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Assoc. Prof. Dr. Babek Erdebilli (B.D. Rouyendegh), Department of Industrial Engineering, Ankara Yildirim Beyazit University, Ankara, Turkey

babek.erdebilli2015@gmail.com or berdebilli@ybu.edu.tr

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Prof. Dr. Babek Erdebilli (B.D. Rouyendegh), Department of Industrial Engineering, Ankara Yildirim Beyazit University, Ankara, Turkey

babek.erdebilli2015@gmail.com or berdebilli@ybu.edu.tr

Editor-in-Chief / Editör

Prof. Dr. Babek Erdebilli (B.D. Rouyendegh), Department of Industrial Engineering, Ankara Yildirim Beyazit University, Ankara, Turkey

babek.erdebilli2015@gmail.com or berdebilli@ybu.edu.tr

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JOURNAL OF OPTIMIZATION AND DECISION MAKING

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Research Articles / Araştırma Makaleleri

A State-of-the-Art Review on Intelligent Models for Transformer Fault Monitoring and Diagnosis

Mostafa Thaer ALJAMMAL[1], Omar Sharaf Al-Deen Al-Yozbaky [2*]

[1]University of Mosul, College of Engineering, Electrical Department, Ninawa, Iraq
ORCID No: https://orcid.org/0000-0002-5073-1536

[2]1University of Mosul, College of Engineering, Electrical Department, Ninawa, Iraq
ORCID No: https://orcid.org/0000-0002-5073-1536

Keywords

Transformer, Finite Elements Method, Magnetic Field, Fault diagnosis, Core losses, IoT

Abstract

For electrical power systems to remain stable, power transformers must operate dependably. If left unnoticed or identified too late, transformer defects can result in expensive downtime and catastrophic breakdowns. Recent developments in intelligent models for transformer failure monitoring and diagnosis are examined in this cutting-edge review. It looks at how machine learning, deep learning, and expert systems can be combined to detect defects such temperature anomalies, winding deformation, and partial discharges. Examined are the efficacy and scalability of significant methodologies, including hybrid algorithms, data-driven tactics, and Internet of Things (IoT) technologies. The analysis also highlights current constraints, including data availability and model interpretability, and suggests future research goals to enhance transformer reliability and predictive maintenance practices. This paper aims to provide researchers and practitioners with a comprehensive grasp of intelligent monitoring systems to transform transformer fault management. This work opens up a wide range of possibilities for creating intelligent models that are more accurate and efficient, improving the models' capacity to handle inconsistent or incomplete data, successfully integrating Internet of Things technologies, making models easier to understand, and creating predictive maintenance systems that work. This significantly affects the longevity of transformers, lowers maintenance costs, and boosts electrical power grid dependability. Studies show that artificial neural networks are the most widely used model in smart monitoring systems, representing 24% of previous work. Of the studies using artificial neural networks, 54% focus on dissolved gas analysis, while 39% of studies using deep learning also focus on dissolved gas analysis. These numbers highlight the importance of dissolved gas analysis and neural networks in monitoring and maintenance efforts.

Research Article
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*Resp author; e-mail: o.yehya@uomosul.edu.iq

1. Introduction

With increasing population growth, urban development, and industrial development in many countries, the demand for electrical energy will increase day by day [1,2]. Electrical transformers are essential components of power distribution and transmission networks and constitute the basis of a dependable and efficient electrical grid. These devices either step up voltage to reduce energy losses during long-distance transmission or step-down voltage to meet local distribution and consumption requirements. Because of this, transformers are an essential interface between different electrical network components [3,4]. Despite their high cost, transformers rank among the most useful and crucial parts of power systems in terms of dependability and performance. The challenges of ensuring their continuous operation are made more onerous by the extended time required for their replacement or maintenance, as downtime can significantly impact grid reliability. Therefore, monitoring transformer conditions while they are in use is essential to maintaining their high efficiency and reducing the likelihood of unplanned breakdowns [5,6]. From small devices with a few kilovolt-amperes of capacity to massive devices capable of handling hundreds of megavolt-amperes, transformers exist in a variety of sizes. These differences reflect their replacement costs, which vary from a few hundred dollars for small units to millions for large transformers powering large power plants. Typically, power transformers are designed to last 20 to 35 years [7]. However, by using modern monitoring systems and following regular maintenance schedules, its operational life can be increased to 60 years or more. This extended lifespan proves the quality of their component parts and the efficacy of their design. Nonetheless, it highlights how important it is to develop advanced diagnostic and inspection tools to enable the early detection of any issues that can jeopardize their long-term functioning [8].

This study emphasizes the importance of proactive maintenance in protecting transformers' internal components, particularly the winding coils, which are the mainstay of the devices. Through the development of monitoring and diagnostic technologies, the project aims to provide reliable, fully automated solutions that reduce expenses and human intervention while ensuring the sustainability of transformer operation and extending their lifespan. It also seeks to offer innovative solutions to operational and technical issues in transformer maintenance by developing advanced analytical tools and monitoring systems driven by artificial intelligence. These technologies will increase power systems' overall efficiency, reduce maintenance costs, and diminish their impact on the performance of the electrical grid by facilitating the early detection of any breakdowns. Unlike many previous studies that focused on individual techniques for transformer fault monitoring and diagnosis, this comprehensive review focuses on integrating multiple technologies, such as machine learning, the Internet of Things, and expert systems, to create a more integrated and effective monitoring and diagnosis system. Additionally, this review provides a critical analysis of the various methodologies used in this field, highlighting the strengths and weaknesses of each, and comparing their effectiveness under different operating conditions. Furthermore, this review aims to identify remaining research gaps in the field of transformer fault monitoring and diagnosis and propose promising future research directions. In particular, this review focuses on inter-winding short-circuit faults and provides an in-depth analysis of the methods used to diagnose this type of fault.

2. Literature Review and Related Work

Artificial neural networks (ANNs) are among the most widely used intelligent models in power transformer fault diagnosis due to their ability to learn complex and nonlinear patterns from data. Recent research has shown that neural networks can achieve high accuracy in classifying various types of faults, such as winding faults, insulation faults, and voltage converter faults, based on data such as dissolved gas analysis, frequency response analysis, and vibration analysis [9,10]. Among the major contributions in this field is the development of neural networks with advanced structures such as convolutional neural networks and recurrent neural networks to improve diagnosis accuracy. However, some research gaps remain, such as the need to develop methods to reduce the reliance on large data for training, improve the interpretability of neural network models, and handle imbalanced data [11–13]. Support vector machines (SVMs) are also intelligent models commonly used in classification tasks and have proven effective in diagnosing transformer faults. SVMs are capable of handling high-dimensional data and finding clear decision boundaries between different classes [14–16]. Recent research has shown that SVMs can be successfully used to classify various types of faults based on a variety of data, including DGA, FRA, and other sensor data. However, there are some challenges in using SVMs, such as selecting an appropriate kernel, tuning model parameters, and dealing with imbalanced data. Recent research trends include the use of optimization techniques such as particle swarm optimization (PSO) to improve the performance of SVMs [17–19].

Fuzzy logic and expert systems in transformer fault management deal with uncertainty and ambiguity in data and represent human knowledge in the form of "if-then" rules. Fuzzy logic can be used to integrate data from various sources, such as DGA, FRA, and sensor data, and provide a comprehensive assessment of the transformer's condition [20,21]. Expert systems can also be used to simulate the decision-making process of human experts in fault diagnosis and maintenance recommendations. Recent research trends include the development of adaptive fuzzy systems and machine learning-based expert systems. However, some research gaps remain, such as the need to develop methods to reduce reliance on human expertise in the design of fuzzy and expert systems and to improve the ability of these systems to handle new and unexpected data [22–24].

With the advent of deep learning techniques, the field of transformer fault diagnosis has witnessed significant developments, enabling the analysis of massive amounts of data and the extraction of complex patterns that are difficult for traditional methods to detect [25,26]. Deep learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long-short memory neural networks (LSTMs), are capable of handling sequential data and data with spatial structure. Recent research has shown that deep learning can achieve high accuracy in classifying transformer faults based on data such as DGA, thermal images, and acoustic signals. However, some challenges remain, such as the need for very large amounts of data to train deep learning models and the difficulty of interpreting the "black box" of these models [27–29]. The integration of the Internet of Things (IoT) into transformer monitoring systems has significantly improved the ability to collect and analyze data in real time. IoT sensors enable the continuous monitoring of a variety of transformer parameters (such as temperature, pressure, oil level, and vibration) and transmit data to a central platform for processing and analysis [30,31]. Recent research has shown that IoT-based monitoring systems can improve maintenance efficiency, reduce downtime, and extend the life of transformers. However, some challenges remain, such as ensuring data security and privacy, addressing connectivity issues in industrial environments, and developing standardized communication protocols [32–34].

Hybrid algorithms combine the advantages of different techniques to achieve better performance in transformer fault diagnosis [35]. For example, neural networks can be combined with fuzzy logic to create a neuro-fuzzy system that combines the learning ability of neural networks with the uncertainty-handling ability of fuzzy logic [36,37]. Optimization algorithms (such as genetic algorithms and particle swarm optimization) can also be combined with machine learning models to improve the performance of these models. Recent research has shown that hybrid algorithms can achieve higher accuracy and greater reliability in transformer fault diagnosis than individual techniques. However, the design and training of hybrid algorithms can be more complex and require greater expertise [38–41] .

3. The Main Objectives and Scope of This Work

With emphasis on winding faults one of the most difficult fault types to identify in their early stages this review study attempts to shed light on internal defects in power transformers. The transformer must be completely shut down in order to detect these defects since their effects on the currents and voltages at the transformer terminals are frequently undetectable while the transformer is operating. Maintenance staff must open the transformer and remove its components in order to reach the windings for a thorough examination, which requires a substantial amount of time and work. The importance of contemporary technologies in offering substitute and superior methods for more rapid and accurate internal fault diagnosis is emphasized in this review. This reduces the need for complete shutdowns and avoids the high costs associated with them. Because they enable efficient post-fault diagnosis and fault prediction before it occurs, computer software and intelligent models based on artificial intelligence and machine learning are crucial parts of these complex systems. The assessment also emphasizes how contemporary smart technologies can be integrated with conventional maintenance testing like chemical and electrical analysis. This includes the application of deep learning, fuzzy logic, and artificial neural networks, which make it easier to analyze data gathered from monitoring systems and identify patterns that point to internal problems.

4. Research Methodology of This Work

To achieve the objectives of this comprehensive review of smart models used in power transformer fault monitoring and diagnosis, a systematic and disciplined search methodology was followed, aiming to provide broad and in-depth coverage of the published literature while ensuring the quality and reliability of the included studies. This methodology included defining the scope of the review to include published studies on smart models used in power transformer fault monitoring and diagnosis, with a focus on short-circuit faults between windings, without excluding other types. Studies that focused solely on distribution transformer design without considering potential faults, monitoring and diagnosis methods, and modern smart methods were excluded. To achieve this, a wide range of relevant keywords were selected, including (but not limited to): “power transformers,” “condition monitoring,” “fault detection,” “fault diagnosis,” “smart models,” “smart systems,” “state-of-the-art review,” “machine learning,” “artificial neural networks,” “support vector machines,” “fuzzy logic,” “deep learning,” “expert systems,” “internet of things,” “dissolved gas analysis,” “frequency response analysis,” “vibration analysis,” “acoustic emission analysis,” “thermal imaging,” “partial discharge analysis,” “short-circuit faults,” “winding faults,” “insulation faults,” “voltage converter faults,” and “iron core faults.”

Synonyms and related terms were derived from these words and used individually or in combinations in searches of the following prestigious scientific databases: Scopus, Web of Science, IEEE Xplore, Science Direct, and Google Scholar. In addition, a focus was placed on leading scientific journals in the field of electrical power engineering and energy systems. To ensure the quality and relevance of the studies, strict inclusion and exclusion criteria were applied. Studies published in English in peer-reviewed scientific journals and accredited conferences that directly address the research topic were included, with a focus on studies published within the last fourteen years (2010–2024). Studies that were irrelevant, of low quality, unavailable, duplicate, or focused exclusively on distribution transformers (unless they presented generalizable methodologies) were excluded. Searches were conducted in the aforementioned databases and journals, titles and abstracts were screened for relevance, and full texts of studies that passed the initial screening were downloaded and reviewed in-depth.

The included studies were critically analyzed, the main findings summarized, strengths and weaknesses identified, results compared, and research trends and gaps identified. This research paper builds on these and other articles, focusing on their applications in power transformers.

Figure 1 illustrates a flowchart summarizing the methodology and steps involved in this recent review of smart models used to monitor and diagnose transformer faults. The process begins with an introduction to transformers, the importance of their normal operation, and their advantages. The flowchart then discusses the challenges of monitoring transformers during normal operation and during electrical faults, focusing on the impact of these faults.

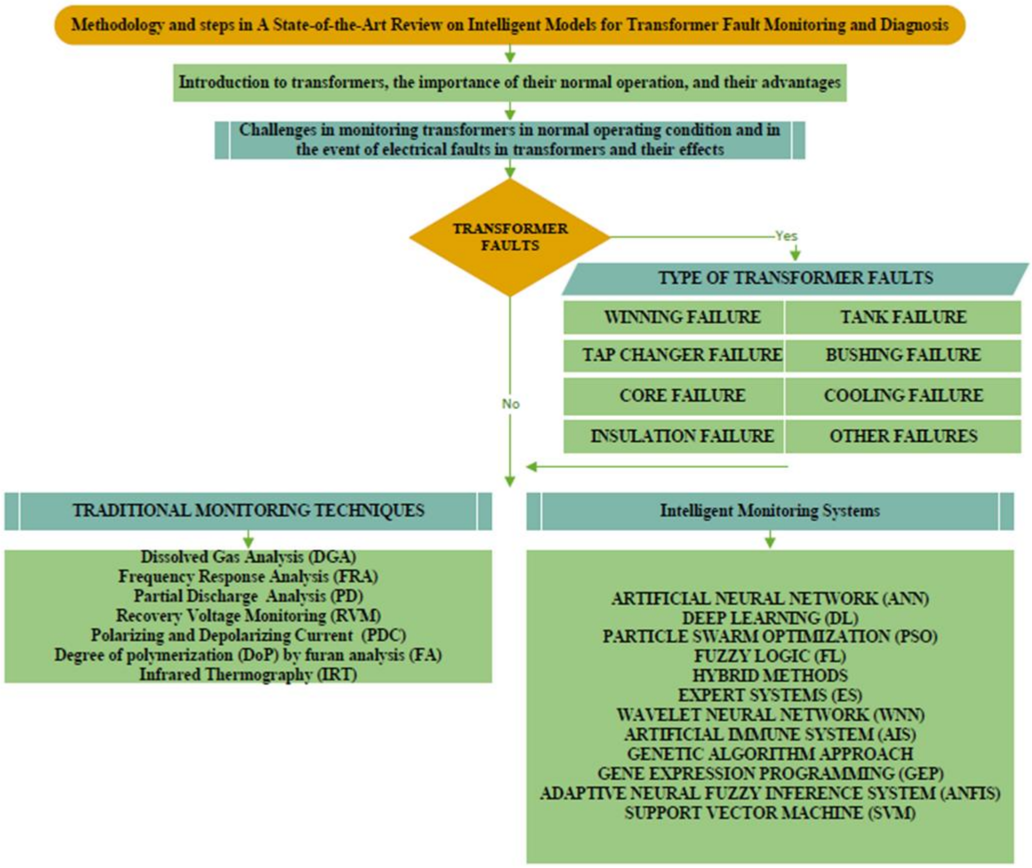

Figure 1. shows a flowchart of the review paper methodology.

