Using Super Resolution Perception for Anomaly Detection in Energy Load Profiles

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Abstract

Detection of anomalies in energy load profiles is crucial for the optimization of energy resources. Although there are many possible approaches to anomaly detection, in this paper it is proposed a novel approach based on the use of an artificial neural network already trained to solve the problem of Super Resolution Perception (SRP) as a method to detect anomalies in energy consumption. Furthermore, a comparison with a conventional autoencoder (AE) is provided to demonstrate that the solution to the SRP problem generates a competitive model which surpasses in several metrics to AE in the anomaly detection task without additional implementation costs.

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1 Introduction

Anomaly detection is one of the research areas that can have the greatest impact on energy consumption since it can be used to identify inefficiencies, device malfunctions and even energy theft. Numerous lines of research exist in this regard, highlighting the use of unsupervised machine learning methods (comparison between similar consumption from other historical moments, or from the same moment of other similar consumers) and the use of supervised methods through the generation of models that acquire the patterns that correspond to normal consumption or infrequent consumption.

Contrary to the usual approaches, in this paper it is proposed not to generate a new model but to use an already trained model in a different task, more specifically in the Super-Resolution of energy consumption task, known as Super-Resolution Perception (SRP). A model trained in SRP contains in its weights general consumption patterns associated with aggregate consumption that were acquired during the training for the solution of the SRP problem.

In this paper it is demonstrated that it is possible to exploit the knowledge of consumption patterns acquired by a model trained in SRP to determine the presence of anomalies in a load profile. In addition, this approach has several advantages over other approaches since the input of an SRP model is an aggregate consumption that can be predicted by forecasting models, which could enable the detection of anomalies in real time.

The paper is structured in an introduction with related work, problem formulation and justification in section 1, a methodology with definition of the model, dataset and anomaly detection process in section 2, a experimentation with the configuration, metrics, results and discussion in section 3 and a final conclusions with future works in section 4.

1.1 Related work

Anomaly detection in energy consumption is an active field being mainly approached with Machine Learning methods. Most of the works focus on supervised learning models that predict the expected consumption with which to compare or the use of unsupervised learning to compare consumptions with other equivalent consumptions of the same load profile or other similar load profiles. In 2018, [3] proposed to decompose the time series in different window sections with the method Adaptive Piecewise Constant Approximation (APCA) and then pass each time window to a different Classification And Regression Tree model (CART) trained for infrequent pattern recognitions, then a fixed set of rules are applied to the results to isolate and visualize anomalous patterns. In 2019, [13] proposed a rule-based algorithm called UNUM to detect anomalies regarding device power on/off events, and compared the result of UNUM applied on simulated anomaly data, with the result of UNUM applied to the reconstruction performed by various Non-Intrusive Load Monitoring (NILM) algorithms from the same simulated failure data; although they concluded that NILM does not capture enough information on anomalies in aggregated lines. Due to the difficulty of establishing comparative frameworks, in the same year, [6] proposed an anomaly labeling method, a public dataset, and a metric comparison framework to be used for anomalies.

In 2020, [5] emphasized the trend towards using massive, deep-learning based, cloud-scaled models as a route to anomaly detection. In 2021, [11] Proposed a data processing methodology that combines classification with anomaly detection using a feature engineering technique that includes a multivariate Gaussian distribution that improves the performance of the classification algorithm, then they evaluated it with several classification methods and determined that Light Gradient Boosting (LGB) model provided the best result for anomaly detection in their problem. At the same time, [7] propose an extensive analysis of techniques and methods used in anomaly detection. In it, they identify a tendency to use models used in other problems as a basis for anomaly detection, such as NILM, encompassing models that perform disaggregation. In 2022, [16] proposed the use of deep autoencoders to detect anomalies like energy theft, [17] proposed techniques for anomaly detection based on rain flow counting, [18] proposed to compare with other similar consumers to detect anomalies in real time without specific models, and [12] proposed to use NILM to detect inefficiencies in energy consumptions.

1.2 Super-Resolution Perception

SRP is the technique of increasing the resolution of a low-resolution energy load profile through machine learning processes. It is a relatively new study field, first formulated in 2020 for energy load profiles by [8,9]. Unlike NILM, SRP doesn't require extensive annotated datasets with disaggregated lines; instead, SRP datasets can be easily built by downsampling an existing dataset and using it as input to the model. Furthermore, the input to an SRP model can be easily approximated by forecasting models.

