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[1]* Xiaogang Wu

[1]Xingwang Chen

[1] Kun Zhang

Analysis of the Monitoring and Identification Effect of Cognitive ServiceTechnology on DC System in Power Grid

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Abstract: - This study investigates the impact of cognitive service technology on the monitoring and identification capabilities within a direct current (DC) system in a power grid. This paper introduces a novel Pattern Recognition Neural Network (PRNN) by integrating a Pattern Recognition Algorithm (PRA) and Convolutional Neural Networks (CNN) to analyse patterns in the DC system's data. With the increasing complexity and interconnectivity of modern power systems, the need for advanced monitoring and identification solutions becomes crucial. Cognitive service technology, known for its adaptability and learning capabilities, offers a promising avenue for enhancing the performance and reliability of DC systems. The research employs a comprehensive approach, incorporating data analysis, modelling, and simulation to assess the effectiveness of cognitive service technology in monitoring and identifying critical parameters within the DC system. The study aims to contribute valuable insights into the application of cognitive services for improving the overall efficiency and resilience of power grids operating on direct current, thereby fostering advancements in smart grid technologies.

Keywords: Power grid, DC system, Power saving, Rectifiers

Introduction

The electrical infrastructure of today hasn't altered in almost a century. Nearing the end of their life are the members of the hierarchical grid. As the electrical the outdated grid and the ever rising cost of electricity [1]. Based to a study by the American Department of Energy [2], demand and use of energy in the US has risen by 2.5% annually over the past 20 years. The modern electrical power distribution network is too complex and antiquated to meet the needs of the 21st century [3]. Some of the shortcomings include inadequate visibility, an absence of automated analysis, mechanical switches that result in sluggish response times [4]. These have played a part in the blackouts that have occurred throughout the previous forty years [5]. Additional deterrents include the growing population and energy demand, the consequences of climate change, equipment failures, problems with energy storage, and limitations in the capacity of electricity generation, one-way interaction, the depletion of fossil fuels, and resilience concerns [6]. Furthermore, the transportation and power sectors are responsible for a large portion of Earth's greenhouse gas emissions [7]. There is an urgent need for a new electrical grid to address these problems [8]. To accomplish these goals, a novel concept called as the "smart grid" for the forthcoming generation of electrical systems has emerged [9]. The smart grid is a state-of-the-art electricity grid architecture that seamlessly integrates sustainable and alternative sources of energy while enhancing effectiveness, reliability, and safety through automated control and modern communications technologies [10]. Renewable energy generators seem to be a promising technological solution to reduce greenhouse gas emissions and fuel usage [11]. Smart grids, among other things, offer effective grid integration for distributed power generation (DG) for demand side management and energy storage enabling DG load balancing, which significantly opens up new network management methods [12, 13].

Researchers have been studying renewable energy sources (RES) extensively [14]. The existing system lacks the sophisticated manufacturing, interactions, and sensing capabilities seen in smart power grid architecture [15]. Communication channels and sensor nodes are connected to one another in order to provide interoperability amongst different system components, including shipment, exchange, and other sub stations, such as residential, commercial, and industrial sites [16]. In the smart grid, accurate and timely information is crucial for the smooth transit of power from the power stations to the end users [17]. The consequences of equipment failures, capacity

[1]China Southern Power Grid Power Dispatching Control Center, Guangzhou, Guangdong,510000, China

*Corresponding author's e-mail: wuxiaogang2024@163.com

Co-author1- Xingwang Chen e-mail： chenxingwang2024@163.com

Co-author2 -Kun Zhang e-mail： zhangkun20240123@163.com

constraints, and natural disasters that cause power disruptions and outages can be lessened with the use of online power system condition monitoring, diagnostics, and protection [18]. Therefore, the advanced control and surveillance capabilities made available by contemporary communication and information technologies will be essential to the energy system of the future [19]. Community (EC) countries have started to do study and development on smart grid-related technologies and applications. The U.S. government, for example, just released the largest grant award for power grid technological advancement, totaling $3.4 billion, which would finance various smart grid technologies. The largest investment in American history is this one. Local Distribution Companies (LDCs) are integrating automation, two-way communication, and advanced metering technologies into their distribution networks. In addition to research and development initiatives, several electric firms are taking minor steps to make smart grid technology a reality. To implement smart grid initiatives, the majority of them are entering into contracts with telecom providers or smart meter suppliers [20]. The AMI integrates data management systems, computer hardware, software, smart meters, and monitoring devices. In essence, it is a two-way communication network that makes data collection and sharing among meters and utilities easier.

