Estimating Energy Consumption in Households for Non-Intrusive Elderly Monitoring

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***Abstract*—Population ageing is becoming a key social issue in recent decades, particularly in Western countries, where this fact, together with the increase of life expectancy, has posed a significant strain on public finances and health services. In this context, many technological developments are often proposed to promote and support the independent living of elderly at their own homes, thus avoiding or postponing possible entries into social residences. Among them, smart meters provide a non-intrusive way to monitor and estimate the tenants' daily activities, by only using a single-point measurement in the mains at the entrance of the household. This work describes a regression approach to estimate the energy consumption of a house by means of a LSTM neural network. For that purpose, a pilot has been run on a house during six months in order to collect the electrical data, which will be used later to train the neural network. After that training, the network tries to estimate the energy consumption every 15 minutes, so any deviation between the predicted sample and the measured one might be used to detect anomalies in the daily routine of the tenant.**

Keywords—Assisted Living, NILM techniques, LSTM

I. INTRODUCTION

Population ageing is becoming a challenging issue in recent years. The ongoing transformation of the population pyramids in most Western countries is straining public finances, as well as social and healthcare systems, in many different ways [1]. One of the consequences coming from a life expectancy longer than ever is the impact and prevalence of certain diseases that imply a cognitive disorder, such as dementia or Alzheimer [2]. These patients require the continuous support and care from their family and caregivers, or even they often get into a specialized residence looking for a more suitable care. In order to avoid this early institutionalization, some technological solutions have risen as promising and feasible tools to redefine new paradigms and services [3], which deal with the daily reality of a population with an increasing degree of dependence, while assuring the expected standards of quality.

In this context, different approaches have been developed recently to monitor and assess the daily activities of elderly living in their own homes. In many cases, they are based on the deployment of a positioning system [4], often consisting of installing a set of beacons in the environment whereas the person carries a tag (emitter or receiver) to be located. In this application, it is possible to find solutions based on ultrasounds, or infrareds, although those based on radio-frequency are likely the most extended [5] [6]. Due to the fact that most people handle a smartphone daily, it is straightforward to dedicate the sensors available in the device to track the user's activity, where WiFi or Bluetooth may implement a location system, or inertial accelerometers and gyroscopes allow the user's movement to be estimated [7]. Another option is to install cameras in the different rooms of the house and to apply image processing to identify and monitor some activities carried out by the tenants. Furthermore, it is possible to apply sensor networks to measure certain environmental parameters, or even to determine some physiological variables about the health status of the patient [8].

Although the aforementioned technologies have achieved promising results in pilot tests, they present a significant drawback, which might imply refusal by most people. They involve a high level of intrusiveness in the normal life of elderly, since people have to admit the installation of sensors in their houses (even cameras in some cases), or to carry a device or tag with them over time in order to obtain a suitable monitoring and assessment. These aspects have implied that the deployment of these monitoring systems is often quite limited.

On the other hand, non-intrusive load monitoring (NILM) emerged in the past as a technique to identify the usage pattern of the electrical appliances in a house by processing data coming from a single measurement point at the entrance of the mains [9]. Initially, NILM was mainly focused on energy management and efficiency, but it became a suitable approach to identity and monitor certain daily activities in a house, associated to the manual on and off switching of certain appliances. The great advantage of using NILM to monitor elderly activity is that the approach presents a very reduced level of intrusiveness, since it is only necessary to install an smart meter at the entrance of the house.

In the field of NILM techniques, Artificial Neural Networks (ANN), as well as other machine learning methods, have already been involved at the different stages. Commonly, load identification is a key aspect in NILM, based on the electrical signals captured from the mains. For that purpose, a convolutional network is proposed in [10]. Similarly, in [11] a feedforward network is also applied to identify different appliances in a certain household. On the other hand, it is also possible to find previous works dedicated to assess the activity and behaviour inside the household under study. In [12] an electrical signature is identified and associated to each person's activity, in order to later derive their health

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conditions. Furthermore, a regression (based on Support Vector Regression and on Linear Regression) is defined to estimate the energy consumption in [13], whereas the real values and the predicted ones are compared then to detect possible anomalies.