1.3 Problem justification

Although a supervised learning approach can be used in case of having anomaly labels, the reality is that there is a lack of large datasets with actual labeled anomalies that can be used for comparison. In addition, its manual labeling is subject to inaccuracies due to the lack of clarity to distinguish the presence of an anomaly in energy consumption, and the need for extensive knowledge in the field for its annotation [7,11]. For this reason, most approaches in this field go through the manual simulation of anomalies, in order to have a ground truth to compare with. For all these reasons, finding alternative methods for this task that do not require training have added value, highlighting the use of trained models for SRP, since their training can be done without the need for anomaly annotations. The possibility of using trained models in other problems is a trend that [7] highlighted in their work. Although they mention that in the temporal disaggregation there is not enough information about the devices, in this paper it is proposed a model trained in SRP as an alternative since it can infer this information by having the normal reconstruction patterns introduced in its weights.

2 Methodology

2.1 Model definition

It is proposed the use of M-SRPCNN published in 2021 [4] as a basis for anomaly detection given that it is able to reconstruct a load profile with hourly resolution from highly aggregated consumption with monthly granularity. This granularity was chosen due to the ease to approximate a monthly consumption in those timestamps where anomaly detection is wanted. M-SRPCNN, shown in Fig. 1, is a fully convolutional neural network that receives as input a monthly energy consumption of a variable window of months, and reconstructs the equivalent consumption with hourly resolution. This model is used under the premise that, being trained to reconstruct data from aggregated data, it has had to store normal patterns of energy consumption in its weights.

Since M-SRPCNN is a generative model, it can be considered the decoder of a hypothetical autoencoder (AE) for which a latent vector can be built through a monthly aggregation operation, without the need for the encoder. The AE is a kind of model that have a direct application in the detection of anomalies, as described in the works of [2, 10, 14–16, 19]. By learning to replicate the most salient features in the training data, the AE is encouraged to learn to precisely reproduce the most frequently observed characteristics. The anomaly detection is then applicable based on the assumption that the AE should worsen the reconstruction performance of the anomalies.

2.2 Dataset

To carry out the experimentation, the SMARKIA SRP private dataset used in [4] was chosen. Specifically, it was selected the test set with which M-SRPCNN was validated. The test set consists of a total of 13,431 time series of active energy, measured in kWh, corresponding to homes and businesses, which cover 2 years from May 2018 to May 2020 and have hourly granularity. The dataset is normalized dividing the consumption by the contracted power, which gives a value between 0 and 1.

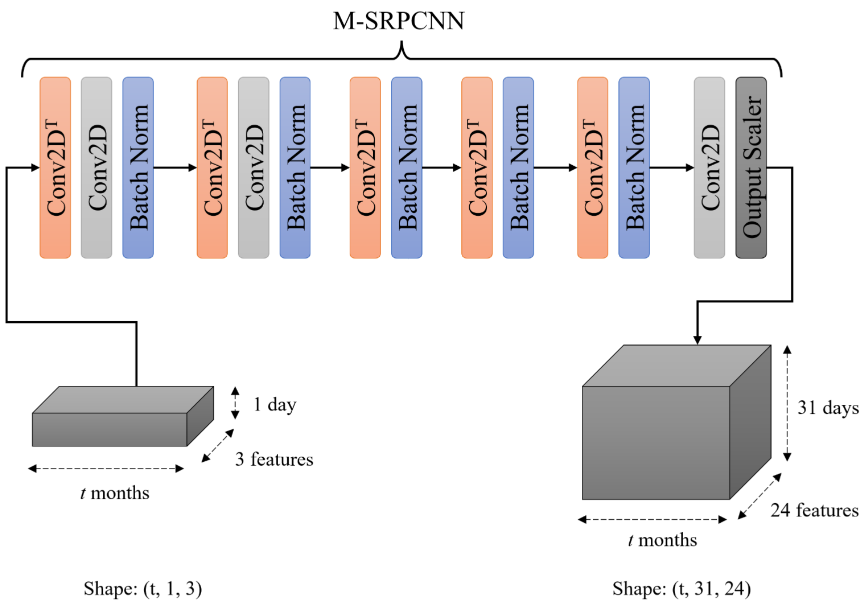

Figure 1: M-SRPCNN architecture used to perform SRP on the aggregated monthly consumption data. Best viewed in color.

2.3 Anomaly simulation

Given the difficulty in finding public datasets with tagged anomalies, it was opted to generate a series of anomaly cases that comprise known cases and apply them to the dataset to generate a ground truth to compare with. The following cases are generated in the dataset:

1. Reduction of consumption in a random section by a factor of 4.
2. Suppression of a random consumption section, setting its values to 0 merged with noise sampled from a normal distribution.
3. Modification of the consumption pattern of a consumption section using a random value sampled from a normal distribution and scaled to the maximum value of the original consumption of that section.

