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Internet Of Things (Iot) – Based Smart Power Quality Cluster Analyzer In Higher Order Statistics For Smart-Grid

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ABSTRACT:

Distribution customers and prosumers are extremely concerned about power quality in relation to the contemporary smart grid for the power industry (PQ). In fact, they choose to pay more money to ensure that they have access to a consistent and high-quality power supply. Even if the quality of the voltage and current offered to customers is a big concern, operators continue to place all of their attention on reliability. There are no established norms for tracking, penalising, or enforcing PQ-based tariff structures in LV distribution networks. To address the challenge of monitoring electrical grids in the face of unexpected occurrences resulting from the introduction of new energy sources, this paper presents a graphical cluster analysis-based approach that could be applied in Smart Power Quality Analysers (SPQAs), a proposed Instrument Class S in compliance with the standard UNE-EN 61000-4-30. Instruments can initiate the measuring operation based on a predetermined PQ threshold, producing the time-domain higher-order statistics (HOS) features necessary for classification in the event of an electrical outage. The results are good, with two separate classes of signals (sags and transients) and an accuracy of 80% over a battery of 160 signals. This paper also introduces the uncertainty inter-cluster area. Grid operators can improve database characterisation and introduce certain qualitative criteria for smart grid monitoring due to analysis of intensity cluster disruptions.

Keywords. Internet of Things, Smart grid, Power Quality, Cluster analyser, higher-order statistics, Energy monitoring.

1. INTRODUCTION

Power quality (PQ) is often neglected in favour of ensuring a steady supply of electricity in nations still on the path to economic development. Although power quality (PQ) problems have been around since the end of the 19th century, they have become more severe and common with the introduction of new power electronic equipment into the distribution network. According to a report by Brookings India [1], low PQ is one of the main reasons why India's distribution sector is the weakest link in the power industry financially and operationally. Utility companies face a significant problem in the monitoring and regulation of PQ. Therefore, utility companies do not monitor or maintain PQ for Low voltage (LV) residential customers. Interestingly, today's consumers, who are aware of the consequences of low PQ, are prepared to pay a premium for a reliable power source [2]. One

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of the effects of low PQ is flickering in the lighting system, as the supply voltage fluctuates and affects the home appliances. The human eye experiences discomfort due to the constant flickering. Furthermore, computers and electronic loads are harmed by oscillatory and impulsive transients or surges [3]. Electromechanical equipment, such as fans and motors, are likewise negatively impacted by voltage fluctuations [4]. Damage to utility infrastructure is a side effect of PQ disturbances experienced by customers. For instance, the DC offset from today's consumer loads can cause distribution transformers to overheat and possibly become saturated. Overheating and premature failure of supply cables is another consequence of harmonics in consumer load current [5]. A European PQ study [6] estimates that annual financial losses in EU-25 nations due to PQ disturbances average roughly 150 billion Euros. The most recent research on India's PQ regulation laws [7] by the Asia Power Quality Initiative found that the country's utilities had a solid system for maintaining a constant frequency and a steady supply. Voltage fluctuations, transients, and harmonic distortion, all examples of poor power quality (PQ), are not being adequately addressed. As a result, the grid and the users bear the costs and consequences of inadequate PQ. Therefore, PQ monitoring and regulation is crucial for utilities in modern smart grids [31].

The expansion of databases made available by sensors and measuring units in the energy industry, particularly in the context of the Smart Grid (SG), necessitates the development of new criteria and methodologies for maintaining a rigorous check on power quality (PQ). Distributed energy resources (DERs) integration is getting increasingly challenging as the energy business adjusts to these new challenges. To better track the health of the network and enhance signal processing, individuals are developing novel data storage methods. Optimization, forecasting, classification, and cluster analysis are just some of the data analytics methods that can simplify the SG's data [8]. On the smart grid of the future, the traditional supply-and-demand relationship for electricity will change. As a result of the shift in operating conditions and the substantial volume of bidirectional power flows, voltage sags, over voltages, and switching transients may increase.

Therefore, it is crucial to standardise methods of measuring and analysing rapid voltage fluctuations in order to reduce the occurrence of PQ problems during grid modernization, which is a consequence of the scenario. To comprehend the recurring events on the power supplied to the end user, new intelligent instruments and PQ parameters that represent the analysis in real time and regulate that the power supplied remain within the limits must be studied. Even if the information collected by the power grid's sensors might be overwhelming, it can be managed with the help of cluster analysis [9]. Cluster analysis is able to reveal the underlying organisation and connections in network data. The network operator must, however, first set up a set of categorization rules that are based on the anticipated results.

Quantifying a power quality parameter separate from many others of the network structure, such as the kind of consumer, climatic conditions, etc., was essential for the construction of a prediction system. Cluster analysis has been proven in previous research to be an effective method of data classification [10].

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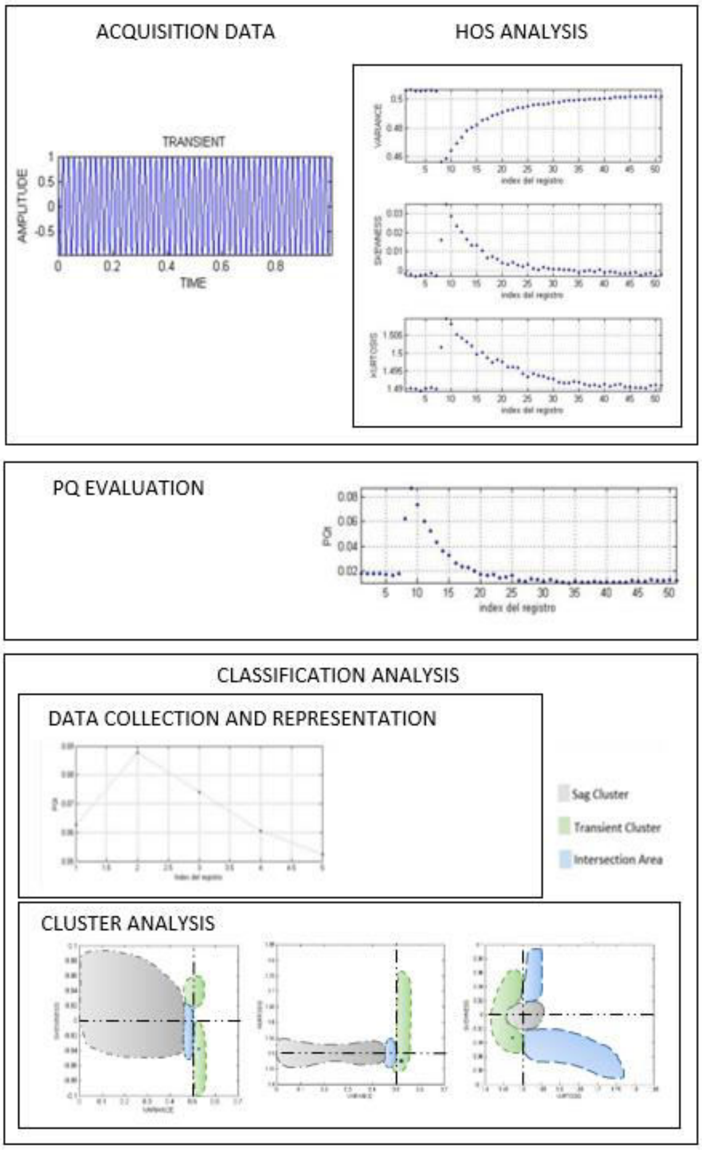

