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Recurrent neural network with density-based clustering for group pattern detection in energy systems

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ABSTRACT

This research explores a new direction in power system technology and develops a new framework for pattern group discovery from large power system data. The efficient combination between the recurrent neural network and the density-based clustering enables to find the group patterns in the power system. The power system data is first collected in multiple time series data and trained by the recurrent neural network to find simple patterns. The simple patterns are then studied, and analyzed with the density-based clustering algorithm to identify the group of patterns. The solution was analyzed in two case studies (pattern discovery and outlier detection) specifically for power systems. The results show the advantages of the proposed framework and a clear superiority compared to state-of-the-art approaches, where the average correlation in group pattern detection is 90% and in group outlier detection more than 80% of both true-positive and true-negative rates.

1. Introduction

The physical connections of the components in the electrical network result with the energy systems. The goal of energy systems is to provide the supply of electrical energy in a good and optimized way [1]. The current challenges of power systems are to ensure the security and minimum cost of energy when the load increases and the size of the network increases [2]. From the second half of the year, the cost of energy is gradually increasing extremely in European countries. Therefore, it is more than necessary to explore data analysis methods for energy systems [3].

In the analysis of power system data, many approaches have been considered [4–6]. The power system-based solutions are generally treated separately to extract simple patterns, and the study of the correlation between these patterns has not yet been explored. However, most events in power systems take place by compromising a group of electrical components. In this case, the data of the compromised electrical components as a group differ from each other. Therefore, separate analysis of individual component data tends to be ineffective when there are a large number of divergent components. This is because they do not explore the various correlations between the simple patterns and do not consider the patterns represented by the group of components as input during the detection process. Approaches from artificial intelligence (AI) and machine learning (ML) are being explored for many domains [7–10] and can be applied to group pattern detection problems.

In our earlier work, we considered a similar problem, but with respect to road traffic in smart cities. We defined the original problem of detecting group patterns in such environments [8] and used innovative approaches to solve the problem, including advanced data mining and deep learning [7]. Similarly, the power system data can be projected as road traffic (trajectories), which intuitively supports the application of our previous solutions to this problem. However, the power system data has some inherent features that do not exist in road traffic. For example, the content of the energy system data includes data on energy consumption, home energy supply, and other features. This requires significant reworking of the models used in our previous solutions before they can be applied to the new context. One possible option for this is to explore the recurrent neural network with density-based clustering. This research will therefore explore the use of an advanced recurrent neural network and density-based clustering to create pattern groups in the power system environment. To the best of our knowledge, this is the first work that addresses group pattern detection in the power system environment and proposes a new framework for creating group patterns from power system data. The main contributions of this research can be

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summarized as follows:

1. We propose an efficient recurrent neural network with attention mechanism and hyperparameter optimization to generate simple patterns from power system data. The input of the recurrent neural network is the various observations of the energy system, while the output is a set of simple patterns that depend on the particular application. For example, in the case of the outlier detection problem, the simple patterns are the set of individual outliers.
2. We develop a novel strategy based on density-based clustering to derive the group of patterns. This algorithm benefits from the projection strategy and the micro-cluster concept to optimize the detection of group patterns. The input of the clustering algorithm is the set of simple patterns, and the output will be the set of group patterns.
3. We evaluate the proposed framework in two use cases (pattern discovery and outlier detection) using large energy system data from 32 European countries and other neighboring countries. The results show a clear superiority of the proposed framework compared to the baseline methods. The proposed framework achieved an average correlation of 90% in group pattern detection and a rate of over 80% in both true positive and true negative rates in group outlier detection.

The remainder of the article is organized as follows. Section 2 discusses the well-known deep learning and data mining methods for power systems. Section 3 summarizes the proposed framework and its main components. Section 4 summarizes the experimental setup and results for two use cases, including pattern discovery and outlier detection. Section 5 discusses other potential use cases of the group of pattern detection. Finally, Section 6 concludes the paper.

2. Related work

This research work explores two main areas including machine learning, and data mining for solving energy systems challenges, which will be discussed and analyzed as follows.

