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From water to energy: low cost water & energy consumptions readings

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Abstract

Water and energy are essential for human existence, and its rational use should be encouraged. According to the literature review, water consumption directly affects energy consumption and are inseparably linked resources. The energy to water part of the water/energy nexus, increasingly highlighted as an important issue for future planning and strategic policy considerations. Joint consideration of both water/energy domains can identify new options for increasing overall resource use efficiency.
This work is part of the project ENERWAT that has as goal to measure *in situ* the water/energy consumption related with water supply end use in rural and urban dwellings in order to validate the data collected by survey. A methodology for low cost measure and store water/energy consumes was developed. Water, Gas and electricity data was stored in image format.
In this paper, a CNN architecture was applied and trained to read water/energy. The models suited their proposed. The achieved accuracy for test set was: water - dozen: 0.98, unit: 0.92; gas: dozen: 0.94, unit: 0.99; and electricity - dozen: 0.99, units 0.99. The more challenge digit was water unit digit due to partial occlusion. It is presented a day of readings and discussed some events.

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Keywords: Water/Energy Nexus; image meter readings; CNN

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1. Introduction

In a time where resources scarcity and climate changes are concern issues, it is vital to research solutions that enables characterizing consumptions of different types of resources. Water and energy are essential purchases, and its rational use should be encouraged. According to the literature review, water consumption directly affects energy consumption and are inseparably linked resources[1,2,3,4,5].

Joint consideration of both water and energy domains can identify new options for increasing overall resource use efficiency. With this research work it is intended to continue the work developed by the research team members in energy and water efficiency fields[6,7,8]. The work presented is part of a task of the project ENERWAT that is focused on the energy consumption in the water production and use, specifically in the case of rural and urban dwellings, given the influence that these variables have on the water and energy consumption profile. The study of these aspects will allow the characterization of the specificities, the similarities and the differences in the consumption behaviors for these two environments. In Portugal there is a big lack of information about the differences in water consumption in rural and urban areas and consequently about the energy consumption linked with water. It is expected to reach these consume patterns, extremely important information to future planning and strategic considerations. Knowing these differences will also allow proposing measures to increase water and energy efficiency in these two different realities. It is well known that there are important differences between the water and energy consumption pattern in rural and urban areas[9,10,11], however these differences are not yet evaluated.

A methodology to measure water and energy and store it in a database was developed. Water, Gas and electricity data was stored in image format. In this paper, the method to read the meters image data is presented and applied to a case study data. The measures results are presented and discussed.

This paper start to presents in section 2, the background work and other previously taken approaches, then in section 3 is presented the methodology adopted to measure and store water and energy consumes. Section 4 presents the reading images strategy and in Section 5 some early results are presented for a single dwelling. Section 6 presents some conclusions from this initial approach and future work.

2. State of Art

Although there is a growing concern about the water energy nexus at the end user´s, the work field carried out at the dwelling level is very scarce, maybe due to the level of intrusion in the houses and, to a certain extent, the invasion of the privacy of the consumers.

Most of the works collects data from surveys and then proceeds to the modulation of water and energy consumptions. Aurelie Dubreuil et al.[12], Steven J. Kenway et al.[13] and Shan Jiang et al.[14] have conducted studies on the relationship between water and energy consumptions at the final consumer level through mathematical models and surveys.

The measurement and analysis of domestic hot water consumption is usually accomplished using one of two methods – the temperature-based event inference method and the flow trace signature analysis method[15]. Amanda N. Binks et al[16] acquired data through home audits, interviews and high-resolution water flow meters in five dwellings in Melbourne and two in Brisbane

Willet Kempton[17] carried out *in situ* measurements of the water consumption in seven dwellings, in a period between 7 and 18 months, using a programmable microprocessor-controlled field and surveys. The instrumentation used allowed recording of the data only when water was used. The author experienced several difficulties, some of them being that due to the costs and the intrusion levels in the instrumentation, they prevented large samples and a random selection of samples. Another problem was that it could not determine the volume of water used in each faucet, due to installation difficulties and expenses that prevented the purchase of volume meters.

Cristina Matos[8] monitored 197 baths in a dwelling over a total of 2 months (October, November, December and January). However, the measurements were performed manually.

Most of the works measure water or energy[18,19] consumptions, not both. The literature review shows that there is work to be done in the field of *in situ* measuring, both water and energy consumptions and analysing its relations.

3. Water and energy data

In a previous step of ENERWAT project, it was developed and proposed a data acquisition system that measures water and energy, and stored data in a server database to be analyze. It follows a brief introduction of the acquisition process and available data.