Figure 1. Real-time examination of a recorded signal depicting a transient presence.

A 50 Hz frequency with a sampling frequency of 20 kHz (400 samples per cycle). The samples indicate that there are 50 PQ indices in the signal. Data collection, performance quality assessment, and classification analysis are the three stages of analysis that have been carried out to categorise the behaviour of disruptions. Once the PQ evaluation of the signal has above the threshold PQ >= 0.05, the HOS analysis of the signal is triggered. Data that is above the cutoff is clustered using the HOS mean for this classification analysis.

In other works, data mining tools and techniques are developed for the efficient reporting of network problems using pattern recognition [11]. This is done by detecting and diagnosing power quality disturbances, failures, and alerts in critical situations. Cluster analysis in power signals, grounded on HOS features, reveals useful insights about PQ occurrences, as demonstrated in [12] and [13], by differentiating between second-, third-, and fourth-order maxima and minima cumulates. A qualitative analysis of the PQ clusters is something that we do in order to hone down on what exactly needs to be observed during a particular session.

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This is important because there are a lot of different cluster analyses to choose from, and we need to sort a lot of data.

In this work, we recommend employing a cluster analysis approach through the use of a virtual instrument (VI). With the specifics of the voltage provided by the general distribution networks UNE EN501690:2007 in mind throughout its construction, the instrument has been designed to process data in real time via a wirelessly configured session. We honed in on the best sessions to use a Class A instrument that checks the power line in accordance with UNE-EN 61000-4-30 regulations (CA 230v, 50Hz).

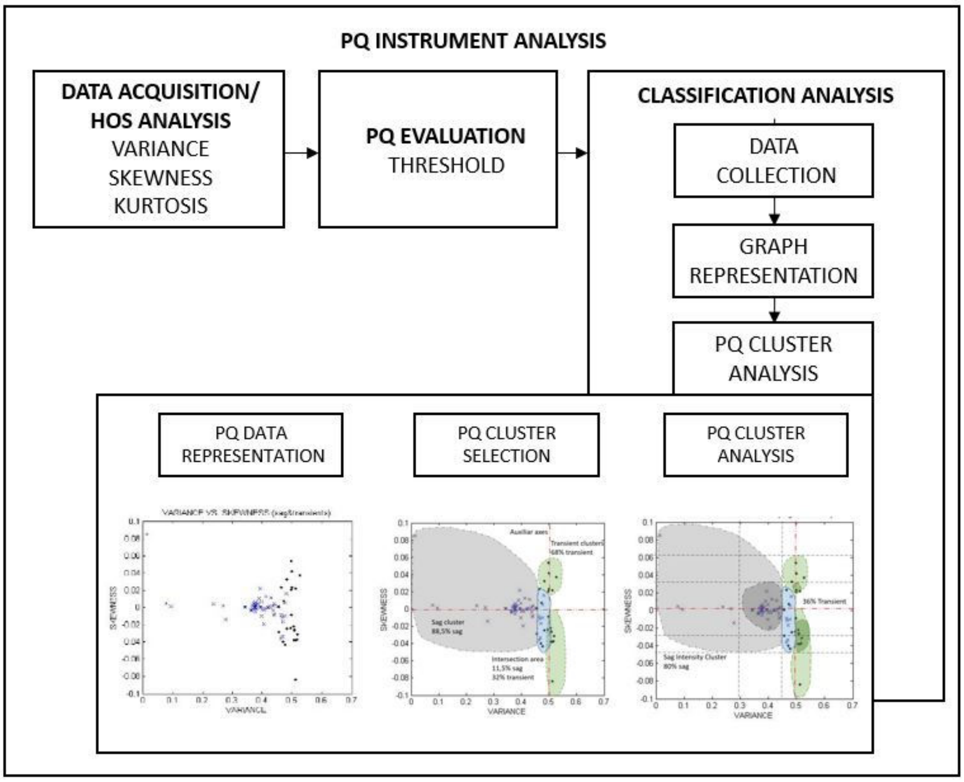

Figure 2. PQ analysis was performed in accordance with the protocol established by the PQ Instrument

The device performs session-based, real-time data processing (on-line). Additionally, a battery of previously collected signals can be analysed (offline). If the value of a PQ index rises beyond a certain threshold, the instrument will begin analysing the measurement time series [14]. (Fig. 1). The HOS-based index incorporates details of the associated PQ events with the identified disruptions. The block diagram shown in Fig.1 depicts: Collecting information, measuring performance, and sorting it. Therefore, a signal space (various clusters) is defined by the events detected and the representations of HOS from the classification analysis aid with this.

In order to more precisely characterise the signal space, it is best to base the categorization analysis (qualitative analysis) on the instrument output and the results of previous working sessions (cluster analysis based in HOS). Narrowing in on certain cluster regions and localities will enhance the smart grid decision-making process (sags and transients clusters, depending on the deviation of the HOS values in a battery of signals analysed). The suggested method of PQ cluster analysis consists of the three basic processes shown in Fig. 2: feature representation, cluster selection, and cluster analysis. Cluster analysis

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is preceded by displaying the data's distribution in terms of its dispersal's skewness, kurtosis, and variance-skewness pairs. The operator can study the session's output and make a decision regarding the network's PQ cluster selection based on the previously represented behaviour of the data. In the end, the clusters' average HOS and data distribution in cluster shape as a function of perturbations are taken into account during the selection's area analysis (PQ cluster analysis). To normalise data distribution and more precisely characterise the signal space of the investigated network, an axis analysis approach (HOS-axes) based on the absolute values of HOS (the theoretical values of the HOS on a healthy signal) has been developed [33]. It provides a visual depiction of the signal's many cluster locations, some of which are unclear inter-cluster spaces and others of which are focused in sag and transient clusters in terms of intensity [34].