2.1. Machine-learning-based solution

Veerasamy et al. [11] developed the long-term short-term memory for high-impedance fault diagnosis in power systems. The data represented by a series of signals are processed using the discrete wavelet transform. The processed data is then fed into the long short term memory to classify whether the power data is generating faults or not. Kisvari et al. [12] developed the gated recurrent neural network for wind energy prediction. The approach is called a data-driven solution because it is data dependent. 12 features were selected and incorporated into the prediction model, namely wind speed at four different heights, generator temperature, and gearbox temperature. Bai et al. investigated the use of the recurrent neural network to predict the energy consumption of industrial enterprises. The results show that the hybrid recurrent neural network with the gated unit significantly outperforms the basic recurrent neural network model. Duan et al. [13] proposed the combination of the recurrent neural network with the error decomposition correction for short-term wind speed prediction. Eskandari et al. [14] used the 2-D convolutional layers to extend the multidimensional features of the electrical time series for load forecasting. The univariate load and temperature data are fed into the hybrid model represented by the recurrent neural network and gated unit with the extended multidimensional features to improve the forecasting process. Lee et al. [15] predicted the hourly energy of energy consumption without relying on contextual information provided by meteorological events. Both long- and short-term patterns are extracted using the gated recurrent network. Shin et al. [16] compared different deep learning architectures based on Markov chains and recurrent neural networks for predicting velocities in power systems. The models were deployed in an embedded system where the input to each architecture is a set of velocity information. The hyper-parameters of the proposed models are optimized using dynamic coordinate search.

2.2. Data mining-based solution

Baloch et al. [17] used the Hilbert transform and data mining to secure the microgrid. The perturbed voltage and time series of signals are transformed into readable signals using the Hilbert transform mechanism, and logistic regression is used to predict the errors from the processed signals. Gao et al. [18] reduced the relative error of the total cost of system expansion planning. Spectral clustering is performed to determine the daily net load duration curve and demand adequacy and flexibility. Herman et al. [19] analyzed country-level environmental policy indicators and proxies in the renewable energy sector, discussing a new link between machine-based methods and environmental policy. Several data mining and machine learning algorithms are explained in the context of applications to pattern discovery for environmental policy goals. Lee et al. [20] provides an adaptation of clustering-based operational signatures to analyze the different patterns in building energy systems. The proposed signature-based clustering can evaluate both normal and deviated operation. It is also easily evaluated in a building automation system with a simple sensor deployment. Liu et al. [21] used both *k*-means and Apriori algorithms for cluster analysis and finding relationship rules between different energy types. The investigated database is based on official energy building models. The results show that the proposed framework is able to successfully identify the energy that remains unused in an office building after working hours. Moreover, the cooling energy affects the total energy most of the time with a certainty of more than 80%. Zhang et al. [22] provides a method for detecting deviating operating patterns in building energy systems in real time. Both expert systems and association rule mining can help. Association rules are used to build association rule bases for deviant and normal operating patterns. The developed rule bases are then used to build an expert system that can detect deviant operating patterns in real time.

Based on this brief literature review, we concluded that both data mining and deep learning-based strategies for discovering patterns in power systems are efficient in inferring simple patterns. However, the relationships between these patterns have not yet been explored. Given the success of group pattern detection [7,8], we introduce a new framework for group pattern discovery in power systems in the next section.

3. GPD-PS: group pattern detection for energy systems

3.1. Principle design

In this section, we present a new architecture based on a recurrent neural network and density-based clustering to discover the group of patterns in power systems. As show in Fig. 1, the proposed architecture first explores the recurrent neural network to infer the simple patterns. The group patterns are then determined from the simple patterns using density-based clustering technique. It allows to study the different correlation among the simple patterns extracted from the recurrent neural network. The particularity of the density-based clustering is to create clusters with different sizes. The micro-clusters are defined in case of detecting group of abnormal patterns, where the macro clusters are defined in case of detecting group of representative patterns. Several optimizations have been explored to determine the simple patterns. The first one is based on the attention mechanism and the second one is based on hyperparameter optimization. Similarly, different optimizations have been developed to well control the detection of group patterns. The first is based on a nonlinear projection method to enable the generation of the projected points of time series data. The second is to

