Mining Multivariate Time-Series for Anomaly Detection in Mobile Networks On the Usage of Variational Auto Encoders and Dilated Convolutions

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ABSTRACT

The automatic detection of anomalies in communication networks plays a central role in network management. Despite the many attempts and approaches for anomaly detection explored in the past, the detection of rare events in multidimensional network data streams still represents a complex to tackle problem. Network monitoring data generally consists of hundreds of counters periodically collected in the form of time-series, resulting in a complex-to-analyze multivariate time-series (MTS) process. Traditional time-series anomaly detection methods target univariate time-series analysis, which makes the multivariate analysis cumbersome and prohibitively complex when dealing with MTS data. In this paper we introduce *DC-VAE*, a novel approach to anomaly detection in MTS data, leveraging convolutional neural networks (CNNs) and variational auto encoders (VAEs). *DC-VAE* detects anomalies in MTS data through a single model, exploiting temporal information without sacrificing computational and memory resources. In particular, instead of using recursive neural networks, large causal filters, or many layers, *DC-VAE* relies on Dilated Convolutions (DC) to capture long and short term phenomena in the data, avoiding complex and less-efficient deep architectures, thus simplifying learning. We evaluate *DC-VAE* on the detection of anomalies in the TELCO dataset, a large-scale, multi-dimensional network monitoring dataset collected at an operational mobile Internet Service Provider (ISP), where anomalous events were manually labeled by experts during a time span of seven-months, at a five-minutes granularity. Results show the main properties and advantages introduced by VAEs for time-series anomaly detection, as well as the out-performance of *DC-VAE* as compared to standard VAEs for time-series modeling. We also evaluate *DC-VAE* in open, publicly available datasets, comparing its performance against other multivariate anomaly detectors based on deep learning generative models. For the sake of reproducibility and as an additional contribution, we make the TELCO dataset publicly available to the community, and openly release the code implementing *DC-VAE*.

KEYWORDS

Anomaly Detection, Deep Learning, Multivariate Time-Series, Dilated Convolution, VAE, Reproducibility, New Datasets

1 INTRODUCTION

Network monitoring data often consists of hundreds or thousands of variables periodically measured and analyzed in the form of time-series, resulting in a complex-to-analyze multivariate time-series (MTS) process. Real-time anomaly detection in such MTS processes is a key ingredient for network operation and management. There is a vast literature on the problem of anomaly detection in time-series using traditional statistical models [1, 3, 4, 10, 25]; due to the non-stationary, non-linear, and high-noise characteristics of network monitoring time-series data, these traditional models have difficulty predicting these data with high precision. Hence, modern approaches to time-series anomaly detection based on deep learning technology have flourished in recent years [16]. Most approaches in the literature address the problem by either focusing on univariate time-series modeling and analysis – running an independent detector for each time-series, or by considering multi-dimensional input data with short-term memory analysis, to avoid the scalability limitations introduced by very deep architectures, or the complexities and delays introduced by recurrent topologies.

In this paper we introduce *DC-VAE*, an unsupervised and multivariate approach to anomaly detection in time-series, based on popular Variational Auto-Encoders (VAEs). VAEs are a generative version of classical auto-encoders, with the particularity of having, by conception, continuous latent spaces; as such, VAEs map the input variables into a multivariate latent distribution, which enables a generative process. A VAE provides a probabilistic manner to describe an observation in the latent space. Thus, rather than training an encoder which outputs a single value describing each latent state attribute, the encoder is formulated to describe a probability distribution for each latent attribute. One of the key advantages of VAEs for anomaly detection is that, for a given input, they produce as output prediction (i.e., reconstruction) not only an expected value, but also the associated standard deviation, corresponding to the distribution the model understands (i.e., has learned) generated the corresponding input. This automatically defines a *normality region* for each independent time-series, which can then be easily exploited for detecting deviations beyond this region. Using VAEs as underlying approach allows the user to visualize the region of normal behavior in a simple and appealing way, enabling fine-grained, per univariate time-series anomaly detection.

To exploit the temporal dependencies and characteristics of time-series data in a fast and efficient manner, we take a Dilated Convolutional (DC) Neural Network (NN) as the VAE's encoder and decoder architecture. DCNNs have shown excellent performance for processing sequential data in a causal manner [15], i.e., without relying on recursive architectures, which are generally less time-efficient and more difficult to train (e.g., gradient exploding/vanishing problems). Compared to normal convolutions, dilated convolutions improve time-series modeling by increasing the receptive field of the neural network, reducing computational and memory requirements, and most importantly, enabling training – and detection – on longer-in-the-past temporal sequences.