2. Related Work

Recent years have seen a multitude of exciting studies conducted on PQ-based smart metres [32]. The purpose of this article is to examine the shortcomings of some of these metres in order to develop a more effective metre that meets all the requirements for practical application. In [15], the authors recommend certain guidelines for designing a PQ-based smart metre, as well as some functionality that should be included. It provides a solid groundwork upon which to build the meter's structure. However, the design is primarily conceptual, with little consideration given to how it might actually be implemented. The smart PQ metre demonstrated in [16] measures voltage and frequency-related PQ indices and events for residential users. Though it does not monitor or measure the consumer current,. In addition, the functionality of energy metering is not integrated and a separate computer is required. Consequently, PQ and energy metering must be implemented using two distinct pieces of hardware. For PQ monitoring, the authors of [17] suggest an Ethernet-based smart metre that uses LabVIEW to evaluate voltage quality. It has a load scheduling feature that can be used to boost PQ instantly [18]. This metre does not measure consumer current distortions and also necessitates an additional computer to run LabVIEW. In [19], the authors suggest a standalone smart metre that, under linear load conditions only, may detect voltage dips and spikes, supply frequency, and power factor. However, neither the voltage harmonic distortion nor the current harmonic distortion of power-electronic powered loads nor the displacement power factor can be accurately measured (DPF). The smart metre produced by the authors in [20] is based on the Raspberry Pi computer and is unable to detect current distortion caused by the consumer. The voltage parameters are the only ones measured by the open-source Raspberry Pi-based PQ analyzer described in [21]. In addition, the utilisation of Raspberry Pi is not only pointless but also costly and has a considerably greater level of power consumption. In [22], a smart metre can measure both energy use and basic PQ, and it also has anti-theft protections. The consumer-facing quality rating features are missing, though. In [23], we see a complex proposal for an FPGA-based PQ monitoring system, but this system requires a separate computer with LabVIEW installed. In [24], another FPGA-based smart energy metre is presented that may be utilised as a standalone device in the home. However, this technology is extremely intricate and too expensive for home use. It's safe to say that home PQ monitoring applications cannot benefit from the portability or low cost of FPGA- and Raspberry-Pi-based smart metres. More recently, several people have voiced worries about the privacy of their data being collected by smart metres. Smart metres can provide a

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comprehensive picture of what appliances are in use because they may collect data incrementally over short time periods. This vulnerability poses a serious threat to consumers' privacy [25] since it can lead to the identification of specific traits that reveal information about a home's socioeconomic position, residence, and equipment. Some institutional adjustments are necessary as data management becomes increasingly important to the advancement of AMI [26].

3. THE PQ EXPERIMENTAL CLUSTER

The analysis is based on 160 50-Hz signals that were sampled at a rate of 20 kHz (400 samples per cycle). The threshold for categorization is a significance level of PQ 0.05, and the types of disturbances that occur are also taken into account (sag or transients) [35]. Previously gathered data was divided into 70 sags and 90 transients. The sags display an irregularity of 10% to 90%. Half of the transients studied exhibited impulsive behaviour while the other half exhibited oscillatory behaviour. All sagging signals exceeded the PQ threshold of 0.05 in a number of cycles, and roughly 27% of transients met the requirements overall. The PQ feature representation of the HOS average of 70 sags and 25 transients is the output (Fig.3-5). The final output of the cluster session is a graphical depiction of the examined data and further exploration into the clusters' behaviour (Fig.2, PQ cluster analysis).

3.1. PQ Data Representation

Data representation is the starting point for PQ cluster analysis (Fig. 3-5). Signals over the PQ threshold, dips, and transients had their average HOS values visually displayed (variance vs. skewness, variance vs. kurtosis, and kurtosis vs. skewness).

3.2. PQ Cluster Selection

The PQ Data Representation's major HOS-axes are used to determine which clusters to use depending on how closely they align with the theoretical values of variance (0.5), skewness (0.0), and kurtosis (1.5). (Figs. 3–5). The axes help characterise novel elements of the clusters, sag, and transients, as indicated by the examined database (as is possible to see in Fig. 6-8).

Cluster analysis is connected to the baseline values of variance (0.5) and skewness (-0.5) on the HOS-axes, as seen in the representation Variance vs. Skewness (0.0). (Fig.6). There is a direct correlation between data signal strength and total HOS volume, as shown by the data's scatter along the main axis. When looking at the data, you can make out three distinct clusters: a sag area, an area with transients, and a cluster where the data disturbances are superimposed. You're in the “uncertainty region,” as they say. To differentiate between the two groups inside the uncertainty region, the PQ classification results for sags and transients (Fig.6) are unclear.

Clusters are chosen based on three criteria: the kind of the disturbance, the quantity of data, and the precision along the HOS axes. The network operator will be better able to choose the cluster based on these factors. In the two temporary groups (Fig. 6), one had positive skewness and variance whereas the other had negative values for these statistical measures. Data is classified as positive or negative based on the skewness of the representation. With a transient presence of 28%, the positive cluster is situated symmetrically with respect to the

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variance axis (quite close to 0.5). Located to the right of the variance axis, this transitory cluster accounts for 36% of the total.