2. Related works

Energy harvesting (EH) and cognitive radio (CR) techniques combined with IoT integration may be able to address SG problems including poor battery life and challenging channel circumstances. Thus, by combining EHand CR, Ozger, M.,[21] disclosed a new networking paradigm for IoT-enabled SG. CRs were employed in IoT- enabled smart gardens to do this, and their advantages and disadvantages are discussed. Furthermore, EH solutionsaddressed the resource constraints faced by wireless devices in the Internet of Things enabled smart grid. The functioning and node structure for energy harvesting cognitive radios, as well as the network architecture of the Internet of Things-enabled smart garden, were used to explain the details of the networking paradigm. To supportthis novel approach, open concerns and future research areas were addressed.

Cognitive radio-based smart-grid networks have been studied recently as a reliable and efficient communications backbone for the power grid of the years to come. The handling of spectrum resources in cognitive radio-based smart grid networks was investigated by Yu, R. [22]. A novel approach for spectrum access was proposed: hybrid spectrum access (HSA). Smart-grid services were built intelligently for the transmission of both licensed and unlicensed spectrum bands under HSA. The topic of admission control was carefully considered under HSA. Furthermore, the impact of spectrum sensing inaccuracy on HSA efficiency was evaluated using a multidimensional Markov chain. Two optimization issues were devised with reference to the practical applications of the smart grid: spectrum management driven by quality of service (QoS) and leasing of spectrum driven by cost.

Galli, S., [23] outlined the most recent technological advancements and provided a summary of what PLC may offer today. The main conclusions from the available research on these subjects were examined, and Smart Grid applications were given treatment as instances of sensor network and network control problems. Subsequently, an extensive examination of the PLC implementation situation within the Smart Grid framework was carried out. Given that modeling is a crucial part of network planning, the two aspects of engineering modeling that were pertinent to our investigation were discussed. In the first section, the PLC channel was represented using fading models. The control of the Smart Grid was also discussed to have a better understanding of the communication requirements.

The hardware execution of rectenna circuits and practical approaches to accomplishing SWIPT in the domains of time, space, power, and antennas were highlighted by Krikidis, I. [24]. The paper also discusses cooperative cognitive radio networks, resource allocation, and the benefits of integrating SWIPT technology into modern communication networks. Strong signals not only boost power transfer but also provide an extremely interesting and challenging circumstance when sources engage in synchronous wireless data and energy transfer (SWIPT).

3. Proposed Methodology

The proposed methodology for the analysis of the monitoring and identification effect of cognitive service technology on the DC system in a power grid involves a comprehensive approach to harnessing the capabilities of machine learning and cognitive services. Initially, data collection will encompass historical and real-time data from various components of the DC system, including voltage levels, current, and temperature. Sensors and smart meters will be strategically placed to capture diverse parameters. Subsequently, data pre-processing and cleaning will be performed to ensure the quality and consistency of the dataset. Key features relevant to monitoring and identification will be selected, emphasizing those indicative of potential faults or abnormalities. The proposed methodology diagram is provided in the Figure 1.