We apply *DC-VAE* to a MTS dataset arising from the monitoring of an operational mobile ISP, detecting anomalies of very different structural properties. Referred to as the TELCO dataset, this *large-scale* – about 750 thousand samples, *long time-span* – seven months'

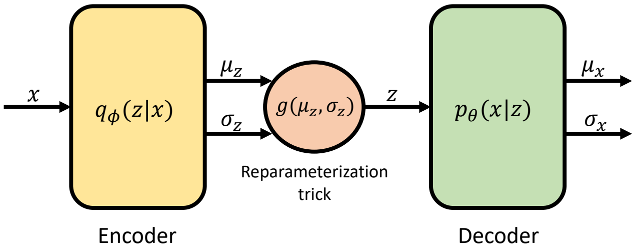


Figure 1: Variational autoencoder and the reparameterization trick.

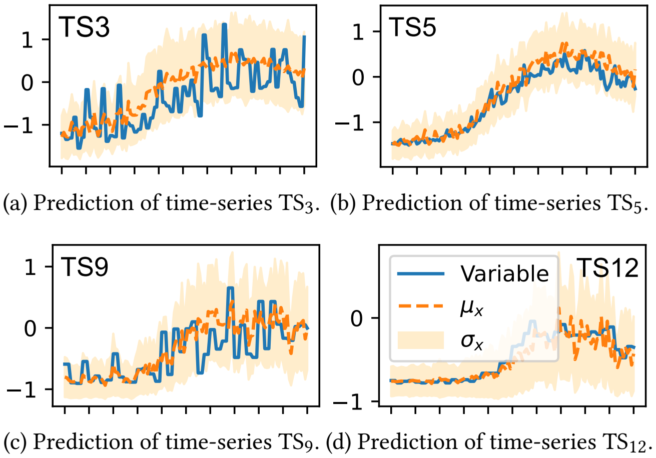
worth of measurements collected at a five-minutes scale, *multi-dimensional* – twelve different metrics (time-series), network monitoring dataset includes ground-truth labels for anomalous events at each individual time-series, manually labeled by the experts of the network operation center (NOC) managing the mobile ISP. We compare *DC-VAE* against a traditional VAE model for snapshot-input-based anomaly detection, where the encoder/decoder architecture is based on standard, fully connected feed-forward neural networks, and the input corresponds to the MTS at the specific time of detection. We shall refer to this model as Standard-VAE (S-VAE). In addition, we evaluate *DC-VAE* in an open, publicly available dataset commonly used in the literature – the SWaT dataset [14], and compare its performance against other MTS anomaly detectors based on deep learning generative models, which have become very popular in recent years. For the sake of reproducibility and as an additional contribution, we make the TELCO dataset publicly available to the community, and openly release *DC-VAE*'s code (due to double-blind reviewing, we would add the link to the repository in case of acceptance of the paper).

The reminder of the paper is organized as follows: Section 2 briefly overviews the related work; in Section 3 we describe the *DC-VAE* model in detail; Section 4 presents the TELCO mobile ISP dataset collected for evaluation, and reports the results obtained with *DC-VAE* in the detection of anomalies in TELCO, benchmarking its performance against S-VAE, as well as against other approaches in the SWaT open dataset. Finally, Section 5 concludes the paper.

2 RELATED WORK

There are multiple surveys on general-domain anomaly detection techniques [3, 4, 10] as well as on network anomaly detection [1, 25]. The diversity of data characteristics and types of anomalies results in a lack of universal anomaly detection models. Modern approaches to time-series anomaly detection based on deep learning technology have flourished in recent years [16]. Due to their data-driven nature and achieved performance in multiple domains, generative models such as VAEs and Generative Adversarial Networks (GANs) have gained relevance in the anomaly detection field [5, 7–9, 13, 22, 23].

Modeling data sequences through a combination of variational inference and deep learning architectures has been vastly researched in other domains in recent years, mostly by extending VAEs to Recurrent Neural Networks (RNNs), with architectures such as STORN [2], VRNN [6], and Bi-LSTM [17] among others. Convolutional layers with dilation have been also incorporated into some of these approaches [11, 21], allowing to speed up the training process based on the possibilities of parallelization offered by these architectures.



(a) Prediction of time-series TS$_3$. (b) Prediction of time-series TS$_5$.

(c) Prediction of time-series TS$_9$. (d) Prediction of time-series TS$_{12}$.