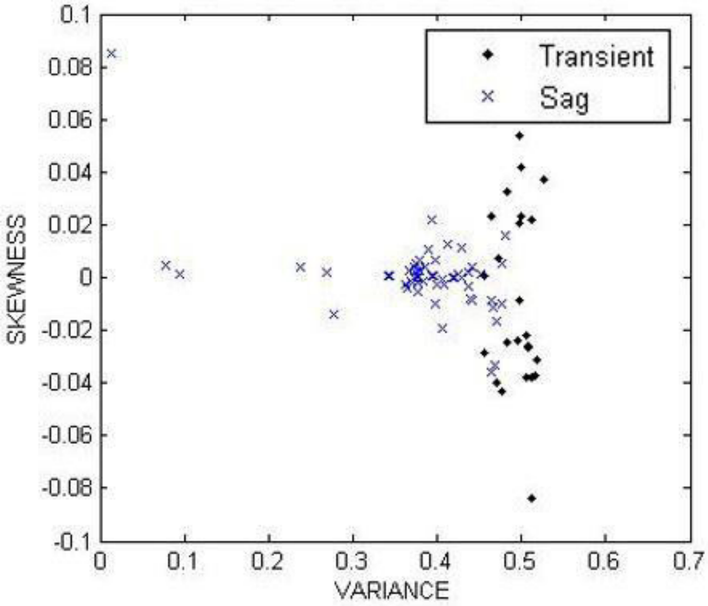

Figure 3. Skewness vs Variance representation

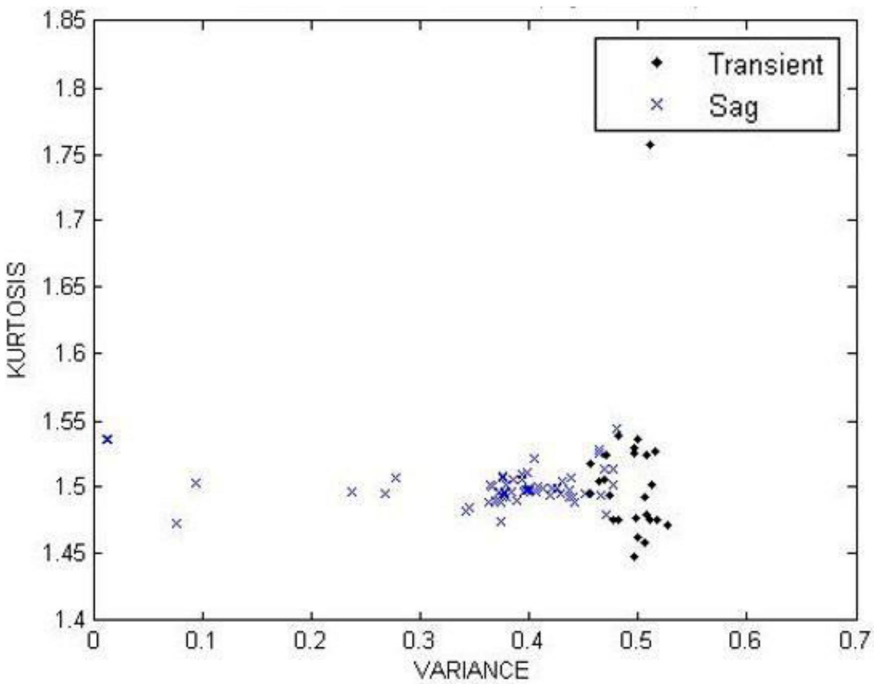

Figure 4. Kurtosis vs variance representations

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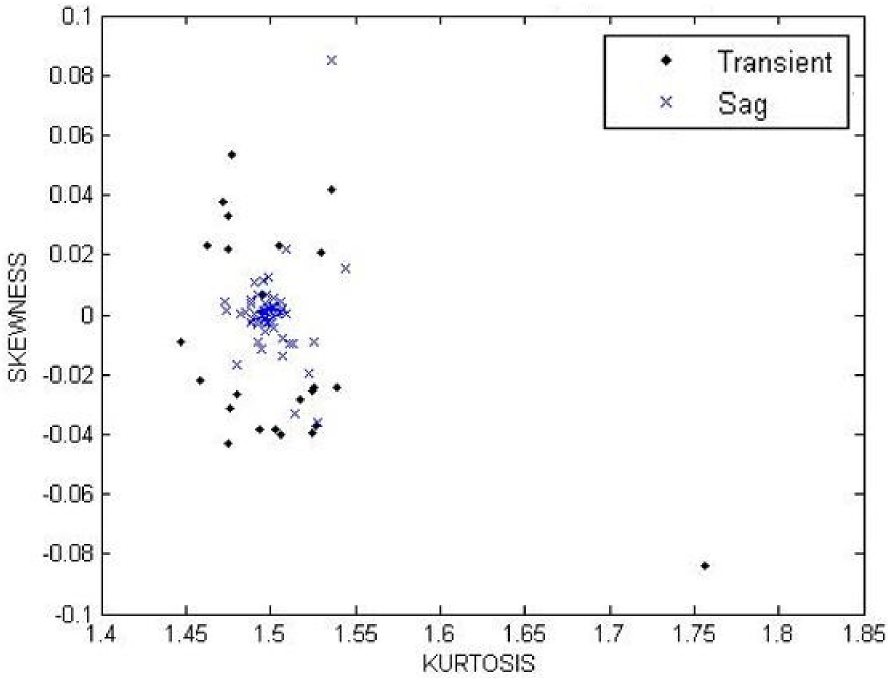

Figure 5. Skewness vs Kurtosis representations

Data in the sag cluster is arranged symmetrically along the skewness axis, making it more stable than the transient cluster [27]. Furthermore, 88.5% of sag data can be classified along the skewness axis (which spans a range between 0.0 and 0.45) with relevance. The layer of uncertainty shows a long area aligned with the variance axis, with the variance values ranging from 0.45 to 0.5. (0.5). The HOS figures showed that most of the data recorded by the instrument tended to be skewed toward negative values for skewness and variance. There are two types of transients found in the data set analysed: impulsive transients, which make up 50% of the total, and oscillating transients, which make up the other 50%. The divergence from the normal symmetry and variance values was induced by the impulsive nature of the transients [28].

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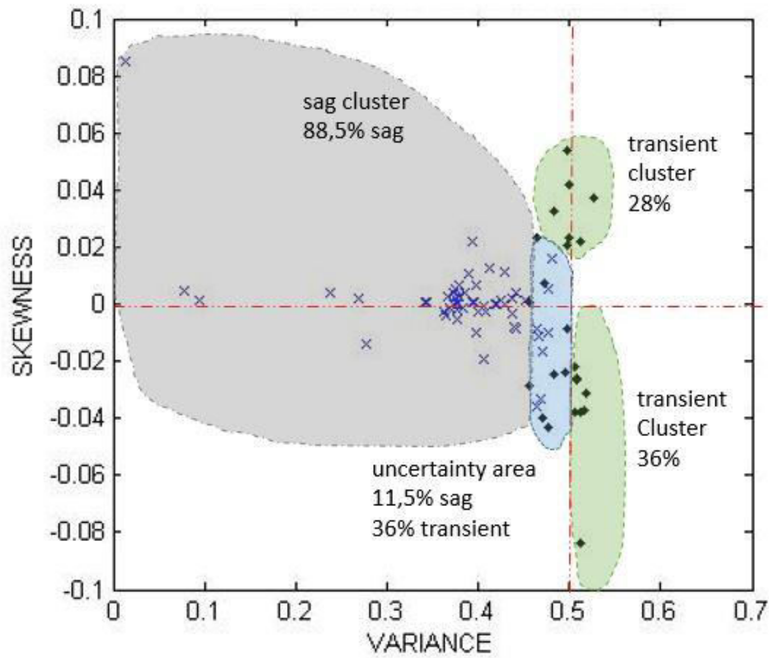

Figure 6. Variance vs Skewness, and cluster selection-based on the proposed method and the analysis of the signal space from the database.

