encoder block are concatenated with the decoder inputs to preserve spatial information lost during downsampling.

The output layer of UNet-WD starts with an N-stage 1D-convolutional stack, followed by global average pooling and a Multi-Layer Perceptron Block (MLP) with ReLU and dropout. These components produce a latent feature vector $\mathbf{z}$ that is given in input to the final MLP block for the multi-target water consumption estimation.

Eventually, the U-shaped architecture facilitates the integration of low-level and high-level data characteristics, while the skip connections effectively combine local and global information and enable the reuse of features, thus reducing the need for redundant parameters, speeding up the computation and preventing overfitting. The UNet architecture can also be easily adapted to any input and output size, making it suitable for different frame lengths and number of fixtures.

B. Cost function

The UNet-WD for multi-target regression is trained by minimizing the Mean Squared Error (MSE) expressed in Eq. 2.

$$L_{MSE}(\hat{\mathbf{y}}, \mathbf{y}) = \frac{1}{TM} \sum_{t=1}^{T} \sum_{m=1}^{M} (\hat{y}_m(t) - y_m(t))^2 \quad (2)$$

T is the length of the temporal window and $\hat{y}_m(t)$ the estimation for the appliance m at a given time t.

The proposed neural network is trained using a sliding window approach where the input to the model is a sequence $\mathbf{s}_{t:t+L} = \{s(t), ..., s(t+L)\}$ of L aggregate measurements. As shown in Eq. 3, the UNet-WD learns to map the sequence of observed inputs $\mathbf{s}_{t:t+L}$ to $\hat{\mathbf{y}}(t+L)$, i.e. the single-point estimate at time $t+L$. Combined with the frame length L of 600, this sequence-to-point approach ensures a good trade-off between receptive field and near real-time disaggregation.

$$\hat{\mathbf{y}}(t+L) = \text{UNet-WD}(\mathbf{s}_{t:t+L}) \quad (3)$$

V. Experimental Setting

We outline the dataset, training strategy, performance metrics and introduce a baseline model for comparison.

A. Dataset

Experiments are conducted on the WEUSEDTO dataset [2] collected in a single residential apartment in Naples, Italy. Water flows (ml/s) by the washbasin, bidet, kitchen faucet, shower, washing machine, dishwasher and toilet were monitored between March to November 2019 and July to October 2020 with a resolution of 1 second, while the whole end-use time series aggregate was sampled at 10s-resolution; however, it spans only two months between September and October 2020. Therefore, to cope with the short overlapping periods between fixtures and aggregated consumption, we build a new household-level time series by summing the individual water flows of the fixtures. The goal is to disaggregate the bidet, kitchen faucet, shower and washbasin and therefore $M = 4$ in the following experiments.

To test the performance of UNet-WD for water disaggregation at different granularity, the data have been resampled at resolutions of 6 seconds, 10 seconds and 1 minute by summing the flow measured at each second within the interval. The frame length $L = 600$ implies 1h, 1h 40m and 10h of aggregate measurements, respectively. Missing values have been filled with 0. Then, a 0.60/0.25/0.15 data split is applied to create train, test and validation sets. For each fixture, we normalize the data by subtracting the mean and dividing by the standard deviation of the training set.

B. Training strategy

We set 128 as the dimension of the latent feature vector $\mathbf{z}$ in UNet-WD, set the number of initial kernels of the encoder to 8, set 16 as the kernel width for convolutions in upsampling and downsampling blocks, dropout at 0.1 and allocate 5 levels for the UNet architecture as more layers allow to learn better features for the task. The number of feature maps is doubled at each downsampling step of the encoding phase, thus producing 256 feature maps at the bottleneck of the autoencoder. The penultimate MLP uses 1024 hidden units, while the final MLP matches the number of appliances M.

The Adam optimizer is initialized with the learning rate $\alpha = 10^{-3}$ and $\beta = (0.99, 0.98)$. The model is trained for at most 50 epochs applying a decay factor of 0.1 if the validation MAE has not improved after 5 epochs, reducing the learning rate to a maximum of 10^{-6}. Early stopping occurs if no improvement has been observed after 10 epochs and then the best configuration of the model is validated on the test set. The batch size is 4096.

C. Performance metrics

The disaggregation performance is evaluated using three metrics for regression tasks: the Estimated Accuracy (EAC), the Normalized Disaggregation Error (NDE) and the Mean Absolute Error (MAE).