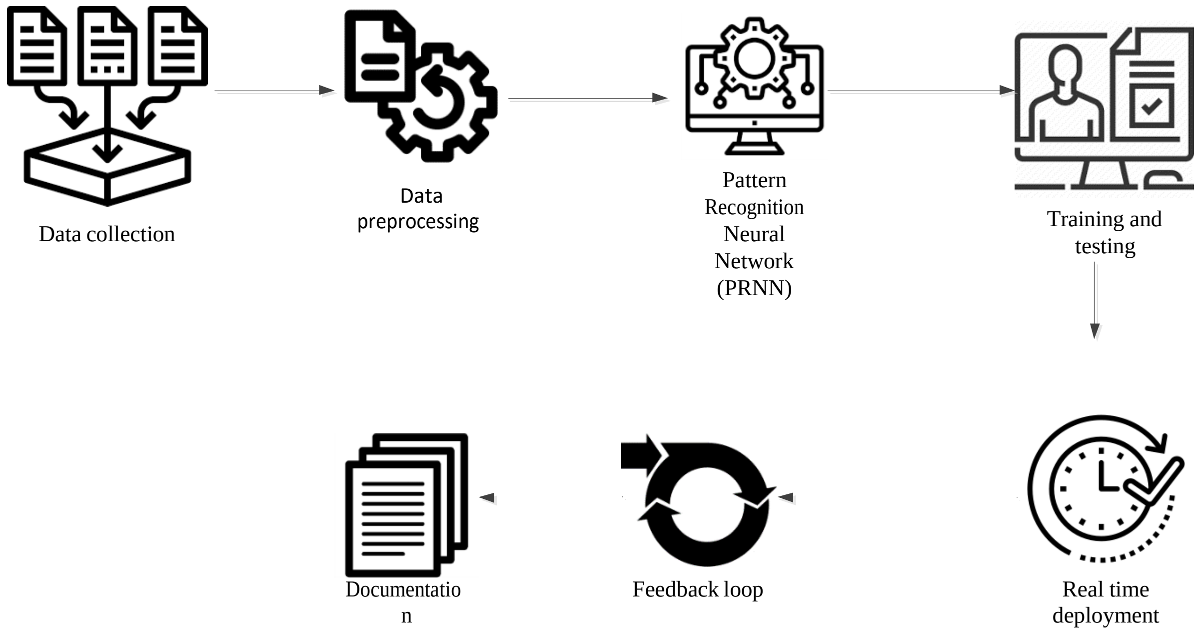

Figure 1. Architecture of the Proposed Methodology

Following this, machine learning models, such as anomaly detection algorithms and pattern recognition models, will be developed using both supervised and unsupervised learning techniques. The models will be trained on historical data, encompassing normal and abnormal operating conditions. The continuous monitoring capabilities will subsequently be improved by the integration for cognitive service technology, which will use picture recognition and natural language processing to understand intricate data patterns.

The system will continuously learn and adapt, contributing to its effectiveness in identifying anomalies. Validation and testing will be carried out using separate datasets, and the system's performance will be rigorously evaluated through metrics such as sensitivity, specificity, and overall accuracy. The final steps involve the deployment of the integrated system in a real-time power grid environment, continuous optimization based on feedback, and comprehensive documentation of the methodology, ensuring transparency and replicability.

3.1 Process of the PRNN model

To comprehensively analyze the monitoring and identification effect of cognitive service technology on a DC system in a power grid, a meticulous data collection approach must be adopted.

3.1.1 Data collection

Firstly, the collection of power grid information is fundamental. This encompasses acquiring historical data on the DC system's performance, encompassing voltage levels, current, power flow, and operational states. Data collected in real time under different circumstances will shed light on the system's dynamic behavior. Additionally, environmental factors, such as weather conditions, temperature, and humidity, should be consideredto understand their impact on the DC system. Collecting data on faults, anomalies, and disturbances in the DC system is imperative for evaluating the cognitive service technology's effectiveness in identifying and responding to irregularities. Operational logs and event data from the power grid's control and monitoring systems will shed light on normal operations and patterns associated with specific events. Maintenance records are also crucial to assessing the impact of cognitive service technology on system reliability, minimizing downtime.

Secondly, the data collection process should encompass outputs generated by cognitive service technologies. This involves gathering visual data, reports, or alerts produced by the algorithms. These outputs serve as indicators of the technology's monitoring and identification results. Sensor data from physical parameters, such as temperature and pressure, aids in assessing the overall health of the DC system. Additionally, communication and network data, including network latency and packet loss, are essential for understanding the performance of communication networks within the power grid. Performance metrics, such as accuracy and precision, should bedefined and collected to evaluate the cognitive service technology's identification capabilities. User feedback fromoperators or users interacting with the technology provides practical insights into its usability and effectiveness. Data pertaining to rules and compliance makes sure that industry norms and laws are followed, which helps the DC system run safely and effectively.The combination of these diverse data sources facilitates a comprehensive analysis of the cognitive service technology's impact on the monitored DC system in the power grid.