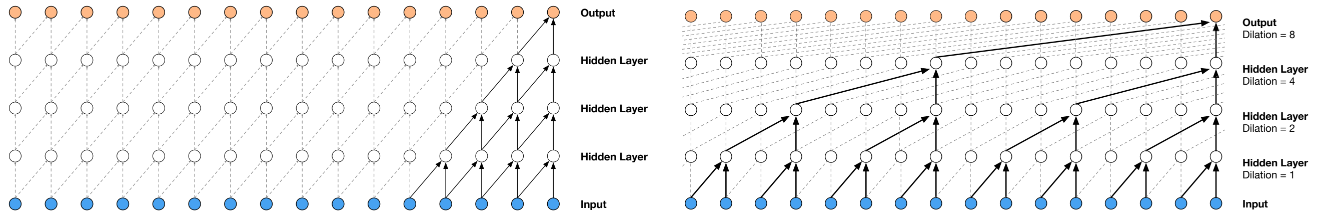
Figure 2: Example of time-series analysis through *DC-VAE*, for the TELCO dataset. The normal-operation region is defined by $\boldsymbol{\mu_x}$ and $\boldsymbol{\sigma_x}$.

Our work is inspired by previous work on generative models for network anomaly detection in mutivariate time-series [8]; the Net-GAN detector [8] follows an architecture based on GANs and RNNs, where Long Short-Term Memory networks (LSTMs) are employed as both generator and discriminator models to capture temporal dependencies in the data.

3 ANOMALY DETECTION WITH *DC-VAE*

Sequential data such as time-series is generally processed through sliding windows, condensing the information of the most recent T measurements. Let us define $\boldsymbol{x}$ as a matrix in $\mathbb{R}^{M \times T}$, where M is the number of variables in the MTS process, i.e., defines the dimension of the problem. We also define $x(t) \in \mathbb{R}^{M \times 1}$ as an M-dimensional vector, representing the MTS at a certain time t, and $x_m(t)$, with $m \in \{1, \ldots, M\}$, as the value of the m-th time-series at time t.

As depicted in Figure 1, for a given input $\boldsymbol{x}$, the trained VAE model produces two different predictions, $\boldsymbol{\mu_x}$ and $\boldsymbol{\sigma_x}$ – matrices in $\mathbb{R}^{M \times T}$, corresponding to the parametrization of the probability distribution which better represents the given input. If the VAE model was trained (mainly) with data describing the normal behavior of the monitored system, then the output for a non-anomalous input would not deviate from the mean $\boldsymbol{\mu_x}$ more than a specific integer $\boldsymbol{\alpha}$ times the standard deviation $\boldsymbol{\sigma_x}$. On the contrary, if the input presents an anomaly, the output would not belong to the region determined by the predicted mean and standard deviation. For reference, Figure 2 presents the main ideas behind the usage of VAEs for time-series anomaly detection, in this case portraying the results obtained in the analysis of the TELCO dataset, used in this paper for evaluation purposes (see Section 4). For each of the displayed time-series TS$_i$ – the TELCO dataset corresponds to



(a) Normal convolution.

(b) Dilated convolution.

Figure 3: (*)Figure taken from the original WaveNet paper [15]. Using CNNs with causal filters requires large filters or many layers to learn from long sequences. Dilated convolutions improve time-series modeling by increasing the receptive field of the neural network, reducing computational and memory requirements, enabling training on long sequences.

tweleve time-series TS_1 to TS_{12}, its real value x_i, along with the outputs of the VAE μ_{x_i} and σ_{x_i}, are reported.

In the VAE model, observations $\boldsymbol{x}$ are assumed to depend on a random variable $\boldsymbol{z}$ that comes from a lower-dimensional *latent* space. The objective is to maximize $P(\boldsymbol{x})$, the probability of the observations through the model. Similar to $\boldsymbol{x}$, $\boldsymbol{z}$ will also be a sequence of length T, but with a smaller number of dimensions $J < M$, $\boldsymbol{z} \in \mathbb{R}^{J\times T}$. In formal terms, given an input sample $\boldsymbol{x}$ characterized by an unknown probability distribution $P(\boldsymbol{x})$, the objective is to model or approximate the data's true distribution P using a parametrized distribution p_θ with parameters θ. Let $\boldsymbol{z}$ be a random vector jointly-distributed with $\boldsymbol{x}$, representing the latent encoding of $\boldsymbol{x}$. We can express $p_\theta(\boldsymbol{x})$ as:

$$p_\theta(\boldsymbol{x}) \quad = \quad \int_{\boldsymbol{z}} p_\theta(\boldsymbol{x}, \boldsymbol{z})\, d\boldsymbol{z}, \tag{1}$$

where $p_\theta(\boldsymbol{x}, \boldsymbol{z})$ represents the joint distribution under p_θ of the observable data $\boldsymbol{x}$ and its latent representation or encoding $\boldsymbol{z}$. According to the chain rule, the equation can be rewritten as:

$$p_\theta(\boldsymbol{x}) \quad = \quad \int_{\boldsymbol{z}} p_\theta(\boldsymbol{x}|\boldsymbol{z}) p_\theta(\boldsymbol{z})\, d\boldsymbol{z} \tag{2}$$