The EAC provides the total estimated accuracy defined in Eq. 4.

$$\mathrm{EAC} = 1 - \frac{\sum_{t=1}^{T}\sum_{m=1}^{M} |\hat{y}_m(t) - y_m(t)|}{2\sum_{t=1}^{T}\sum_{m=1}^{M} y_m(t)} \tag{4}$$

The NDE in Eq. 5 normalizes the squared error between the prediction and the ground truth.

$$\mathrm{NDE} = \frac{\sum_{t=1}^{T}\sum_{m=1}^{M} (\hat{y}_m(t) - y_m(t))^2}{\sum_{t=1}^{T}\sum_{m=1}^{M} y_m(t)^2} \tag{5}$$

The MAE in Eq. 6 computes the average error in predicting the target value at every time step.

$$\mathrm{MAE} = \frac{1}{TM}\sum_{t=1}^{T}\sum_{m=1}^{M} |\hat{y}_m(t) - y_m(t)| \tag{6}$$

Higher EAC, lower NDE and lower MAE indicate better performance. For a fair comparison, each experiment is run 5 times and we report the mean. We denormalize the final prediction to resume the original data scale.

D. 1D-CNN baseline

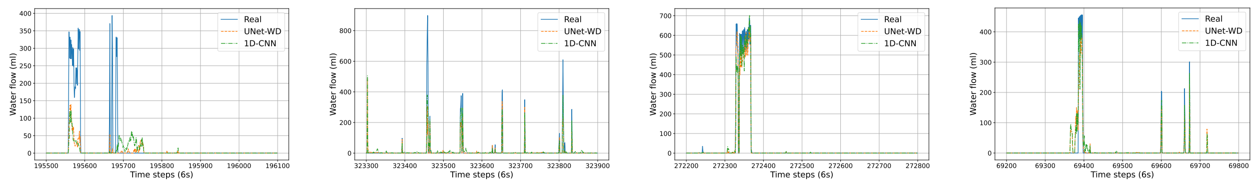
We compare the performance of the proposed UNet-WD to a 1D-CNN baseline. It consists of a four-stage CNN stack using 16, 32, 64 and 128 feature maps with stride equal to 2. The first two CNN layers use a filter size of 5, while it is 3 for the last two layers. The four CNN layers are followed by batch normalization and ReLU, with the final one preceding an adaptive average pooling layer with an output size of 16 and three MLP layers. The MLP block at the end estimates the appliances' consumption.

VI. Discussion of results

Tables I, II, III report the results for UNet-WD and 1D-CNN for the three metrics respectively. Each table reports the scores computed individually for each appliance and the average among the appliances for all time resolutions. We conduct a quantitative and qualitative analysis based on these tables and Fig. 3.

EAC. UNet-WD leads to improvements of EAC for all appliances in all time resolutions in Table I, getting an average increment of 5.94%, 6.4%, 10.81% respectively for 6s, 10s and 1m horizons. Kitchen faucet and washbasin benefit the most from the proposed architecture with increments of 14.04%, 10.35%, 13.46% for the former and 3.79%, 7.88%, 27.99% for the latter. Improvements of UNet-WD over 1D-CNN for the bidet and shower are minor. The shower's EAC ranges in a short interval of [0.75, 0.77] for 1D-CNN and [0.75, 0.79] for UNet-WD for all the considered time resolutions; conversely, other fixtures like washbasin show a drop in performance when the time interval increases. The shower is in absolute terms of EAC the fixture with the best estimation outcomes and the bidet is the one with less accurate results. The shower may yield better results primarily due to its consistent and prolonged water consumption pattern impacting on the aggregate. A shower typically consumes a great amount of water continuously over a relatively extended period during each use and it is not as intermittent throughout the day as other fixtures like kitchen faucets (Fig. 3b) and washbasins (Fig. 3d) may be. This predictability and consistency in usage contribute to a clearer disaggregation of its water consumption as shown in Fig. 3c. The bidet's EAC score is low (around 0.20) due to its inherently less predictable pattern. The sporadic usage makes it challenging to isolate from the aggregate and attribute water consumption solely to bidet activities. UNet-WD and 1D-CNN catch the time interval of the first usage on the left-hand side of Fig. 3a but not the magnitude, while they miss the second one and estimate an increment a few steps later that did not occur.

NDE. UNet-WD outperforms 1D-CNN in every setting with average improvement of NDE of 7.39%,



(a) Bidet (b) Kitchen faucet (c) Shower (d) Washbasin

Fig. 3: Disaggregation of 6s-resolution water flows (ml) for the bidet, kitchen faucet, shower and washbasin.

TABLE I: Estimated accuracy (EAC). Higher is better.

	Bidet		Kitchen faucet		Shower		Washbasin		Average	
Time	1D-CNN	UNet-WD	1D-CNN	UNet-WD	1D-CNN	UNet-WD	1D-CNN	UNet-WD	1D-CNN	UNet-WD
6s	0.206	0.229	0.333	0.38	0.775	0.791	0.408	0.424	0.43	0.456
10s	0.201	0.227	0.343	0.379	0.764	0.781	0.37	0.399	0.42	0.44
1m	0.163	0.211	0.308	0.349	0.757	0.756	0.26	0.333	0.372	0.412

TABLE II: Normalized disaggregation error (NDE). Lower is better.