3.1.2 Pre-processing

In preparing data for the analysis of the monitoring and identification effect of cognitive service technology on a DC system in a power grid, a robust preprocessing strategy is crucial. Initially, data cleaning procedures involve handling missing values, outliers, and noise within the collected datasets. Filtering techniques may be applied to remove redundant or irrelevant information, ensuring that the input data are pertinent to the analysis. Standardization and normalization methods are implemented to bring disparate data scales into a uniform range, preventing biases during analysis. Temporal alignment of time-stamped data is essential for ensuring chronological consistency in time series datasets. Using feature engineering, pertinent features can be extracted from unprocessed data, improving the algorithm's capacity to identify patterns.

Moreover, addressing imbalances in the dataset, if present, ensures that the cognitive service technology is trained on a representative dataset. Data pre-processing plays a pivotal role in refining the quality and suitability of the dataset, laying a solid foundation for the subsequent analysis of cognitive service technology's efficacy in monitoring and identifying anomalies in the DC system of the power grid.

$$L(o,q) = median\{X_g\} \quad (1)$$

3.1.3. Convolution map

In the context of analyzing the monitoring and identification effect of cognitive service technology on a DC system in a power grid, the convolution map serves as a vital element in the preprocessing stage. Convolution involves the mathematical operation of merging two sets of information to extract essential features. In this application, the convolution map is employed to highlight patterns and relevant features within the input data. By convolvingthe raw data with a set of filters or kernels, the convolution map reveals spatial relationships and distinctive characteristics that are crucial for understanding the behavior of the DC system. This process enhances the ability of cognitive service technology to recognize meaningful patterns, potential anomalies, or specific events in the power grid's DC system. The convolution map acts as a visual representation of the convolutional neural network's learning, providing insights into how the algorithm interprets and processes the input data. This aids in fine-tuning the cognitive service technology for optimal performance in monitoring and identifying critical aspects of the DC system within the power grid. The Convolution operation is represented in equation (9). The size of the filters, which are frequently squared $i_x * i_y$, and the number of convolution maps it includes N_j determine the configuration of a convolution layer. Following equation shows how the feature map N_j is calculated:

$$N_j = d_j + \sum_i V_{ji} * Y_i \quad (2)$$

Where, Y_i is the i^{th} input channel V_{ji} is its sub-kernel, and d_j is a bias term, and $*$ is the convolution operator. In simpler terms, the convolution operation of each feature map is performed by applying distinct 2D squared convolution features along with a bias term. Unlike SIFT, which makes use of well-designed general feature extractors, CNN's value lies in its ability to learn the properties and biases of numerous feature maps, leading to task-specific, efficient feature extractors. Additionally, to provide nonlinearity to the CNN, the Rectified

Nonlinear Activation Function (ReLU) is run after each convolution. A particularly well-known activation function called the ReLU is described as,

$$p(a) = \max(0, a) \quad (3)$$

Where, a represents the input of the neuron, which receives a set of input nodes, runs activation function, and produces the results.

3.1.4. Max-pooling map

Subsampling layers come after convolution layers in the convolutional neural network design. Each sub-sampling layer reduces the size of the convolution maps while introducing normalization to any modest revolutions and flips that may be present in the input. A variation of this layer known as a max-pooling layer has demonstrated various advantages in usage. The greatest excitation intensity in the input nodes across window segments inside every feature map determines the max-pooling layer's output. The procedure of max-pooling reduces the total number of the feature maps.

3.1.5. CNN classification

In the analysis of the monitoring and identification effect of cognitive service technology on a DC system in a power grid, Convolutional Neural Network (CNN) classification plays a pivotal role. CNNs are well-suited for image recognition tasks, and in the context of power grid data, they can be adapted to classify patterns and events within the DC system. The CNN classification process involves feeding the pre-processed data, possibly represented as convolution maps, into the neural network layers. These layers consist of convolutional and pooling operations, followed by fully connected layers that interpret the hierarchical features extracted from the data. Through training on labeled examples, the CNN learns to recognize distinctive features associated with various states or conditions of the DC system. Once trained, the CNN can effectively classify new, unseen data, enabling cognitive service technology to identify specific events, anomalies, or operational states within the power grid's DC system. The use of CNN classification enhances the accuracy and efficiency of the monitoring system, providing valuable insights for proactive maintenance, troubleshooting, and overall optimization of the power grid infrastructure.