At each house, the locations where the inputs/outputs of water and energy occur are identified. In urban environments, the most common places are bathrooms, kitchens, marquees and halls. In each division, a single board computer (SBC) is installed for acquire the states of the taps, machines, water heaters and meters. Acquired data is daily upload through a virtual private network (VPN) to the server, and stored in a database. At Fig. 1, it can be seen examples of the sensors used for data acquisition.

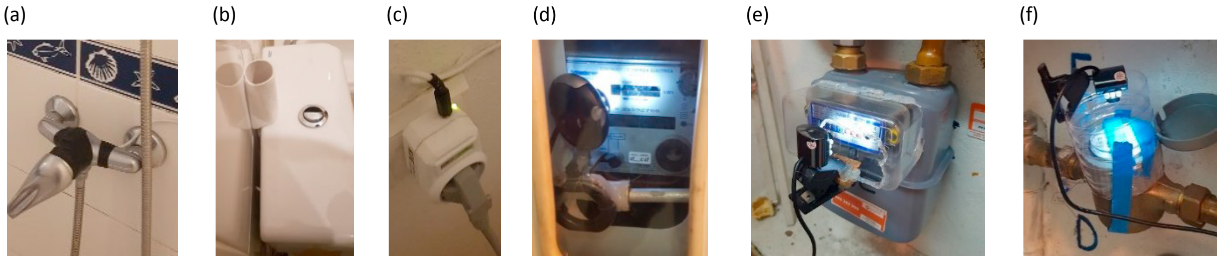

Fig. 1. Sensors: (a) Shower, (b) Flushing cistern, (c) Washing machine sensor, (d) Electricity meter, (e) Gas meter, (c) Water meter.

Fig. 1a) shows mixer tap instrumentation, where three magnetic sensors signal six tap positions (Table 1). Simpler tap was instrumented with one magnetic sensor signal close/open.

Table 1. State of the water faucet relation with type of water output.†

State	Close	Hot only	Hot & little	Both	Little cold	Cold only
Hot water	0%	100%	100%	100%	50%	0%
Cold water	0%	0%	50%	100%	100	100%

†Note: percentages are indicative and will be estimated based on consumption history read at water meter.

Fig. 1b) shows flushing cistern signaled by one magnetic sensor indicating water buoy down/up and Fig. 1c) shows an electric plug that signals ON/OFF the moment when the plug has a load or not. These electric plugs are used to register dishwashing and laundry machines use.

Fig. 1d), e) and b) shows installed webcams used to register analog electricity, gas and water meters, respectively. Cameras have integrated light emitter diodes (LED) used to illuminate the meters. The SBC acquire successive images of lower significant digit. When changes are detected it save digits' grayscale images to SD card. Each digit has the resolution of 30x20px. It was decided to concatenated the 2 less significant digits (image 30x40 px) – dozens and units– and save it every 200 ms with the timestamp in the name. In order to get a global reference and recover from malfunctions, every hour it save the 4 less significant digits (image 30x80 px), i.e., thousands, hundreds, dozens and units. Electricity meter, measures in thousands watts and run much slower than others meter. Therefore, for this meter dozens and unit's digits are save every 20 seconds.

Fig. 2 a), b) and c) shows example hour images for meter gas and water.

Fig. 2. Images from meters: (a) Gas in litres; (b) Water in litres ;(c) Electricity in thousands watts.

Noted that the water unit digit has the number partial occluded Fig.2 b) due to meter fault – there is misalignment between the unit wheel and the display board. As the numbers can be read and it can occur in other meters, they were considered valid number.

All data are stored in local SBC SD card in two type of files: ON/OFF data are stored daily in a text file, adding messages with time stamp, magnet ID, and state ON/OFF; Image files are aggregated daily in a TAR file.

4. Reading image data

From observation meters' images (Fig 2), digits are read as integer unless the least significant digit for gas and water meters, that has grids that permits to read values with precision of 0.2 units, e.g. Fig.3 a). The least significant digit of electricity meter does not have grid, although it turns continuous. From the perspective of water, gas, and electricity consumptions, it was decided meters' reads should have half unit precision.

In gas and water observable digits with decimal ".0", ".2" and ".4" should be read with decimal ".0" and values with ".6" and ".8" should be read with decimal ".5", see Fig.3 b). For electricity reads, two grid lines were added to the image at 5/8 and 3/8 of its high, in order to enable objective reads. Images where digits are overlapped simultaneously with the two lines should read with decimal ".0", e.g. Fig.3 c), otherwise were read with decimal ".5", e.g. Fig.3 d). The integer digits should be read only after its right digit turn to 0.