Transformer faults are categorized into different types (winding faults, voltage converter faults, iron core faults, insulation faults, tank faults, insulation sleeve faults, cooling system faults, etc.). The flowchart then outlines two main methods for monitoring and diagnosing faults, as illustrated in the figure. This flowchart provides a visual and organized overview of the key steps and phases followed in this review, making it easier for the reader to understand the logical sequence of the process.

5. Challenges of Electrical Faults in Transformers and Their Impacts

Electrical transformers face complicated operational challenges due to extreme weather and ongoing stress. The primary windings, load changers, bushings, the insulation system (oil and paper), and the tank are among the essential parts of a transformer that deteriorate due to lightning, switching operations, and short circuits [42–44]. These factors weaken transformer components over time, increasing the possibility of catastrophic failures like fires or explosions that result in large financial losses and lengthy power outages for consumers. One of the main issues with transformers is the high cost and prolonged downtime of repairs or replacements for electrical faults. Deploying a new transformer can often take over a year, which makes the operational and financial consequences of such breakdowns worse. Additionally, transformer failures during operation present significant safety risks to employees due to the potential for explosions and the environmental dangers posed by insulating oil spills [45]. To ensure business continuity and minimize the negative effects of such accidents, it is critical to understand the basic physics and reasons of transformer failures. Transformers are constructed with sufficient mechanical and electrical strength to withstand unusual conditions, such as transient voltages and short circuits, early in their operational lives. However, the insulation system eventually deteriorates due to prolonged use and frequent electrical and thermal stressors, making transformers more susceptible to operational problems. Transformer protection and failure risk reduction require investments in state-of-the-art condition monitoring equipment and preventative maintenance programs. These include insulating oil monitoring sensors, vibration analysis, and artificial intelligence to spot patterns that indicate upcoming issues. Power utilities must take these steps to improve system reliability, lower operating losses, and prolong transformer lifespan [46,47].

6. The Importance of Early Detection of Faults and The Role of Intelligent Monitoring Models

For electrical systems to remain operational and efficient, early transformer detection and condition monitoring are essential. Early fault diagnosis lowers operating costs and minimizes power outages by identifying possible problems before they become major ones [48–50]. This procedure uses sophisticated techniques to calculate the transformers' remaining lifespan and failure probability. In order to improve the accuracy of fault assessment and prediction, industry standards have established a number of methods for integrating both normal and specialized test data using contemporary computing technologies [51].

A wide range of traditional and sophisticated tests are included in diagnostic techniques, such as electrical tests to determine the integrity of winding and bushings, specialist tests like dissolved gas analysis (DGA), and chemical analysis to determine the state of insulating oil and its constituent parts. These diagnostic procedures help to provide a thorough picture of the transformer's existing state [52,53].

7. The Role of Artıficial Intellıgence in Enhancing The Effıciency of Power Systems

Thanks to technological advancements, artificial intelligence (AI) solutions have become a crucial part of improving preventative maintenance operations. Artificial intelligence (AI) has shown significant promise as a tool for transformer maintenance due to its ability to analyze complex data, identify trends, and predict potential issues. This will make maintenance operations more accurate and efficient [54,55]. As shown in Figure 2, which highlights the diagnostic procedures and their particular areas of use, these methods rely on sophisticated instruments.

Artificial Neural Networks (ANNs)

- used to analyze data and predict future failures based on discovered patterns.

Fuzzy logic

- provides the ability to deal with uncertainty and ambiguity in data.

Deep learning

- enables the extraction of patterns from large amounts of complex data.

Support Vector Machines (SVM)

- used for classification and performance analysis.

Genetic Algorithms and Particle Swarm Optimization (GA & PSO)

- used to find optimal solutions in multi-criteria systems.

Expert Systems

- rely on knowledge bases to provide recommendations similar to maintenance experts

Figure 2. Depicts each diagnostic method along with its corresponding areas of application.

In order to improve decision-making effectiveness and offer proactive solutions, machine learning models demonstrate remarkable competence in evaluating and learning from data collected across several monitoring systems. Preventive maintenance schedule can be enhanced with the use of cognitive analytics, which lowers operational risks and increases transformer lifespan. Additionally, knowledge-based intelligent models, such fuzzy logic and expert systems, mimic human cognition to provide accurate recommendations based on data insights and empirical experience, increasing the efficacy of maintenance techniques [56,57].

8. Transformer Faults

Transformers are pivotal elements within power systems, playing a critical role in energy transmission. However, they are vulnerable to various faults, which can significantly impact their operational efficiency and reliability. Faults are generally categorized into internal and external types [58,59]. Internal faults encompass issues related to windings, insulation, cooling systems, iron cores, among others, while external faults arise from factors like extreme environmental conditions, such as high ambient temperatures, inclement weather, vandalism, and faults in connected transmission lines. To comprehend and diagnose power transformer faults effectively, it is essential to identify the key components that constitute the transformer's basic structure and understand their respective functions [60]. Figures 3 and 4 illustrate the transformer and its internal and external components, respectively. Each component plays a crucial role in the transformer's functioning. Consequently, any malfunction or degradation of these components can result in faults with varying degrees of severity.

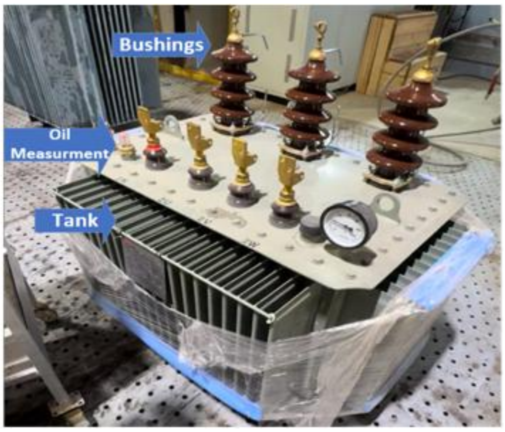

Figure 3. Transformer and its external components.

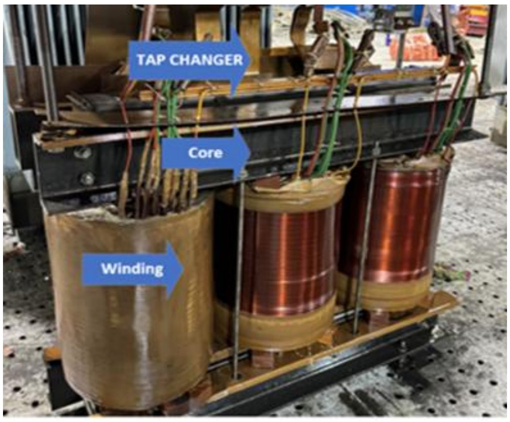

Figure 4. Transformer and its internal components.

Fault origins vary from design and manufacturing defects, environmental influences such as humidity or lightning strikes, to operational failures, including overloading and overheating. Gaining an understanding of these components facilitates accurate fault analysis, enabling the identification of root causes. This, in turn, aids in developing proactive maintenance strategies and diagnostic methodologies that mitigate fault impacts and ensure continued operational integrity [61].

Studies by recognized organizations such as IEC, CIGRE, and IEEE provide detailed statistical analysis of fault locations within transformers, differentiating between internal and external faults. External faults, while rare, include phase-to-ground faults, two-phase faults, and symmetrical three-phase faults occurring outside the transformer fault zone [62]. Regarding internal faults, Figure 5 presents the fault distribution by location within power transformers. It highlights that windings and voltage regulators account for the highest proportion (68%) of internal transformer failures, thereby emphasizing the significance of internal fault research. This data is critical for efficient transformer asset management, enabling the prioritization of maintenance efforts on the most critical components [63,64].

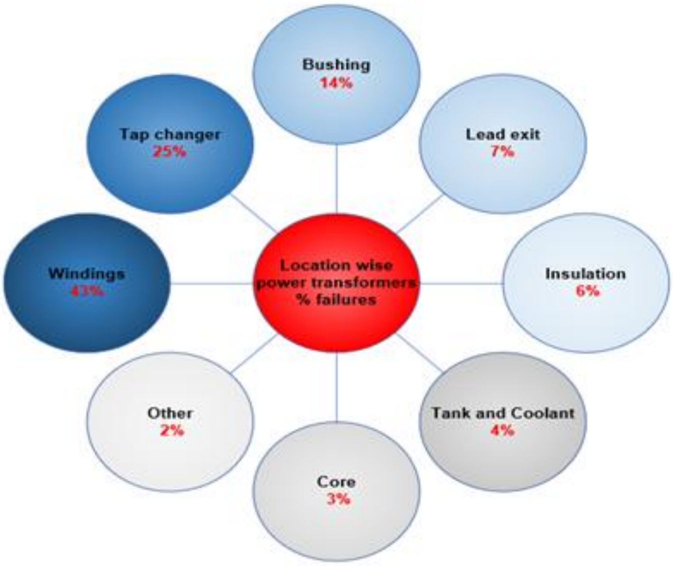

Figure 5. Fault ratio by location in power transformers.

Factors Affecting Transformer Failures Electrical transformers, similar to other equipment, face numerous factors that can contribute to their failure. These include mechanical stressors like vibrations and short-circuit forces, thermal stresses from high temperatures and excessive current, and electrical stresses like lightning strikes and partial discharge [65]. Similar to fault location analysis, Figure 6 shows the reasons of failure grouped by industry standards (IEC, CIGRE, IEEE). These studies provide a thorough knowledge of the underlying reasons by offering a detailed analysis of failure distributions by component and fault site.

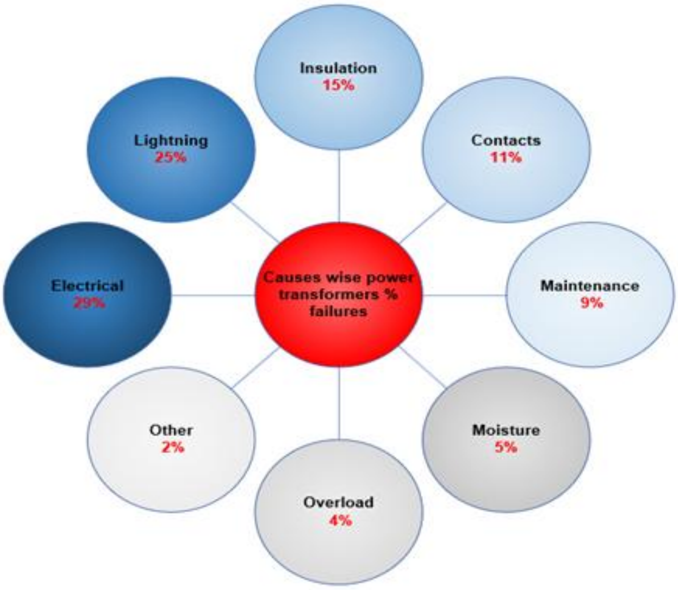

Figure 6. percentages of factors that contribute to electrical transformer failure.

Chemical stressors that impact both insulation and metallic components, such as moisture, oxidation, and corrosive sulfur, are important contributors to transformer deterioration. Transformer failure is also influenced by poor maintenance procedures and manufacturing flaws. These elements work together to affect transformer longevity and performance, highlighting the necessity of regular maintenance and good manufacturing standards to reduce the possibility of faults. It is imperative to use a thorough diagnostic strategy that includes component-specific diagnosis, ongoing monitoring, and planned maintenance procedures [66].

8.1. Winning Failure

The essential parts in charge of converting and transferring electrical energy are transformer windings. They are usually made up of copper conductors that are shielded from the environment, such as the core and tank, by a complete insulation system that includes paper insulation and isolation between the windings [67,68]. Under a variety of operational conditions, this system guarantees protection against errors. According to research, winding failures are responsible for over 43% of all transformer breakdowns, highlighting the significance of determining the underlying reasons and creating preventative strategies to lessen these problems. Short circuits, which happen when surge currents or network overloads put too much strain on the insulation, are a primary cause of winding failure [69]. A short circuit between windings is shown in Figure 7, and conductor burnout and bending failure brought on by thermal and mechanical deformations at maintenance facilities are shown in Figure 8.

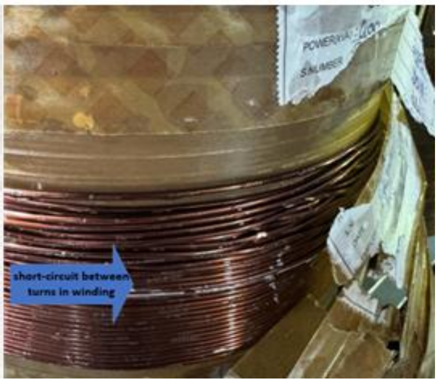

Figure 7. A short circuit between the windings

Figure 8. At maintenance facilities, mechanical and thermal deformations cause conductor burnout and bending failure.

High internal temperatures are the main cause of ground faults, which can also result from insulation failure between the windings and grounded components like the core and tank. In addition, problems like contact resistance and open circuits are significant causes of hot spots inside transformers, which erode insulation and eventually harm the windings over time. The possibility of failure might be further increased by mechanical deformations such bending or tilting of the conductors, which are frequently brought on by incorrect transformer handling or short-circuit and surge currents [70,71]. Another cause of internal deformation that lowers the capacity to sustain operating loads is winding movement brought on by mounting system failure. Buckling is caused by axial and radial forces produced by short-circuit currents, which alters the windings' shape and insulation integrity. Thus, to increase transformer longevity and efficiency, it is imperative to maintain the insulation system and apply preventative maintenance using cutting-edge technology. The need of carefully analyze the various types of insulation solid, liquid, and gaseous and how they impact transformer performance is further highlighted by recent studies. AI-based early diagnostic methods could significantly reduce the likelihood of catastrophic failures. Investigating the effects of environmental factors including temperature, humidity, and pollution on winding lifetime will be essential. Future studies should concentrate on improving winding designs for better cooling and reduced losses, as well as creating novel materials with improved resistance to heat and stress.