3.1.6. Convolutional layer

The first layer in CNN creation is usually a convolutional layer. $P \times Q \times 1$ are acceptable input layers for CNN.

The dimensions of a two-dimensional picture with a single layer are $P \times Q$. The outcome is the final image, which is produced by convolving the input image with this curve or shape. The convolution process results in greater values for the shape that closely resembles the input image's curve and is represented by the filter. Convolution may be represented as equation (11),

$$f(e) = (t^{*}u)(e) \quad (4)$$

3.1.7. Pooling layer

Using a pooling layer, the amount of the data is kept to a minimum. The matrix data is divided into segments, and each segment is then changed to a single value. Figure 2 demonstrates how the extreme or average of all values inside the current segment is used to swap the segmented matrices. In the context of analyzing the monitoring and identification effect of cognitive service technology on a DC system in a power grid, the incorporation of a pooling layer in the computational model holds significant importance. Downsampling feature maps produced during the convolutional process is a critical function of the pooling layer, a basic part of convolutional neural networks (CNNs).

This layer reduces the geographic extent of the map of features, capturing important information while reducing computational complexity. It is often done as maximum pooling or average pooling. Pooling layers help to abstract characteristics by choosing representative values from nearby areas, which enables the CNN to concentrate on important details in the power grid data. This abstraction enhances the cognitive service technology's ability to monitor and identify patterns or anomalies in the DC system effectively. The pooling layer makes it easier to extract important data and identify crucial traits linked to various operational stages, which improves the overall efficacy and precision of the power grid's monitoring and identification process. The figure 2 shows the architecture of the CNN for the DC system.

