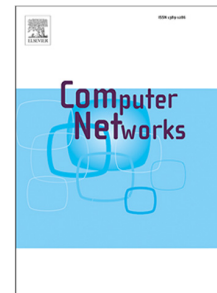# Journal Pre-proof

Time-series clustering for sensor fault detection in large-scale Cyber-Physical Systems

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Time-Series Clustering for Sensor Fault Detection in Large-Scale Cyber-Physical Systems

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Abstract

Large-scale Cyber-Physical Systems (CPSs) are information systems that involve a vast network of sensor nodes and other devices that stream observations in real-time and typically are deployed in uncontrolled, broad geographical terrains. Sensor node failures are inevitable and unpredictable events in large-scale CPSs, which compromise the integrity of the sensors measurements and potentially reduce the quality of CPSs services and raise serious concerns related to CPSs safety, reliability, performance, and security. While many studies were conducted to tackle the challenge of sensor nodes failure detection using domain-specific solutions, this paper proposes a novel sensor nodes failure detection approach and empirically evaluates its validity using a real-world case study. This paper investigates time-series clustering techniques as a feasible solution to identify sensor nodes malfunctions by detecting long-segmental outliers in their observations' time series. Three different time-series clustering techniques have been investigated using real-world observations collected from two various sensor node networks, one of which consists of 275 temperature sensors distributed around London. This study demonstrates that time-series clustering effectively detects sensor node's continuous (halting/repeating) and incipient faults. It also showed that the feature-based time series clustering technique is a more efficient long-segmental outliers detection mechanism compared to shape-based time-series clustering techniques such as DTW and K-Shape, mainly when applied to shorter time-series windows.

Keywords: Cyber-physical systems (CPSs), Wireless sensor networks(WSNs), Time-series clustering, Dynamic time warping, K-Shape, Characteristics based time-series clustering

1. Introduction

Cyber-Physical Systems (CPSs) can be seen as networks of physical components such as sensors and often actuators effectively incorporated using a computational and communication core (Törngren et al., 2017; Platzer, 2019). Sensors collect physical environment

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measurements and transmit them as raw data to a computational unit. The computational unit generates feedback and sends it to the actuators that regulate the physical conditions based on the received data. This cycle ultimately achieves the self-awareness of the CPS via its ability to assess and correctly adjust its behaviour and performance in real-time (Kounev et al., 2018). Large-scale CPS applications, such as environmental monitoring systems, typically involve many low-cost sensor nodes deployed in broad geographical terrains, forming a large-scale Wireless Sensor Network (WSN) (Okafor et al., 2020; de Aquino et al., 2019; Abid et al., 2015). Ecological factors may compromise the accuracy of sensor observations, as extreme temperature (Banerjee et al., 2020) or humidity (Okafor et al., 2020). Failures in sensor nodes and sensor networks are inevitable events in large-scale CPS applications, which may cause severe data loss, producing invalid information and potentially reducing the quality of their service (Li et al., 2019; Ghosh et al., 2020). In general, sensor nodes in WSNs have limited computing power, storage capacity and transmission radius (Lawson and Ramaswamy, 2016; Bhuiyan et al., 2017). Therefore, wireless sensor nodes cannot directly send observations to a remote data destination (sink). Instead, a hub device or another sensor node works as a bridge to transfer readings from other sensor nodes. Sensor nodes closer to the sink consume more power because they support other sensors to transmit their observations, and they are expected to have more power failures causing sensor node failure issues (Liao et al., 2019; Togneri et al., 2019). Thus, sensor nodes may determine the network lifetime based on their battery capacity and affect the system's quality of service (Du et al., 2016; Curiac and Volosencu, 2012).

The contribution of this research lies in the successful implementation of time-series clustering techniques as a sensor failure detection mechanisms based on detecting long-segmental outliers associated with sensors faults. It investigates the possibility of utilising time-series clustering as a sensor node failure detection mechanism, focusing on detecting long-segmental outliers associated with halting and incipient sensor failure patterns. Dynamic Time Warping (DTW), K-Shape and the Characteristics-based time-series clustering techniques are tested to prove the validity of the proposed approach. The accuracy of these methods in detecting the incipient sensor node failure pattern is empirically evaluated using time series collected from a local ambient temperature sensor node network deployed at the University of East London, UK. The accuracy of these methods in detecting the halting sensor node failure pattern is evaluated using time-series collected from a large-scale sensor node network comprising 275 ambient temperature sensors distributed around London.

This paper is organised as follows: Section 2 provides details of the related work, Section 3 is an introduction to time-series clustering. Section 4 describes the research data set, Section 5 presents the implementation results of the Dynamic Time Warping (DTW) and K-Shape time-series clustering techniques, and Section 6 provides the results of testing the Characteristics-based time-series clustering technique. Finally, Section 7 presents the concluding remarks.

2. RELATED WORK

Many sensor node failure detection methods were proposed in the literature, which can be mainly categorised as; technical-based and data mining-based sensor failure detection techniques.

Technical-based sensor node failure detection techniques are domain-specific solutions designed to detect sensor failures in particular applications. For example, Togneri et al. (Togneri et al., 2019) utilised signal processing as sensor's failure detection mechanism for monitoring the hardware status of a large-scale weather sensor network. The Togneri et al. (Togneri et al., 2019) sensor's failure detection approach cannot be adopted as a generic solution for detecting sensor failures. Thus, it does not present a systematic or generic approach for detecting sensor node failures in large-scale CPS applications. Furthermore, this approach requires direct access to the sensor management network to check their status, and such access may not be guaranteed in large-scale CPS applications.

Data mining-based sensor failure detection techniques utilise data analysis models to detect abnormal data patterns (outliers) in sensor observations associated with sensor node failures, mainly categorised into the anomaly and predictive analysis models (Chen et al., 2018; Alwan et al., 2020). Where an outlier is an extreme sensor node's measurement, it is "an observation which deviates so much from other observations as to arouse suspicions that a different mechanism generated it" (Hawkins, 1980).

1. **Anomaly analysis**, also known as outlier detection, identifies unusual data patterns that do not comply with well-established normal behaviour (Appice et al., 2014). Suppose the absolute value of a sensor observation deviation is significantly diverted from observations of other neighbouring (spatially correlated) sensors at the same point in time. In that case, this observation is an outlier and potentially streamed from a faulty sensor node (Lee and Choi, 2008; Chen et al., 2018). Anomaly analysis is a significant research field that is mainly investigated using statistical and machine-learning based outlier detection techniques. For example, Deep Neural Networks (DNN) (Hanrong Lu et al., 2016), K-Nearest Neighbours algorithm (KNN) (Hanrong Lu et al., 2016), K-means clustering algorithm are machine-learning-based outlier detection methods (Liu et al., 2019). In contrast, standard deviation, correlation coefficient (Xinrui et al., 2019) and the density-based spatial clustering of applications with noise (DBSCAN) are statistical-based outlier detection methods (Jayswal and Shukla, 2016; Abid et al., 2017; Nesa et al., 2018). Outlier detection techniques rely on the assumption that the value of sensor nodes' observations is correlated spatially, temporally, or both spatially and temporally. However, these assumptions are not necessarily always valid, especially in large-scale CPS applications where the correlations between sensor nodes may be violated by many external effects, such as the size of the deployment environment and the geographical distribution of sensor nodes (Laso et al., 2017). For example, outlier detection cannot be applied directly to ambient temperature observations collected from the sensor nodes distributed around London because of a phenomenon known as the Urban Heat Islands (UHI), as shown in the heat profile map of London in Figure 1 (MetOffice, 2019; Chandler, 1965). UHI causes up to 6 degrees C^0 of unexpected divergence among ambient temperature sensors observations, violating the spatial continuity constraints among these sensors and undermining the effectiveness of anomaly analysis methods in identifying unusual data patterns that do not comply with typical ambient temperature sensors observations in comparison with nearby ambient temperature sensors.