8.2. Tap Changer Failure

A key transformer component, the TAP changer is essential for regulating the output voltage, preserving the electrical system's stability, and meeting operating requirements. According to studies, TAP changers account for up to 25% of failures, making them the second most prone transformer component. Its main purpose is to modify the transformation ratio so that voltage can be changed based on operating circumstances [72–74]. There are two primary types of TAP shifters. The first is the On-Load Tap Changer (OLTC), which is perfect for systems that need continuous voltage modulation since it permits voltage control without turning off the transformer. Low-voltage selector switches and high-voltage transfer switches are two subtypes of this type. The second kind, known as a No-Load Tap Changer (DETC), is usually utilized in less demanding applications and requires disconnecting the transformer from the grid in order to modify the voltage. There are typically five adjustment roles available at DETCs. Usually, the TAP changer is found in a separate compartment or inside the transformer's main tank. It is prone to failure despite its intricate design for a number of main reasons [75,76]. Open contacts, which can be caused by internal short circuits, inadequate connection, contact deterioration, or isolated hotspots, are one of the main causes. Another is contact carbonization, which can be brought on by crimping problems or overheating of the contact surface. Furthermore, weak springs or damaged contacts may cause the drive mechanism itself to malfunction. With the broken contact springs clearly apparent, Figure 9 offers a useful example of a drive mechanism failure in a voltage converter.

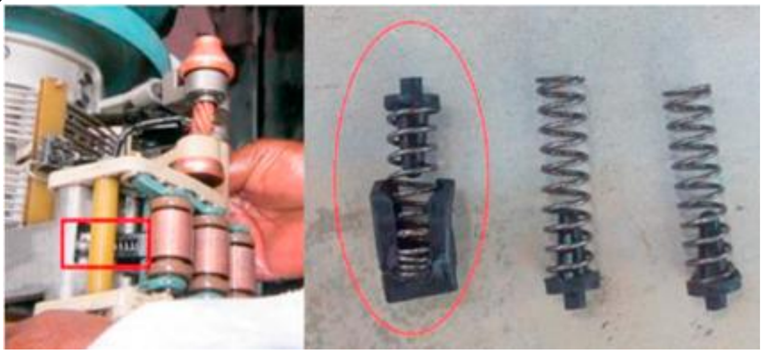

Figure 9. Example of drive mechanism failure in a voltage converter [5].

To mitigate these problems, regular maintenance of the TAP changer and the use of effective diagnostic tests, such as partial discharge analysis and contact measurements, are essential for improving transformer performance and ensuring long-term reliability [77,78]. It is crucial to broaden the scope of the investigation in addition to the technical issues. It is critical to examine the operational and financial effects of TAP changer failures, including grid stability, repair expenses, and downtime. The analysis would be improved and maintenance efforts may be prioritized with the inclusion of particular statistical data on transformer kinds, failure modes, and operating conditions. It's also critical to investigate the function of cutting-edge technologies like online monitoring, predictive maintenance, and material/design advancements. The results of this study would be strengthened even more by a thorough discussion of mitigation techniques and an examination of real-world case studies.

8.3. Core Failure

The core is the active part of the transformer, responsible for carrying the magnetic flux. Transformer core plates are electrically insulated and magnetically bonded through thin layers of insulating material, reducing eddy current losses. The core is isolated from the grounded mechanical assemblies and deliberately grounded at a single point. Core failures contribute 3% of all transformer failures [79–81].

The identified causes of core failure include:

- Short-circuited core plates: Partial damage to the core plates or deteriorating insulation, debris contact with the core, and core pin failures.
- Multiple grounding: Insulation failure between the core and the ground, or between the core and the mounting system arrangement.
- Ungrounded core: Manufacturing defects, high resistance of the core grounding contact, and externally disconnected grounding.
- Core deformation: Shocks to the active part, either during transportation or due to seismic activity, with excessive short-circuit effects along the axial/radial direction contributing to core deformation [82]. Based on Figure 10 depicting transformer core plates, it is evident that the design and finishing were carried out meticulously.

Figure 10: Iron core plates of an electrical transformer.

Nevertheless, it's possible that some factors, such edge angles and cutting accuracy, were missed in earlier research, which could have affected the sheets' complete contact and decreased air gaps. Further research may also be necessary to optimize the hole configuration to fit the mounting columns and prevent any magnetic interference during installation. Finally, it is crucial to research how the final finishing affects hysteresis losses in order to minimize energy loss in the transformer.

6.4. Bushing Failure

Bushings are crucial components in electrical transformers, serving as insulating structures that support the active conductor carrying current through the grounded transformer tank. These active conductors can either be directly connected to the bushing's base or passed through its center via a separate conductor, known as a lead-pull or rod-pull bushing [83]. Bushings are broadly classified into two primary types: solid bushings, which are used for low voltage applications (up to 25 kV), and graduated-capacity bushings, designed for high voltages (above 25 kV). The main components of a bushing include the conductor and the insulation material. In solid bushings, mineral oil acts as the insulating medium between the conductor and the insulating component. On the other hand, graduated-capacity bushings utilize advanced insulation materials such as oil-impregnated paper, resin-impregnated paper, and resin-bonded paper. Statistical studies indicate that approximately 14% of transformer failures are attributed to bushings, making them the third most failure-prone component in transformers [84].

Bushing failures arise from a range of factors that compromise their functionality and durability. Among the most critical causes is electrical overstress, where short circuits within the capacitive graded layers increase capacitance and exert stress on the insulation. This leads to a voltage drop at the capacitor terminals, often aggravated by transient surges. Thermal overloading is another significant factor; excessive heat caused by overloading within the network generates thermal expansion, leading to cracks in the porcelain structure and overheating of transformer oil, which further degrades the insulation [85]. External factors, including mechanical damage due to lightning strikes, flashovers, or external short circuits, also play a major role in bushing deterioration. These forces can result in structural damage such as cracks or failures in the porcelain coatings, rendering the bushing prone to further failures. Figure 11 illustrates a typical case of end screen failure, a defect often encountered in bushings subjected to the aforementioned issues.

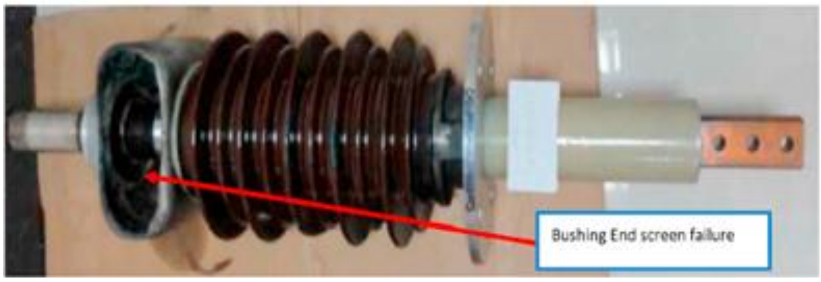

Figure 11. Illustration of an end screen failure in a bushing [5].

There are still a number of gaps in our understanding of bushing failures, despite a great deal of research and technological breakthroughs in transformers. Not enough research has been done on the creation of sophisticated insulating materials that can increase efficiency and lower failure rates. Inadequate attention is paid to preventive maintenance techniques, which are crucial for early fault identification and prompt component replacement. Additionally, not enough research has been done on how environmental elements like humidity and extremely high or low temperatures affect bushing performance. Another significant disadvantage is the paucity of comprehensive study on modern monitoring tools capable of continuously measuring the heat and stress levels inside bushings.

8.5. Insulation Failure

The first line of defense in electrical transformers is insulation, which keeps short circuits at bay and guarantees safe operation. Solid insulation and liquid insulation (oil) are the two main parts of the insulation system. Compressed cardboard, which is further separated into two kinds, makes up the majority of solid insulation. Spacers, barriers, and clips are examples of primary insulation, whereas secondary insulation is more concerned with protecting the winding. In order to provide the required cooling, improve electrical insulation, and stop the internal transformer components from oxidizing, liquid insulation usually in the form of oil is essential. According to studies, insulation materials more especially, paper and oil are among the most susceptible parts of transformers, contributing to about 6% of failures [86,87]. Water buildup in the oil or paper is one of the main reasons for insulation degradation, while there are other contributing variables as well. The presence of water during the paper-making process, water leaking through the transformer's breather during load cycles, or moisture entering during maintenance and repair operations are some of the possible sources of this moisture. Furthermore, the problem may be made worse by internal oil oxidation or water seeping through the transformer tank.

Another important factor in insulation failure is the thermal deterioration of paper and oil insulation. Poor cooling system performance, frequently brought on by insufficient oil circulation, overloading, high core temperatures, or the influence of circulating currents and stray magnetic flux, may be the cause of this degeneration [88]. Another important factor in the degradation of insulating materials is their age. Internal and external issues like short circuits, inrush currents, extended use at high temperatures, and moisture seeping into paper or oil are some of the causes of this aging. Additionally, aging is accelerated by exposure to dangerous operating situations. Real-world instances of insulation deterioration are depicted in Figures 12 and 13. While Figure 12 shows indications of aged oil with sludge development, indicating considerable contamination and insulation breakdown, Figure 13 emphasizes degradation in paper insulation.

Figure 12. Failure of paper insulation due to degradation [5]

Figure 13. Older oil that has formed sludge [5]

Despite numerous research, there are still many unresolved questions about transformer insulation failures. Current research largely ignores contemporary techniques for improving the quality of paper and oil insulation, such as adding nanoparticles or looking at alternative insulation materials. Additionally, a more comprehensive evaluation of how insulation degradation affects the environment is required, including for problems like oil spills and the removal of contaminated materials. Additionally, no proactive measures are in place to track the moisture and oxidation levels of the transformer's insulation system in real time. Additionally, external factors like industrial pollutants and seismic activity have not been adequately considered when assessing their effects on insulating systems. A greater focus on boosting cooling system efficiency and facilitating timely repairs to prolong the life of insulating components is necessary to improve transformer dependability.

8.6. Tank Failure

As the primary container for the insulation oil used in cooling and insulation procedures, the transformer tank is an essential part of electrical transformers. Furthermore, the tank offers structural support for a range of control devices and transformer accessories. Despite its significance, the tank is prone to malfunctions; it accounts for roughly 4.37% of all transformer failures and is the fifth most vulnerable part of the system [89,90]. Internal rupture is one of the main reasons why tanks fail. Excessive internal temperatures, frequently brought on by overloading, or high internal pressure brought on by gas production can both cause this.

Leakage is another common cause of failure that has a big effect on how well the transformer works [91]. An example of tank gasket seal leaking is shown in Figure 14, along with the effects it has on the transformer's operation. Leakage usually results from a number of causes, such as gasket seal deterioration, tank wall fissures, and material corrosion.

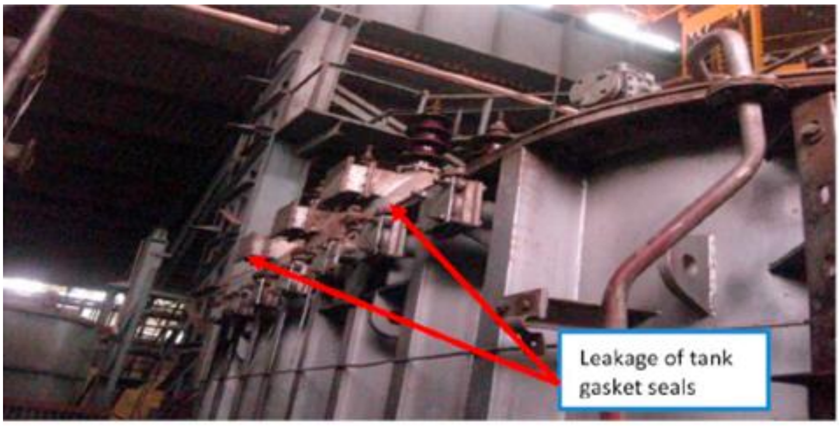

Figure 14. Leakage in the tank gasket seal, showing how transformer function is affected [5].

Several significant gaps remain in our knowledge of transformer tank breakdowns despite a great deal of research. For instance, there isn't much discussion on the creation of advanced techniques for early leak detection. Technologies like pressure sensors and thermal imaging cameras may be highly useful in identifying breaches before they result in significant damage. Furthermore, not enough study has been done on enhancing tank materials to make them more resistant to corrosion. Moreover, modern designs that mitigate the impacts of gas pressure and heat are still few. Such designs may be able to prevent internal ruptures by optimizing the tank's internal heat dissipation and pressure distribution. The importance of implementing preventive maintenance practices, such as the use of high-durability gaskets, is frequently understated. Proactive material selection techniques and advanced monitoring technology may significantly help lower tank failure rates and increase transformer dependability.

8.7. Cooling System Failure

An essential part of transformers is the cooling system, which dissipates heat produced by copper and iron losses while the transformer is operating. Water-cooled heat exchangers, oil pumps, and cooling fans are some of their essential components. These components work together to regulate the transformer's temperature within acceptable operational limits [92]. However, when the cooling system fails, heat accumulates within the transformer, causing severe negative effects on its components. Prolonged overheating can also increase internal gas pressure, which may result in catastrophic failures, including transformer explosions. Cooling system failures account for approximately 3.79% of all transformer failures, making it the sixth most vulnerable transformer component. Various causes contribute to cooling system failures. For instance, pump-related issues such as leakage, motor malfunctions, oil flow blockages, and pipe corrosion often stem from inadequate maintenance practices. Similarly, system efficiency may be jeopardized by cooling fan failures brought either by mechanical problems or power interruptions. Radiator defects, such material deterioration or structural fissures, are very frequent, particularly in hard operating environments [93,94].

There are still large research gaps in spite of the large number of studies that have been done on cooling system components and failure processes. The variety of cooling system designs used in transformers is mainly ignored in these investigations. Furthermore, there is insufficient discussion of contemporary technologies meant to increase cooling efficiency, such as better heat exchanger designs or sophisticated cooling algorithms. Moreover, little research has been done on how oil type affects cooling performance or how environmental elements like high ambient temperatures or industrial pollutants affect the efficiency of cooling systems. For the creation of reliable and effective transformer cooling systems, these gaps must be filled.

8.8. Other Failures

Transformer failures are also attributed to operational errors, inadequate maintenance, and failures in protection systems, which collectively account for 2.60% of total failures. Transformers are complicated devices by nature, and advanced procedures are needed to identify or diagnose problems [95]. Multi-parameter monitoring methods, which involve assessing various operational parameters simultaneously, are essential for early fault detection and enhancing transformer reliability. Understanding how transformer components behave and fail during operation is crucial for implementing preventive measures [96,97]. Proper diagnostic and monitoring strategies can significantly improve transformer performance and extend its service life. However, existing studies often lack sufficient detail regarding specific multi-parameter monitoring techniques and how they are implemented. Furthermore, these studies usually fall short in offering specific illustrations of preventive actions that could reduce hazards and improve transformer dependability. Practical methods for putting condition-based maintenance systems into place or improving operating conditions to lessen stress on transformer components, for instance, are not given enough attention. To close these gaps, more research into customized preventive maintenance plans, sophisticated monitoring systems, and actual case studies illustrating efficient transformer management techniques are needed.