In the vanilla VAE, $p_\theta(\boldsymbol{x}|\boldsymbol{z})$ is considered a Gaussian distribution, and therefore, $p_\theta(\boldsymbol{x})$ is a mixture of Gaussian distributions. The computation of $p_\theta(\boldsymbol{x})$ is very expensive and in most cases even intractable. To speed up training and make it feasible, it is necessary to introduce a further function to approximate the posterior distribution $p_\theta(\boldsymbol{z}|\boldsymbol{x})$, in the form of $q_\phi(\boldsymbol{z}|\boldsymbol{x}) \approx p_\theta(\boldsymbol{z}|\boldsymbol{x})$. In this way, the overall problem can be easily translated into the autoencoder domain, in which the conditional likelihood distribution $p_\theta(\boldsymbol{x}|\boldsymbol{z})$ is performed by the *probabilistic* decoder, while the approximated posterior distribution $q_\phi(\boldsymbol{z}|\boldsymbol{x})$ is computed by the *probabilistic* encoder, cf. Figure 1.

To train this autoencoder and make the application of backpropagation feasible, a so-called *reparameterization trick* is generally introduced. The main assumption on the latent space is that it can be considered as a set of multivariate Gaussian distributions, and therefore, $\boldsymbol{z} \sim q_\phi(\boldsymbol{z}|\boldsymbol{x}) = \mathcal{N}(\boldsymbol{\mu_z}, \boldsymbol{\sigma_z}^2)$. Given a random matrix $\boldsymbol{\varepsilon} \sim \mathcal{N}(0, \boldsymbol{I})$ and $\odot$ defined as the element-wise product, the reparameterization trick permits to explicitly define $\boldsymbol{z} = g(\boldsymbol{\mu_z}, \boldsymbol{\sigma_z}) = \boldsymbol{\mu_z} + \boldsymbol{\sigma_z} \odot \boldsymbol{\varepsilon}$. Thanks to this transformation, the variational autoencoder is trainable and the probabilistic encoder has to learn how to map a compressed representation of the input into the two latent vectors $\boldsymbol{\mu_z}$ and $\boldsymbol{\sigma_z}$, while the stochasticity remains excluded from the updating process and is injected in the latent space as an external input through $\boldsymbol{\varepsilon}$.

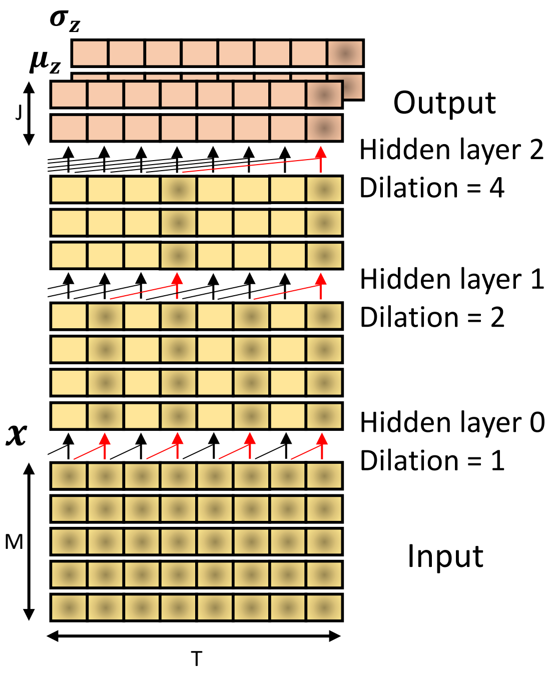


Figure 4: Encoder architecture using causal dilated convolutions, implemented through a stack of 1D convolutional layers.

To exploit the temporal dimension of the input time-series, we proposed an encoder/decoder architecture based on popular CNNs, using Dilated Convolutions (DCs) [15]. DC is a technique that expands the input by inserting gaps between its consecutive samples. In simpler terms, it is the same as a normal convolution, but it involves skipping samples, so as to cover a larger area of the input. Figure 3 explains the basic idea behind DCs. The convolutions must be causal, so that detection can be implemented in real-time. Because such architectures do not have recurrent connections, they are often much faster to train than RNNs, and do not suffer from

dataset	# samples	duration	# anomalous samples
training	310,974	3 months	5,672 (**1.8%**)
validation	103,680	1 month	385 (**0.4%**)
testing	317,953	3 months	3,080 (**1.0%**)
total	732,607	7 months	9,137 (**1.2%**)

Table 1: TELCO dataset. Seven-months worth of measurements were manually labeled, for twelve different metrics.