These cases were checked by applying each anomaly pattern a total of 4 times per time series, distributing their location randomly, ensuring that they do not overlap, and each anomalous consumption section lasting a total of 7 days. This process makes a total of 53,724 cases of anomalies in the dataset, spanning a total of 42,160,128 hours ($\sim 3\%$ of the dataset).

2.4 Detection process

Given the monthly aggregated load profile, the hourly resolution was reconstructed using the generative models described in 2.1. Then, a rolling average of 100 timesteps adjusted experimentally was applied to smooth the noise outliers in both the hourly simulated consumption and the model reconstruction. Subsequently, the difference between the reconstruction and the simulated consumption was calculated so that remaining differential contained a high value when the simulated consumption is below the reconstructed value. In this regard, the negative values were clipped so inefficiencies below the expected consumption were targeted. Then, the Chebyshev's inequality was used, proposing as anomalies those sections of the time series that exceeded the upper threshold marked by $\mu + 2 \cdot \sigma$ [1], a range that tends to represent 95% of the data, where μ is the mean differential of the reconstruction versus the original series, and σ is its corresponding standard deviation. With Chebyshev's inequality it is assumed that anomalies are more likely to be reflected in the 5% of data error not represented by the defined range, if they exist.

3 Experimentation

The performance of M-SRPCNN was compared with a conventional AE trained on the same simulated anomaly dataset described in section 2.3 and following the same detection process described in section 2.4. A version of the AE was generated for each case defined in section 2.3.

In addition, since the latent vector accepted by M-SRPCNN is the monthly consumption, it is possible to use forecasting models to approximate this value in months for which the total consumption is unknown to enable the detection of anomalies in real time. In order to know the performance of M-SRPCNN in the hypothetical case of having an approximation of the monthly consumption predicted by a forecasting model, it was also added a comparison of the performance of M-SRPCNN by using the aggregate values of the original dataset as input, understanding these as the best value that can be obtained from an approximation of monthly consumption.

The results and discussion of the experimentation can be seen in section 3.3.

3.1 Configuration

The experimentation was executed in a Xeon-W 2123 environment with 8 threads and 64 GB of RAM, equipped with an NVIDIA GeForce RTX2080 Ti GPU. The AE models were trained for a total of 1000 epochs, in order to match the number of epochs for which M-SRPCNN was originally trained in [4].

3.2 Metrics

For the evaluation of the proposed methodology, the metrics Precision (1), Recall (2), F-Score (3) and Mathews Correlation Coefficient (MCC) (4) were chosen.

$$Precision = p = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = r = \frac{TP}{TP + FN} \tag{2}$$

$$F_{\beta} = \frac{(\beta^2 + 1) \times p \times r}{\beta^2 \times p + r} \tag{3}$$

$$\begin{aligned} N &= TN + TP + FN + FP \\ S &= \frac{TP + FN}{N} \\ P &= \frac{TP + FP}{N} \\ MCC &= \frac{TP/N - S \times P}{\sqrt{PS(1-S)(1-P)}} \end{aligned} \tag{4}$$

Where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.

The F_{β} metric eases the evaluation of the accuracy of the model and settles the base for comparison of models by unifying the *Precision* and *Recall* metrics into a single value. In the experimentation, it was adjusted $\beta = 1$ to give equal importance to p and r. However, a second metric MCC was also reported since the F_1 is less informative for binary classification problems, as it does not take into account the values of TN. F_1 takes values between 0 and 1; and MCC takes values between -1 and 1, the prediction being better the higher the value in both metrics.

3.3 Results and Discussion

A comparison of the performance of M-SRPCNN with respect to an AE trained with the anomaly dataset can be seen in Table 1. It can be stated that M-SRPCNN outperforms the AE in both the F_1 and MCC metrics in all the cases, even though further tweaking of the AE hyperparameters could end up reaching similar metric values given that both models metrics are relatively close. However, a clear advantage can be seen for the M-SRPCNN model, since it does not require retraining or adjustment for the task at hand. A visualization of a sample for each casuistry can be seen in Fig. 2.

Table 1: Metrics for each anomaly casuistry defined in section 2.3. The closer to 1, the better.