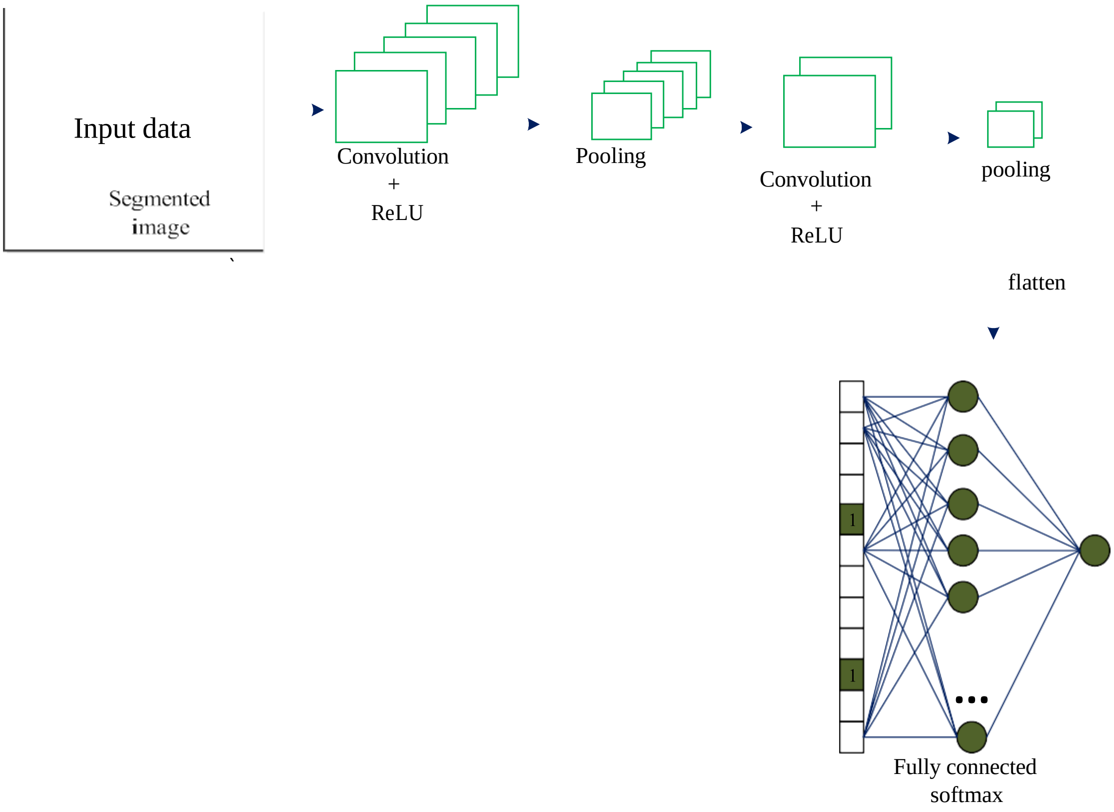

Figure 2. CNN architecture

Lower your stress level immediately because a 1-phase 380 V DC power network with a larger nominal voltage RMS value has lower cable power losses than a 1-phase 230 V AC power system. One hundred meters of power cable (3 x 2.5 mm2) is utilized for every pair of 18 lights in the experiment's bed layout in a rather lengthy corridor. Equation (1) has been used to calculate the current stress for each cable sub-section. Since most LED luminaires function like loads with a constant, controlled power, they are regarded as electrical demands in this equation.

For a group of luminaires using a 380 V DC cable, the estimated cable loss per 18 luminaires is 0.32% (2.2 W), while for a single luminaire, it is 0.89% (6.0 W). Starting from the automatic circuit breaker and ascending to the first luminaire, the first cable portion is 15 meters in length. Between every two luminaires, there are five meters of additional cable sub-sections. At the beginning of the DC cable and the beginning of the AC cable, the maximum cable current density is 0.72 A/mm2 and 1.19 A/mm2, respectively. At the end of a 100 m cable, the maximum voltage loss is 0.43 % for DC cables and 1.2% for AC cables.

4. Results and Discussion

This section discusses the outcomes of the suggested PRNN. The proposed PRNN's performance is examined, and the results are contrasted with those obtained using cutting-edge methodology.

4.1 Performance Evaluation

The true PQ disturbances are random noise-riding signals brought on by electromagnetic waves or communication cables that cross nearby networks for the transmission and distribution of electric power. Thus, the proposed technique has been tested in a noisy environment. An additive white Gaussian noise that is uniformly distributed across all signals is typically investigated in PQ analysis studies. Using the proper wavelet, the de-noising technique is used for the classification results in a strong performance. The effectiveness of the proposed approach is assessed using parametric equations by subjecting the signals to different noise levels, i.e., signal-to-noise ratios (SNR) of 20, 30, 40, and 50 dB, for all types of disturbances. The figure 3 shows the loss distribution across the cable sub-sections.

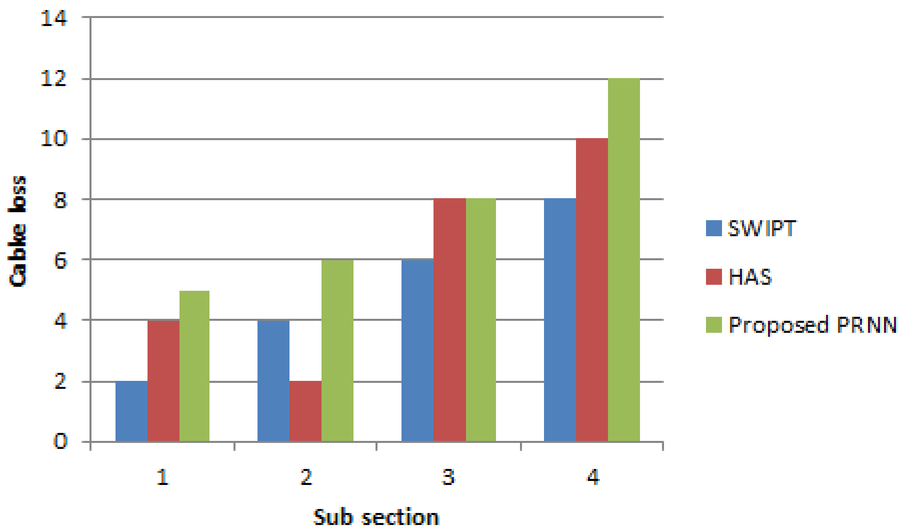

Figure 3. Loss distribution across cable sub-sections

The average AC input power of the Current grid central rectifier is shown on the x-axis of this diagram throughout the course of a monitoring interval; the value is reduced in the presence of solar power. Over the span of a couple of days, from April 24 to April 26, 2014, the lowest average power input from the AC ever recorded was recorded due to intense sun radiation. The sub-system's 2% average savings in electricity when linked to the DC grid are ultimately explained by the 0.6% savings when cable loss and the 1.4% power savings from avoiding rectifier failure in employing DC solar power in DC loads. Figure 4 displays the relative power savings of the DC grid subsystem at the center rectifier AC input.