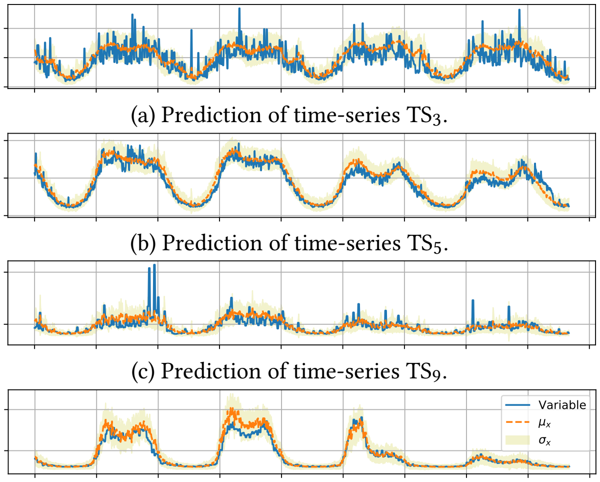
complex-to-tame gradient exploding/vanishing problems. Using DCs instead of standard convolutions has several advantages for real-time analysis: (i) they increase the so-called receptive field, meaning that longer-in-the-past information can be fed into the detection; (ii) DCs are computationally more efficient, as they provide larger coverage at the same computation cost; (iii) by using DC, the pooling steps are omitted, thus resulting in lesser memory consumption; (iv) finally, for the same temporary receptive field, the resulting network architecture is much more compact.

Figure 4 depicts the encoder architecture used in *DC-VAE*. The network architecture must be such that the output values depend on all previous input values. The length T of the sliding window plays a key role here, as it must ensure that the output at t depends on the input at that time and at $\{t-1, t-2, \ldots, t-T+1\}$. The simplest way to achieve this is to use filters of length $F = 2$ and DCs with dilatation factor $d = F^h$, which grow exponentially with the layer depth $h \in [0, H-1]$, where H is the number of layers of the network. Subsequently, H is the minimum value that verifies: $T \leq 2 * F^{H-1}$. In the example, the window length is $T = 8$, and the target is achieved by taking $H = 3$ layers. This direct relationship between T and the network architecture has a strong practical impact, making it easy to construct the encoder/decoder, based on the desired temporal-depth of the analysis.

Model training is conducted on top of normal-operation data, to capture the baseline for anomaly detection. Once trained, the detection process runs continually, rolling the sliding window of length T by a unitary-time step. At each time t, the *DC-VAE* model takes as input the matrix $\boldsymbol{x} \in \mathbb{R}^{M \times T}$, constructed out of the last T samples observed in the MTS, and produces as output matrices $\boldsymbol{\mu_x}$ and $\boldsymbol{\sigma_x}$ – for notation brevity, we define $\boldsymbol{\mu} = \boldsymbol{\mu_x}$ and $\boldsymbol{\sigma} = \boldsymbol{\sigma_x}$. From these two output matrices, the anomaly detection only considers their values at time t, corresponding to two vectors $\mu(t)$ and $\sigma(t)$. For each of the univariate time-series m, an anomaly is detected at time t if its value $x_m(t)$ falls outside the normal-operation region, defined by $\mu_m(t)$ and $\sigma_m(t)$. More precisely, an anomaly in time-series m is declared at time t if:

$$|x_m(t) - \mu_m(t)| > \alpha_m \times \sigma_m(t), \tag{3}$$

where $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_m, \ldots, \alpha_M)$ is a vector of M detection sensitivity thresholds, where each α_m can be set independently for each time-series, allowing for fine-grained, per time-series calibration of the detection process.



(a) Prediction of time-series TS$_3$.

(b) Prediction of time-series TS$_5$.

(c) Prediction of time-series TS$_9$.

(d) Prediction of time-series TS$_{12}$.

Figure 5: Example of time-series analysis through *DC-VAE*, for the TELCO dataset, using $T = 512$ samples – almost 2 days of temporary receptive field in the past.

4 TELCO AND *DC-VAE* EVALUATION

4.1 The TELCO Dataset

A recent study [19] alerts on the limitations of evaluating anomaly detection algorithms on popular time-series datasets such as Yahoo, Numenta, or NASA among others. In particular, these datasets are noted to suffer from known flaws such as trivial anomalies, unrealistic anomaly density, mislabeled ground truth, and run-to-failure bias. For this reason, we decided to evaluate *DC-VAE* in a proprietary MTS dataset, corresponding to real measurements collected at an operation mobile ISP – note that we are publicly releasing this dataset to the community. The TELCO dataset corresponds to twelve different time-series, with a temporal granularity of five minutes per sample, collected and manually labeled for a period of seven months, between January 1 and July 31, 2021. This temporal length is seldom available in other publicly available datasets of this nature, and is highly relevant and useful to allow for long-term seasonal behavior analysis.