This work proposes the application of the NILM techniques to the estimation of the energy consumption in a household under analysis. For that purpose, a recurrent neural network, based on Long Short Term Memory (LSTM) layers, is trained and validated with the energy data coming from the house during three initial months roughly. After the training, the network is capable of regressing the expected energy consumption of the house for the next 15-minutes interval. This estimated value may be compared with the real consumption in order to detect any anomalous behaviour of the tenant over the day. The rest of the manuscript is organised as follows: Section II describes the global overview of the proposal; Section III details the architecture of the LSTM neural network; Section IV provides some preliminary experimental results; and, finally, conclusions are discussed in Section V.

II. Global Description of the Proposal

The proposal is based on analysing the energy consumed by a household in intervals of 15 minutes, denoted by p_k, with k being the time sample every 15 minutes. In order to detect any anomalous behaviour, the ANN topology shown in Fig. 1 is proposed. It consists of two LSTM (long short-term memory) layers, and a final dense layer. The ANN predicts the energy consumption $\hat{p}_{k+1}$ in the next 15 minutes from the consumption values recorded during the last 48 hours and denoted by the 192x1 vector $\mathbf{p_{k,192x1}}$, which is directly input to the ANN (note that a 15-minutes interval implies 4 samples per hour, so the final input vector has a size of 192 samples for two days). Furthermore, in order to provide more information to the ANN, the day of the week and the hour of the day are both inserted in the intermediate dense layer in a normalized way, since these might allow the ANN to learn about particular consumption cycles depending on working days and weekends. All the layers present a ReLU (Rectified Linear Unit) activation function.

For training this ANN, the energy consumption data have been collected from a household during a period of six months roughly, from 23rd June 2022 until 31st December 2022, complying with the 15-minutes interval. The 60% of samples are dedicated to training, 20% to validation and the last 20% for test.

After this regression, the actual consumption p_{k+1} and the estimated one $\hat{p}_{k+1}$ are compared in order to detect any anomaly. These comparisons are carried out with regard to three daily activities hereinafter: sleeping, breakfast and lunch. Sleeping is actually evaluated in the interval from 1 a.m. to 7 a.m., breakfast is from 8 a.m. to 11 a.m., and lunch is assessed from 12 p.m. to 3 p.m. It is worth noting that these intervals strongly depend on cultural and social aspects, related to the family customs, seasonal or weather conditions, or even the country's routines. In this way, they may be easily modified to fit better the behaviour of the people under analysis.

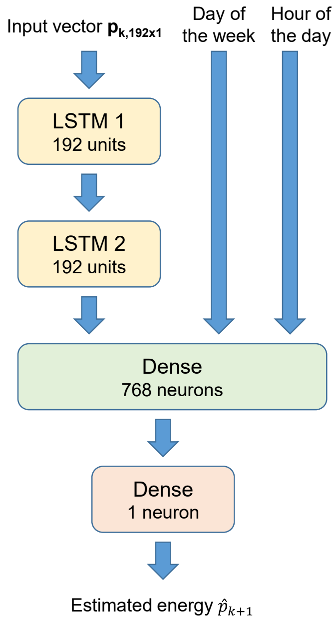

Fig. 1. LSTM topology proposed for the regression of the energy consumption in a household.

As for the aforementioned activities of breakfast and lunch, it is possible to obtain the error $\mathbf{e} = \hat{\mathbf{p}} - \mathbf{p}$, or the difference between the actual consumption and the estimated one for its corresponding activity time interval. Afterwards, an anomalous consumption is considered whether the averaged predicted consumption $\bar{\hat{\mathbf{p}}}$ for that interval of interest is higher than the averaged real one $\bar{\mathbf{p}}$ plus the error standard deviation σ_e in that activity interval, according to (1).

$$a = \begin{cases} 1 & if\ \bar{\hat{\mathbf{p}}} > \bar{\mathbf{p}} + \sigma_e \\ 0 & if\ \bar{\hat{\mathbf{p}}} \leq \bar{\mathbf{p}} + \sigma_e \end{cases} \tag{1}$$

This comparison checks that an anomalous situation (a=1) should be represented by a predicted consumption much higher than the real one, which might imply that the corresponding activity does not follow the ordinary pattern, in terms of appliance usage. Note that the proposal may provide only one possible warning at the end of the activity interval for the breakfast and lunch.