2. **Predictive analysis** is the process of mining current and historical data to identify
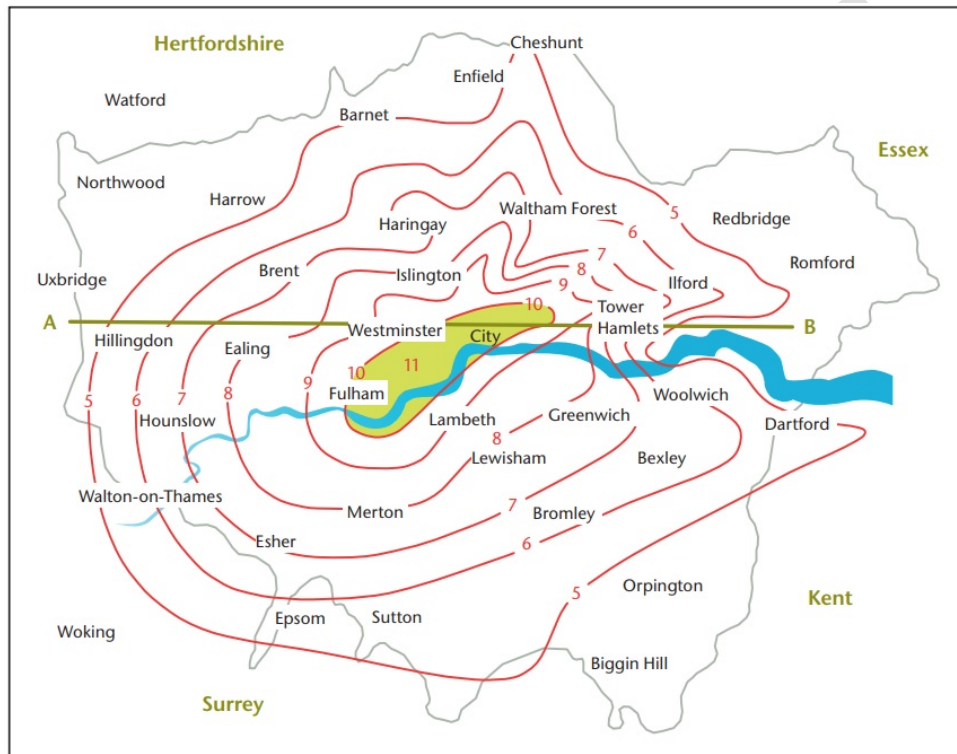
Figure 1: The ambient temperature profile of London and the effect of the Urban Heat Islands (MetOffice, 2019).

patterns and forecast the future values of time series (Adhikari et al., 2015; Rawat et al., 2015). Predictive analysis can be conducted using statistical or machine-learning-based techniques (Ratner, 2017). For example, a machine learning model based on the Random Forest Prediction (Random Forest Regression) technique is adopted by (Farooqi et al., 2018) for developing an anomaly detection mechanism for weather data. Another example is based on statistical predictive analysis, using the one step-forward approach of the Autoregressive Moving Average (ARMA) model, to tackle the inevitable challenge of sensors and sensor network failures in power terminals (Li et al., 2019). Some applications require a mixed-methods approach, where both machine-learning and statistical methods are used to tackle a particular data quality challenge. For example, Okafor et al. (2020) investigated the use of artificial neural networks and linear regression for calibrating low-cost environmental monitoring sensors to improve their service life by reducing the probability of their failure due to battery failure. Predictive analysis methods rely on models developed using historical data as a training data set. Therefore, predictive analysis is most suitable for detecting measurement errors that appear for a short time interval (short outliers). Measurement errors that occur for a relatively long time affect the ability of the predictive models to render accurate predictions. The pattern of time series with

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long outliers will be distorted to a certain extent, reflecting the wrong measurement as the standard pattern, leading to higher forecast errors and limiting the ability of predictive analysis modes to detect data accuracy issues correctly (Berk, 2015).

Outliers in sensor node networks are mainly categorised into short, simple and long-segmental outliers (Aggarwal, 2013). Long-segmental outliers, also known as shape outliers, are irregular observations that emerge for a relatively long time (Zhuang and Chen, 2006) and change the time-series pattern (set of observations) (Aggarwal, 2015). Long-segmental outliers occur in particular cases where a phenomenon has a long-term impact, such as forest fires or oil spills or due to sensor nodes failure (Ghorbel et al., 2015). Long-segmental outliers associated with sensor failures are categorised according to the behaviour of faulty sensor nodes (Sailhan et al., 2010) into:

- **Continuous halting faults:** long outliers that show no or minimal variation in the value attribute of their data stream for a relatively long interval of time.

- **Abrupt (emerging) and incipient faults:** a constant or linear increase offset to the measurement values that occur over a longer time interval than expected.

As long-segmental outliers occur for a relatively long time and change data patterns, they break the temporal correlation of observations after and before the anomaly and violate the possibility of using predictive outlier detection techniques to detect this type of anomalies (Berk, 2015).

This paper investigates time-series clustering as a novel solution that addresses the limitations of both anomaly and predictive analysis approaches in detecting long outliers associated with sensor node failures in the context of large-scale CPSs.

3. Time-Series Clustering

Time-series similarity measures define outliers in time-series windows by comparing them with other non-overlapping windows using a measurement metric, such as the Euclidean distance, which measures the distance between different time series (Aggarwal, 2015; Dean, 2014; Aghabozorgi et al., 2015). Therefore, time-series similarity measures were utilised in time-series clustering methods to compare the pattern of an entire or a substantial time series window with another based on their long-term temporal correlation (Dean, 2014; Aggarwal, 2017). The purpose of time-series clustering is to identify faulty sensor nodes by comparing the shape or features of their time series with the time-series of other properly functioning sensor nodes. In this paper, Dynamic Time Wrapping (DTW) time-series clustering technique is tested as an anomaly detection mechanism. The DTW test has been extended to include K-Shape and Characteristic-Based Clustering techniques to find a higher performance clustering technique that can render accurate results while examining shorter time series.