Each time-series corresponds to aggregated data from different sources; to keep business confidentiality, we do not specify the exact type of data reflected by each time-series. The twelve time-series are typical data monitored in a mobile ISP, including number and amount of prepaid data transfer fees, number and cost of calls, volume of data traffic, number of SMS, and more.

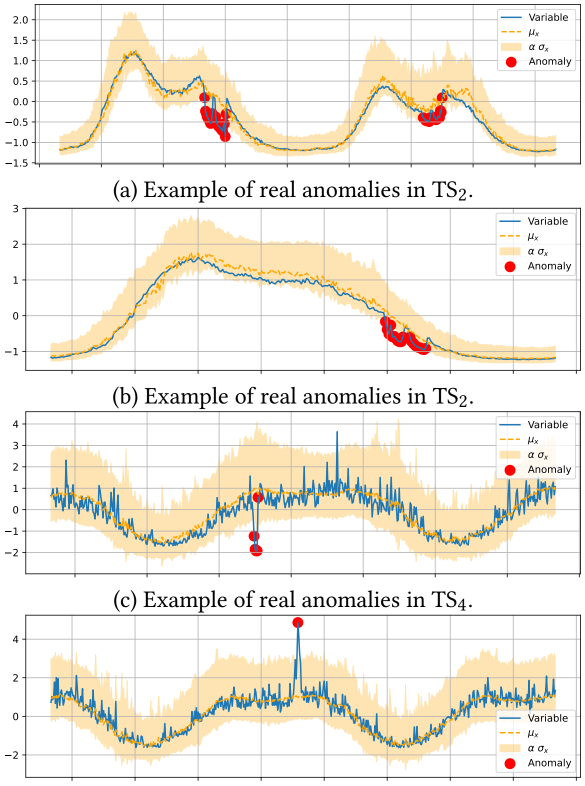
Table 1 presents the main details of the dataset. Note in particular how strongly imbalanced is the dataset in terms of normal-operation and anomalous samples, which is the typical case for real network measurements in operational deployments. By definition, anomalies are rare events. We split the full dataset in three independent, time-ordered sub-sets, using measurements from January to March for model training, April for model validation, and May to July for testing purposes.

4.2 Anomaly Detection Results in TELCO

Figure 5 shows *DC-VAE* in action, using a sliding-window of length $T = 512$ samples, corresponding to roughly two days of past measurements. This length of time-window is the one providing better validation results in the TELCO dataset. We take the same time-series depicted in Figure 2 as reference, but now considering a longer time span of four days. *DC-VAE* can properly track different types of behavior in the time-series, including the strong seasonal daily component, but also the operation during weekdays and weekends, e.g., visible in Figure 5(d). In this example, time-series TS_3 and TS_9 are noisier than time-series TS_5 and TS_{12}, which justifies the need for different sensitivity thresholds α_m to address the underlying nature of each monitored metric. Note in addition how different periods of time-series variability result in more or less tight normal-operation regions estimated by *DC-VAE*, as defined by $\sigma(t)$.

To apply *DC-VAE* for anomaly detection, we have to calibrate the sensitivity thresholds $\boldsymbol{\alpha}$, which is usually done in a supervised manner, relying on the labeled anomalies available in the training and validation datasets. This step is the only one which requires certain level of "supervision" (in the sense of ground-truth availability), but could also be done in a self-supervised manner, by labeling anomalies through outlier detection techniques. In our specific problem, each sensitivity threshold α_m is calibrated on a per time-series basis, by maximizing the $F1$ score over the training and validation datasets, doing a grid-search of integer values from 1 to 5. In a nutshell, we decide how many standard deviations σ_m shall be considered as tolerance for the normal-operation variability of the data.

Figure 6 reports some examples of real (i.e., labeled) anomalies present in the TELCO dataset, in particular for time-series TS_2 and TS_4, along with their corresponding identification by *DC-VAE*, where sensitivity thresholds $\boldsymbol{\alpha}$ were calibrated as mentioned before. *DC-VAE* can detect different types of anomalies present in the data, of a more transient and spiky nature in the case of TS_4, or on a more structural basis in the case of TS_2. Note also how some of the actual measurements fall significantly outside the normal-operation region – e.g. in Figure 6(c), but still these were not labeled as anomalous by the expert operator. Whether or not this is a false-positive produced by *DC-VAE*, or a non-labeled anomaly missed by the expert operator is difficult to know.



(a) Example of real anomalies in TS_2.

(b) Example of real anomalies in TS_2.

(c) Example of real anomalies in TS_4.

(d) Example of real anomalies in TS_4.

Figure 6: Examples of real anomalies present in the analyzed dataset, and their identification by *DC-VAE*.