On the other hand, for the analysis of the sleeping activity, the approach is similar, although here it is allowed a higher variability before generating an anomaly, therefore involving three times the error standard deviation σ_e (2). Furthermore, this warning a_k can be launch at any sample during the time interval, by comparing the measured energy p_k with the averaged predicted consumption $\bar{\hat{\mathbf{p}}}$ for that interval of interest.

$$a_k = \begin{cases} 1 & if\ p_k > \bar{\hat{\mathbf{p}}} + 3 \cdot \sigma_e \\ 0 & if\ p_k \leq \bar{\hat{\mathbf{p}}} + 3 \cdot \sigma_e \end{cases} \tag{2}$$

III. Experimental Results

The home under analysis is a flat in the central area of Spain, where a person over 70 years old and with a slight cognitive disorder lives in. The power consumption in that household has been monitored during the last six months of 2022 by means of a Metis device [14], which provides the global consumption every minute. Nevertheless, in order to reduce the computational complexity of the proposal, this interval has been decimated at 15 minutes. Fig. 2 shows the general aspect of the global consumption, as well as a zoom for a particular date, where it is possible to identify the sleeping interval with low consumption, and the peaks corresponding to the three daily meals: breakfast, lunch and dinner.

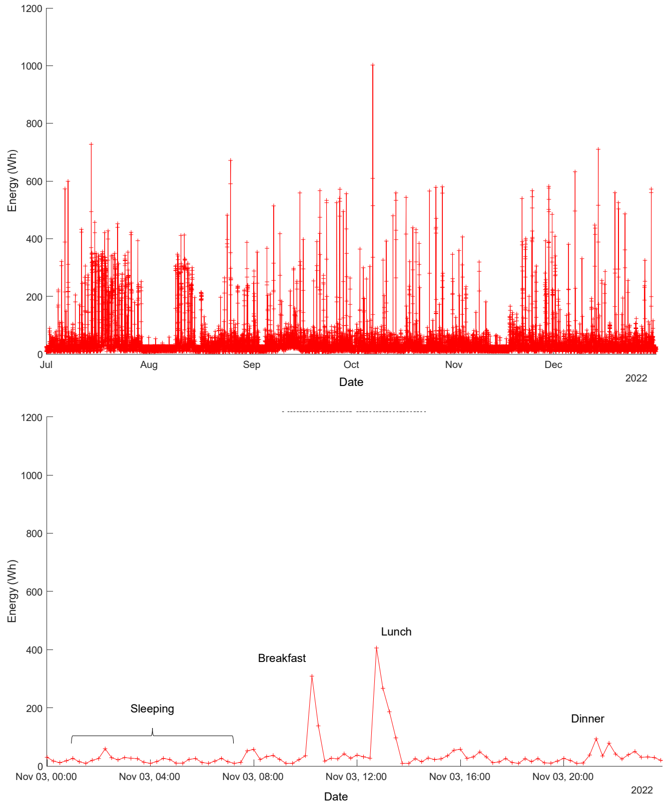

Fig. 2. General view (top) of the energy consumption every 15 minutes for the household under analysis, as well as a zoom (bottom) of a particular date, 3rd November 2022.

With these input data for training (60% of initial samples, from July to mid-October), the ANN presented before has been trained with an Adam optimizer, defined for a learning rate of 10^{-4}, that varies with a decay rate of 10^{-6}. A maximum number of epochs is set at 300, with early stopping and patience of 15 epochs. The loss function in the training is determined by the mean squared error (MSE).