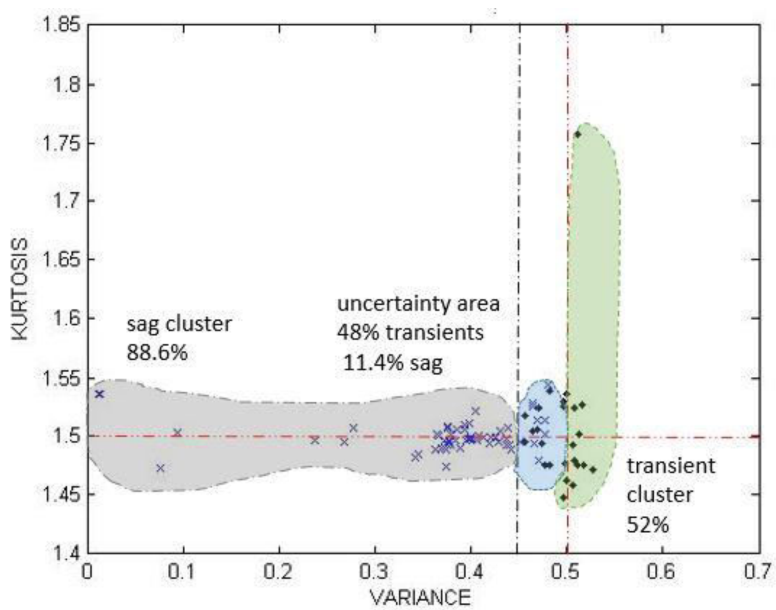

Figure 7. Analysis of the signal space in the database and the proposed method for selecting PQ clusters, comparing the variance and kurtosis. The HOS axes are shown.

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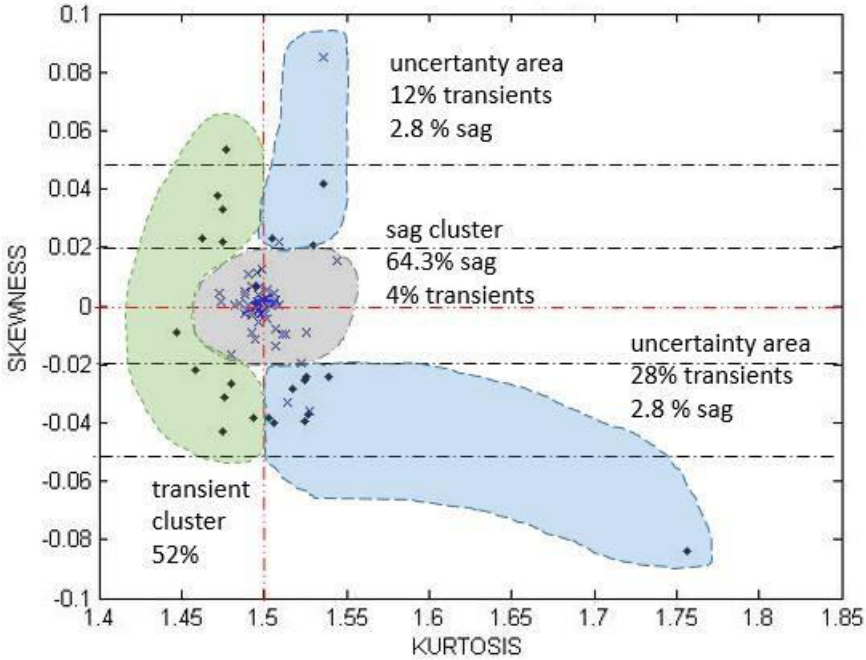

Figure 8. The signal space in the database is analysed, and PQ clusters are selected based on their Kurtosis and Skewness values, as per the recommended technique. The HOS axes are shown.

As shown in Fig. 7, the variance (0.5) and kurtosis (1.5) serve as the HOS-axes in a representation of variance versus kurtosis (1.5). (1.5). The sag and ephemeral clusters are shown within an uncertainty region. The percentage of transients in the transient cluster is 52%, whereas the percentage of sags in the sag cluster is 88.6%. The variance and kurtosis values in both sags and transients exhibit little variation (uncertainty). The data's behaviour in the zone of uncertainty reveals a compacted region, with 48% transients and 11.4 percentage points of sags. In Fig.8 we see a representation of skewness and kurtosis where the HOS-axes, kurtosis (1.5), and skewness (0.0), show a cluster graph that leans toward centrality. It turns out that 64 percent of the sag cluster members are stationary, whereas 4% are merely passing through [29].

When considering the relationship between the transient cluster and the uncertainty region, the kurtosis axis acts as a boundary. There are two distinct regions of uncertainty, one positive and one negative, demonstrating the skewness's impact. Transients account for 12% of the data, while sags account for 2.8%, in the positive uncertainty region. Of the total data, 28% are temporary fluctuations, and 2.8% are a sag, all of which occur in the region of negative uncertainty. There are 52% of records in the temporary cluster. Determining a more precise cluster is aided by the trend of 3rd-4th order disturbances (skewness and kurtosis values) in the sag.

4. RESULTS AND DISCUSSION

4.1. Cluster Analysis

The graphs are expected to be much simplified by the cluster analysis. To further encompass high-intensity regions, the study incorporates new spatial criteria of HOS along with extra

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axes (Fig.9). Sag cluster analysis reveals, in reality, that there is a notably concentrated group of sags (80%) between the values of variance (0.3-0.45) and between the values of skewness (0.3-0.45). (-0.3). Similar analysis of cluster intensity can be performed on the transient's cluster, allowing for the discovery of two more intensity clusters between values of variance (0.5-0.55) and skewness (0.05-0.02) and (-0.02-0.02). (-0.05). 30.8% of the intensity clusters are affected by the transient.