We also run a quantitative performance analysis of *DC-VAE* in the testing dataset (cf. Table 1). As performance metrics, we consider an elaborated version of the traditionally used, per-sample evaluation metrics, to consider a more natural and practical approach for real anomaly detection applications, evaluating detection performance in the form of anomaly temporal-ranges. Traditional metrics can make sense for point anomalies where a true positive corresponds to a correct detection at the precise point in time. However, as shown for example in Figure 6(b), many anomalies occur in the form of multiple, consecutive point anomalies, defining an anomaly range. In such scenarios, it could be already enough to have a partial overlap between the real anomaly range and the predicted anomaly interval to consider a correct detection. Previous work have considered these observations [12, 18, 20], defining new metrics which prioritize early or delayed detection, or focusing mainly on range anomalies. We therefore take the extended definitions of recall and precision as defined in [18] to generalize for ranges of anomalies, considering a correct detection if at least one of the samples between the start and the end of the actual anomaly are flagged by the model. We refer to these extended, range-based metrics as R_r, P_r, and $F1_r$, for recall, precision, and f1-score, respectively. Finally, evaluations are reported independently for each to the twelve time-series TS_m in the TELCO dataset.

To show the advantages of *DC-VAE* as compared to the usage of standard, vanilla VAEs for anomaly detection in time-series, we define the Standard-VAE (S-VAE) as a snapshot-input-based anomaly detection model, where the encoder/decoder architecture is based on a standard 3-layers, fully connected feed-forward neural network, and the input corresponds to the MTS at the specific time of detection – i.e., $T = 1$ in S-VAE. Table 2 reports the corresponding results in the testing dataset, independently for each time-series, and as an average value. The first observation is that achieved results are in general rather poor, achieving $F1_r$ scores around 60% for eight out of the twelve time-series, and below for the rest. This is highly in contrast with the high $F1$ scores usually reported in the literature, when dealing with simulated or flawed datasets [19]. Indeed, dealing with in-the-wild measurements and human-labeled, highly-imbalanced datasets is more complex than what the results in the literature usually report – real, in practice MTS anomaly

	S-VAE			*DC-VAE*		
TS ID	R_r	P_r	$F1_r$	R_r	P_r	$F1_r$
TS_1	23%	56%	32%	58%	71%	**64%**
TS_2	16%	92%	27%	74%	20%	**67%**
TS_3	71%	50%	59%	86%	47%	**60%**
TS_4	63%	25%	**36%**	63%	21%	32%
TS_5	50%	20%	29%	75%	50%	**60%**
TS_6	14%	100%	25%	57%	83%	**68%**
TS_7	45%	100%	63%	72%	90%	**80%**
TS_8	57%	35%	43%	44%	80%	**57%**
TS_9	6%	4%	4%	17%	11%	**13%**
TS_{10}	39%	81%	52%	52%	59%	**55%**
TS_{11}	67%	17%	27%	100%	25%	**40%**
TS_{12}	0%	0%	0%	100%	11%	**22%**
mean	38%	48%	33%	**67%**	47%	**52%**
median	42%	43%	31%	**68%**	49%	**59%**

Table 2: Anomaly detection performance with *DC-VAE* and S-VAE.

detection is highly complex. Performance is significantly different for some of the time-series, which corresponds to the different nature and underlying behavior (cf. Figure 5). Nevertheless, the outperformance of *DC-VAE* as compared to S-VAE is outstanding, largely improving both detection of anomalies (i.e., R_r) as well as overall performance (i.e., $F1_r$), by almost a factor of two on average.

A preliminary assessment on the low performance obtained for some of the time-series reveals issues linked to poor labeling in some cases, as well as lack of sensitivity in some others (i.e., finer-grained $\boldsymbol{\alpha}$ values might be needed). Still, *DC-VAE* results in terms of its modeling and tracking capabilities for multivariate time-series data are promising, and its application to real measurements additionally permits to evidence the difficulties behind a broadly studied, yet unsolved problem. A deeper evaluation of *DC-VAE* in the TELCO dataset is part of our ongoing work, including the benchmarking of other anomaly detection approaches in this dataset.

4.3 Benchmarking *DC-VAE* in SWaT

For the sake of completeness and to provide a stronger and more comprehensive benchmarking, we compare *DC-VAE* against other deep-learning-based MTS anomaly detectors in SWaT. The SWaT dataset consists of 51 time-series of data collected over eleven days in 2015-2016, on a water treatment operational test-bed, which represents a small-scale version of a large modern cyber-physical system. The dataset contains two sub-sets temporally split; the first week is anomaly free and is considered as the training dataset, whereas the last four days of data contain 36 attacks of different nature and duration (from a few minutes to an hour), and is meant for testing purposes. The total number of anomaly samples accounts for about 5.8% of the total measurements.