Fig. 3 shows the resulting comparison between the real consumption and the predicted one for the test period, from 24th November 2022 until 31st December 2022. In the corresponding zoom, it is possible to observe a detail of both signals for a certain date. Note that the regression actually presents difficulties to achieve a perfect match with the real values, mainly due to the variability of this signal. Nevertheless, since the final goal is the detection of anomalies in some activities based on significant deviations in the consumption during the intervals of interest, the approach is still suitable in this application. In general terms, the regression achieves a mean squared error of 0.0024 p.u. and a mean absolute error of 0.0233 p.u. (note that the energy consumption is normalized hereinafter).

Finally, the corresponding warning generation is implemented according to the method described in previous Section. As can be observed in Fig. 4, alarms are detected in sleeping (green asterisk), breakfast (red circle) and lunch (magenta cross), and plotted in the upper part of the Fig. It is worth mentioning that the sensitivity in the alarm launching may be adapted by modifying the conditions described in (1) and (2). Note that the proposal does not require an additional stage dedicated to the validation of energy consumption peaks, as those plotted in Fig. 2. The warning generation just consists of a comparison between the estimated values and the real measured ones, in order to decide whether a certain situation might be considered as an anomaly.

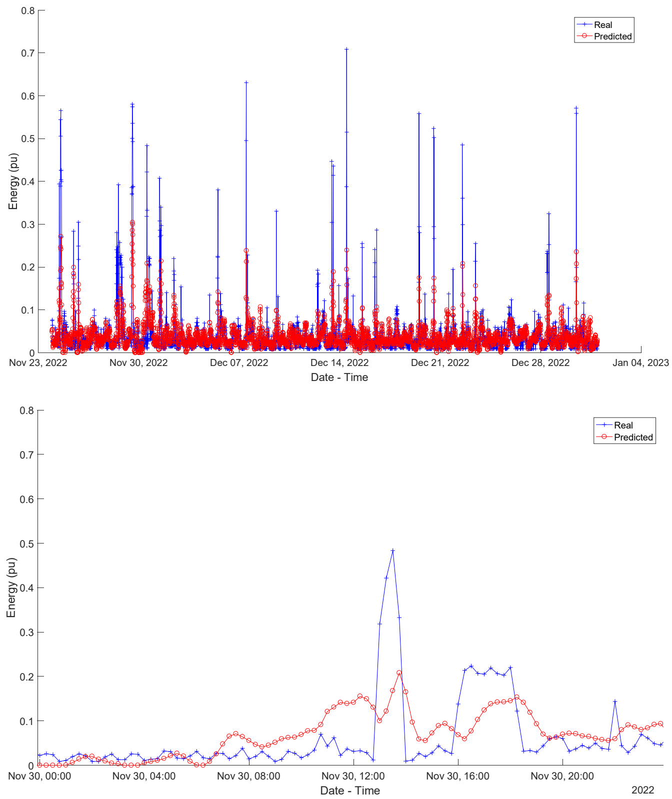

Fig. 3. General view (top) of energy regression every 15 minutes during the test period, from 24th November 2022 to 31st December 2022, for the flat under analysis; and a zoom (bottom) of a particular date, 30th November 2022. Note that the consumption values are normalized.

Since there is no a ground-truth available, provided by the tenant in the house under analysis, it has been generated manually by a person that visually inspected the measured energy consumption in the test period, and annotated when an activity (sleeping, breakfast and lunch) was considered anomalous. This manually annotated ground-truth has been used to assess the performance of the proposal in Table I. It provides the accuracy, precision, recall and F1-score for the test set, not only for the general warning generation, but also disaggregated for every considered activity.

TABLE I. PEFORMANCE OF THE WARNING GENERATION FOR THE PROPOSED METHOD

	Accuracy	Precision	Recall	F1-score
Global	0.98	0.72	0.89	0.80
Sleeping	0.99	0.66	1.00	0.79
Breakfast	0.79	0.75	0.83	0.79
Lunch	0.87	0.85	0.79	0.81

It is possible to observe in Table I that the accuracy keeps a high value (close to one) for the global and the sleeping