9. Traditional Monitoring Techniques

Traditional methods (e.g., thermal monitoring, dissolved gas analysis). Power transformers are one of the most important components of electrical power networks, playing a vital role in the efficient transmission and distribution of electrical energy [98]. Given their importance, ensuring the safety and serviceability of these transformers is of paramount importance to maintaining the continuity of power supply. A variety of conventional methods are used to assess the health status of transformers and detect any potential faults at their early stages, which helps in taking necessary preventive measures and avoiding power outages [99–101]. To illustrate the conventional methods for assessing the condition of transformers, Table 1 shows the offline and online methods with their working principle, uses, advantages and disadvantages, in addition to the references that have worked in these fields, and which are considered better than the rest of the methods.

Table 1. shows the offline and online methods with their working principle, uses, advantages and disadvantages, in addition to the references

Traditional Monitoring techniques		
Implementation Offline and Online		
Method Dissolved Gas Analysis (DGA)	Method Frequency Response Analysis (FRA)	Method Partial Discharge (PD) Analysis
Description Analysis of dissolved gases in transformer oil to determine the type and severity of the fault.	Description Injecting an electrical signal into the transformer coils, measuring the resulting frequency response, and comparing it with a reference response.	Description Measurement of electrical pulses resulting from partial discharge.
Used Detect faults such as partial discharge, thermal and electrical faults.	Used Detect mechanical deformations in transformer coils, such as cracks or bends.	Used Detect the presence of partial discharge in the insulation
Advantages It is an effective way to detect any fault in its early stages. It helps to accurately determine the type of fault. Disadvantages It depends on the expertise of specialists to interpret the results of the analysis. It may give conflicting results in some cases.	Advantages It is a very sensitive method to any form of file corruption. It helps to pinpoint the exact location and severity of the failure. Disadvantages Additional sophisticated hardware is required. Some file faults may not be detected in the early stages.	Advantages It is an effective way to detect the presence of partial discharge. It helps to Disadvantages Expensive equipment required. Some electrical pulses from partial discharge may not be detected.
References [102–109]	References [110–113]	References [114–117]

Despite their value, traditional transformer failure diagnosis techniques still have certain drawbacks. Dissolved Gas Analysis (DGA) procedures, for example, have inconsistent interpretation methodologies and are unable to detect new fault types or effectively diagnose problems under boundary operating circumstances. The interpretation of frequency response analysis (FRA) is still largely dependent on human skill, which could introduce subjectivity. Additionally, FRA has trouble differentiating various fault types that share features. Despite its effectiveness, partial discharge (PD) analysis faces challenges such as the high cost and installation of sensors, as well as the incapacity to identify tiny PD pulses that are obscured by noise during online testing. These discrepancies show how traditional diagnostic techniques require more study and advancement to increase their precision, dependability, and affordability.

An overview of the offline methods' principles, applications, benefits, and drawbacks is also provided in Table 2, along with references that have been used in these domains and are thought to be superior to the other approaches. Table 2 emphasizes the value of traditional transformer failure diagnosis techniques; it also identifies a number of shortcomings. First, more research is needed to determine how insulator design affects Recovery Voltage Monitoring (RVM) and whether it can distort estimates of moisture content. Second, a major obstacle to reliable and impartial diagnosis is the need on human judgment to interpret Polarization and Depolarization Current (PDC) measurements. Last but not least, the high expense of laboratory-based Furan Analysis (FA) makes it necessary to look into less expensive options. Filling in these areas will increase transformer fault diagnosis's precision, effectiveness, and accessibility.

Table 2. it shows the detailed diagram of the offline methods with their working principle, uses, advantages and disadvantages, in addition to the references

Traditional Monitoring techniques Implementation Offline		
Method Recovery Voltage Monitoring (RVM)	Method Polarizing and Depolarizing Current (PDC) Measurement	Method Degree of polymerization (DoP) by furan analysis (FA)
Description Charge the insulation for a known period of time, then discharge it to ground, and measure the resulting recovery voltage.	Description Apply a DC voltage to the insulation, measure the resulting polarization current, then remove the voltage, and measure the depolarization current.	Description Measurement of the concentration of furan compounds in transformer oil.
Used Detection of moisture content in wrapping paper insulation.	Used Detect the moisture content of insulation.	Used Detect old insulation status.
Advantages It is one of the best ways to evaluate the condition of old insulation and its moisture content. It helps determine if the insulation needs to be replaced. Disadvantages The insulation geometry may affect the measurement results. In some cases, accurate results may not be given.	Advantages It is a non-destructive method of assessing the condition of insulation. It helps determine if the insulation needs to be replaced. Disadvantages It depends on the expertise of specialists to interpret the measurement results. It may not give accurate results in some cases.	Advantages It is an effective way to evaluate the condition of old insulation. It helps determine if the insulation needs to be replaced. Disadvantages It takes a long time and money to perform the analysis. And it may not give accurate results in some cases.
References [118–121]	References [122–124]	References [125,126]

As for the methods online, Table 3 shows the method that is online, with its working principle, uses, advantages and disadvantages, in addition to the references that have worked in these fields. The charts in the previous figures illustrate the traditional methods used in diagnosing power transformer faults. These charts aim to provide an overview of each method, highlighting its advantages and disadvantages. By analyzing the information contained in the charts, the following can be concluded: The traditional methods used to diagnose power transformer faults vary, and each method focuses on a specific aspect of the transformer.

Table 3. shows the method that is online, with its working principle, uses, advantages and disadvantages, in addition to the references.

Method Infrared Thermography (IRT)
Description Capture thermal images of the transformer using a thermal camera.
Used Detect any hot spots on the surface of the transformer.
Advantages It is a non-surgical and non-destructive method. It helps to accurately locate the fault. Disadvantages Results may be affected by several factors, such as ambient temperature. In some cases, results may not be accurate.
References [127–130]

Table 3 indicates a notable research gap even though it emphasizes the use of Infrared Thermography (IRT) for transformer fault identification. In particular, little is known about how environmental variables like humidity and ambient temperature affect the precision of IRT temperature readings. To ascertain the magnitude of these factors and create plans to lessen their impact on diagnostic precision, more research is required. It can be inferred that certain conventional techniques, such DGA and IRT, can be applied online, enabling ongoing transformer state monitoring. Other techniques, like FRA and RVM, necessitate removing the transformer from the network in order to do tests. Certain techniques, like DGA for identifying insulation breakdown, are known for their excellent diagnostic accuracy. Other approaches could find it challenging to differentiate between various fault kinds. Certain techniques, like FRA, depend on the knowledge of engineers and technicians to interpret the findings. Other approaches, like IRT, rely on automated data analysis.

There are benefits and drawbacks to each approach, and no single approach is ideal. The type of defect to be diagnosed, the diagnostic capabilities available, the cost, and the ease of implementation all influence the technique selection. For engineers and technicians involved in power transformer maintenance, these charts offer useful information that aids in understanding the various defect diagnosis techniques. Select the approach that works best in a given circumstance. Consider the benefits and drawbacks of each approach. Make wiser choices about upkeep. By enhancing the power transformer maintenance procedure, these charts help lower maintenance expenses, prevent significant failures, and increase transformer operation efficiency. Generally speaking, the charts in the above figures offer useful details regarding conventional techniques for identifying power transformer problems. These charts make it easier to comprehend these approaches, evaluate them, and select the best one for a given circumstance.

10. Intelligent Monitoring Systems

Helps in the intelligent control of transformers as part of ensuring the safety of electrical networks, especially with the world's trends towards network technologies. These electronics rely on a set of advanced bodies for innovative installations and complete fault diagnosis, which helps prevent miracles and maintenance effectiveness. The importance of smart monitoring in achieving safety is represented as it helps prevent damage that leads to catastrophic failures that may lead to power outages or telephone equipment [16,131]. In addition to implementing as it works to improve the efficiency of transformers during a comprehensive review and any good repairs. As well as in achieving victory and does not help to identify potential elements in the transformations before their agreement, which allows the conviction of many miracles. As well as in achieving smart networks, monitoring systems are an essential part of the data and information for smart networks, as they provide the necessary data for complete control of the network and integration. Intelligent transformer monitoring systems consist of several main components, including sensors that are used to collect data about the transformer's condition, such as temperature, vibration, pressure, and oil level. Control units that process and analyze the data received from the sensors to determine the transformer's condition [132]. A user interface that allows operators to monitor the transformer's condition and receive alerts in the event of any problems. Communication systems that connect all components of the monitoring system and allow data exchange between them. Intelligent transformer monitoring systems perform several important functions, such as monitoring and measuring the transformer's temperature and alerting operators if it rises above safe levels. Monitoring and ensuring that the oil level in the transformer is within the specified range. Detecting any oil or gas leaks from the transformer. Diagnosing and analyzing data to identify any potential transformer faults. Managing and scheduling preventive maintenance work based on the transformer's condition [133]. This is illustrated in Figure 15, which shows a detailed diagram of how data is used in Intelligent Monitoring Systems research studies. The diagram shows the data flow from data collection to condition assessment and preventive maintenance of a power transformer.

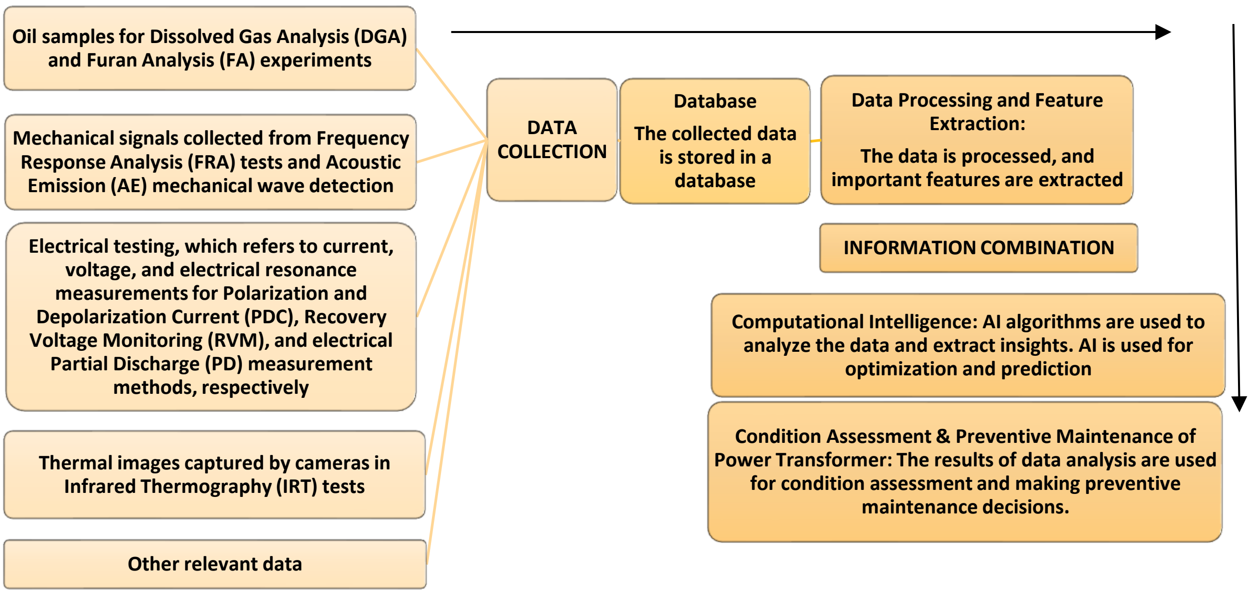

Figure 15. a detailed diagram of how data is used in Intelligent Monitoring Systems.

The procedure of using data in AI research for power transformers is depicted in the figure. From data collection to the use of Intelligent Monitoring Systems for condition assessment and preventative maintenance, it describes the steps. The process begins with data collection, which comprises gathering several types of information relevant to the transformer's condition [134]. This data includes:

• Oil samples: These are used to evaluate the condition of the transformer's insulation using Furan Analysis (FA) and Dissolved Gas Analysis (DGA).
• Mechanical signals: Frequency Response Analysis (FRA) and Acoustic Emission (AE) tests are used to gather mechanical signals in order to identify mechanical irregularities in the transformer's components.
• Measurements of voltage, current, and electrical resonance are examples of electrical tests.

They are employed in techniques including polarization and depolarization current (PDC) measurement, recovery voltage monitoring (RVM), and partial discharge (PD) analysis.
• Thermal imaging: Using Infrared Thermography (IRT), these images help identify the areas of the transformer that produce abnormal heat.

The collected data is subsequently organized and stored in a database. After employing data processing procedures to clean and prepare the data for analysis, feature extraction is done to identify the most salient characteristics relevant to problem diagnosis. The features and processed data are then used to models for smart confrontation systems.
These models, which include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Fuzzy Logic (FL), and Genetic Algorithms (GA), are used for tasks such as:
• Optimization: modifying parameters and increasing the efficacy of diagnostic processes.
• Prediction: Calculating how long the transformer will last and foreseeing potential problems.

Finally, the information obtained from the Smart Confrontation Systems study is used to assess the transformer's status. This means evaluating health and identifying potential issues. This evaluation can be used to make well-informed judgments on preventative maintenance that will guarantee the transformer's continuous dependable operation. The graphics essentially show how modern Smart confrontation systems techniques combined with a variety of data sources can provide a more proactive and efficient approach to transformer maintenance.

10.1. Using Advanced Technologies In Machine Learning And Artificial Intelligence

The power transformer is one of the main elements of the electrical network, which ensures the connection of networks with different voltages. Ensuring the stability and reliability of the electric power system (EPS) largely depends on the technical condition of power transformers and especially automatic transformers [135,136]. Transformer failure significantly affects the EPS operating mode when the disturbance can lead to the following situations:

• Overloading of network elements, operation of equipment overload control automation (EOCA), network splitting, cascading accidents.

• Voltage drop at control points, operation of under voltage control automation (UCA), consumer failure in a particularly difficult situation.

• Steady-state instability, emergency central control automation or local stability control automation (SCA) operation, disconnection of consumers or generation of trips according to written or specified action schedules.

• Development of cascading accidents in the event of a transformer circuit breaker failure and operation of circuit breaker failure protection (CBFP).

• Also, the technical condition of the transformer as a business asset, and, accordingly, the equipment maintenance strategy (based on it) significantly affect the business operations of the electric power company [137].Therefore, the evaluation of the technical condition of power transformers is a major issue from a technical and economic point of view. The issue of evaluation of the technical condition of power transformers has been widely discussed in studies that can be classified according to the following degrees of methods shown in Table 4.

Table 4. Methods and techniques used in evaluating the condition of electrical transformers.