Detector	R	P	$F1$
Auto Encoder	53%	73%	61%
EGAN	68%	41%	51%
NET-GAN-(G)enerator	65%	98%	**78%**
NET-GAN-(D)iscriminator	65%	29%	40%
MAD-GAN-P (best precision)	55%	100%	70%
MAD-GAN-R (best recall)	100%	12%	22%
MAD-GAN-F1 (best F1 score)	64%	99%	**77%**%
DC-VAE	67%	94%	**78%**

Table 3: Anomaly detection performance benchmarking against deep-learning generative models in SWaT.

GAN-based MTS detectors are very popular in the literature, given their flexibility to model a complex MTS process without making any assumptions on the underlying distributions. GANs are a powerful approach to learn the underlying distributions of data samples, in a purely data-driven, model-agnostic manner. Such models can be used in the practice to construct better normal-operation baselines, improving the identification of instances which deviate from this baseline. We therefore compare *DC-VAE* against three GAN-based detectors proposed in recent years, including EGAN [24], MAD-GAN [13], and NET-GAN [8].

To train *DC-VAE* in SWaT, we take an architecture using $J = 16$ as dimension of the latent space, and a sequence length $T = 128$, both parameters calibrated in the same way we did it in TELCO. We train both *DC-VAE* and NET-GAN in the SWaT training dataset, using a small share of samples from the attacks for calibration. Regarding EGAN and MAD-GAN, we decided to report in here the results obtained by the authors in [13], which would generally correspond to the best performance which could be achieved by these methods. Finally, we also include a standard Auto Encoder (AE) model as the simplest approach comparable to *DC-VAE*.

Table 3 reports the results obtained in the testing dataset in terms of recall, precision, and $F1$ scores. We fall back to the standard evaluation on point anomalies instead of range anomalies, to be consistent with the results obtained in SWaT as reported in the literature. We consider two variations of NET-GAN detectors [8], one using the generator function (NET-GAN-G), and the other one the discriminator function (NET-GAN-D). We also consider three different variations of MAD-GAN, optimized for best precision (MAD-GAN-P), recall (MAD-GAN-R), and $F1$ score (MAD-GAN-F1). *DC-VAE* results are comparable to those obtained with NET-GAN-G and MAD-GAN-F1, and significantly better than EGAN or the AE model. In addition, absolute results are also significantly better than those obtained in TELCO, helping us demonstrating that anomaly detection in real data as the one in TELCO, dealing with the error-prone process of human labeling, is much more complex than what the literature usually reports on such benchmarks. To sum-up, we can claim that *DC-VAE* realizes state-of-the-art detection performance, while again, flagging its underlying advantages.

5 CONCLUDING REMARKS

DC-VAE is a novel approach to anomaly detection in multivariate time-series, leveraging dilated convolutional neural networks and variational auto encoders. *DC-VAE* detects anomalies in multivariate time-series, exploiting temporal information without sacrificing computational and memory resources. In particular, instead of using recursive neural networks, large causal filters, or many layers, *DC-VAE* relies on dilated convolutions to capture long and short term phenomena in the data, avoiding complex and less-efficient deep architectures, simplifying learning. The application of *DC-VAE* to real measurements collected at a mobile ISP showed that its underlying architecture is better than traditional, vanilla VAEs when it comes to time-series anomaly detection, showing as such promising results. The parametrization of *DC-VAE*'s architecture is basically defined by a single parameter, namely the length of the sliding window used for temporal analysis, and the normal operation region can be easily adapted on a per time-series basis by adjusting a single integer value, all of these important advantages in practice.

The quantitative and qualitative advantages of *DC-VAE* with respect to S-VAE evidenced the contribution of the convolutional layers in capturing a longer time horizon. The benchmarking on the SWaT dataset shows the on-par performance to state-of-the-art MTS anomaly detectors in the literature.

In addition to the open publication of the code implementing and evaluating *DC-VAE*, the release of the TELCO dataset to the community provides a real, more representative environment for assessment and benchmarking of anomaly detectors, providing as such a strong contribution to advance the domain.

ACKNOWLEDGMENT

This work has been partially supported by the Austrian FFG ICT-of-the-Future project *DynAISEC – Adaptive AI/ML for Dynamic Cybersecurity Systems*, by the ANII-FMV project with reference FMV-1-2019-1-155850 *Anomaly Detection with Continual and Streaming Machine Learning on Big Data Telecommunications Networks*, and by Telefónica. Gastón García was supported by the ANII scholarship POS-FMV-2020-1-1009239, and by CSIC, under program *Movilidad e Intercambios Académicos 2022*.

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