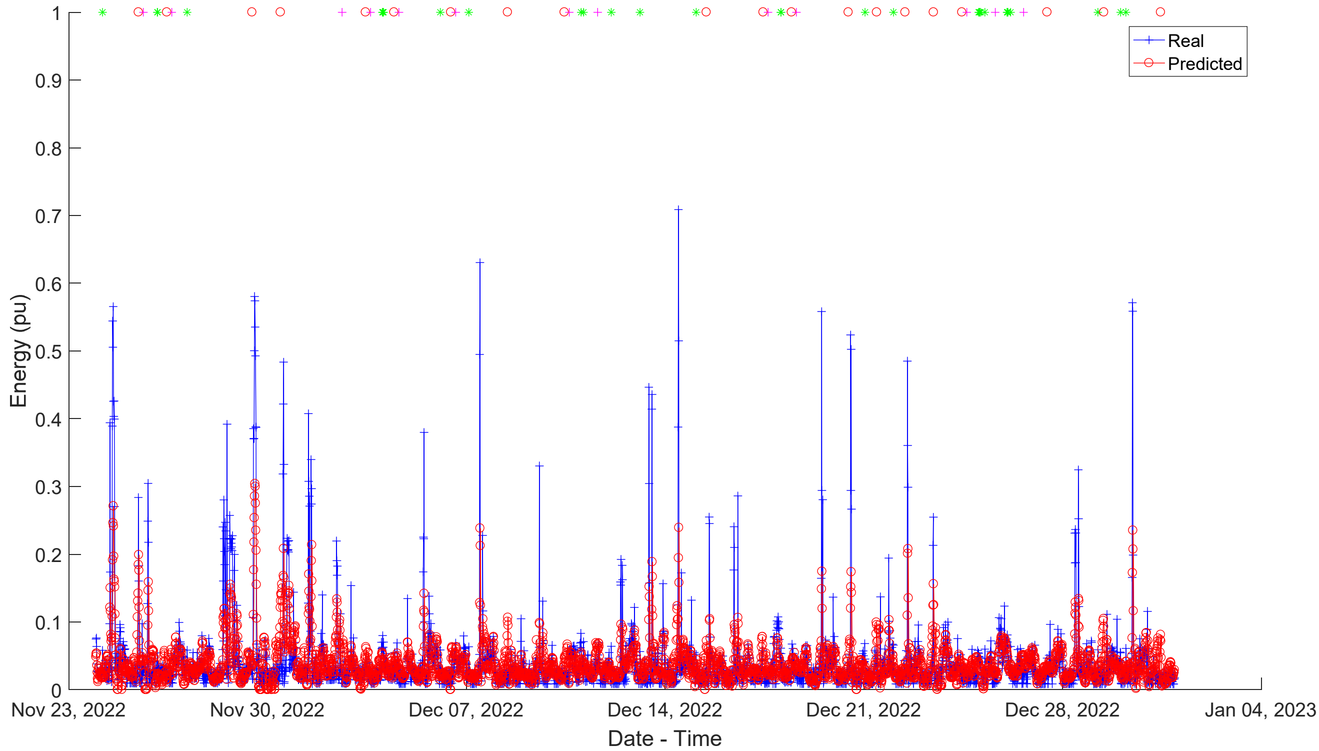

Fig. 4. Warning generation based on the difference between the real consumption and the predicted one for the three considered activities: sleeping (green asterisk), breakfast (red circle) and lunch (magenta cross).

warnings, due to the fact that most of the samples analysed by the system in the sleeping interval do not imply any warning. Since these non-anomalous samples are properly considered by the proposal as true negatives (TN), and the number of true negatives is close to the total number of samples available, the resulting accuracy is a high value. Actually, the metric recall is much more interesting, since it defines how well warning cases are detected (in this application, being sure that all the anomalous situations are detected may be a priority). It can be verified that warnings related to sleeping are always detected, since any significant energy consumption in the night hours is easily identified by the proposal. On the other hand, breakfast and lunch present a recall about 80%, mainly due to the fact that sometimes the energy estimate is low and a warning is not consequently launched. Finally, the metric precision depicts how reliable a warning can be considered when it is generated. This value is around 80% for breakfast and lunch, but a bit lower for sleeping, which implies that some false warnings may be avoided by being more restrictive when applying the condition defined in (2). For further detail, Table II shows the values of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN), together with the initial positive cases (PC) and negative cases (NC) existing in the period. These values are used to obtain the metrics in Table I.