Method	Description	References

expert knowledge to weigh test results	It relies on the expertise of specialists in interpreting the results of various tests such as dissolved gas analysis, loading history, and thermal scanning. The test results are weighted by indicators determined by specialists based on their expertise. This method is one of the oldest methods and relies heavily on the personal experience of specialists.	[138,139]
conventional statistical approaches	Statistical tools are used to analyze transformer data and evaluate their condition. These tools include Bayesian analysis, regression, and hazard graphs. This approach makes it possible to investigate the connection between transformer age and damage.	[75,140,141]
fuzzy logic theory	Uncertainty in technical condition assessment data is addressed by it. Its foundation is a continuous membership function that represents the transformer's level of health and accepts values between 0 and 1. Damage to power transformers can be identified and categorized using this method.	[142–144]
reliability theory	used to investigate the likelihood that a transformer may fail within a given time frame. considers the transformer's state while it is being repaired. aids in choosing the right maintenance options	[145]
artificial intelligence methods	Transformer data is analyzed using machine learning methods like Support Vector Machines (SVM) and Artificial Neural Networks (ANN). This approach makes it possible to pinpoint underlying patterns in the data and accurately evaluate the technological state. Additionally, it is employed in the examination of dissolved gas in transformer oil.	[58,131,133,134,146–151]
health index (HI) table	It is predicted on a collection of indicators that assess various facets of the transformer's state. An overall transformer health score is calculated by adding the values of these indicators. This technique is used to evaluate the technical state fast and easily.	[152]
multi-feature factor analysis	It is employed to identify the elements that have the biggest impact on the transformer's technical state. To ascertain the relationship between many components, correlation analysis is the foundation. It facilitates comprehension of the reasons for transformer failure.	[153]
wavelet network analysis	Used to analyze transformer test data such as operating current and vibrations. Enables the identification of signal distortions that may indicate damage. Especially used in evaluating the condition of transformers in nuclear power plants.	[154]
thermal aging theory	Used to evaluate the effect of temperature on transformer life. Based on mathematical models to describe the thermal aging process. Helps in estimating the remaining life of the transformer.	[155]
mixed mathematical and expert approaches	Combines mathematical methods and specialized knowledge to assess technical conditions. Enables the use of the accuracy of mathematical models and the experience of specialists. Used to improve the accuracy of technical condition assessment.	[156]

Although useful, the transformer condition evaluation techniques outlined have some drawbacks. These include a lack of real-time analysis skills, a lack of integration with cutting-edge technologies like deep learning and the Internet of Things, and an inability to adequately account for the effects of operational and dynamic environmental elements like pollution, humidity, and the expanding usage of renewable energy sources. Future studies should focus on developing cost-benefit analysis models for maintenance optimization, integrating IoT sensors and time-series analysis for continuous data acquisition, integrating environmental factors into degradation models, adapting assessment methods for renewable energy integration, utilizing big data and deep learning for improved accuracy and predictive capabilities, creating dynamic assessment metrics that capture changing conditions, and integrating assessment methods with real-time predictive monitoring systems to enable proactive maintenance. By addressing these issues, transformer status evaluation will become much more effective, improving dependability, lowering maintenance costs, and extending operating lifespan.

10.2. Iot INTEGRATION

Distribution transformers play a vital role in power distribution networks, transporting electrical energy from generation stations to consumers. With the increasing demand for energy due to technological advancements, the power sector faces major challenges, the most important of which is the declining life of transformers as overload, overheating, and faults in the feeder lines significantly shorten the life of transformers. The difficulty of monitoring faults as traditional monitoring systems (SCADA) are limited in deployment, which hinders efficient detection of faults in the feeder lines [157]. To address these challenges, the research proposes an advanced IoT-based system to monitor the load of the distribution transformer and detect anomalies in real time. The system consists of a low-cost IoT gateway and a sensor unit which collects data on three-phase load current, oil levels/temperature from the transformer network [158]. Figure 16 Block diagram of distribution transformer monitoring system in an IoT network. The Isolation Forest algorithm is used to intelligently detect potential faults 24 hours before they occur. A mobile application that allows users to interact with the system, visualize the status of transformers in real time, and track them geographically. This system aims to reduce maintenance costs through accurate real-time monitoring. And predicting faults to avoid them and maintain service continuity.

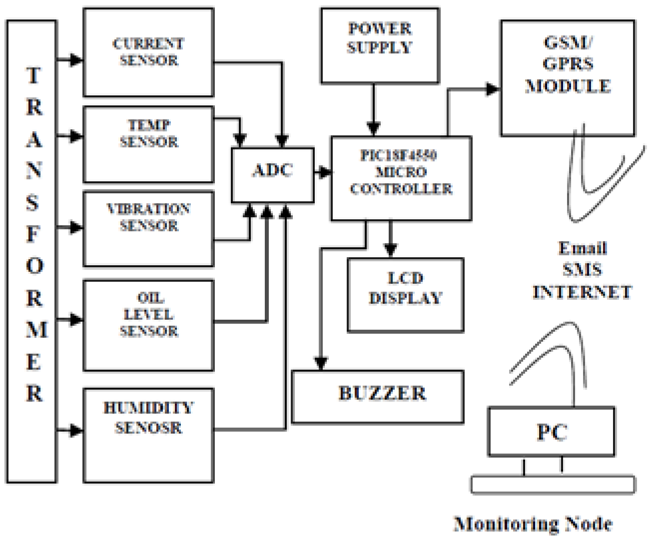

Figure 16. Block diagram of distribution transformer monitoring system in an IoT network [159].

A summary of the current work on transformer intelligent monitoring systems can be found in Table 5. and the image shows how data flows in the Internet of Things network are classified to make the process clearer [160]. It is described using two primary steps. and offers an overview of current research on smart transformer control and monitoring. Details about each paper are shown in the table, including its origin, use, execution, and constraints. The many approaches that have been developed for smart transformer monitoring and management can be compared and contrasted using this table. It can also assist you in recognizing the limitations of existing approaches, which can direct further study in this field. The table, for instance, demonstrates that a large number of existing approaches do not make use of machine learning or the Internet of Things. Furthermore, certain techniques don't offer real-time monitoring. When creating new techniques for smart transformer monitoring and management, this data can be utilized to pinpoint areas that want improvement. All things considered, it can be a useful tool for scholars who are interested in smart transformer management and monitoring. Understanding the state-of-the-art and pinpointing areas in need of development might be beneficial.

Table 5. Summary of current works in intelligent transformer monitoring systems with IoT Integration algorithm [62].

Monitoring system	Restrictions	Implementation	References
Monitoring transformers	without using IoT and machine learning	Measure voltage, current, power and temperature. Communicate with GSM modem to remote database server	[161]
Monitoring transformers using IoT	does not provide real-time monitoring	PIC microcontroller to interact with sensors and GPRS module to send readings	[160]
Transformer health monitoring	The system has not been tested in operational scenarios and does not use machine learning for fault detection.	GSM-based system integrated with PIC microcontroller to monitor load currents, overvoltages, transformer oil level and oil temperature	[162]
Monitoring transformer health using IoT	does not use machine learning to detect faults.	Monitoring transformer temperature, voltage and current. PIC microcontroller to interact with sensors and send data over GSM-enabled network	[163]
Monitoring and protection of IoT-based transformers	does not use machine learning to detect faults.	Monitoring of current, voltage, temperature and humidity data. Sensors are connected to a NodeMCU microcontroller. Buzzers, LEDs and a web application provide cost-effective and easy-to-use remote monitoring	[164]
Remote monitoring system for transformers	The system has not been tested in operational scenarios and does not use machine learning to detect faults.	A PIC microcontroller was used to interface temperature and oil level sensors. A power meter provided information on transformer load and a microphone was used to measure humming noise	[143]
Real-time monitoring and maintenance of distribution transformers based on IoT	The system has not been tested in operational scenarios and does not use machine learning for fault detection.	Monitoring of voltage, load current, temperature, and oil level by connecting sensors to ATMEGA328 microcontroller. The system uses MQTT for energy efficient and faster communication	[165]

While pointing out several shortcomings, such as the absence of IoT integration and real-time monitoring, the researcher's review of earlier research on smart transformer monitoring and management ignores a number of other important factors. Interestingly, the analysis ignores the limited application of machine learning in certain research for automated failure prediction and fault detection. Furthermore, it ignores the absence of real-world testing in operating settings, which casts doubt on the systems' performance and practical application. Additionally, the integration of other data sources, such as weather and energy usage data, which might greatly improve prediction accuracy, is not covered by the researcher. Additionally, the review ignores the crucial problem of security and privacy in IoT-based transformer monitoring systems, as well as the usability of user interfaces, which is a crucial component in user acceptance.

8.3. Big Data Analysis

The world is witnessing a massive transformation in the energy sector with the advent of “smart grids". Huge amounts of data are being collected at an unprecedented rate from a variety of sources such as smart meters, sensors, geographic information systems, and social media. This data is known as "big data" and is characterized by its enormous volume, variety, and varying speed [166]. Sources of big data in smart grids include smart meters that record energy consumption on a regular basis; phase measurement units (PMUs) that measure voltage and current with high accuracy; and sensors installed on grid equipment such as transformers. As shown in the Figure 17 [167].

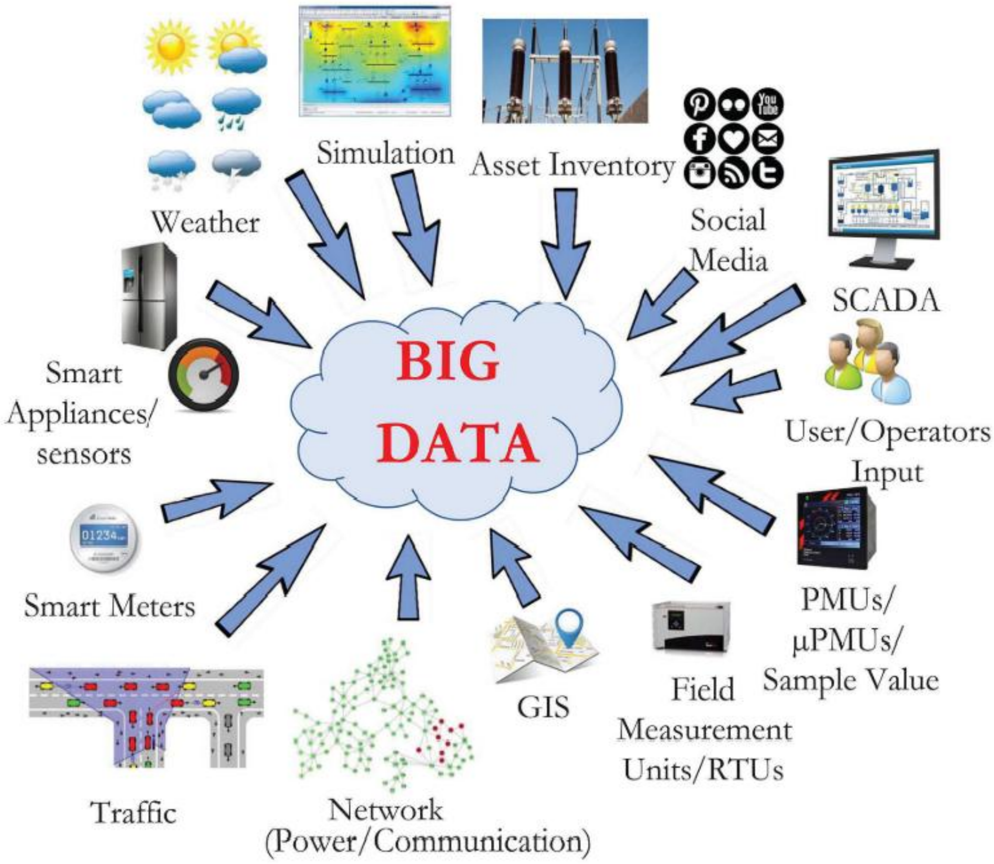

Figure 17. Sources of non-electrical and electrical big dataset in smart grids [158].

The characteristics of big data in smart grids are the massive size, where terabytes of data are collected annually. The diversity, where structured and unstructured data, synchronous and asynchronous. The speed: data is collected in real time and at varying speeds. The variability in accuracy may contain inconsistencies, duplications, and missing data [168]. The benefits of using big data in smart grids are in improving network monitoring. As shown in Figure 18 where it works to comprehensively understand network conditions, consumer behavior, and the availability of renewable energy. Making informed decisions in terms of extracting valuable information to make effective decisions in planning and operating networks. Improving network efficiency, where network assets, distributed energy resources, and energy consumption are controlled in real time. Developing new services by innovating customized services for consumers based on their data [169].

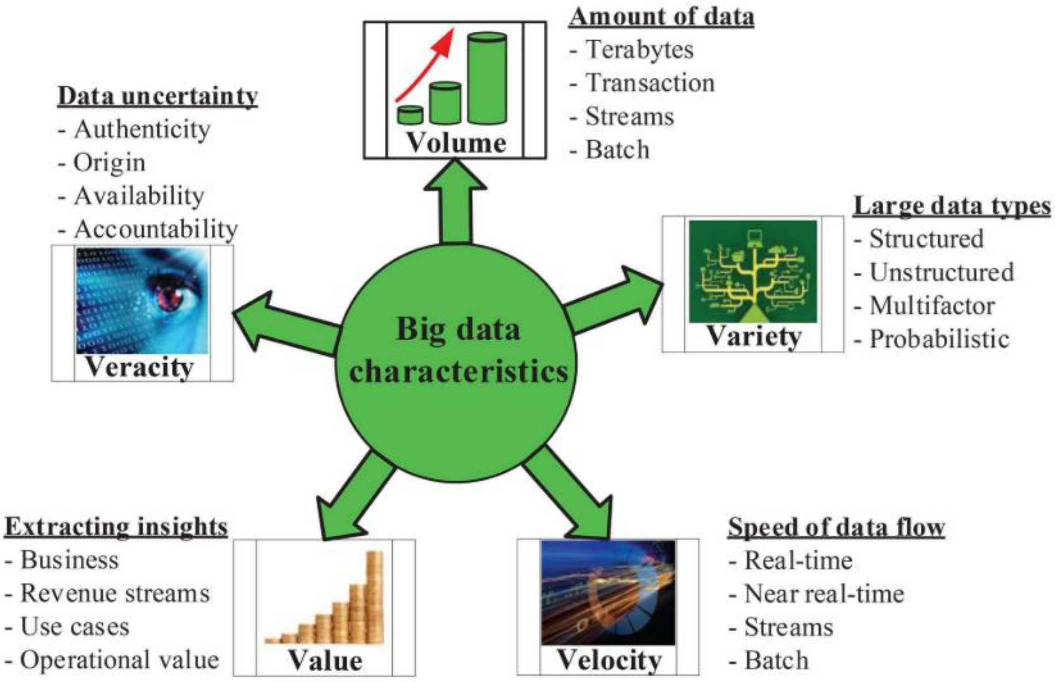

Figure 18. Key characteristics of smart grid big data [158].