3.1. Dynamic Time Warping

Dynamic Time Warping (DTW) is a time-series clustering technique that finds corresponding regions of similarity between time-series. DTW can stretch or shrink (warp)
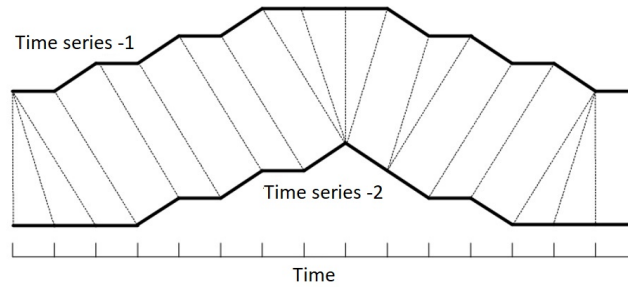
Figure 2: An illustration of how DTW warps one time-series into another one (Salvador and Chan, 2007).

time-series non-linearly along its time axis to find the optimal correlation between different time-series (Salvador and Chan, 2007), as shown in Figure 2.

DTW has many implementations in different disciples, such as gesture recognition, robotics, and manufacturing. However, it was mainly used for data mining as a distance measure between time-series data points (Salvador and Chan, 2007). DTW is not sensitive to time-shifting, and it does not require the time-series to be on the same length as a condition to compare among them (Bankó and Abonyi, 2012). To compare time-series T1, T2 of lengths n and m, DTW is going to measure the distance (T1, T2) with time complexity of $(n*m)$. Thus, DTW is a computationally expensive method for simultaneously clustering long time-series or numerous time-series (Aggarwal and Reddy, 2014).

3.2. K-Shape

K-Shape and Dynamic Time Warping (DTW) are shape-based time-series clustering methods. K-Shape is a time-series clustering algorithm that uses cross-correlation measures to measure the distance and the centroids for time-series clusters. K-Shape analyses the shape of the time series while clustering them. The theory behind K-Shape is similar to the one used by the K-means algorithm. K-means is a distance-based clustering algorithm that divides the unlabelled dataset into several k non-overlapping subsets (clusters), each of which is represented by the mean of the distance between its data points (Hartigan and Wong, 1979). Both K-Shape and K-means rely on the iterative refinement procedure, which scales linearly and produces equivalent and sufficiently separated clusters. K-Shape is considered a highly efficient and more domain-independent time-series clustering method than the DTW method. DTW considers the shape similarity between time series regardless of differences in amplitude and phase. At the same time, K-Shape relies on the time-series cross-correlation measures, which are significantly faster than the time-series distance measures method adopted by DTW (Paparrizos and Gravano, 2016).

3.3. Characteristic-Based Time-Series Clustering

Characteristic-based time-series clustering is also known as features extraction-based or statistical characteristics-based time-series clustering. Unlike the shape-based time-series clustering methods, such as DTW or K-Shape, the characteristic-based clustering does not use the distance measure or the cross-correlation measures methods. Alternatively, this method clusters time-series based on their captured global characteristics using classical

statistical methods. The features extracted from each time series can be fitted into any arbitrary clustering algorithm. The extracted features describe a time series' statistical characteristics (global measures). These features can be extended to over 100 different features, such as the absolute sum of changes, autocorrelation, standard deviation and partial autocorrelation. Characteristic-based clustering reduces time-series dimensions, making it much less sensitive to the effect of missing values or noisy data. The advantage of characteristic-based clustering is its high performance, even if used to perform similarity searches or clustering amongst very long time series (Wang et al., 2006).

4. Experimental Settings and London Case Study

Time-series clustering techniques are used in this study to detect continuous (halting), abrupt (emerging) and incipient faults using real-world datasets collected from two different sensor node networks, as follows:

4.1. Large-Scale Sensor Node Network

Large-scale sensor node network is the primary data source of this study. It consists of 275 temperature sensor nodes distributed around London and managed by different providers, such as the Meteorological Office (Met Office) (MetOffice, 2021), Open Weather Map (OpenWeatherMap, 2021) and Smart Citizen (Citizen, 2021). The geographical distribution of these sensors is shown in Figure 3.

Data streams from these sensor nodes were coordinated by an Internet of Things (IoT) search engine called Thingfull (Thingful, 2021). Thingful is owned by a U.K. based company named Umbrellium.Ltd (Umbrellium, 2021) specialises in IoT projects associated with smart cities, connected vehicles, machine learning and big data analytics. These sensor nodes data streams collected through the Thingful network will be utilised to test the ability of the time-series clustering techniques to detect continuous (halting) and abrupt (emerging) long-outliers. Thus, these types of long-outliers have been detected in some time series of this large-scale dataset while focusing on temperature time series. Typically, temperature time-series show daily seasonality and a trend, as shown in Figure 4.

Therefore, temperature time series with a constant value attribute or a very low seasonality for a relatively long-time (long-outlier) are highly likely to encompass data quality issues related to observations accuracy. This behaviour can be related to a sensor node's hardware failure that affects their detection ability, or it may indicate that these time-series were streamed from sensor nodes that are down, and the system compensates for their missing observations by repeating the last observation received from these faulty sensors. An example of long-segmental outliers is shown in Figure 5. Figure 5 shows the time-series of two sensors which displays constant readings (Figure 5 Sensor ID= kt3m3nw5 and rw4egmaw/ Smart Citizen) for a relatively long time, compared to another time-series (Figure 5 Sensor ID=47qwbfba/ Meteorological Office) generated by a functional sensor node managed by the Meteorological Office during the same time window.

The accuracy and performance of the three time-series clustering methods, DTW and K-Shape and the characteristics-based time-series clustering technique, examined in this study are evaluated based on their ability to identify time-series with halting or emerging long-segmental outliers and the time required to render the clustering results. The evaluation
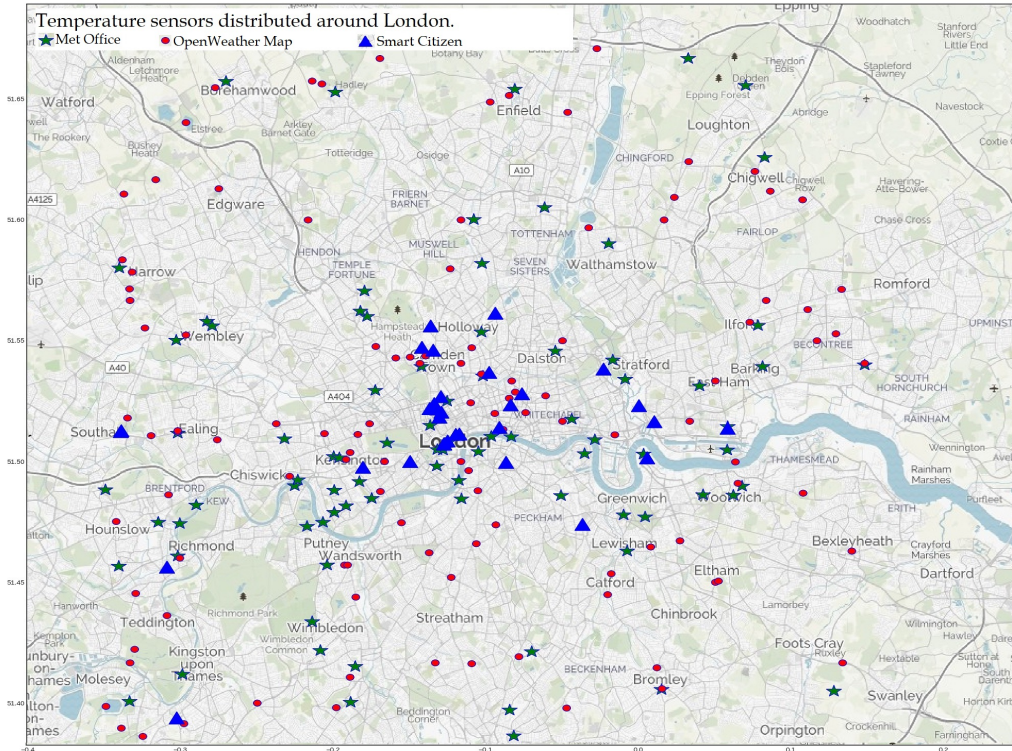
Figure 3: The geographical distribution of the real-world sensor nodes adopted in this study.