A majority (80%) of the sags in the batteries of the examined signals are consistent with PQ values in the sags between 80 and 90% of disturbance, as shown by the intensity cluster analysis results. Various different HOS representations of cluster intensity have been investigated, after the PQ cluster process was first implemented. The data are more condensed in Fig. 10's Variance vs. Kurtosis graph, making it simpler to distinguish between the sag and transient cluster areas. Consequently, the chosen clusters are linked to the primary axes, while the uncertainty region is determined by the secondary axes. Cluster intensity between variance (0.3-0.45) and between kurtosis (about 1.5) is consistent, suggesting a high degree of confidence in the sag cluster (1.55-1.45). Between these variance and kurtosis values, the fleeting cluster remains stable (1.55-1.45). As a consequence, the impact of the cluster variance accurately portrays the sag intensity clusters. Database clustering is stabilised by kurtosis in such a way that it is impossible to determine which transients are oscillating and which are impulsive.

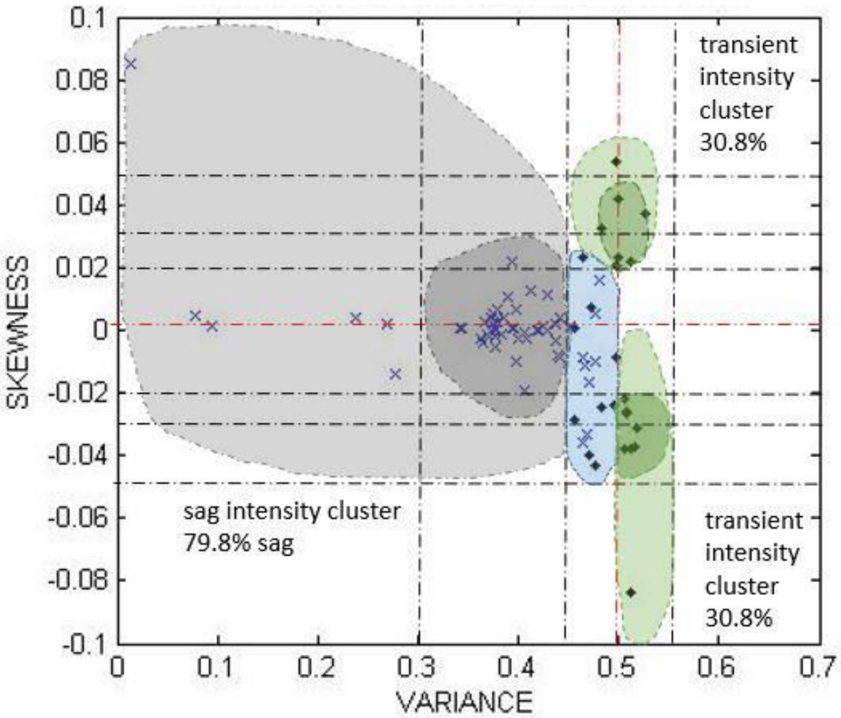

Figure 9. A PQ cluster analysis of variance vs. skewness is performed using the proposed method in conjunction with the signal space obtained from the database. In addition, more cluster intensities are revealed, and additional HOS-axes are traced.

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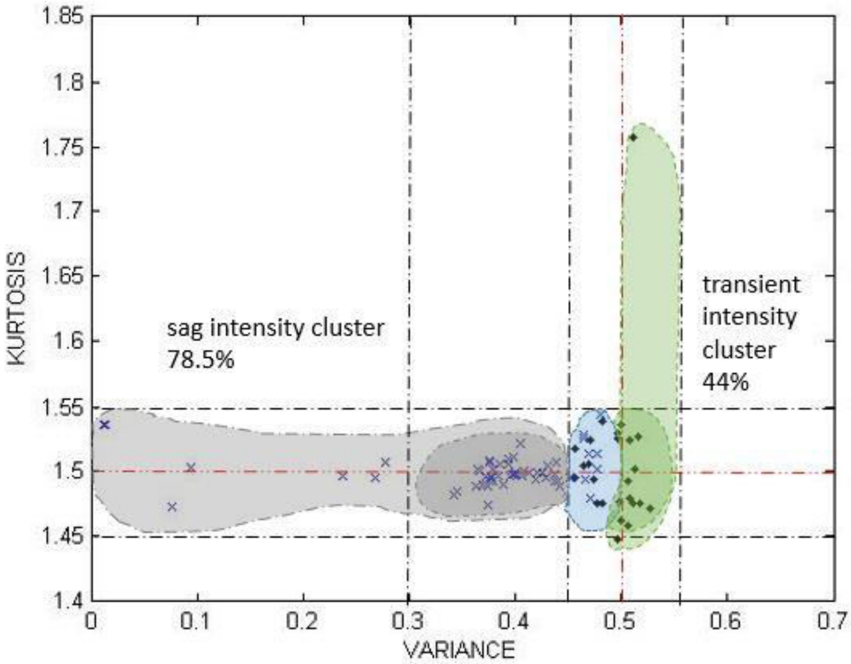

Figure 10. According to the proposed method and the examined database, PQ Cluster Analysis, Variance vs. Kurtosis. Other cluster intensities are displayed, and more HOS axes are traced.

An analysis of kurtosis vs skewness (shown in Figure 11) that makes use of the extra axes reveals that the HOS behaviour has a tendency toward the formation of intensity clusters, with two transients' clusters (one positive and one negative) and two uncertainty zones. In addition, there are two potential grey regions (one positive and one negative). Eight percent of the data is transient, and 2.8% of the sags fall into the 1.5-1.55 range (positive uncertainty zone) of kurtosis and skewness (0.05–0.02). In the region of uncertainty characterised by a negative value between kurtosis (1.5-1.55) & skewness (-0.02-0.2), 32% of the data are transients, and 4.2% sag (-0.05). Approximately 16% of the total population may be part of the positive transient cluster (with kurtosis values between 1.45 and 1.5 and skewness values between 0.05 and 0.02). The negative transient cluster accounts for 20% of the data (between kurtosis 1.45 and 1.5 and skewness -0.02 and -0.05). The greatest density of information lies inside a small elliptical region that accounts for 24.2% of the total area of the sag intensity cluster (sag cluster core).