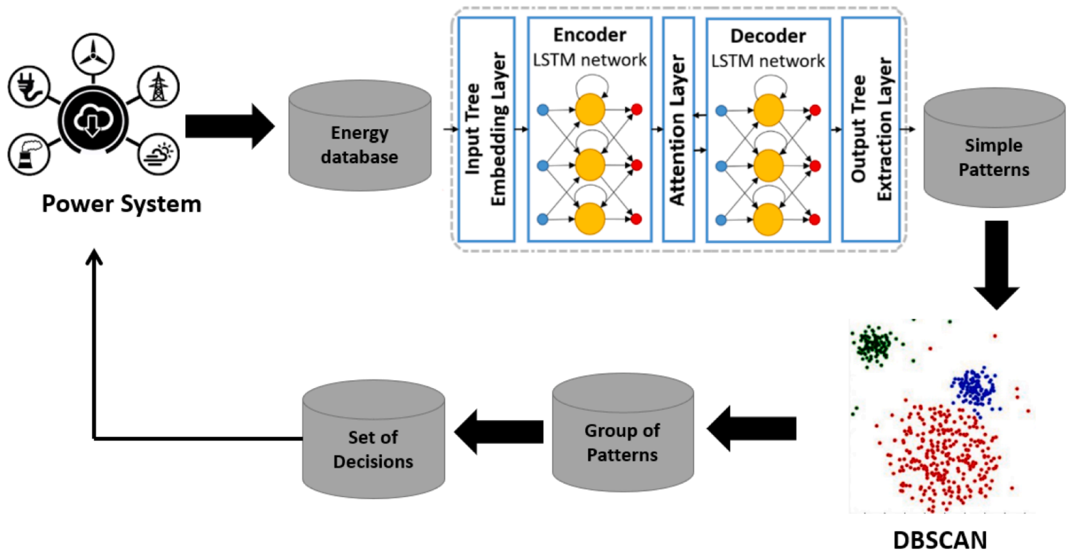

Fig. 1. Developed GPD-PS Framework: Set of energy data is collected by the power system, and injected it to the recurrent neural network for extracting the simple patterns. These patterns are grouped using DBSCAN algorithm to derive the group of patterns which will be used to make a set of decisions that will be set in the power system.

initiate microclusters, and macroclusters to correctly estimate the group of patterns in power systems. Below, an explanation of each step is elaborated.

3.2. Extracting simple patterns

The recurrent neural network with attention mechanism and hyperparameter optimization was used to learn the simple patterns from the energy systems. We consider as input of the deep learning model the sequence of observations collected by the energy system. The output is a set of simple patterns describing the various correlations between the observations or the abnormal behavior of the observations. Each observation collected at a particular time contains information about the behavior of the energy system at that time. The model learns the mapping between the input (the observations) and the output (simple patterns). In the inference step, we will extract the simple patterns of the new observations by performing a propagation of the model with the final learned weights. The following sections explain the model developed in this research:

1. Recurrent Neural Network: we applied ASRNN (Attention Sequence Recurrent Neural Network) algorithm [23] to find the simple patterns. ASRNN explores a complex recurrent neural architecture to estimate the output based on the input data. The idea of ASRNN is that the attention mechanism is used together with the recurrent neural network. Two models of long- term memory are trained separately on the time series of power system data. Context vectors are generated based on energy consumption and input to the first recurrent neural network model, where local features are learned using the second recurrent neural network. These two recurrent neural network models are connected to the fully connected layer, which is followed by the output represented by the simple patterns. The main difference between the ASRNN developed in [23], and our ASRNN consists of the attention mechanism used in the learning process. We use different attention mechanism layer which will be described as follows.
2. Attention mechanism: soft attention mechanism is used to improve the developed recurrent neural network model. The purpose of the attention mechanism is to focus on the most important regions in the time series that have the greatest impact on the learning process. We used local attention, where one group of neurons is strongly connected to the other neurons in the next layer.
3. Hyper-parameter optimization: an intelligent process is used to efficiently learn the hyper-parameters of the developed model. A genetic process is used in which the solution space is represented by a set of vectors, each of which is the set of values of the hyper-parameters of the model. Exploration of the solution space is performed using standard genetic operators such as crossover, mutation, and selection. Each solution is evaluated by the fitness function, which indicates the accuracy of the number of corrected simple patterns provided by the model.