Processing vast volumes of data, evaluating heterogeneous and varied data, and guaranteeing the data's quality and integrity are the difficulties it encounters. Big data is therefore a revolution in the field of smart grids since it makes it possible to increase network efficiency, aids in decision-making, and opens up new avenues for creativity. However, overcoming the difficulties of collecting and evaluating this data is necessary to maximize its potential [170].

10.4. Specific Models and Algorithms Applied in Fault Detection in Transformers

Transformers are one of the most important components of electrical transmission and distribution systems, and their design aims to accurately determine the dimensions of all their parts, to provide the manufacturer with the necessary data [171]. Transformers should be designed in a way that ensures their cost-effectiveness, light weight, small size, and high performance, while considering compliance with all international standards. Many researchers have used artificial intelligence techniques to improve transformer design and analyze their performance, but the true potential of these techniques has not yet been fully explored in this area. I will mention a brief review of research and development in the field of transformers, using many methods mentioned in scientific research, mentioning their references, advantages, disadvantages, and their category [172].

10.4.1. Artificial Neural Network (Ann)

An Artificial Neural Network (ANN) is a computational model inspired by the structure and function of the human brain. It consists of interconnected units called nodes or neurons, organized in layers (an input layer, one or more hidden layers, and an output layer). These networks are used in a variety of tasks, including pattern recognition and prediction. Table 6 shows a summary of this algorithm.

Table 6. shows a complete summary of the Artificial Neural Network (ANN) algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : Artificial intelligence methods			
Description: Artificial intelligence methods are Techniques that enable machines to mimic human intelligence.			
Category: Machine Learning References: [84,111,132,159,173–176]	Advantages: High ability to learn and adapt. Effective in solving classification and prediction problems. Able to handle non-linear and complex data.	Disadvantages: Difficulty understanding how it works and interpreting its results. Requires a large amount of data for training. May be overfitting if not trained properly.	Applications: Diagnose transformer faults using dissolved gas analysis (DGA). To predict the condition of transformers. Improve transformer efficiency.

10.4.2. Deep Learning (Dl)

Deep learning is a type of machine learning that uses complex artificial neural networks with multiple layers to process data and extract patterns. Deep learning is used in many applications, such as image recognition and natural language processing, and has the ability to achieve high-accuracy results. Table 7 shows a summary of this algorithm.

Table 7. shows a complete summary of the Artificial Deep Learning (DL) algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : Deep Learning (DL)			
Description: Mimicking the human brain's learning process to analyze complex data.			
Category: Machine Learning References: [107,158,164,169,177,178]	Advantages: It can manage enormous volumes of data. It achieves high accuracy in classification and prediction. It can extract features automatically.	Disadvantages: Requires significant computing resources. Difficult to understand and interpret. May be subject to over-specialization.	Applications: Image classification for transformer fault detection. Analysis of audio signals for fault detection. Prediction of transformer status.

10.4.3. Particle Swarm Optimization (Pso)

Particle Swarm Optimization (PSO) is an optimization algorithm inspired by the social behavior of birds or fish in a flock. A set of particles search the search space for the best solution to a problem by adjusting their positions and velocities based on the best position found by each particle and the best position found by the entire swarm. This algorithm is used in a variety of applications, such as optimizing mathematical functions and training neural networks. Table 8 shows a summary of this algorithm.

Table 8. shows a complete summary of the Particle Swarm Optimization (PSO) algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : Particle Swarm Optimization (PSO)			
Description: Particle Swarm Optimization Mimicking bird flocking behavior to find optimal solutions.			
Category: Optimization Algorithm References: [157,165,178–180]	Advantages: Easy to implement. Effective in finding optimal solutions in large search spaces. Can handle complex, non-linear problems.	Disadvantages: You may stumble upon local optimal solutions. It may be slow at times. You need to adjust many parameters.	Applications: Image classification for transformer fault detection. Analysis of audio signals for fault detection. Prediction of transformer status.

10.4.4. FUZZY LOGIC (FL)

Fuzzy logic is an approach to computing based on "degrees of truth" rather than the usual "true or false" in traditional logic. This approach allows the representation of vague or imprecise concepts, such as "tall" or "short," and deals with them in a flexible way. Fuzzy logic is used in a variety of applications, including control systems, robotics, and artificial intelligence. Table 9 shows a summary of this algorithm.

Table 9. shows a complete summary of the Fuzzy Logic (FL) algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : Fuzzy Logic (FL)			
Description: Fuzzy Logic Representing imprecise knowledge, like dealing with concepts such as "tall" or "short".			
Category: Knowledge-Based System References: [147,181–184]	Advantages: Can handle ambiguous and imprecise information. Easy to understand and interpret. Effective in solving control and decision-making problems.	Disadvantages: Fuzzy rules may be difficult to design. May be less accurate than other methods. Relies on expert experience.	Applications: Diagnosis of transformer faults using DGA. Control of transformer temperature. Protection of transformers from faults.

10.4.5. Hybrid Methods

Hybrid methods in computer science combine two or more artificial intelligence techniques, such as neural networks and fuzzy logic or genetic algorithms, to take advantage of the strengths of each technique and overcome its weaknesses. These methods are used to improve the performance of intelligent systems in a variety of applications, such as data analysis, automatic control, and decision making. Table 10 shows a summary of this algorithm.

Table 10. shows a complete summary of the Hybrid methods algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : Hybrid Systems			
Description: Hybrid Systems: Combining different approaches for a more robust and effective system.			
Category: Combining two or more computational intelligence methods. References: [63,108,185]	Advantages: Combines the advantages of different methods. Improves the accuracy and efficiency of diagnosis.	Disadvantages: May be complex to design and implement. Requires more computing resources.	Applications: Combining ANN and FL to improve transformer fault diagnosis accuracy. Combining PSO and SVM to improve the efficiency of classification algorithms.

10.4.6. Expert Systems (Es)

Expert systems are computer programs that emulate the decision-making process of a human expert in a particular field. These systems store knowledge and experience in a database and use logical inference mechanisms to reach conclusions and make recommendations based on available information. Expert systems are used in a variety of fields, such as medical diagnosis, financial analysis, and industrial process control. Table 11 shows a summary of this algorithm.

Table 11. shows a complete summary of the Expert Systems (ES) algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : Expert systems			
Description: Expert Systems Computer programs that mimic human expertise in a specific field.			
Category: Knowledge-Based System References: [186–188]	Advantages: Simulates the expertise of human experts. Effective in solving complex problems that are difficult to model.	Disadvantages: You need a comprehensive knowledge base. It can be expensive to develop and maintain.	Applications: Diagnose transformer faults based on rules derived from experts. Provide recommendations for transformer maintenance.

8.4.7. Wavelet Neural Network (Wnn)

A Wavelet Neural Network (WNN) is a type of artificial neural network that combines the advantages of wavelet analysis and neural networks. These networks use wavelet functions as activation functions for neurons, allowing them to efficiently analyze signals in both the frequency and time domains. Wavelet neural networks are used in various applications, such as image processing, pattern recognition, and time series prediction. Table 12 shows a summary of this algorithm.

Table 12. shows a complete summary of the Wavelet Neural Network (WNN) algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : Wavelet Neural Network (WNN)			
Description: Wavelet Neural Network Combining Wavelet networks with neural networks for data analysis.			
Category: Neural Networks	Advantages:	Disadvantages:	Applications:
References: [189–191]	Effective in signal processing. Can extract information from time and frequency domains.	It can be complex to design. You need to adjust many parameters.	Analysis of vibration signals to detect transformer faults. Analysis of current signals to detect faults.

10.4.8. Artificial Immune System (Ais)

An Artificial Immune System (AIS) is a type of artificial intelligence system inspired by the principles of the immune system in living organisms. This system uses processes such as pattern recognition, learning, and adaptation to face challenges and solve problems in changing environments. AIS systems are used in applications such as security intrusion detection and fault diagnosis. Table 13 shows a summary of this algorithm.

Table 13. shows a complete summary of the Artificial Immune System (AIS) algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : Artificial Immune System (AIS)			
Description: Artificial Immune System Inspired by the human immune system to solve computational problems.			
Category: Evolutionary Computing	Advantages:	Disadvantages:	Applications:
References: [192–195]	Able to learn and adapt to changing environments. Able to detect abnormal patterns.	It can be complex to implement. It requires tuning many parameters.	Detect transformer faults based on system behavior. Predict transformer status.

10.4.9. Genetic Algorithm Approach

A genetic algorithm is a search method inspired by the process of natural selection in biology. It is based on the principle of "survival of the fittest," where a set of possible solutions is created, and the best solutions are selected from among them based on their suitability to solve the problem. These solutions are used to create a new generation of solutions through processes such as "crossover" and "mutation." Genetic algorithms are used in a variety of applications, such as improving engineering design, scheduling tasks, and solving complex optimization problems. (Table 14) shows a summary of this algorithm.

Table 14. shows a complete summary of the Genetic algorithm approach algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : GA Genetic Algorithm			
Description: Genetic Algorithm Mimicking the natural selection process to find optimal solutions.			
Category: Search-Based References: [60,175,196–198]	Advantages: It has global search capability.Average accuracy is within 80%-90%.	Disadvantages: Poor local search ability .Easily shows early convergence phenomenon .Easily falls into the local optimal solution Time consuming.	Applications: Works with diagnostic techniques dissolved gas analysis, frequency response analysis and differential protection.

10.4.10. Gene Expression Programming (Gep)

Gene expression programming (GEP) is an evolutionary algorithm used to find solutions to complex problems. This algorithm combines the advantages of genetic algorithms and expression programming, where solutions are represented as fixed-length linear chromosomes and are transformed into nonlinear expression trees of different sizes and shapes. This algorithm is used in various fields, such as data analysis, prediction, and modeling. Table 15 shows a summary of this algorithm.

Table 15. shows a complete summary of the Gene expression programming (GEP) algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : Gene Expression Programming (GEP)			
Description: Gene Expression Programming An evolutionary algorithm used for knowledge discovery and performance optimization.			
Category: Evolutionary Computing References: [52,199]	Advantages: Effective in finding optimal solutions to complex problems.Able to handle non-linear data.	Disadvantages: It can be expensive in terms of time and computing resources.You need to adjust many parameters.	Applications: Optimize ANN and FL parameters. Design of controllers for transformers.

10.4.11. ADAPTIVE NEURAL FUZZY INFERENCE SYSTEM (ANFIS)

Adaptive Neural Fuzzy Inference System (ANFIS) is a type of hybrid artificial intelligence system that combines the advantages of artificial neural networks and fuzzy logic. This system uses fuzzy "if-then" rules to represent knowledge and adjusts the parameters of these rules using learning algorithms in neural networks. ANFIS is used in a variety of applications, such as controlling industrial processes, financial forecasting, and medical diagnosis. (Table 16) shows a summary of this algorithm.

Table 16. shows a complete summary of the Adaptive Neural Fuzzy Inference System (ANFIS) algorithm in terms of category, references, description, advantages, disadvantages, and applications.

Method : ANFIS Adaptive Neuro-Fuzzy Inference System			
Description: Adaptive Neuro-Fuzzy Inference System Integrating neural networks with fuzzy logic for enhanced performance.			
Category: Knowledge Based Network References: [9,15,200–202]	Advantages: Excellent at identifying fuzzy relationships. Membership functions and fuzzy rules can be obtained and modified automatically. No predefined fixed weights are needed for input parameters.	Disadvantages: The ability to extract detailed information will become less when the number of nodes and fuzzy rules increases greatly..	Applications: Works with diagnostic techniques dissolved gas analysis, infrared thermography and degree of polymerization.

10.3.12. SUPPORT VECTOR MACHINE (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression. It aims to find the best linear (or non-linear using the "kernel trick") separator that separates data classes with the largest possible margin. SVM is used in a variety of applications, such as image recognition, text analysis, and prediction. Table 17 shows a summary of this algorithm.

Table 17. shows a complete summary of the Support Vector Machine (SVM) algorithm in terms of category, references, description, advantages, disadvantages, and applications [65].

Method : SVM Support Vector Machine			
Description: Support Vector Machine: An algorithm used for classifying data and separating it into groups.			
Category: Data-Driven References: [54,203–205]	Advantages: It has excellent generalization ability. It achieves satisfactory classification results when the training data is small. The dimension of the classified vectors has no distinctive effects, and it is suitable for application in faulty classification.	Disadvantages: It is difficult to determine the important parameters of SVM.	Applications: Works with diagnostic techniques dissolved gas analysis, frequency response analysis (offline), frequency response analysis (online), polarization current, depolarization and differential protection.

In these Specific models and algorithms applied in fault detection in transformers, the authors summarize the advantages and disadvantages algorithms supported by power transformers applications references. In the advantages, the authors indicate that algorithms have an excellent average accuracy rate between 85% and 95% in most applications. However, they did not mention the exact accuracy rate achieved in each of the applications listed in the applications column. In the disadvantage's column, the authors mention that algorithms have difficulty in determining network structures and parameters, but they did not specify which network structures and parameters are difficult to determine.

9. Case Studies and Applications

The cases mentioned in the practical research and in the field of diagnosis and prediction were studied and reviewed, and scientific publications on smart systems were distributed from 2010 to 2021. It was found that what was worked on and researched in the field of electrical transformers, their faults and their diagnosis with smart systems is shown in Figure 18. which shows publications of different smart confrontation system for power transformer fault diagnosis from 2010–2021 [141]. Figure 18 provides a valuable overview of the relative distribution of publications concerning Intelligent Monitoring Systems methods for transformer condition assessment between 2010 and 2021. The figure effectively illustrates the dominance of Artificial Neural Networks (ANN) as the most widely used model in this domain, highlighting its significance in the field. This visual representation not only allows researchers to quickly grasp the current trends in transformer condition assessment using Intelligent Monitoring Systems but also underscores the need for further exploration and development of other promising methods, such as Deep Learning (DL), Fuzzy Logic (FL), and Support Vector Machines (SVM), to advance the field further.

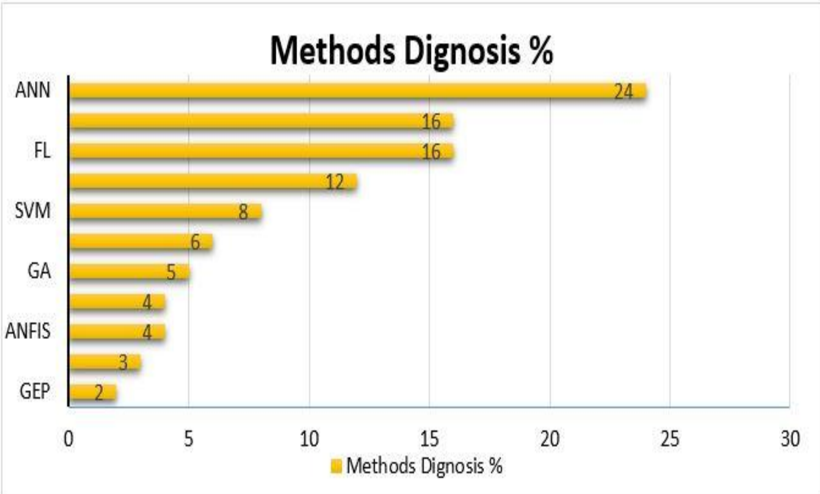

Figure 18. publications of different smart confrontation system for power transformer fault diagnosis from 2010–2021.