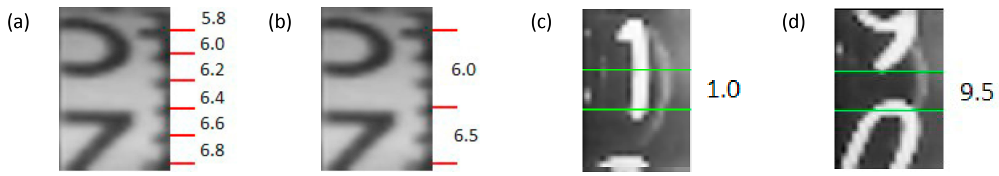

Fig. 3. Water meter images: (a) digit units with 0.2 grid, (b) digit units with 0.5 grid, (c, d) electricity unit's digits with grid.

Conventional OCR read integer digits, but they cannot read numbers with half precision. Thereby, it was decided to use a machine learning approach that is suited for both cases.

Early in 1998, LeCount[20] proposed a convolution neural network (CNN) known as LeNet for reading handwriting number with great success. This approach use convolution to add spatial relation to input image and after several evolutions in the learning process become an efficient and relatively simple to use and available today.

Therefore, two CCN where implemented and trained in Keras with Tensor flow backend, one to read integer digits (dozen digits) and the second one to read digits with half unit precision (unit digits). It follows the description of the used architectures, datasets and their results.

4.1. Convolution neural network architecture

The implemented CNN architecture are similar to the proposed by LeNet as can be seen in the Fig. 4 - architecture for unit digits:

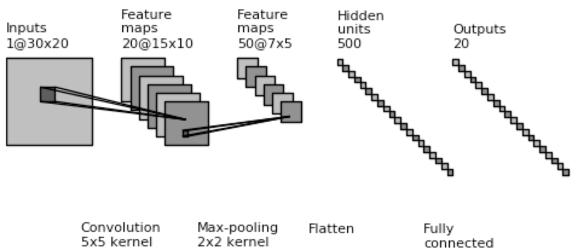

Fig. 4. Convolution neural network architecture - Read unit digits.

The architecture is the same in both models, they have an input images of 30x20px, two groups of layers conv-pool-dropout, a flatten layer and two fully connected layers. The only difference is the number of output nodules: for digit prediction with 0.5 precision (unit digit), the output has 20 nodes and for integer prediction (other digits), the output has 10 nodes. The first convolution layer has 20 filters and the second has 50 filters, both with 5x5 size and follow by batch normalization and a rectified linear unit (ReLU) activation function in order to prevent nonlinearity saturation in the model. Max polling layers have 2x2 size and are followed by a dropout of 0.5. The first fully connected has size 500, batch normalization and a ReLu as activation function. Finally, the last layer (fully connected layer) has size 20 (in the case of unit digit), or size 10 (in the cases of dozen digit), and has a “softmax” activation function in order to output probabilities.

It was used “categorical cross-entropy” as loss function optimized by “adam” method with learning rate of 0.001, beta1 of 0.9, beta2 of 0.999, fuzz factor of 1e-08 and learning rate decay over each update of 0.0.

4.2. Dataset

The dataset was annotated with a developed tool in MS Excel datasheet that reads images files from a directory and draws a read line in the middle, as can be seen in Fig.5 a) for gas and water and b) for electricity.

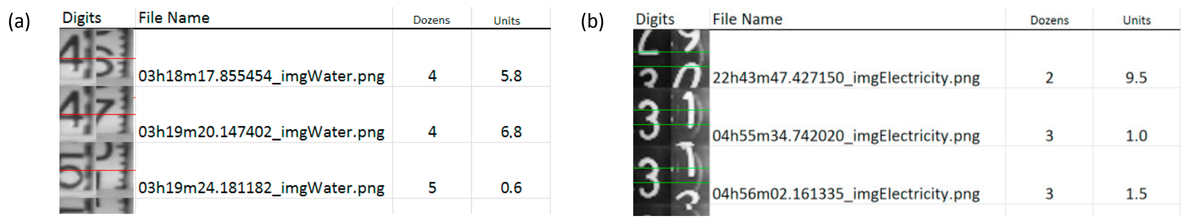

Fig. 5. Annotation tool: (a) for gas and water, (b) for electricity.