was conducted using two different time-series windows. The first is a seven-day time-series window. The second is a two-day time-series window used to evaluate the accuracy and performance of time-series clustering techniques compared to the seven-day time window. The time series were collected from a local network of four sensor nodes and a large-scale network of 275 sensor nodes distributed around London.

4.2. Local Sensor Node Network

This time series was used as a benchmark dataset to test the ability of the time series clustering techniques to detect incipient faults with consistent offset (long-outlier). The local sensor node network consists of four high-quality sensor nodes deployed at The University of East London. One of these network sensor nodes is installed indoors, and the other three are deployed outdoors. Since all the local sensor nodes were distributed in a relatively small geographical area, their time-series do not show significant differences in the shape of their trend. However, they show some differences in the value attribute, especially with the indoors sensor, which streamed a time series with a consistent offset of 10-15 C^o from other sensors. Thus, the indoors sensor node, in this case, represented a sensor with an incipient fault pattern, as shown in Figure 6. Furthermore, since this time series is a high-quality dataset with no missing values or outliers, it was used as a benchmark to test and calibrate the time-series clustering techniques before applying them to the large-scale
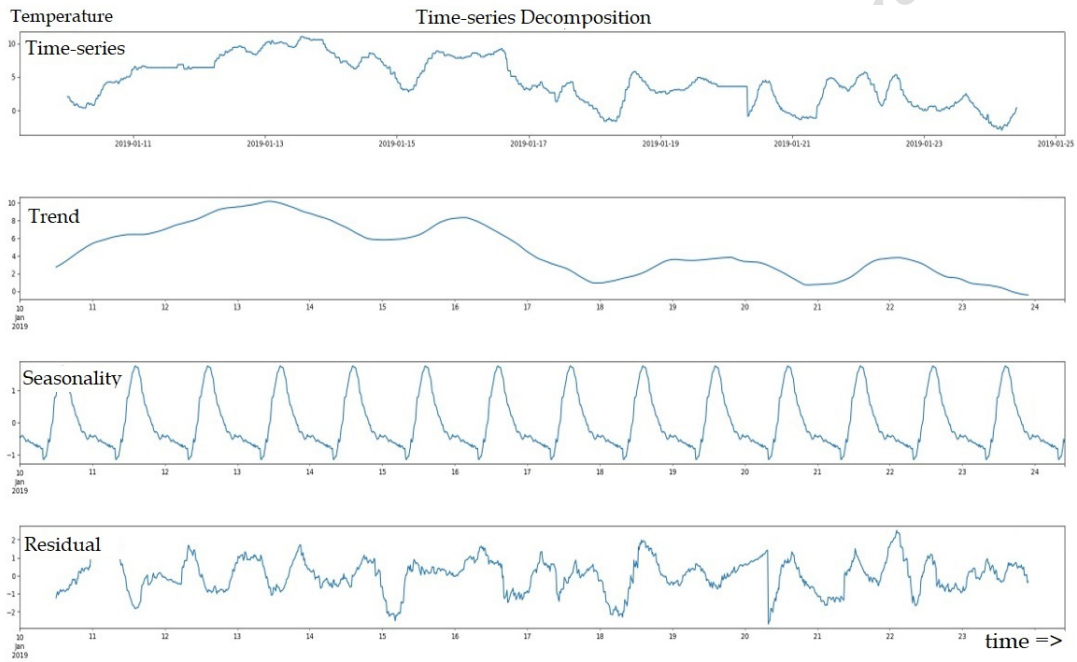
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Figure 4: Time-series decomposition of a single time-series collected from a real-world temperature sensor node of the large-scale sensor network distributed around London.
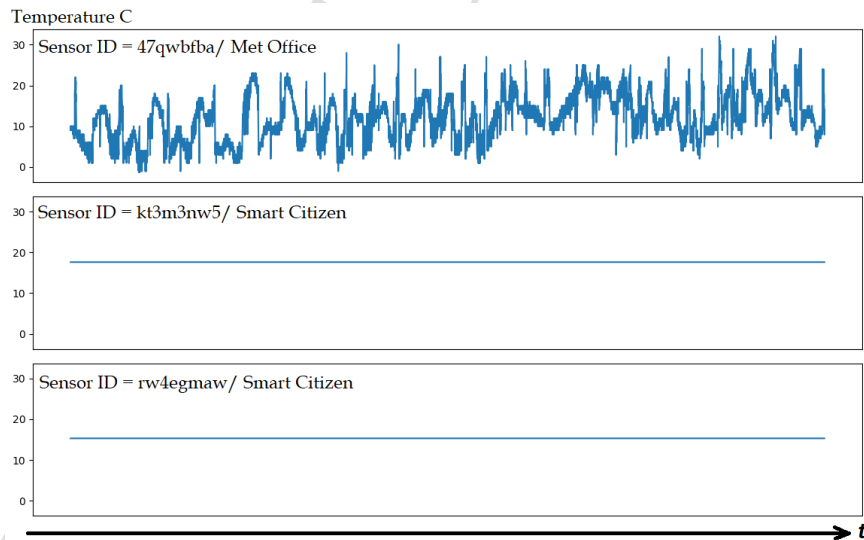