	Bidet		Kitchen faucet		Shower		Washbasin		Average	
Time	1D-CNN	UNet-WD	1D-CNN	UNet-WD	1D-CNN	UNet-WD	1D-CNN	UNet-WD	1D-CNN	UNet-WD
6s	0.874	0.853	0.569	0.494	0.185	0.168	0.653	0.598	0.571	0.528
10s	0.835	0.834	0.542	0.527	0.189	0.17	0.705	0.624	0.568	0.539
1m	0.942	0.863	0.719	0.658	0.178	0.169	0.825	0.728	0.666	0.604

TABLE III: Mean absolute error (MAE). Lower is better.

	Bidet		Kitchen faucet		Shower		Washbasin		Average	
Time	1D-CNN	UNet-WD	1D-CNN	UNet-WD	1D-CNN	UNet-WD	1D-CNN	UNet-WD	1D-CNN	UNet-WD
6s	0.494	0.479	0.91	0.846	0.739	0.685	0.905	0.881	0.762	0.723
10s	0.829	0.802	1.495	1.414	1.293	1.198	1.608	1.533	1.306	1.237
1m	5.259	4.957	9.542	8.969	8.040	8.073	11.439	10.312	8.57	8.078

5.06%, 9.24% for 6s, 10 and 1m time resolutions in Table II. Scores by the kitchen faucet and washbasin confirm the largest margin of improvement like in the analysis based on EAC: UNet-WD overcomes 1D-CNN by 13.17%, 2.76%, 8.55% and 8.50%, 11.43%, 11.74% respectively for all temporal settings. Improvements for the bidet and shower are more contained, except for an 8.38% lower NDE for 1m-resolution for the first of the two fixtures. The metrics by UNet-WD are quite stable and, once again, the shower achieves far better scores than the bidet like we have observed for EAC. It may be evident, though, that the NDE scores of the kitchen faucet are lower (i.e. better) than the washbasin, while the EAC scores are lower (i.e. worse): this contradiction requires some reasoning. Looking at Eq. 4 and Eq. 5, it is clear that EAC is based on the mean absolute error (MAE) and NDE on the mean squared error (MSE). MAE considers the average mismatch between predicted and actual values, giving equal weight to all deviations regardless of their magnitude; on the other hand, MSE amplifies the effect of larger errors being squared, thus penalizing outliers more. Given these characteristics, MSE is more sensitive to outliers, making it less forgiving of large errors. This means that when disaggregating water usage, if there are occasional spikes like unexpected high water usage, MSE will penalize these deviations more severely. Considering the usage patterns of kitchen faucets and washbasins, we can state that kitchen faucets are typically used more regularly and predictably, often associated with specific activities like cooking and dishwashing after meals. In contrast, washbasins are typically used for personal hygiene routines at any time throughout the day. A kitchen faucet generally has a higher flow rate compared to a washbasin, resulting in a higher amount of water consumption. In Fig. 3b, for example, the maximum water flow of the kitchen faucet is doubled the maximum of the washbasin and spikes related to the kitchen faucet regularly span over time.

This regularity makes it easier for models to estimate water usage by kitchen faucets; conversely, the sporadic usage pattern of washbasins increases the likelihood of outliers and deviations from the expected water usage pattern, thus resulting in higher MSE and NDE.

MAE. The UNet-WD improves the average MAE scores for all appliances of 1D-CNN in Table III by 5.14%, 5.31% and 5.74% for each time horizon. Unlike EAC and NDE, MAE is not a normalized metric. This implies that error grows as we aggregate more data over time. A water end-use dataset is more sparse than energy data because no fixture is continuously used. Therefore, all water fixtures exhibit long periods with zero consumption interrupted by intervals or spikes of actual consumption. The sparse nature of the data makes it easier for models to miss the rise in flow magnitude when a high amount of water has accumulated from some appliance. This is reflected by the poorer EAC, NDE and MAE scores passing from short to longer time intervals. This observation points to a critical aspect of water disaggregation: the need for designing a training strategy based on a cost function that penalizes predictions during actual consumption periods. Indeed, the large prevalence of zero consumption values in sparse datasets can affect the model's optimization if not properly addressed. A potential approach may involve incorporating a weighted loss function that assigns higher penalties to errors for non-zero consumption instances while ensuring that the model can detect periods with no consumption.

VII. Conclusion

The release of the first high-resolution smart meter dataset for water end-use analysis marks an unprecedented opportunity to design and validate methods for water disaggregation. Motivated by remarkable advancements in non-intrusive load monitoring (NILM), we explore the potentiality of deep learning by proposing a neural network - named UNet-WD - for near real-time multi-appliance water consumption estimation. Positive results across various sampling intervals prompt discussion on sparse data challenges, guiding future research. In conclusion, we underscore the need for further open water end-use datasets as they are necessary for evaluating the models' generalization to unseen houses, encompassing heterogeneous water consumption profiles. This broader assessment is fundamental for implementing and deploying real-time water disaggregation solutions that enhance monitoring, management, and conservation in the residential sector.

Acknowledgments

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