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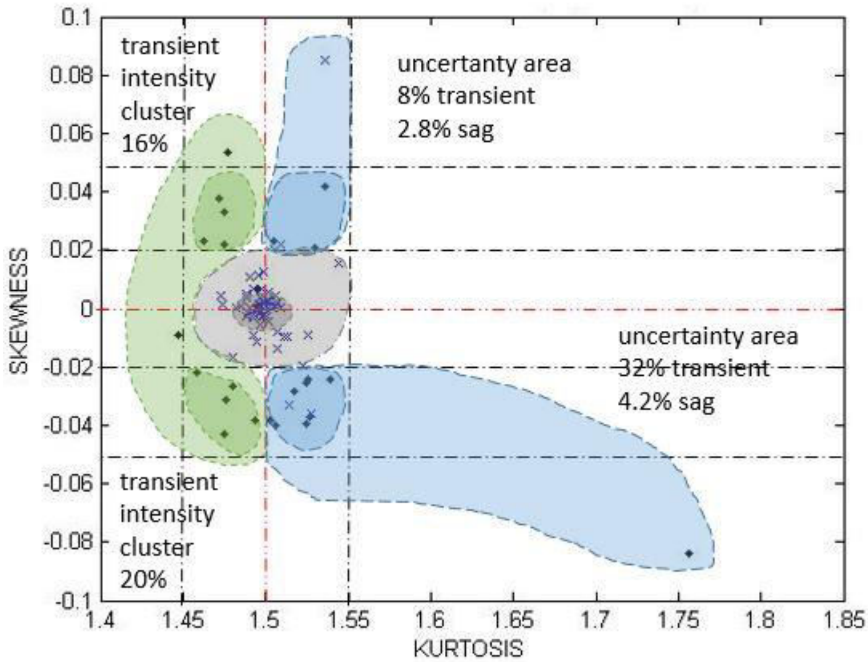

Figure 11. Kurtosis against skewness in a PQ cluster analysis, using the proposed method and the examined data. Other cluster intensities are displayed, and more HOS axes are traced.

The proposed method of the PQ Cluster Analysis is part of the PQ Virtual Instrument's classification process. The findings of a clustering session are typically displayed in the form of graphs that reveal the nature of the data examined as well as any constraints that may apply. PQ Data Representation, the initial stage of the process, uses the averaged value of the collected HOS to identify patterns in the data.

Second, PQ Cluster Selection adds a new criterion by requiring that the primary HOS-axes coincide with the theoretical HOS values of variance (0.5), skewness (0.0), and kurtosis (1.5), which are indicative of a high-quality signal. This additional criterion was included to guarantee optimal precision when doing PQ Cluster Selection. The fundamental HOS-axes provide a first step in classifying data in HOS spaces. The symmetrical analysis means that the cluster can contain a negative component with regard to the skewness axis in some circumstances. Since variance plays a key role in defining the sags cluster, visualisations that emphasise variance also serve to clearly distinguish it. In any case, the 3rd-4th order representation (Skewness vs. Kurtosis) is useful in that it provides extra clusters for which to undertake more robust identification.

In the final phase, PQ Cluster Analysis, we expand on the conventional cluster selection by defining new criteria and a new space for clustering (Fig 3-5). Locating intensity clusters that are in accordance with the usual PQ values at the measurement point allows us to characterise typical occurrences at a certain place on the grid. The most prevalent causes of outages at various nodes may be better understood, and potential smart grid infrastructure flaws can be more easily located, using this data (including distributed smart metres). To sum up, PQ Cluster Analysis shows how disturbances behave in operation through the HOS spatial

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representation, and it gives you the option of defining an offline signal database or an online, real-time session (online).

5. Conclusion

This article presents a qualitative PQ cluster analysis. In order to conduct this analysis, the PQ Virtual Instrument, a Smart Power quality Analyzer, is being used. Multiple types of real-world data were used to test the effectiveness of the analysis. Both signal space definition and battery signal categorization can benefit from the PQ Cluster Analysis. The PQ Cluster Analysis provides illustrative examples of the characteristics of the database that was examined. HOS do exceptionally well when it comes to discovering novel features in the electrical signal. Cluster analyses verify HOS can tell the difference between two types of electrical problems. We can now more accurately identify and classify sag and ephemeral clusters. A similar procedure is used to pinpoint a zone of overlap and ambiguity. An improved definition of the clusters is made possible by using the axis analysis approach (HOS-axes), which allows for the classification of 80% of the most important occurrences. We hope that future research will bring new criteria for the detection of various disturbances. The cluster selection process now in use relies on qualitative analysis, which points to a viable direction for future use of data mining tools. However, the grid operator would be able to learn a great deal more about the network and make more informed choices in future sessions with this level of detail. To manage the trade-off between database size and usefulness for analysis, the PQ clustering method suggested here introduces the criteria of capturing and storing data over a PQ Threshold. Since PQ problems may occur as a result of the degree of DER, and new PQ indices are becoming increasingly necessary in grid modernization, the HOS-based intensity clusters present new regions of alarms and critical reports that might be applied in a monitoring session of the SG.

6. References

[1] Hosseinzadeh, M., Hemmati, A. & Rahmani, A.M. Clustering for smart cities in the internet of things: a review. Cluster Comput (2022). https://doi.org/10.1007/s10586-022-03646-8.

[2] Balakrishna, S., Thirumaran, M.: Semantics and clustering techniques for IoT sensor data analysis: a comprehensive survey. Princ. Internet Things (IoT) Ecosyst. 2020, 103–125 (2020).

[3] Kousis, A., Tjortjis, C.: Data mining algorithms for smart cities: a bibliometric analysis. Algorithms 14(8), 242 (2021).

[4] Md. Tanvir Ahammed, Imran Khan, Ensuring power quality and demand-side management through IoT-based smart meters in a developing country, Energy, Volume 250, 2022, 123747.

[5] I. Khan, M.W. Jack, J. Stephenson Dominant factors for targeted demand side management—an alternate approach for residential demand profiling in developing countries Sustain Cities Soc, 67 (102693) (2021), pp. 1-17.

[6] Gouse Baig Mohammad, S Shitharth. Wireless sensor network and IoT based systems for healthcare application, Materials Today: Proceedings, pp. 1-8, 2021.

[7] Salman Ali Syed, K Sheela Sobana Rani, Gouse Baig Mohammad, Krishna Keerthi Chennam, R Jaikumar, Yuvaraj Natarajan, K Srihari, U Barakkath Nisha, Venkatesa Prabhu Sundramurthy. Design of resources allocation in 6G cybertwin technology

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11,S Iss 1, Nov 2022

using the fuzzy neuro model in healthcare systems, Journal of Healthcare Engineering, vol. 2022, 2022.

[8] Kemal Polat, Raman Dugyala, N. Hanuman Reddy, V. Uma Maheswari, Gouse Baig Mohammad, Fayadh Alenezi. Analysis of Malware Detection and Signature Generation Using a Novel Hybrid Approach, Mathematical Problems in Engineering, vol. 22, Issue. 1, pp. 1-13, 2022.

[9] L. Gelazanskas, K.A.A. Gamage Demand side management in smart grid: a review and proposals for future direction Sustain Cities Soc, 11 (2014), pp. 22-30.