Figure 5: An example of two temperature time-series with (halting) long-segmental outliers (Sensor ID= kt3m3nw5 and rw4egmaw/ Smart Citizen) comparing with a normal time-series collected from a functional sensor node (Sensor ID=47qwbfba/ Meteorological Office).
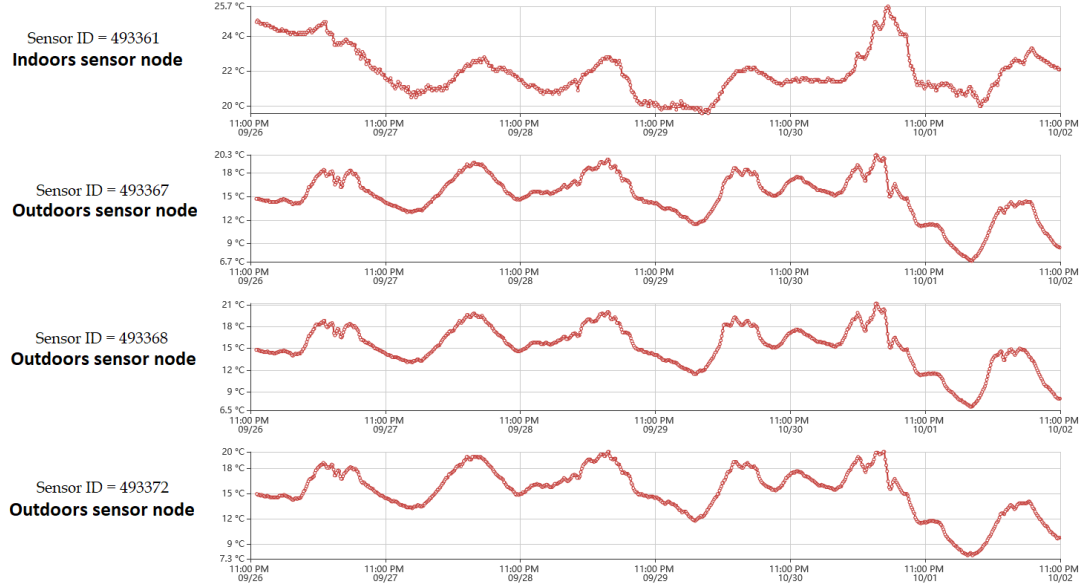
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sensor node network time series.

Figure 6: Time-series of the local sensor node network do not show significant differences in the shape of their trend. However, they show differences in the value attribute, especially with the indoors sensor (Sensor ID = 493361) which streamed a time-series with a consistent offset of 10-15 C^o from other sensors.

5. Dynamic Time Warping (DTW) and K-Shape

The Dynamic Time Warping (DTW) and K-Shape time-series clustering were applied using the Python package *tslearn.clustering* provided by Scikit-learn (Pedregosa et al., 2011). The outcome from applying the DTW and K-Shape time-series clustering techniques to the local sensor node network dataset is shown in Figure 7 (identical outcome).

Both DTW and K-Shape time-series clustering techniques successfully identified the time series of the indoor sensor node (the incipient fault pattern Sensor ID = 493361) from the other time series of the outdoor sensor nodes. This result is significant because both DTW and K-Shape are shape-based time series clustering techniques, and all the time series used in this test exhibit a significant similarity in the shape pattern, as shown in Figure 6. The top graph line in Figure 7 is the indoors sensor (Sensor ID = 493361) time series in the first cluster (incipient), while Cluster2 (the bottom graph lines) presents the other (normal) time-series.

The time series used in the second test were collected from the large-scale sensor network. The dataset of this test is much larger than the dataset of the local sensor node network. Both DTW and K-Shape rendered identical clustering results when applied to the seven-day time series, as shown in Figure 8 and Figure 9.

Both DTW and K-Shape successfully separated time-series with long-segmental outliers from the other time-series that exhibit typical variation in the trend and seasonality when
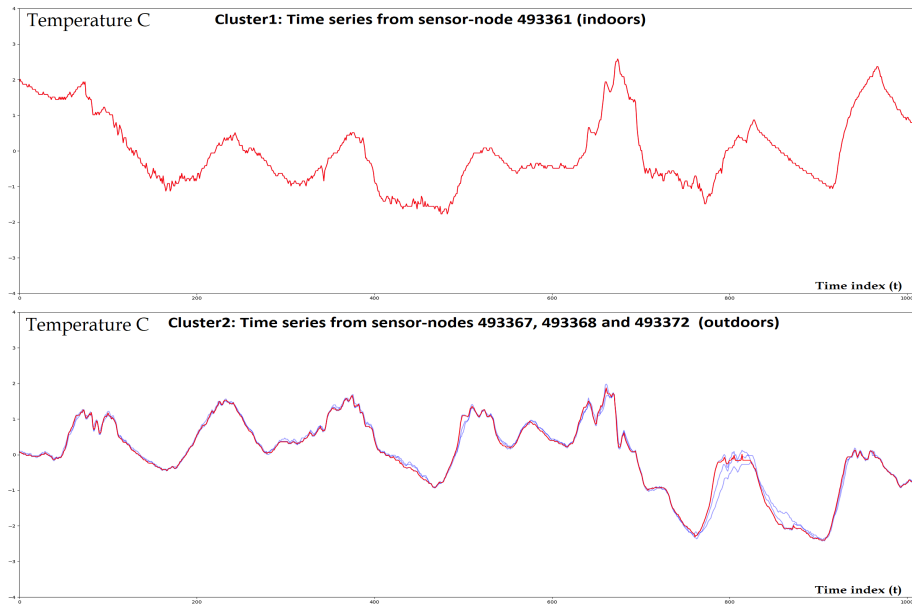
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Figure 7: DTW and K-Shape were able to successfully differentiate the incipient faults time-series of indoor sensor-493361 from the other (normal) outdoors time-series.
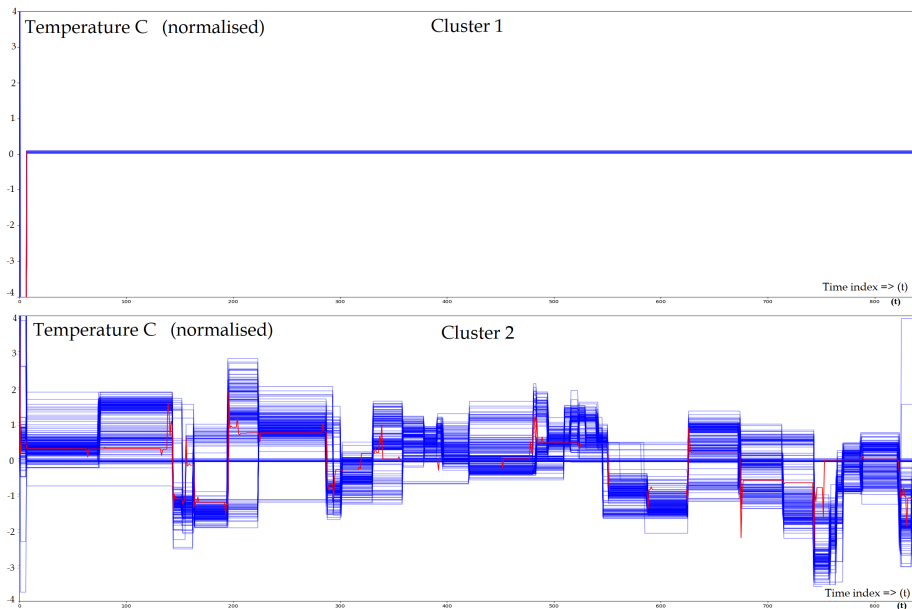