A total of 49 329 digits were annotated manually (electricity: 9 454, gas: 18 612, water: 21 263), one for dozen digits and other for unit’s digits. The histograms of datasets can be seen in Fig. 6.

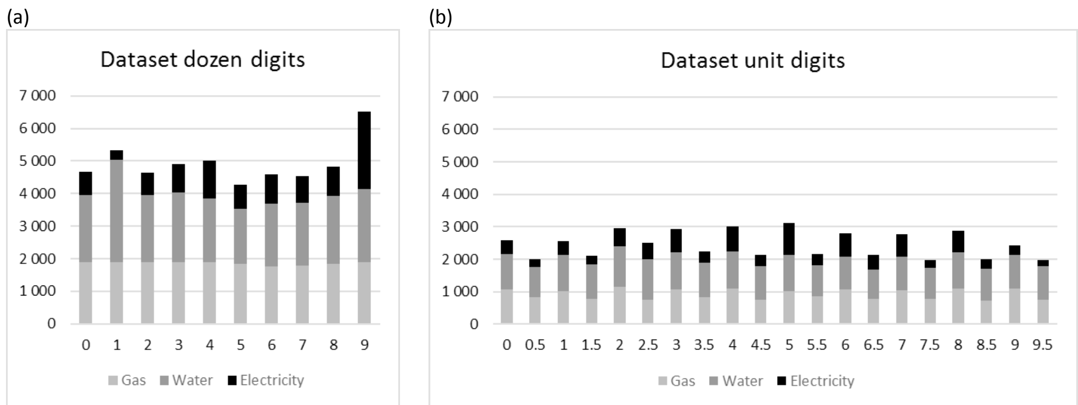

Fig. 6. Dataset histograms: (a) dozen digits, (b) unit digits.

As can be seen, the distribution of the digits is uniform for gas and water. In the case of electricity, it has less images than the others sets. The "1" digit of the dozens has occurrence substantially lower than the other digits, and the "9" is considerably higher. In the case of the unit digits, the half values occurred less than the integer values. As can be seen in the next section, CNN results (5.3), these differences did not compromise the results, so it was decided not to balance the sets.

The datasets were divided, 90% training and 10% for test. In order to improve robustness to right and left translations, data augmentation was done during runtime in both datasets. Each digit was shifted left and write, 2 pixels, twice – training set increase 4 times.

4.3. CNN results

All models were trained with 20 epochs with batch size of 128. Water unit digit was more challenge and were trained in 100 epochs. The results are shown in Table 2:

Table 2. Training and validate results.

		Water		Gas		Electricity	
		Dozens	**Unit**	**Dozen**	**Unit**	**Dozen**	**Unit**
Training	**Epochs**	20	100	20	20	20	20
	Accuracy	0.9988	0.9861	0.9994	0.9948	0.9990	0.9948
	Loss	0.0039	0.0346	0.0021	0.0136	0.0035	0.0146
Test	**Accuracy**	0.9888	0.9249	0.9477	0.9930	0.9996	0.9956
	Loss	0.1801	1.1882	0.8417	0.1092	0.0019	0.0127

The results were very good as can be seen by the accuracy reached for training and test sets. The more challenge digit was water unit digit, as expected, due to occlusion – it was necessary to increase the number of training epochs to 100. Nevertheless, the model archived a good accuracy (training: 0.9861, test: 9249). The dozen digits for Gas stands out since it presented a decrease of the precision of the training for the test (training: 0. 9994, test: 9477). Even so, the result is good enough for counter reading.

Even with the referred accurate readings, were found two situations where the readings were erroneous: few erratic digits read and when unit digit turns to zero, dozen digits does not change in the same frame - the models reads digits independently. To correct these situations, in the former case is used time coherence - digits are restrained to change increase accordingly to digit max know velocity and in the latter case units from 9.5 transition to 0.0 are used to introduce coherence.

5. Case study: urban, 3-bedroom apartment

The data acquisition system was installed in an urban 3-bedroom apartment, where a couple lives with a teenager son. The dwelling has two bathrooms and a kitchen, and is supplied by public water, electricity and natural gas, with three meters installed in the entrance hall of the building – instrumentation was shown Fig.1. The heating is done through a natural gas boiler. There is also a dishwashing machine and a laundry machine. On/Off consumption readings were performed on faucets and flushing cisterns and on dishwasher and laundry machines. Image consumption readings were performed on water, gas and electricity meters and were registered. Bathrooms and kitchen taps are mixer tap – see Fig. 1a).