[10] N. Yadav, L. Truong, E. Troja and M. Aliasgari, "Machine Learning Architecture for Signature-based IoT Intrusion Detection in Smart Energy Grids," 2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON), 2022, pp. 671-676.

[11] M. S. ALiero, K. N. Qureshi, M. F. Pasha and G. Jeon, "Smart home energy management systems in internet of things networks for green cities demands and services", Environmental Technology & Innovation, pp. 101443, 2021.

[12] A. Ullah, M. Azeem, H. Ashraf, A. A. Alaboudi, M. Humayun and N. Jhanjhi, "Secure healthcare data aggregation and transmission in iot—a survey", IEEE Access, vol. 9, pp. 16 849-16 865, 2021.

[13] S. M. A. A. Abir, A. Anwar, J. Choi and A. S. M. Kayes, "Iot-enabled smart energy grid: Applications and challenges", IEEE Access, vol. 9, pp. 961-50, 2021.

[14] Ahmad, A.; Kashif, S.A.R.; Saqib, M.A.; Ashraf, A.; Shami, U.T. Tariff for reactive energy consumption in household appliances. Energy 2019, 186, 115818.

[15] Jay, D.; Swarup, K.S. Game theoretical approach to novel reactive power ancillary service market mechanism. IEEE Trans Power Syst. 2020, 36, 1298–1308.

[16] Cerbantes, M.C.; Fernandez-Blanco, R.; Ortega-Vazquez, M.A.; Mantovani, J.R.S. Incorporating a Nodal Reactive Power Pricing Scheme Into the DisCo's Short-Term Operation. IEEE Trans. Smart Grid 2018, 10, 3720–3731.

[17] Viciana, E.; Alcayde, A.; Gil Montoya, F.; Baños, R.; Arrabal-Campos, F.M.; Zapata-Sierra, A.; Manzano-Agugliaro, F. OpenZmeter: An Efficient Low-Cost Energy Smart Meter and Power Quality Analyzer. Sustainability 2018, 10, 4038.

[18] Chang, T.Y.; Wang, Y.; Sun, H.J. The Design of Smart Meter with Power Quality Monitoring. Electr. Meas. Instrum. 2012, 49, 74–77.

[19] Ramos, N.R.; Pereira, P.; Martins, J. Smart-meter in power quality. In Proceedings of the 2017 International Young Engineers Forum (YEF-ECE), Costa da Caparica, Portugal, 5 May 2017; Institute of Electrical and Electronics Engineers (IEEE): New York, NY, USA, 2017; pp. 42–46.

[20] Das, H.; Saikia, L. Ethernet based smart energy meter for power quality monitoring and enhancement. In Proceedings of the 2017 Recent Developments in Control, Automation & Power Engineering (RDCAPE), Noida, Indi, 26–27 October 2017; Institute of Electrical and Electronics Engineers (IEEE): New York, NY, USA, 2017; pp. 187–191.

[21] Madhu, G.M.; Vyjayanthi, C.; Modi, C.N. Design and Development of a Novel IoT based Smart Meter for Power Quality Monitoring in Smart Grid Infrastructure. In Proceedings of the TENCON 2019-2019 IEEE Region 10 Conference (TENCON), Kochi, India, 17–20 October 2019; pp. 2204–2209.

[22] Luckey, D., Fritz, H., Legatiuk, D., Dragos, K., Smarsly, K.: Artificial intelligence techniques for smart city applications. In: International Conference on Computing in Civil and Building Engineering, pp. 3–15. Springer, Cham (2020).

ISSN PRINT 2319 1775 Online 2320 7876
Research paper UGC CARE Listed (Group -I) Journal Volume 11,S Iss 1, Nov 2022

[23] Lytras, M.D., Visvizi, A., Sarirete, A.: Clustering smart city services: Perceptions, expectations, responses. Sustainability 11(6), 1669 (2019).
[24] Torabi, M., Hashemi, S., Saybani, M.R., Shamshirband, S., Mosavi, A.: A Hybrid clustering and classification technique for forecasting short-term energy consumption. Environ. Prog. Sustain. Energy 38(1), 66–76 (2019).
[25] Nabipour, M., Nayyeri, P., Jabani, H., Shahab, S., Mosavi, A.: Predicting stock market trends using machine learning and deep learning algorithms via continuous and binary data; a comparative analysis. IEEE Access 8, 150199–150212 (2020).
[26] Puliafito, A., Tricomi, G., Zafeiropoulos, A., Papavassiliou, S.: Smart cities of the future as cyber physical systems: challenges and enabling technologies. Sensors 21(10), 3349 (2021).
[27] Alazab, M., Lakshmanna, K., Reddy, T., Pham, Q.-V., Maddikunta, P.K.R.: Multi-objective cluster head selection using fitness averaged rider optimization algorithm for IoT networks in smart cities. Sustain. Energy Technol. Assess. 43, 100973 (2021).
[28] Feng, X., Zhang, J., Ren, C., Guan, T.: An unequal clustering algorithm concerned with time-delay for internet of things. IEEE Access 6, 33895–33909 (2018).
[29] Lee, D.; Hess, D.J. Data privacy and residential smart meters: Comparative analysis and harmonization potential. Util. Policy 2021, 70, 101188.
[30] Buchmann, M. Governance of data and information management in smart distribution grids: Increase efficiency by balancing coordination and competition. Util. Policy 2017, 44, 63–72.
[31] IEEE Std 3001.2. IEEE Recommended Practice for Evaluating the Electrical Service Requirements of Industrial and Commercial Power Systems; IEEE: New York, NY, USA, 2017; pp. 1–76.
[32] Mohkami, H.; Hooshmand, R.; Khodabakhshian, A. Fuzzy optimal placement of capacitors in the presence of non-linear loads in unbalanced distribution networks using BF-PSO algorithm. Appl. Soft Comput. 2011, 11, 3634–3642.
[33] IEEE Std 1459. IEEE Standard Definitions for the Measurement of Electric Power Quantities Under Sinusoidal, Nonsinusoidal, Balanced, or Unbalanced Conditions; IEEE: New York, NY, USA, 2010; pp. 1–50.
[34] Z. Niu, J. Wu, X. Liu, L. Huang, P.S. Nielsen Understanding energy demand behaviors through spatio-temporal smart meter data analysis Energy, 226 (120493, pp.) (2021), pp. 1-15.
[35] A. Melillo, R. Durrer, J. Worlitschek, P. Schütz First results of remote building characterisation based on smart meter measurement data Energy, 200 (2020).