3.3. Extracting group of patterns

At the end of the previous step, a set of simple patterns is created. These are used to generate a set of patterns that are highly correlated. In this context, we used the density-based clustering algorithm. The adapted algorithm *DBSCAN* (Density-based spatial clustering of applications with noise) [24] is proposed to generate the group of patterns from the simple patterns. *DBSCAN* is the well-known algorithm for clustering. It aims to create similar clusters, where the data that belong to the same cluster are similar and the data that belong to different clusters are dissimilar. The concepts of microclusters, and macroclusters are defined. The process of DBSCAN started by determining the ϵ-neighborhood of each simple pattern. We define the ϵ-neighborhood of pattern p as the set of simple patterns that are similar to p in the ϵ-ratio. This means that the distance between each pattern in the ϵ neighborhood and p is less than ϵ, where ϵ is the user's threshold. Next, the core of patterns is determined, where each simple pattern is called a core pattern if and only if the number of elements in its ϵ-neighborhood is greater than a certain threshold value chosen by the user. DBSCAN then iteratively collects dense reachable patterns directly from these core patterns, which require it to merge some dense reachable clusters. The process ends when no new pattern can be merged into a cluster. The process of DBSCAN creates multiple clusters with different sizes. In this study, we are interested into two kinds of groups:

1. Microclusters: A micro-cluster is defined by the number of patterns smaller than the threshold γ, where γ is $\in [1\ldots|P|]$ and P is the set of all simple patterns extracted by the recurrent neural network. Each microcluster is then considered as a group of abnormal patterns.

2. Macroclusters: A macro-cluster is defined by the number of patterns larger than the threshold γ, where γ is $\in [1 \ldots |P|]$ and P is the set of all simple patterns extracted by the recurrent neural network. Each macrocluster is then considered as a group of representative patterns.

To optimize the whole process of *DBSCAN*, a nonlinear projection-based approach is performed to promote projected patterns, where each pattern can be represented by high-dimensional time series values. The self-organizing map is then applied to the derived projection to efficiently select the relevant features of the simple patterns. These features are then used throughout the *DBSCAN* process, as explained above.

Algorithm 1: GPD-PS Algorithm

1: **Input**: $\mathscr{D} = \{\mathscr{D}_1, \mathscr{D}_2, \ldots, \mathscr{D}_m\}$: the set of m observations collected from energy system.
2: **Output**: *model*: The trained model to identify the simple patterns.
3: *GP*: the set of the group patterns derived from *D*.
4: *************Extracting Simple Patterns*****************
5: $model \leftarrow Adapted\_ASRNN()$;
6: $model \leftarrow model \cup Attention\_Layer$
7: $Batches \leftarrow CreatingBatches(D)$;
8: $Hyper\_Param \leftarrow GA(fit(model, Batches))$;
9: $P \leftarrow Inference(D_{new}, model, Hyper\_Param)$;
10: *************Extracting Group of Patterns*****************
11: $GP \leftarrow AdaptedDBSCAN(D)$;
12: **return** $< model, GP >$.

Algorithm 1 presents the pseudo-code of the developed GPD-PS algorithm. The process starts by building the deep learning model represented by the ASRNN with novel attention mechanism layer (lines 5–6). The batches of data are created from the database D (line 7). The genetic algorithm is then applied to optimize the hyper-parameters of the deep learning model by performing the training phase on the created batches (line 8). The inference phase is then executed on the trained model in order to retrieve the simple patterns (line 9). This step depends on the problem at hand. The adapted DBSCAN is finally applied to the retrieved simple patterns and derive the group of patterns (line 11). The output of the algorithm is the set of group of patterns *GP*, and the trained model for extracting the simple patterns *P* (line 12).

4. Performance evaluation

In this section, we describe the experimental setup, the evaluation metrics, and the results obtained.

4.1. Experimental settings

Rigorous experiments were conducted to evaluate the proposed framework on the open data of energy systems of 32 European countries[1]. It contains data for energy systems modeling represented by a collection of time series. It includes information on electricity prices, electricity consumption, wind and solar energy, and power generation. The data is organized by country, including 32 European countries and some neighboring countries. The information is displayed in hourly resolution, with the original data collected in higher resolution. The data is retrieved for the period 2015 to 2020. The evaluation examines two case studies on both frequent patterns and outlier detection as follows:

1. Frequent pattern mining: this is the process of extracting a set of patterns that describe the data. These patterns can be considered as a set of correlations or dependencies between the entire data. The proposed framework is compared with two algorithms that are considered the state of the art in pattern recognition. The first one is SSFIM (Single Scan for Frequent Itemset Mining) [25], which is based on a single scan of the data to extract the relevant patterns. Adaptation of the algorithm is used to extract the set of patterns. The data is scanned observation by observation, where we create a group of candidate patterns for each observation. The second one is GA-Apriori (Genetic Algorithm with Apriori) [26], it combines both evolutionary computation and Apriori heuristics to explore the pattern space. The adaptation of this algorithm is used to derive the group patterns. First, the solution space is considered, where each solution is a group of pattern, the crossover, and the mutation operators based on the Apriori heuristic [27] are used to explore the solution space. Three evaluation metrics were used to compare the proposed framework, which are described below:

$$Support(G) = \frac{|D_G|}{|D|}, \tag{1}$$

where G is the identified group pattern, D is the total data, and D_G is the set of observations in which the group pattern G occurred.

$$Correlation(G) = avg(Lift(e_1, e_2), \forall (e_1, e_2) \in G^2), \tag{2}$$

where, avg(Lift(e_1,e_2)) is the average lift for all elements in G. The lift between two different elements in G is defined as follows:

$$Lift(e_1, e_2) = \frac{D_{e_1} \cap D_{e_2}}{D_{e_1} \cup D_{e_2}} \tag{3}$$

2. Outlier detection: this is a well-known machine learning task that involves automatically detecting outliers. These outliers can be considered as observations that deviate greatly from the normal ones. We compare the proposed framework with two well-known algorithms for detecting outliers. The first one is LOF (Local Outlier Factor) [28], it is based on density calculation. We adapt this algorithm to identify the group of outliers. The group of outlier candidates is generated and the density of each group is determined. Based on the density, we estimate whether this candidate is an outlier or not. The second algorithm examines the CNN (Convolution Neural Network) [8]. The inputs of the CNN are the observations, while the outputs are the outlier group. Determining the outlier group from the power system data has not been explored in the research literature. Therefore, there is no ground truth for the data used in the experiments. Therefore, the outlier groups are generated by inserting noise into similar observations. The evaluation is performed using the True Positive Rate (TPR) and True Negative Rate (TNR), which are commonly used to evaluate outlier detection systems. The metrics used are described below:

$$TPR = \frac{TP}{TP + FP} \tag{4}$$

$$TNR = \frac{TN}{TN + FP} \tag{5}$$

Note that TP is the number of true positives, FP is the number of false positives, and TN is the number of true negatives.

All implementations were performed on a computer equipped with a 64-bit Core i7 CPU running Windows 10 and 16 GB RAM and an Nvidia Tesla C2075 GPU with 448 CUDA cores (14 multiprocessors with 32 cores each) and a clock speed of 1.15 GHz. It has a total memory capacity of 2.8 GB, a shared memory capacity of 49.15 KB and a warp size of 32. Simple precision is used on both CPU and the GPU.

To manage the evaluation process well, the testing data is also divided into different buckets. Each of them contains data randomly selected from the whole data. The buckets contain different number of samples. The first bucket contains 20% of the test data, the second 50% of the test data, the third 80% of the test data and the last 100% of the test data.

[1] https://data.open-power-system-data.org/time_series/2020-10-06

4.2. Pattern discovery

The first case study of the developed pattern recognition framework was conducted to validate its applicability to energy systems. The models are first trained and then the inference is performed with the test data to calculate the average support and average correlation values. Fig. 2 shows the average support and average correlation when varying the percentage of data used as input from 20% to 100% on power system data. The results show the superiority of the proposed solution compared to pattern recognition solutions. These results are obtained thanks to our methodology in which the simple patterns are computed by the recurrent neural network and the group of patterns is derived by finding the similar patterns from the simple patterns.

The second experiments of this case study are used to show processing at runtime. In this part, the data is split into 10 different buckets. The first bucket contains 10% of the test data, the second 20% of the test data and so on until the last bucket which contains all the test data. Fig. 3 shows the runtime when varying the percentage of data used as input from 10% to 100% on energy system data. The results show that the proposed solution is faster than the others. This can be explained by the fact that the other algorithms consider the group detection problem as an overall problem, while our solution reduces the search space by first enumerating the simple patterns and then finding the group of patterns.