Figure 8: DTW successfully separated time-series with the long-segmental outliers (Cluster 1) from other (typical) time-series (Cluster2) when applied to seven-day window real-world dataset.
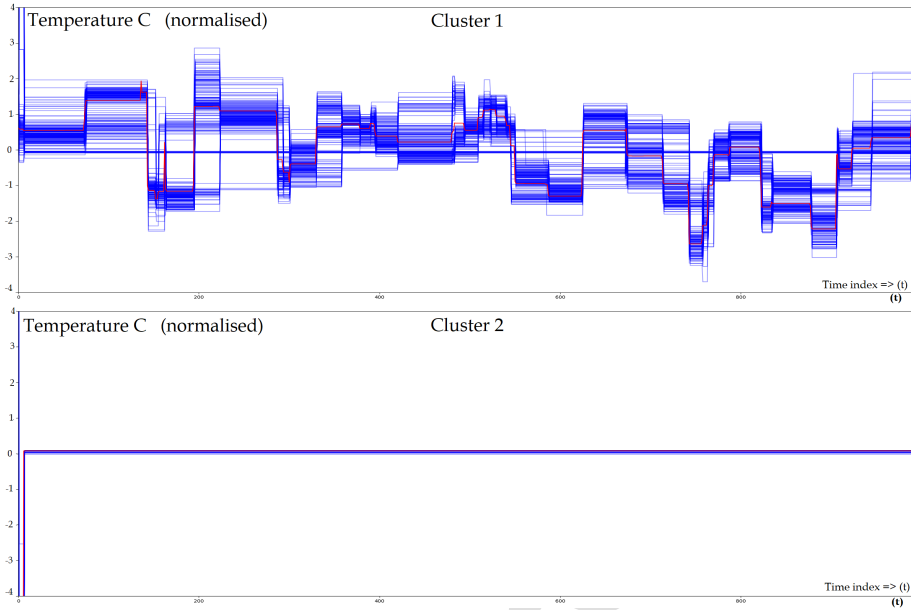
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Figure 9: K-Shape successfully separated time-series with the long-segmental outliers (Cluster2) from the other (typical) time-series (Cluster1) when applied to seven-day window real-world dataset.

applied to the seven-day time window. The temperature axis (y-axes) in Figure 8 and Figure 9 do not reflect the actual value attribute of the observations, since all time-series were normalised using the Python package *"tslearn.preprocessing.TimeSeriesScalerMeanVariance"* (Pedregosa et al., 2011) so that each output time series had zero mean and unit variance before being fitted to the time-series clustering models, as shown in Figure 12. Applying DTW and K-Shape to the two-day time series showed that DTW is more sensitive to the window length of the clustered time series than the K-Shape. The ability of the DTW to differentiate the faulty time-series from other (typical) ones was more significantly affected compared to K-Shape, as shown in Figure 10 and Figure 11.

In general, both shape-based time-series clustering techniques require relatively long time series to enhance their clustering results, especially the DTW. Figures 10 and 11 illustrate that K-Shape can maintain its clustering accuracy when applied to a relatively shorter time series than DTW. Both techniques were able to differentiate time-series that showed the patterns of the continuous and abrupt long-segmental outliers with 100% accurate detection ratio when applied to seven days, or longer time-series, as shown in Figure 8 and Figure 9. The main technical steps required to fit all available time series from all sensor nodes as a three-dimensional data array to the DTW and K-Shape models are illustrated in the process flowchart diagram shown in Figure 12.

6. Characteristics-Based Time-Series Clustering

The characteristics (features) based time-series clustering technique was implemented using (Christ et al., 2018)'s Python *tsfresh* package and the time series collected from the
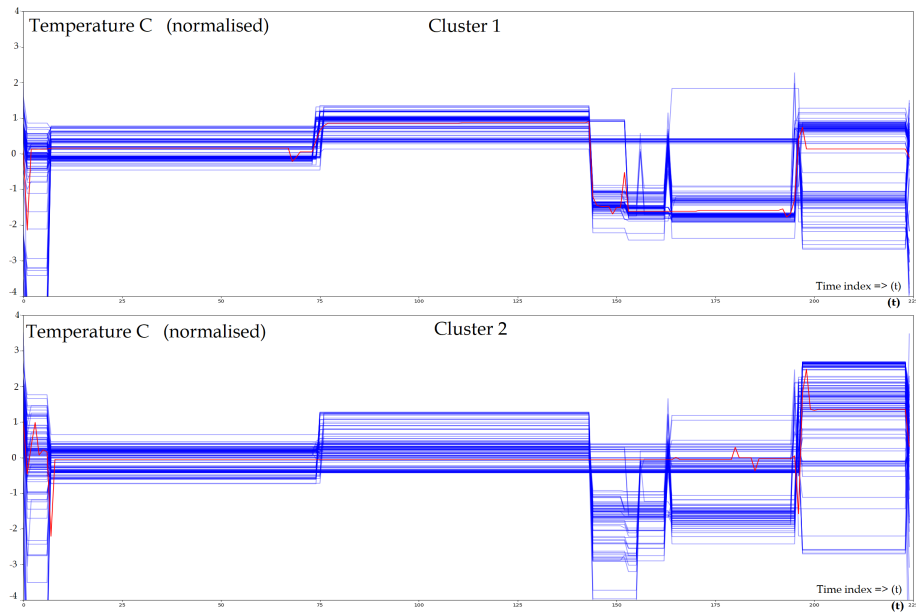
Figure 10: DTW is not able to differentiate time-series with long-segmental outliers from other typical time-series when it was applied to a shorter two day time-window of real-world time-series.
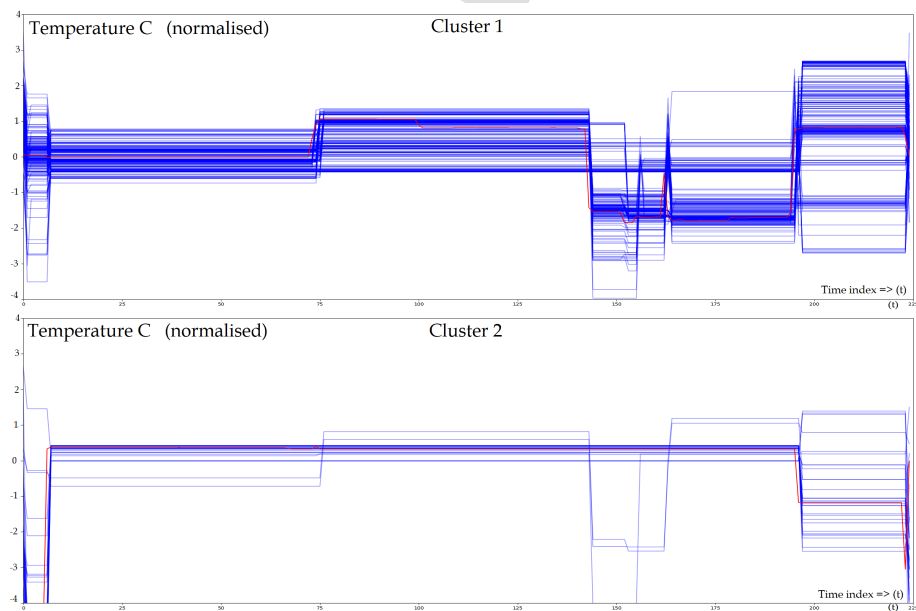