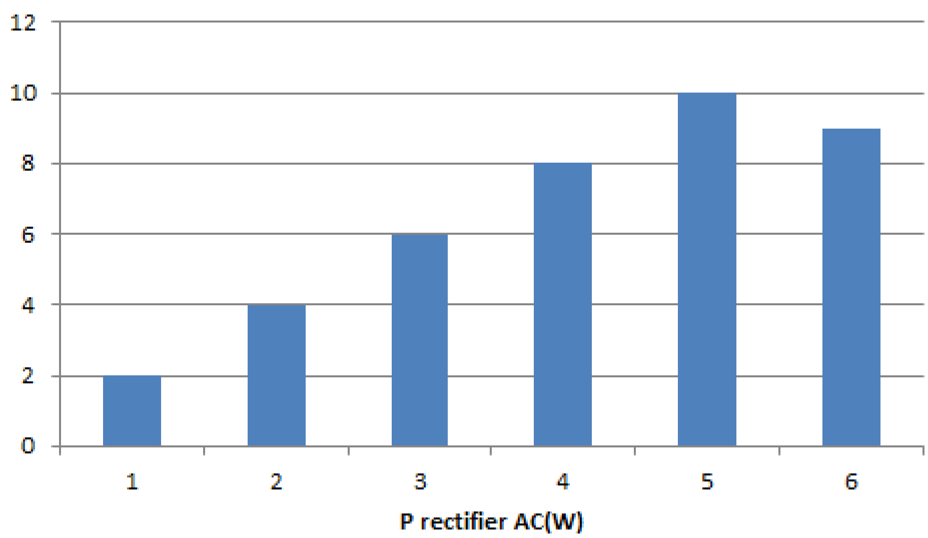

Figure 4. DC grid subsystem relative power savings at the central rectifier AC input

The vibration signal is re-sampled from 32,768 Hz to 4096 Hz in order to disperse the wavelets of packet dispersion of energy and make it more evenly distributed throughout the entire frequency band. After resampling,the highest point of the vibrations frequency range is 2048 Hz, according to wavelet packet (WP) theory. Following WPD, the vibration energy is primarily dispersed throughout the sub-bands of 1 to 8, which fall withinthe 1024 Hz frequency range. The major vibration energy occurs between 0–128 Hz and 256–384 Hz prior to DCbias. The predominant vibration energy appears in the frequency range when DC bias is present. Considering thevibration energy in the sub-bands 3 to 8 to those of power transformers operating normally reveals a significant increase. Consequently, the vibration feature that may be used to identify DC bias is the wavelet packet energy distribution.

5. Conclusion

In conclusion, the analysis of the monitoring and identification effect of cognitive service technology on a DC system in a power grid underscores the potential for transformative advancements in the field of power system management. The integration of cognitive service technology, coupled with advanced algorithms and neural network architectures, proves instrumental in enhancing the efficiency and reliability of monitoring DC systems. Through comprehensive data collection, pre-processing, and application of convolutional neural networks (CNNs) with pooling layers, the cognitive service technology demonstrates its ability to discern intricate patterns and anomalies within the power grid. The findings suggest that leveraging cognitive service technology, particularly through deep learning approaches, empowers the power grid infrastructure to adaptively respond to dynamic conditions, thus minimizing downtime, improving fault detection, and optimizing overall system performance. To refine and advance these methodologies, the integration of cognitive service technologies into power grid management holds great promise for fostering a resilient, intelligent, and self-aware energy distribution system. This research lays the groundwork for future innovations that can further revolutionize the monitoring and identification processes in DC systems within power grids, contributing to the sustainable and reliable operation of modern energy networks.

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