The Fig. 7 presents a graph of the meters reads for a weekday.

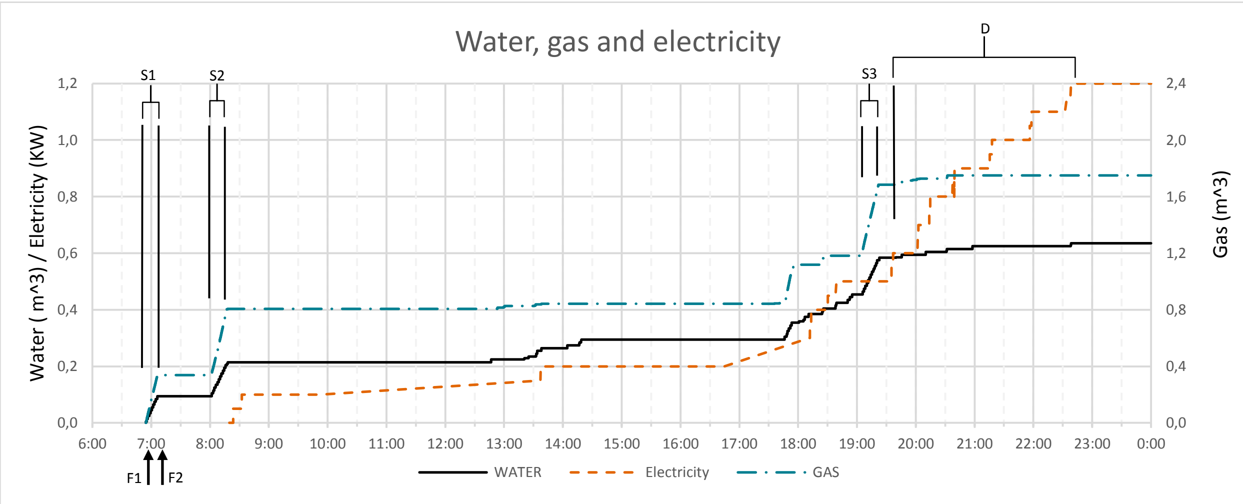

Fig. 7. Water, gas and electricity meter reads.

As can been seen in the Fig. 7 the records are only from 6a.m to 12p.m because before that there were no event of water consumption.
Based on ON/OFF events registration, some example of events and their water, gas and electricity consumptions were selected as example and can be seen in the Table 3.

Table 3. Training and validate results.

				Water (litres)	Gas (litres)	Electricity (KW)
		Start	Duration	Read	Read	Read
Shower	S1	06:56:22	00:09:53	72.5	281.0	N.A.*
	S2	08:01:13	00:15:57	115.0	468	N.A.*
	S3	19:04:56	00:16:55	128.0	469	N.A.*
Flushing Cistern	F1	06:55:07	00:01:03	9.0	N.A.*	N.A.*
	F2	07:11:39	00:00:33	4.0	N.A.*	N.A.*
Dishwashing Machine	D	19:36:50	03:01:10	44.5	N.A.*	6.0

* N.A – Not applicable

Showers, S1, S2 and S3 are easily recognized in the Fig. 7, by the increasing in consumption of water and gas. water and gas reads are proportional, approx. 7 litre/min of water and 28 litre/min of gas. In case of S3 it was 27 litre/min. The cistern flushing, e.g. F1 and F2, are very fast and water consumption is low, so it cannot be seen in the Fig.7. In fact, F1 is a full flush (9 litres) that took 1 min refilling the cistern and F2 was a partial flush (4 litres) and took half the time refilling the cistern.
During dishwashing machine cycle, it were read 6 kW of electricity and 44.5 litres of water. Other consumption occurred simultaneously that should be used to estimate the real consumption such as TV and lights. These estimations are out of the scope of this paper.

6. Conclusions and Future work

A convolutional neural network architecture models, similar to LeNet, was applied to successful recognize dozens and unit digits of water, gas and electricity meters for a low cost measurement of water and energy consumptions. A total of 49 329 digits were annotated manually (electricity: 9 454, gas: 18 612, water: 21 263) and used to train and validate the proposed architectures. The results were very good as models suit their proposed. The achieved accuracy for test set was: water - dozen: 0.9888, unit: 0.9249; gas: dozen: 0.9477, unit: 0.9930; and electricity – dozen: 0.9996, units 0.9956. The more challenge digit was water unit digit, as expected, due to partial occlusion. In order to illustrate the applications of the model, it was presented a day of water, gas and electricity readings and discussed some events.

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