Figure 11: K-Shape is less able to differentiate time-series with long-segmental outliers from other typical time-series when it was applied to a shorter, two day time-window, of real-world time-series.
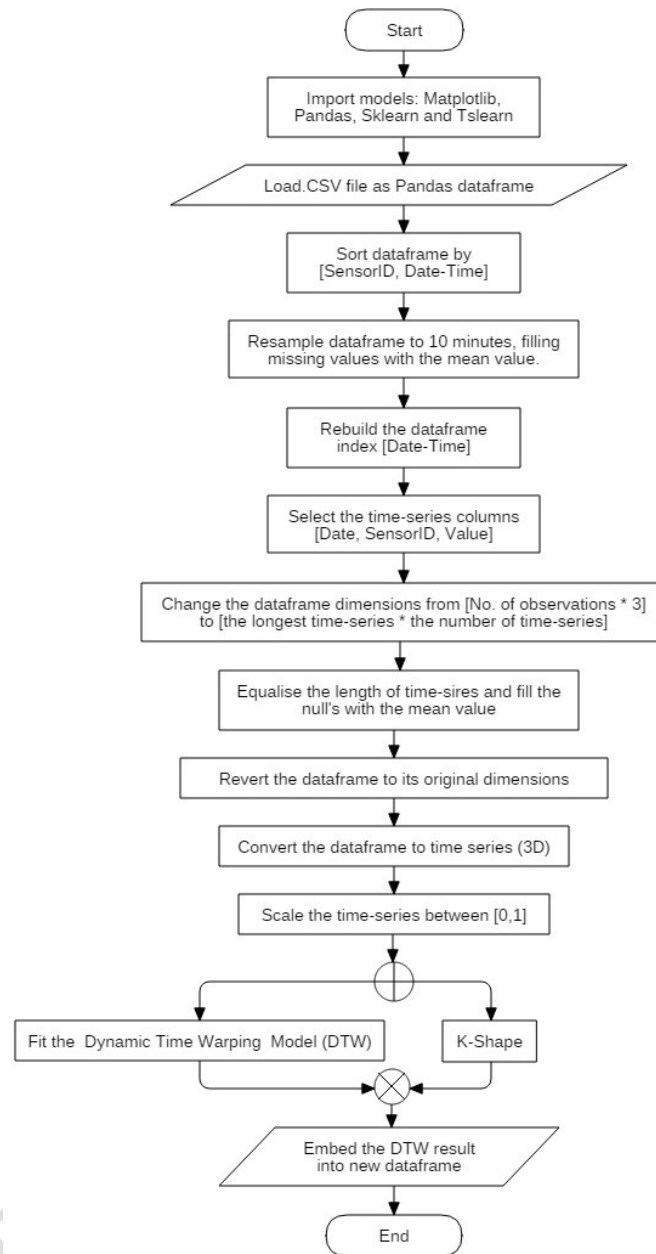
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Figure 12: The process diagram of the technical steps implemented to fit all available time-series as a 3D array into the Dynamic Time Warping (DTW) and K-Shape time-series clustering models.

local sensor node network as a benchmark test. The characteristic-based time-series clustering technique successfully separated the time-series of the indoors sensor node (incipient faults pattern) from the rest of the time series, as shown in Figure 13.
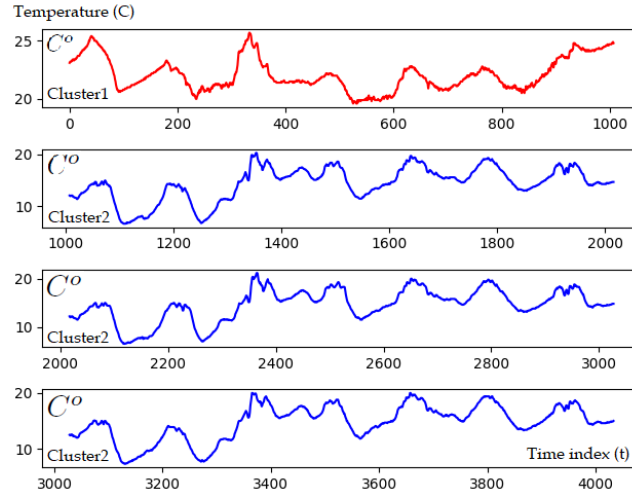

Figure 13: The feature-based time-series clustering method differentiated the indoors time-series (Cluster1) from the other typical time-series (Cluster2) of the ideal dataset.

The characteristics based time series clustering model relies on using arbitrary clustering algorithms, such as K-means, for clustering the set of features extracted from the examined time series. The selected features may vary from one application to another based on the characteristics of the time series chosen to be used as clustering reference. In this case study, the "absolute sum of changes" was the main parameter used and fitted to the K-means clustering model to detect continuous (halting/repeating) faults of sensors time series that show no or minimal variation in their observations value attributes. The outcome of applying the feature-based time-series clustering technique to the time series of the large-scale sensor node network is shown in Figure 14 and Figure 15.

The feature-based time series clustering technique successfully categorised time series with long-segmental outliers even when applied to the relatively short two-day time-series window, as shown in Figure 15. The technical aspects required to fit all available time series to the characteristic-based time-series clustering models are illustrated in the flowchart diagram in Figure 16.