In general, the figure indicates a growing interest in using Intelligent Monitoring Systems to diagnose power transformer faults, with Artificial Neural Networks (ANN) being the most widely used method in this field. The following figures illustrate the applications of various traditional methods in conjunction with studies using Artificial Neural Networks. Figure 19 Shows the distribution of applications of different traditional diagnostic methods in studies using Artificial Neural Networks.

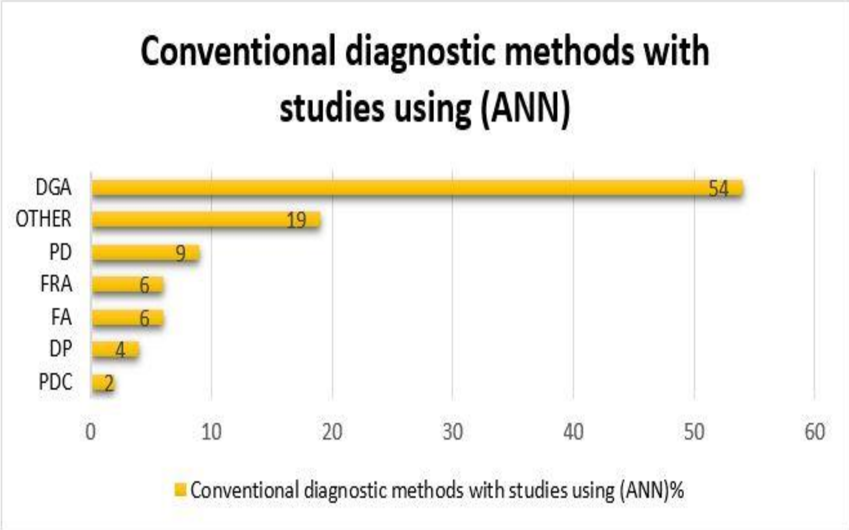

Figure 19. Various traditional diagnostic applications in conjunction with studies using artificial neural networks.

Applications of traditional methods with ANN: The graph shows that 54% of studies using ANN focus on dissolved gas analysis (DGA), while 16% focus on frequency response analysis (FRA), 9% focus on partial discharge analysis (PD), 6% focus on furan analysis (FA), 3% focus on polarization and depolarization current measurement (PDC), and 19% of studies address other applications. As for the other algorithm, Figure 20 Various traditional diagnostic applications in conjunction with studies using PSO.

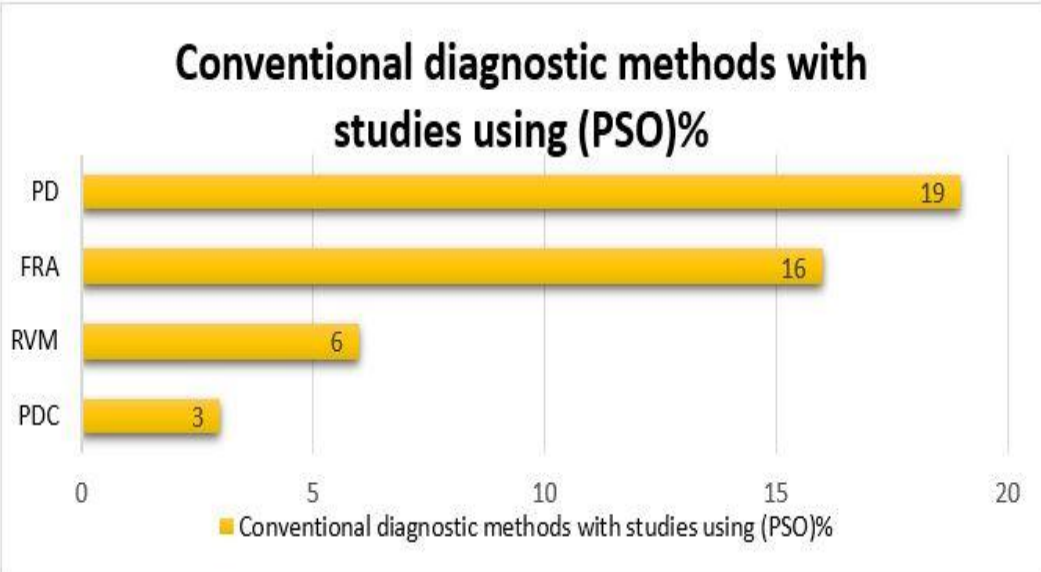

Figure 20. Various traditional diagnostic applications in conjunction with studies using PSO.

Applications of traditional methods with PSO: The graph shows that 34% of studies using PSO focus on DGA, while 22% focus on FRA, 19% focus on PD, and 22% address other applications. As for the other algorithm, Figure 21 Various traditional diagnostic applications in conjunction with studies using FL.

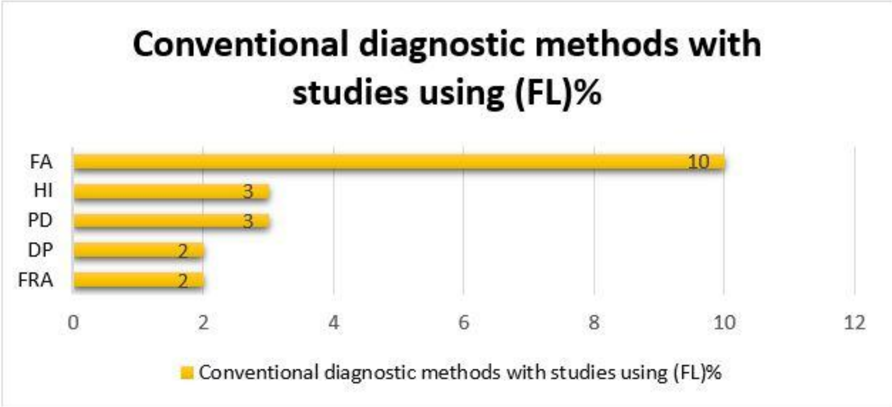

Figure 21. Various traditional diagnostic applications in conjunction with studies using FL.

Applications of traditional methods with FL: The graph shows that 63% of studies using FL focus on DGA, while 10% focus on FA, 2% focus on FRA, 2% focus on PD, 3% focus on health index (HI), and 17% address other applications. As for the other algorithm, Figure 22 Various traditional diagnostic applications in conjunction with studies using DL.

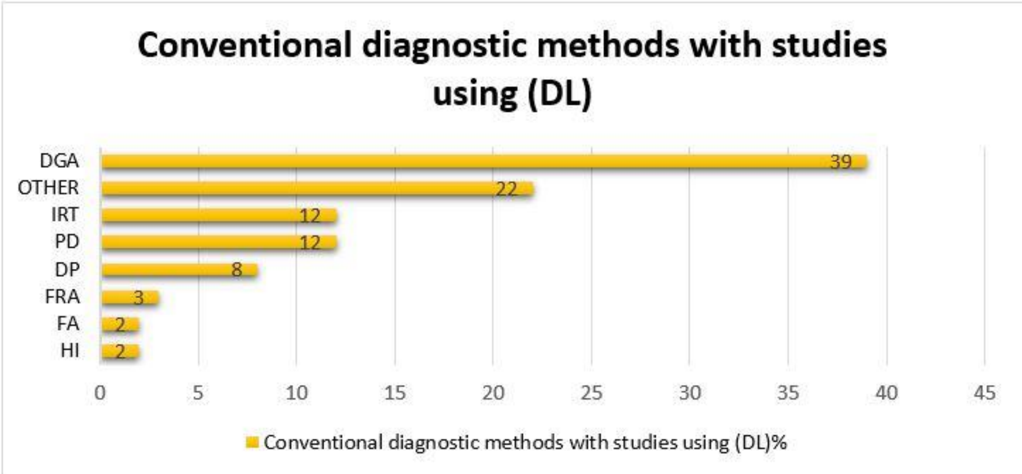

Figure 22. Various traditional diagnostic applications in conjunction with studies using DL.

Applications of traditional methods with DL: The graph shows that 39% of studies using DL focus on DGA, while 12% focus on infrared thermography (IRT), 12% focus on PD, and 22% address other applications. In general, the figure shows that DGA is the most common application of conventional methods with all smart confrontation systems.

10. Summary and Future Work

Among the most frequent transformer malfunctions are insulation failure and winding distortion. Short-circuit forces cause mechanical breakdowns in the windings, while thermal, electrical, chemical, and mechanical stressors cause insulation to deteriorate. In this instance, various traditional diagnostic techniques, such frequency response analysis (FRA) and dissolved gas analysis (DGA), are employed to identify these issues. Dissolved Gas Analysis (DGA) uses specific dissolved gases in transformer oil to identify electrical and thermal faults of different intensities, normal aging, and partial discharge of low and high energy density. With this technique, a sample of transformer oil is taken, the gases are extracted, and the extracted gas mixture is subjected to gas chromatography analysis.

Conversely, Frequency Response Analysis (FRA) determines the transformer windings' mechanical condition. By injecting a signal into one of the transformer's terminals, a reference signal for the FRA computation is created that is measured in relation to the ground (the transformer's tank). Transformer malfunction diagnostics has made extensive use of Intelligent Monitoring System techniques. Fuzzy Logic (FL) and Artificial Neural Networks (ANN) are two of the most used techniques. While fuzzy logic is utilized to handle ambiguous and imprecise information pertaining to input values for additional mathematical analysis and inference, artificial neural networks are used to learn the relationship between physicochemical data and DGA chromatographic analysis.

It is anticipated that intelligent monitoring systems will become more crucial in the identification of transformer faults. By examining large amounts of data from many sources, such as DGA and FRA, these methods can detect potential transformer failures early on. This can improve transformer dependability and efficiency while reducing maintenance costs. Moreover, intelligent monitoring systems can be used to create real-time transformer monitoring systems that facilitate prompt fault detection and identification even while the transformer is in operation. By using Intelligent Monitoring Systems, transformer owners and operators can significantly improve the performance and maintenance of their assets. This study demonstrates significant advancements in transformer failure management by examining advanced data-driven strategies, hybrid algorithms, and predictive maintenance techniques.

Issues including data accessibility, model interpretability, and IoT technology's interface with existing systems continue to impede widespread implementation. Addressing these problems will improve the accuracy and scalability of intelligent models while strengthening their ability to handle missing or inconsistent input. Future research must focus on developing robust frameworks and transparent, interpretable models to combine IoT systems with intelligent algorithms. Such programs can significantly reduce maintenance costs, extend transformer lifespans, and improve the overall resilience of electrical networks. By addressing existing gaps, intelligent monitoring systems can transform fault management and pave the way for a more reliable and efficient power system architecture.

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CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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An integrated approach to evaluate the performance of psychiatric hospitals with the spotlight of ergonomics and job satisfaction

Zahra Hamdi [1], Fateme Ataei [1], Zahra Mohammadnazari [2*], Fariborz Jolai [1]

[1] School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran,
ORCID No: https://orcid.org/0009-0005-8596-2149
ORCID No: https://orcid.org/0000-0002-4251-999X
ORCID No: https://orcid.org/0000-0003-0824-8513
[2] School of Strategy and Leadership, Faculty of Business and Law, Coventry University, United Kingdom, CV1 5FB
ORCID No: https://orcid.org/0000-0003-0214-8394

Keywords

Performance evaluation, Data envelopment analysis, Artificial neural network, psychiatric hospitals, Ergonomics, Job satisfaction

Abstract

This study evaluates the performance of psychiatric hospitals during the Covid-19 pandemic by integrating macro- and micro-ergonomics with job satisfaction indicators. An efficiency assessment framework was developed using Data Envelopment Analysis (DEA), enhanced by noise analysis to improve accuracy. To gather relevant data, a structured 44-item questionnaire was distributed among staff members, resulting in responses from 61employees across three major psychiatric hospitals in Tehran. The DEA results were further validated using an Artificial Neural Network (ANN), specifically a Multilayer Perceptron (MLP), ensuring the robustness of the findings. The analysis revealed that Hospital 3 was the most efficient, while Hospital 1 had the lowest efficiency score. Sensitivity analysis highlighted "Information and Communication Systems" and "Physical Conditions" as key areas needing improvement across all hospitals. A significant correlation between the DEA and ANN results (Spearman coefficient = 0.716) confirmed the reliability of the evaluation framework. The study presents a novel and validated approach for assessing hospital performance, particularly under crisis conditions such as pandemics. Its findings provide hospital administrators with valuable insights for identifying performance gaps and implementing targeted improvements in ergonomics and job satisfaction to enhance overall healthcare service delivery during emergencies.

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1. Introduction

Health care systems are complex configurations that provide patients' primary, secondary, and tertiary care (Lin, Rouse, Wang, Lin, & Zheng, 2023).

* Resp author; e-mail: ad8993@coventry.ac.uk

Rising healthcare costs have made it essential to manage staff performance effectively, deliver quality services, and enhance system efficiency (Al-Refaie, Fouad, Li, & Shurrab, 2014; Sarıhan, 2024). One of the pillars of health care systems are psychiatric hospitals specializing in treating severe mental disorders such as schizophrenia, bipolar disorder, and major depressive disorder. The Covid-19 pandemic since 2020 has affected the provision of psychiatric care services worldwide (Bojdani et al., 2020). Ergonomic principles are increasingly recognized in global healthcare systems as essential tools for improving both patient outcomes and staff efficiency. For instance, Kwon, Jung, You, and Kim (2009) argued that integrating ergonomics into organizational strategy fosters sustainable performance. Similarly, Carayon et al. (2006) emphasized the systems approach in human factors engineering for patient safety, suggesting that poor work design often leads to avoidable medical errors. Cui, Wang, and Wang (2020), in China, introduced the challenges that Covid-19 has created for the provision of psychiatric services and provided solutions for them. They showed that the treatment of patients with mental disorders has been difficult for various reasons during the epidemic period, and public hospitals cannot meet the needs of such patients. Byrne, Barber, and Lim (2021) showed that Covid-19 has caused an increase in the prevalence of mental illnesses among people without a history of illness, the deterioration of the condition of patients with mental disorders, as well as an increase in stress and pressure caused by work in mental health services.