TABLE II. TRUE POSITIVES (TP), TRUE NEGATIVES (TN), FALSE POSITIVES (FP) AND FALSE NEGATIVES (FN), TOGETHER WITH THE INITIAL POSITIVE CASES (PC) AND NEGATIVE CASES (NC), IN THE TEST DATA

	PC	NC	TP	TN	FP	FN
Global	53	973	47	955	18	6
Sleeping	21	929	21	918	11	0
Breakfast	18	20	15	15	5	3
Lunch	14	24	11	22	2	3

For clarity's sake, Fig. 5 shows an example of two false positives for the 25th of November. It can be checked that both, the breakfast and the lunch, were done on that date, although they involved short medium peaks of energy. This implied that the average estimated energy consumption in that interval resulted in a higher value than the real one according to (1), thus launching the corresponding warning. This type of cases may be solved in the future by elaborating a more complex threshold detection than the one defined in (1). On the other hand, Fig. 6 depicts a false negative, where the estimated consumption do not increases significantly in the morning of the 5th December, so the lack of real consumption is not detected when compared in (1) with the estimated one and the anomalous situation is not reported. It is worth remarking that the regression neural network tends to minimize the variation of its predictions when the house is empty for some days and there is not consumption, as it is the case on 5th December (see this situation in Fig. 6). This aspect should be also studied in the future, analysing its relation with the fact that the input data vector corresponds the samples from the last 48 hours.

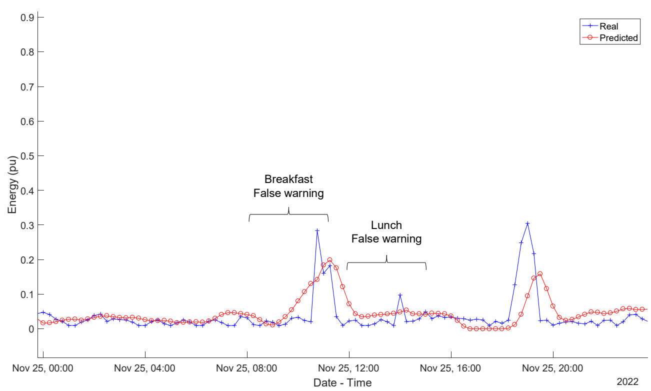

Fig. 5. False warnings (positive) for breakfast and lunch on 25th November 2022.

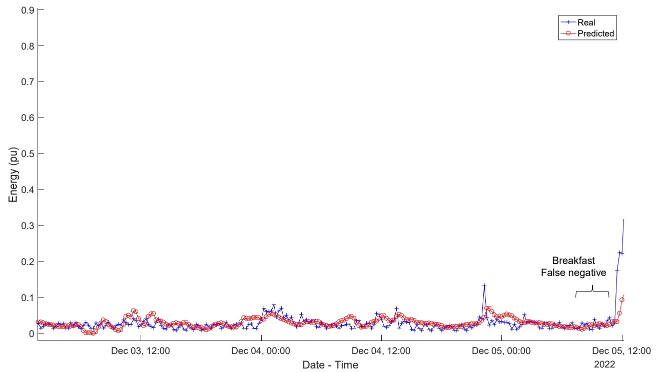

Fig. 6. False negative of breakfast (the lack of breakfast activity is not suitable detected) on 5th December 2022, when the house is empty for some previous days and there is not energy consumption registered.

IV. Conclusions

This work proposes the use of a LSTM neural network to estimate the energy consumption for the next sampling interval in a household. The network processes the consumption samples from the last 48 hours, in intervals of 15 minutes, and regresses the expected next sample. This value is then used to detect anomalies in the electrical consumption of the house, by comparing the predicted figure with the real measured one. When the real one is lower than the predicted one within certain tolerances, the behaviour of the tenant is considered not similar to the one learned from the training set. This comparison is based on an experimental aspect and can be adjusted according to the sensitivity required by every case. The proposal has been preliminary validated in a flat with one person living in, where consumption data have been acquired and processed during the last six months.

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