Since all the used time-series clustering techniques (DTW, K-Shape and Characteristics-Based Time-Series Clustering) were applied to the same dataset, it was possible to evaluate the performance of each of these methods based on the time spent to render their clustering results. DTW required a significant amount of time to render the results, around 360 seconds compared to the feature-based and K-Shape time-series clustering techniques which required around 30 seconds when applied to the seven-day time window. It is essential to highlight that these results may vary according to the number and the type of the extracted features and the selected clustering algorithm. Although DTW demanded more
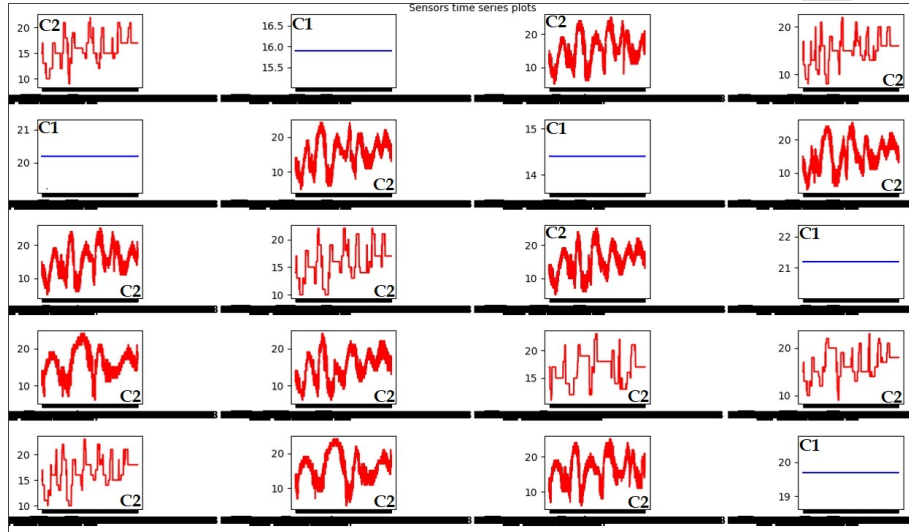
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Figure 14: The feature-based time-series clustering technique successfully differentiated time-series with long-segmental outliers (C1 = Cluster1) from other typical time-series (C2 = Cluster2) when applied to the real-world seven-day time window.
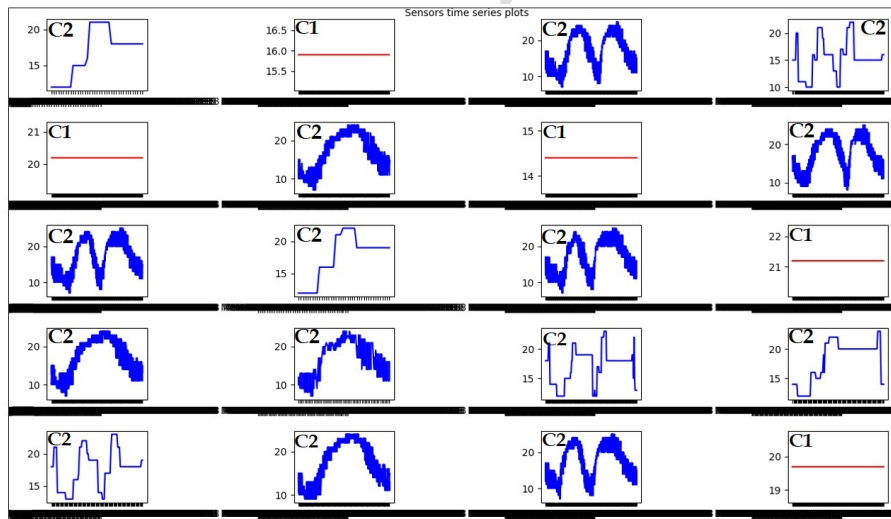

Figure 15: The feature-based time-series clustering technique successfully differentiated time-series with long-segmental outliers (C1 = Cluster1) from other typical time-series (C2 = Cluster2) even when applied to relatively short time-series (two-day time window) of the real-world dataset.
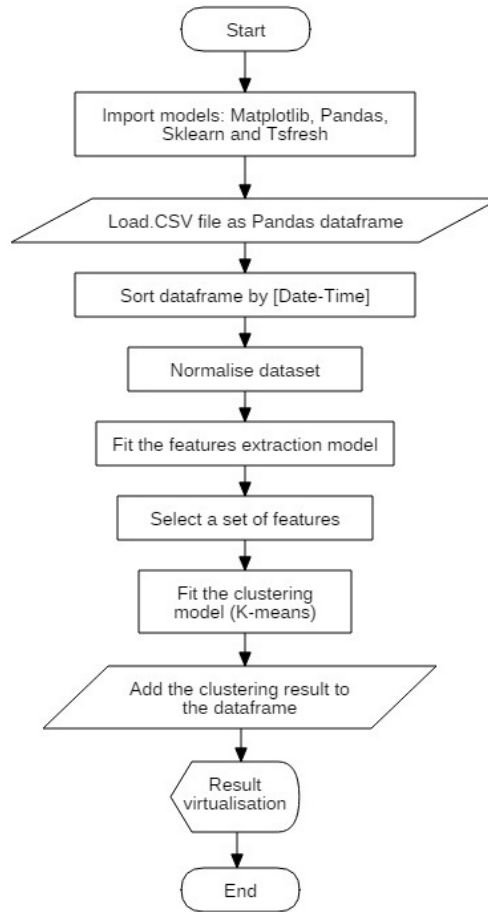
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Figure 16: The process diagram of the technical steps implemented to fit time-series to the characteristic-based time-series clustering model.

time than K-Shape to render the clustering results, it seems that the K-Shape Python package managed the processing resources of the CPU cores more efficiently than DTW, as shown in Figure 17.

Note : All tests of this study were conducted using Python 3.7 64 bits installed over a Linux (Fedora 64 bits) workstation. The processor of the workstation is an Intel(R) Core (TM) i7-7920HQ CPU @ 3.10GHz (4 CPUs), 3.1GHz with 32 GB of RAM.

7. Conclusion

The novelty of this research lies in the successful implementation of time-series clustering techniques as a sensors failure detection mechanism via detecting long-segmental outliers associated with time-series of faulty sensors. The purpose of this study is to test Dynamic Time Warping (DTW), K-Shape, and the Characteristics-based time se-
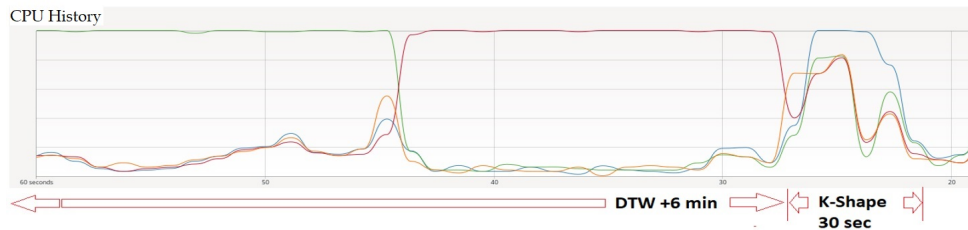
17

Figure 17: The performance of the CPU cores and the time required to perform the same task by DTW comparing to K-Shape, each graph line represents the performance of a single CPU core.

ries clustering technique as long-segmental outlier detection methods for sensor node fault detection in large-scale CPSs. The study focused on detecting the failures of continuous (halting/repeating) and incipient sensor nodes. The time series clustering techniques were evaluated using real-world observations collected from two real-world sensor node networks. All of the examined time series clustering techniques proved their ability to detect sensor node faults associated with long-outliers in their time series with some differences in accuracy and complexity. The feature-based time series clustering technique maintained its detection accuracy even when applied to a relatively short time series compared with the shape-based (DTW and K-Shape) time series clustering techniques. Furthermore, the empirical tests of these techniques showed that feature-based time-series clustering could be a more efficient long-segmental outlier detection mechanism than the shape-based time-series clustering techniques, such as DTW and K-Shape, mainly when applied to shorter time-series windows.

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No conflicts of interest to declare.

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Declaration of interests

☒ 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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