4.3. Outlier detection

Another case study on outlier detection was conducted to validate the applicability of the proposed framework to energy systems. The models are first trained and then the inference is performed with the test data to calculate the TPR and the TNR values. Fig. 4 shows the true-positive rate when varying the percentage of data used as input from 20% to 100% on power system data. The results show the superiority of the proposed solution compared to the outlier detection solutions. These results are obtained thanks to our methodology in which the simple outliers are computed by the recurrent neural network and the group of outliers is derived by finding similar patterns from the simple outliers.

The second experiments of this case study are used to show processing at runtime. In this part, the data is split into 10 different buckets. The first bucket contains 10% of the test data, the second 20% of the test data and so on until the last bucket which contains all the test data. Fig. 5 shows the runtime when varying the percentage of data used as input from 10% to 100% on power system data. The results show that the proposed solution is faster than the others. This can be explained by the fact that the other algorithms consider the group detection problem as an overall problem, while our solution reduces the search space by first enumerating the simple outliers and then finding the group of outliers.

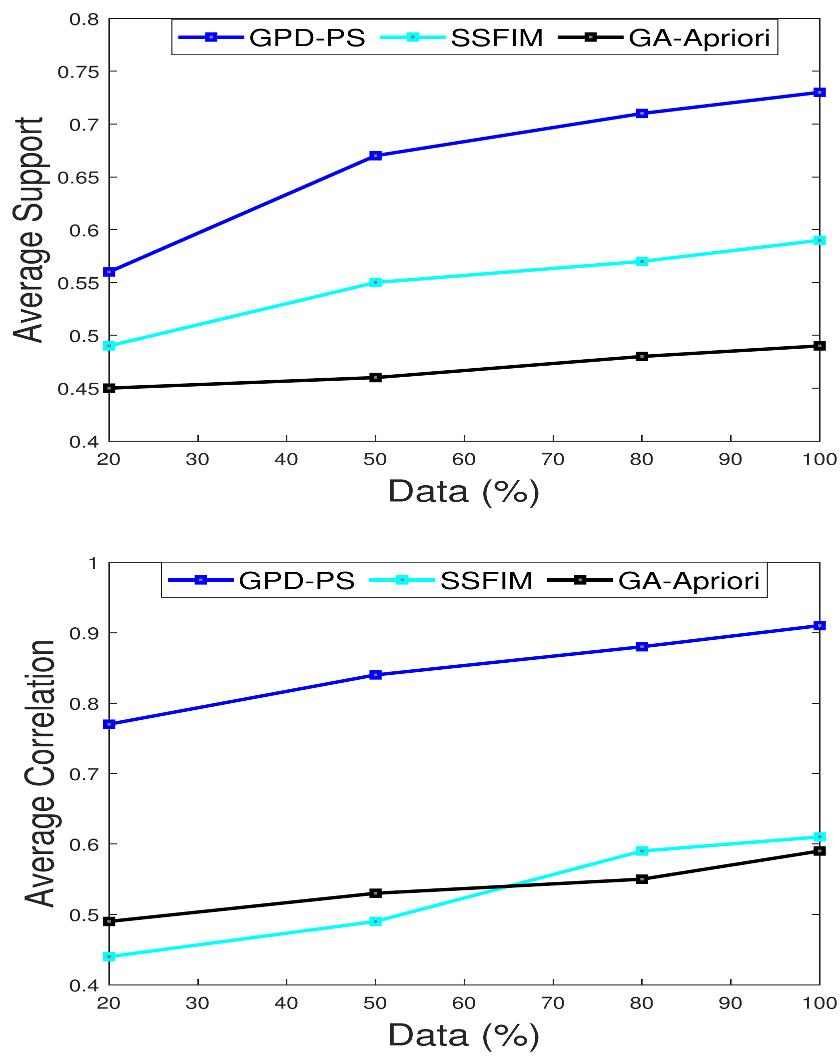

Fig. 2. Accuracy performance of the proposed solution compared to the group pattern detection.