Casuistry	***Precision***	***Recall***	$\boldsymbol{F_1}$	***MCC***	***Method***
1	0.274	0.430	0.335	0.322	AE
	0.286	**0.569**	**0.381**	**0.383**	**M-SRPCNN**
2	**0.362**	0.475	0.411	0.396	AE
	0.325	**0.575**	**0.415**	**0.411**	**M-SRPCNN**
3	**0.379**	0.545	0.447	0.437	AE
	0.361	**0.666**	**0.468**	**0.473**	**M-SRPCNN**

On the other hand, and contrary to the AE, in M-SRPCNN a latent vector can be built without the need to retrain a model that approximates it, using an estimate of monthly consumption. With this latent vector, the hourly consumption of a specific month can be reconstructed and the same anomaly detection process can be started. In this context, Table 2 shows the performance of M-SRPCNN with the hypothetical best approximation of the latent vector that can be made, for which the original values aggregated by months can be used as a proxy. On this basis, the metrics improve significantly over the use of aggregated simulated data as a source in M-SRPCNN.

Table 2: Metrics for each anomaly casuistry defined in section 2.3 when reconstructing using the original monthly aggregated value. The closer to 1, the better.

Casuistry	***Precision***	***Recall***	$\boldsymbol{F_1}$	***MCC***	***Method***
1	0.362	0.693	0.475	0.484	M-SRPCNN
2	0.405	0.670	0.505	0.504	M-SRPCNN
3	0.441	0.770	0.561	0.569	M-SRPCNN

4 Conclusions

In this paper it was demonstrated that a model trained for SRP can be used to detect anomalies without the need for labels present, the result of which is comparable and, in some metrics superior, to the anomaly detection that can be performed with a conventional AE. Furthermore, the SRP model is equivalent to a decoder for which the representative latent vectors of each sample can be known in advance, which allows to use forecasted lower resolutions predictions as source for predictions and enable real-time anomaly detection.

This scheme has the advantage of saving computation and time due to the use of an already trained model for a different task, without the need to

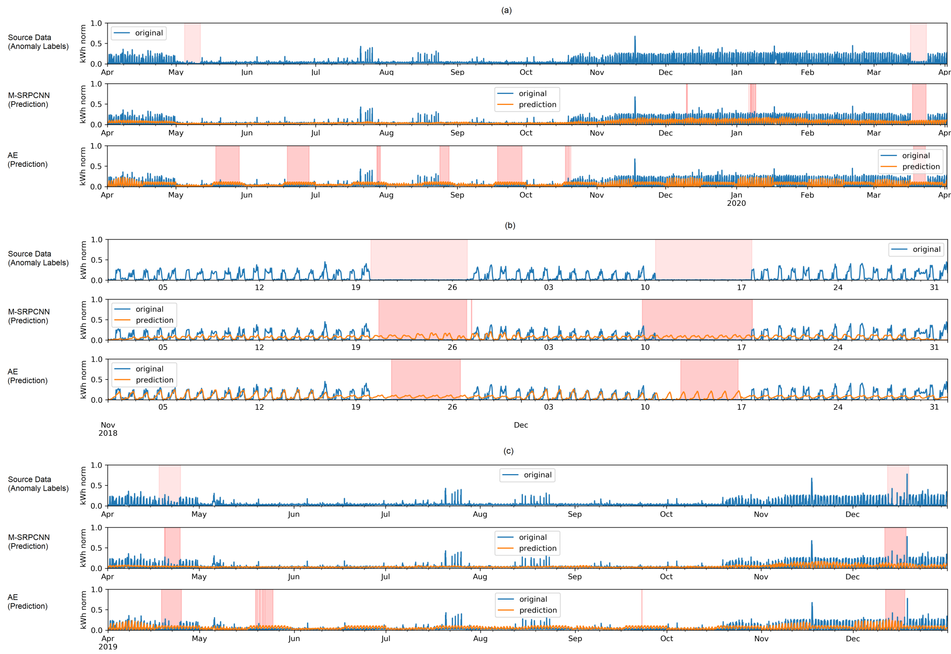

Figure 2: A visualization of the source data with the anomaly labels highlighted as red sections, followed, in order, by the prediction of M-SRPCNN and the prediction of the AE with the corresponding anomalies detected on each. The three casuistries are shown: (a) Anomalies based on consumption reduction by a factor of 4, (b) Anomalies based on consumption suppressed and filled with noise and (c) Anomalies based on consumption replaced by noise scaled to the original consumption values. Best viewed in color.

readjust it for anomaly detection. Depending on the scenario to be applied, the kind of anomalies to be detected are highly influenced by the resolution that the SRP model is capable of generating. In this line, future work is expected to evaluate the impact on the detection of anomalies based on the level of resolution extended by the SRP model, and the influence of the prediction based on an estimate of the aggregate consumption instead of the real consumption.

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