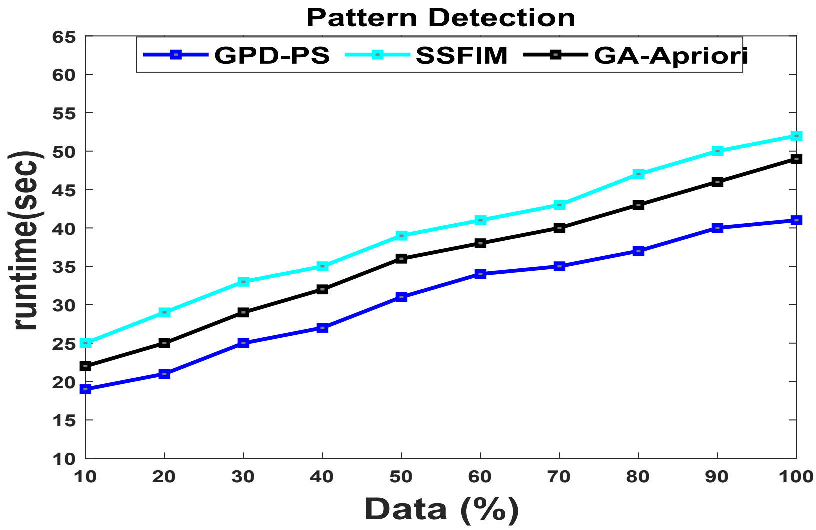

Fig. 3. Runtime performance of the proposed solution compared to the group pattern detection.

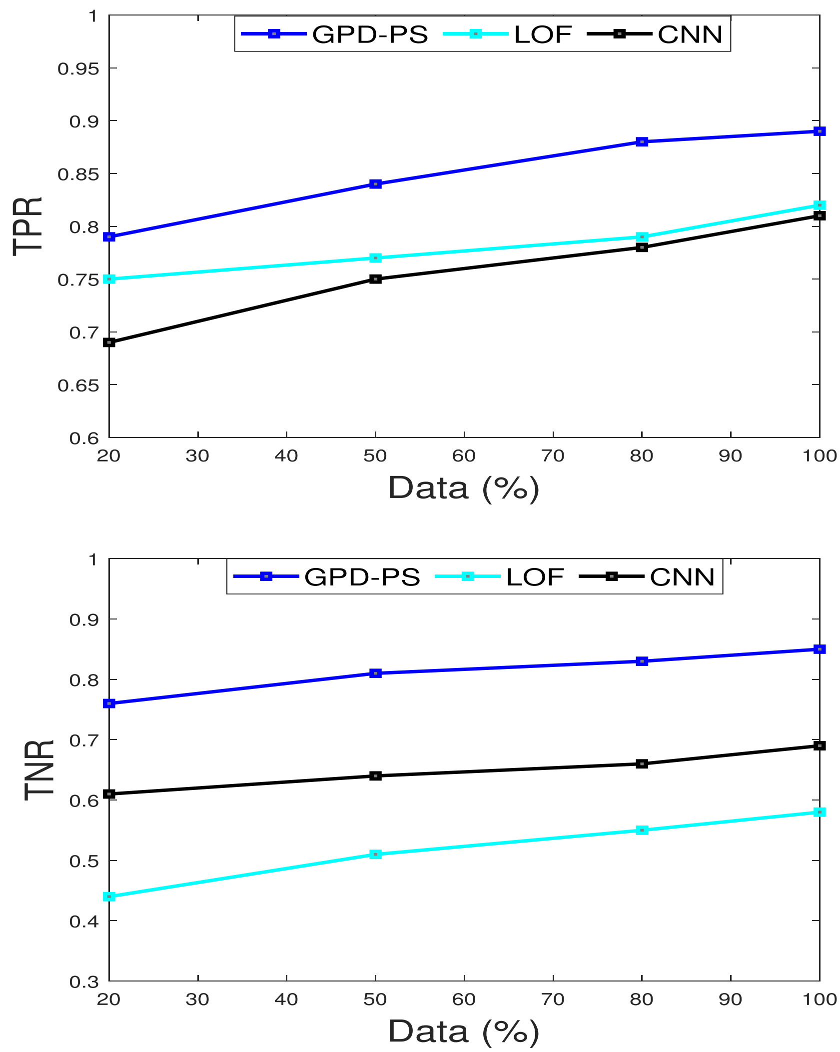

Fig. 4. Accuracy performance of the proposed solution compared to the group outlier detection.

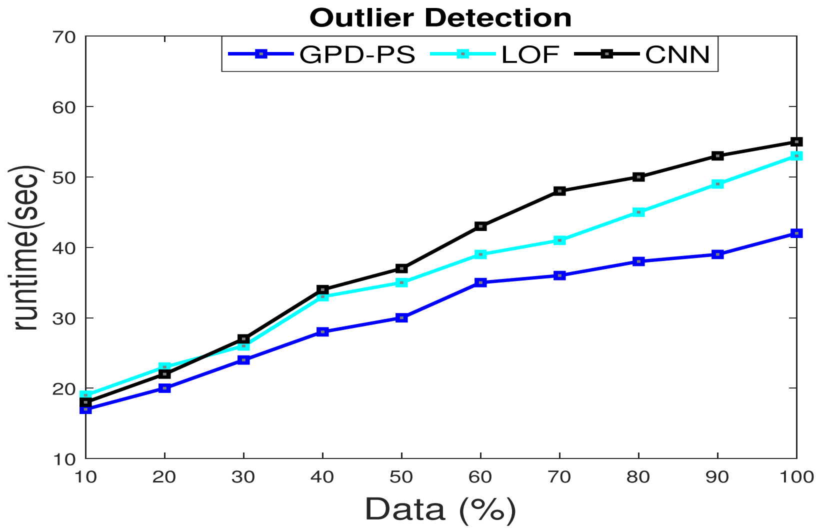

Fig. 5. Runtime performance of the proposed solution compared to the group outlier detection.

5. Future directions: other potential use cases of group of pattern detection

With gentrification and the rise of cities, transportation infrastructure is being put to the test, causing traffic congestion, excessively long commute times, and, most importantly, increasing environmental pollution. Infrastructure use can be improved by predicting traffic flows and traffic-related events in intelligent transportation systems so that the average traveler takes less time and the environment is less polluted. Thus, group pattern recognition helps achieve the United Nations' 11th Sustainable Development Goal: Sustainable Cities and Communities. The world's growing demand for energy has serious implications for the environment and the health of the world's population. Cleaner and more sustainable energy generation (especially those typically considered "unclean"), as envisioned in the smart Industry use case, contributes to the seventh Sustainable Development Goal UN: Affordable and Clean Energy. In this section, two real-world applications are used to demonstrate the capabilities of group pattern recognition.

1. **Intelligent transportation**: Learning from measured traffic flow is one part of intelligent transportation. For example, precise long-term traffic flow distribution prediction allows operations with no defined schedule but a limited time frame to be organized optimally, reducing time spent stuck in traffic and increasing output. Existing models [29,30], however, only allow prediction or detection of individual traffic flows. Group pattern detection allows the correlation between traffic flow data to be examined and group dips to be detected. Another approach that group pattern detection can take in the context of intelligent traffic is traffic dispersion [31,32]. The link between traffic flows of nearby areas can be used to create a rule-based system which propagate traffic flows from one area to another and identify congestion points. Group pattern recognition, as a final application, seeks to forecast occurrences in a city based on present and historical traffic conditions, as well as prior events and their duration inside a city.
2. **Smart manufacturing**: As part of the transition to Industry 4.0, machines have been equipped with an increasing number of sensors that generate a large amount of time series data. However, it is not always clear how to make sense of the information collected. One important task is to identify when a manufacturing process is likely to exceed its predefined parameters, such as when a worn tool causes the production of defective parts or when a production process is ready to pollute the environment. Existing time-series-based manufacturing anomaly detection solutions [33,34] are unable to efficiently identify outliers from a large number of data streams, and thus can only consider individual outliers that are likely to be of greatest importance to the solution. We can use group pattern detection as an alternative solution to this problem, eliminating the need to constrain the data streams analyzed.

6. Conclusion

In this research study, we have investigated a new problem in the field of energy systems. The goal is to discover the group of patterns that are highly correlated with power system data. The proposed framework is a combination of deep learning and data mining strategies, where the recurrent neural network is first used to generate the simple patterns and then density-based clustering is performed to detect the group patterns. The solutions are improved by developing various optimizations, including the attention mechanism and hyperparameter optimization for the recurrent neural network, nonlinear projection, microclusters, and macroclusters for density-based clustering. The proposed framework has been analyzed in two case studies (pattern discovery and outlier detection) using power system data from 32 European countries and some other neighboring countries. The results show the advantages of the proposed framework and its clear superiority compared to state-of-the-art approaches. In the future, we plan to investigate other intelligent solutions for pattern group identification. Exploration of high performance computing is also on our future agenda.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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