As a result, considering the increase in demand for psychiatric services and the negative impact of the Covid-19 epidemic on the performance of psychiatric hospital employees, for the proper effectiveness of psychiatric services, paying attention to the factors affecting the performance and efficiency of the employees of these hospitals becomes very important(Yaesoubi et al., 2023). We will introduce these influential factors and review the studies in the following. “Ergonomics (or human factors) is concerned with the understanding of interactions among humans and other elements of a system, in order to optimize human well-being and overall system performance.” (IEA Council, 2000). Ergonomics are examined in two areas: macro ergonomics and micro ergonomics. Micro Ergonomic considers those factors of machine, design and work posture that affect the user interface and working conditions related to the job or task design. In a macro ergonomics study, ergonomic factors are considered in parallel to organizational and managerial aspects of working conditions in the context of a total system design. Moreover, it attempts to create an equilibrium between, the organization, operators and machines. It focuses on total "people-technology" systems and is concerned with the impacts of technological systems on organizational, managerial and personnel subsystems (M. Azadeh et al., 2000; Lim & D'Souza, 2020; Zhang, Li, & Tian, 2023). Many studies have been done on the impact of ergonomics on performance of systems. Pearce, Mutlu, Shah, and Radwin (2018) propose an optimization framework that generates tasks and schedules for a human-robot team to improve time and ergonomics. Using the strain index method to quantify human physical stress, they create a set of solutions with the priorities set for each goal. Christy (2019) discusses the importance of employee engagement for organizational and business performance through the prism of ergonomics and finally concludes that macro ergonomics plays an important role in today's work culture to strengthen employee engagement and it is very important to retain employees and make profits. Recent studies have shown that hospital efficiency metrics vary significantly across countries due to differing healthcare policies and management structures.

Stock, Redaelli, and Lauterbach (2007) used DEA to assess public hospitals in Greece and found that non-financial factors such as staff satisfaction and resource allocation play critical roles in performance. In another international study, Hollingsworth (2008) systematically reviewed efficiency measurement in healthcare and highlighted the global trend toward incorporating both quantitative and qualitative performance indicators.

A. Azadeh, Haghighi, Gaeini, and Shabanpour (2016) improved an approach, analyzing the impact of macro ergonomics factors in the healthcare supply chain (HCSC) by DEA. According to results by SA, the most effective factor was "teamwork". Fan et al. (2014) evaluated task Performance and surgical ergonomics with simulated surgical tasks. The endo-surgical simulator was set on surgeons and measuring Ergonomics Parameters showed The EMG range accrued from shoulders and left lumber, fatigue from muscles, and loading between feet were more balanced. Mazzoni et al. (2018) Developed the Human Performance and Productivity Cycle (HPC) technique to enhance the overall performance of a wagon workshop. Principles of ergonomics, technical knowledge, and adequate human Performance had been viewed as well. Ahmed, Irshad, Demirel, and Tumer (2019) applied virtual reality, computer-aided design, and human subjects to filter design ideas Proposing an ergonomic approach. The evaluation between the full computational and VR Prototypes was executed in designing the cockpit of Boeing 767. Rothmore, Aylward, and Karnon (2014) searched “OvidSP” journal’s database for Papers utilizing the strategy and quality assessment approach. Results reveal that ergonomics' value is moderate and concentrated on the financial impact of employers. Faez, Zakerian, Azam, Hancock, and Rosecrance (2021) evaluated the ergonomic climate in two power plants and examine its association with self-reported pain, performance and well-being. Finally, it was concluded that this issue can become the baseline for prioritizing the values of organizations and finding ways to improve the organization's performance and the employees' health. Colim et al. (2021) analyzed the industrial implementation of a collaborative robotic workstation for assembly tasks performed by workers with musculoskeletal complaints through the synergistic integration of principles of ergonomics, human factors, and lean manufacturing. The results showed that the hybrid workstations achieved a reduction of production times, an improvement of ergonomic conditions and an enhancement of workers’ wellbeing. Also, many studies have been conducted on performance evaluation based on ergonomics and other indicators.

Zarrin and Azadeh (2019), evaluated the impacts of Resilience Engineering (RE) principles on integrated health, safety, environment, and ergonomics (HSEE) management system in the petrochemical industry. They used a novel Z-number cognitive map approach, combining the concept of Z numbers and fuzzy cognitive map (FCM) approach. Zeinalnezhada et al. (2018) studied the implementation of health, safety, Environment, and ergonomics management systems (HSEEMS) in the supply chain. A. Azadeh and Sheikhalishahi (2015), presented a unique framework for optimizing the performance of generation companies based on health, safety, environment and ergonomics (HSEE) indicators. Performance evaluation and ranking have been done by combining data envelopment analysis (DEA), principal component analysis (PCA) and Taguchi methods. A. Azadeh, Fam, Khoshnoud, and Nikafrouz (2008), designed a fuzzy expert system for performance evaluation based on health, safety, environment (HSE) and ergonomic system indicators in a gas refinery. Also, some studies investigated the impact of ergonomics on healthcare systems in the era before or after Covid-19 .Salmon, Stevens, McLean, Hulme, and Read (2021), argue that systems human factors and ergonomics methods can help to understand and optimize the return from Covid-19 lockdown. They used domain analysis to develop an abstract hierarchical model of a generic " return from lockdown restrictions " system to demonstrate this. Rodríguez and Hignett (2021) present a model for integrating human factors/ergonomics (HFE) into healthcare systems to make them stronger and more resilient during and after the Covid-19 pandemic and play an important role in improving safety and increasing the effectiveness of healthcare services. This new model recognizes the interrelationship between HFE and other system properties such as capacity, coverage, robustness, integrity, and resilience. Norris, West, Anderson, Davey, and Brodie (2014) utilized a multi-disciplinary approach totally based on ergonomics to create safer healthcare. Dennerlein et al. (2020)provide an integrated Total Worker Health (TWH) approach, which includes key human factors and ergonomic principles, to support the safety, health and well-being of workers during the Covid-19 pandemic, using a theoretical framework and guidelines for integrating safety and health management systems into an organization. Researches like A. Azadeh and Zarrin (2016), have shown that the application of ergonomics in designing systems has a positive effect on enriching productivity and job satisfaction. Locke (1976) described job satisfaction as "a pleasurable or positive emotional state resulting from the appraisal of one's job or job experiences". Studies show that by increasing job satisfaction, the motivation of employees and as a result, their performance and the organization's efficiency improves (Sapta, MUAFI, & SETINI, 2021). A. Azadeh, Yazdanparast, Zadeh, and Keramati (2018), evaluated and analyzed Resilience Engineering (RE), job satisfaction, and patient satisfaction with Data Envelopment Analysis (DEA) and two artificial neural network algorithms in one of Tehran's emergency departments. This study aimed to determine the strengths, weaknesses and opportunities to improve safety, performance, and satisfaction of employees and patients. Job satisfaction is widely acknowledged as a determinant of organizational health across sectors. Herzberg's two-factor theory, though initially developed in the 1950s, still guides contemporary workforce research globally. In a study of nurses in South Africa, Pillay (2009) found that intrinsic factors such as recognition and role clarity contributed more to job satisfaction than extrinsic factors like salary.

A cross-national survey by Lu, Barriball, Zhang, and While (2012) further established that job satisfaction correlates strongly with retention rates among healthcare workers in Asia and Europe. Many researchers have studied employee performance assessment and job satisfaction based on ergonomics. A. Azadeh, Rouzbahman, Saberi, and Fam (2011) evaluated and improved the job satisfaction of operators of a gas refinery based on health, safety, environment and ergonomic indicators with Artificial Neural Network (ANN) algorithm. Yarandi, Shaafi, and Golabchi (2020) studied the effect of workplace ergonomics on Project staff of Iranian gas engineering and development organization's job satisfaction. Workplace ergonomics were measured with the aid of survey method. Ramos-García et al. (2022) confirmed the influence of ergonomic factors on job satisfaction by way of offering a structural equation model during the SARS-CoV-2 pandemic. The method was applied to university workers, using a job satisfaction–occupational health questionnaire. Rahman, Hossain, and Khan (2022) collected data using Likert's Five Point Scale and proved the relationship between ergonomics and bank employee satisfaction in the workplace using Pearson Correlation Matrix. In a comparative study of ergonomic interventions across Brazil and Germany, Da Costa and Vieira (2010) found that participatory ergonomics consistently resulted in higher satisfaction and fewer musculoskeletal complaints. This aligns with global trends emphasizing worker involvement in redesigning workflows to reduce physical and cognitive strain. As the tasks of nursing have increased over the years, Kumari and Kaur (2019) used a subjective scale to determine job satisfaction level among nurses besides measuring the degree of relationship between ergonomic factors and nurses' job satisfaction through Spearman's rank correlation coefficient. Suitable occupational footwear selection balances occupational satisfaction. Henriques-Thompson (2022) studied Hospital Healthcare Workers (HHCW) in the US to determine healthcare workers' modest ergonomic load-bearing working conditions. Saad and Ebraheem (2019) aimed to study ergonomics and investigated a descriptive-analytical cross-sectional design and, data was collected by ergonomics and job satisfaction evaluation questionnaire. Kazemzadeh et al. (2011) used Nordic Musculoskeletal questionnaire (NMQ) and General Health questionnaire (GHQ28) In order to maximize health gratification and job satisfaction, concerning nursing staff. Ikonne (2014) investigated the influence of workstation and work situation ergonomics on job satisfaction. Librarians were included in the survey research that operated the total enumeration technique. Hence, health and safety systems require a constant and systematic effort to achieve long-term success. Although many studies have examined ergonomics and job satisfaction in general hospitals, little attention has been given to other types of healthcare facilities, such as psychiatric hospitals. None of the literature we reviewed has used macro and micro ergonomic indicators to perform the mentioned assessment. Due to the spread of the coronavirus and the possibility of new pandemics, the importance of properly performing these hospitals' staff becomes more critical. Many people are suffering from the loss of their loved ones, the amount of anxiety in life has raised, and psychiatry disease such as obsessive-compulsive disorder has been seen more prevalent. Therefore, the workload in many psychiatry hospitals has increased.

In this study, we will examine the performance evaluation and ranking of psychiatric hospitals, in addition to the psychiatric hospital staff's job satisfaction based on macro and micro ergonomic indicators. The method used and validated in this research is data envelopment analysis (DEA). Since we are pursuing our objectives considering the Covid-19 pandemic, our study is different from other researches. In other words, our study is the only study that evaluates the performance of psychiatric hospital employees with the DEA method during the Covid-19 pandemic and the high work pressure of psychiatric hospitals due to the negative consequences of this pandemic on the mental state of people and carefully examines the suitability of their work system with the principles of macro and micro ergonomics, as well as their job satisfaction.

1.1 AI and hospital performance

Hospital performance assessment plays a crucial role in optimizing healthcare delivery and resource allocation (Kahya & Oral, 2018). Traditionally, performance evaluation relied on static metrics and manual analyses, which often lacked precision and efficiency. The integration of AI and ANN into this process introduces a paradigm shift, allowing for dynamic, data-driven assessments that can adapt to the complexities of modern healthcare systems.

AI, as a broad field, encompasses various technologies such as machine learning, natural language processing, and computer vision. In the context of hospital performance assessment, AI applications are designed to analyze vast datasets, identify patterns, and provide actionable insights. Machine learning algorithms can process clinical and administrative data to predict patient outcomes, assess resource utilization, and optimize operational workflows(Savulescu & Polkowski, 2017). AI-driven performance assessment tools enable hospitals to move beyond traditional metrics and consider a broader spectrum of factors influencing performance. For instance, predictive modeling can forecast patient admission rates, enabling proactive resource allocation and improved patient flow management. Additionally, AI can aid in identifying potential areas for cost reduction and enhancing overall financial performance. ANN inspired by the human brain's neural structure, excel in recognizing complex patterns within large datasets. ANNs have proven effective in analyzing healthcare data, facilitating accurate predictions and decision-making. In hospital performance assessment, ANNs can be employed to model intricate relationships between various performance indicators, enabling a more holistic understanding of hospital dynamics(Read, Pfahringer, Holmes, & Frank, 2021).

The adaptability of ANNs allows for real-time analysis, accommodating the dynamic nature of healthcare systems. By considering interdependencies between variables, ANNs contribute to a more nuanced evaluation of hospital performance, going beyond isolated metrics to offer a comprehensive assessment of the healthcare ecosystem. As technology continues to evolve, the future of hospital performance assessment lies in the synergistic integration of AI and ANN with other emerging technologies such as blockchain and Internet of Things (IoT). Collaborative efforts among healthcare stakeholders, researchers, and technology developers are essential to creating robust, ethical, and effective systems for performance evaluation. The landscape of healthcare performance assessment has traditionally been dominated by studies focusing on general hospitals, often delving into specific facets such as ergonomics or job satisfaction indicators(Araujo, Wanke, & Siqueira, 2018; Lisboa, 2002; Saul & Rostami, 2022). However, this research contributes significantly to the academic discourse by introducing a comprehensive framework that considers both macro and micro ergonomics indicators, alongside job satisfaction, for the assessment of psychiatric hospitals. The array of ergonomics indicators, including mental power, physical conditions, workplace conditions, human resource management, information and communication systems, teamwork, effective communication, knowledge, situation assessment, and situation analysis, marks a departure from the conventional studies, demonstrating a more holistic approach to evaluating the complex dynamics within psychiatric healthcare settings.

1.2 Research gap and contributions

Most studies have dedicated their work to assess the performance of the general hospitals regarding either ergonomics or job satisfaction indicators (A. Azadeh, Saberi, & Anvari, 2010; John & Nwiabu; Stevens, Ikeda, Casillas, Palacio-Cayetano, & Clyman, 1999). This paper presents a framework considering both macro ergonomics and micro ergonomics indicators and job satisfaction. The paper's ergonomics indicators include mental power, physical conditions, workplace conditions, human resource management and work culture, information and communication systems, teamwork and effective communication, knowledge, situation assessment and situation analysis and, specifications of work and equipment. Proposed framework is utilized to evaluate the performance of psychiatric hospitals in order to help healthcare authorities reach a better understanding of psychiatric hospitals with regard to ergonomics and job satisfaction factors. Since this study is perused during Covid-19 pandemic, the effects obtained from this global disease is also significant on people's mental health status and is considered through the whole investigation. The novelty of this research consists of ranking hospitals based on their performance assessment and determining their strengths and weaknesses per the mentioned indicators. A notable aspect of this study is its timeline by being conducted during the Covid-19 pandemic. The pandemic's far-reaching effects on individuals' mental health are considered throughout the investigation, adding a layer of complexity and relevance to the study's findings. This acknowledgment reflects the study's commitment to capturing the contemporary challenges faced by psychiatric hospitals and underscores the need for nuanced approaches in healthcare management during global crises. The primary novelty of this research lies in its proposal of a unique performance assessment framework tailored specifically to psychiatric hospitals. Unlike many previous studies employing Data Envelopment Analysis (DEA), this research introduces an optimal DEA model for evaluating hospital performance. This departure from conventional methodologies enhances the accuracy and reliability of the performance assessment. Furthermore, the study employs ANN validation, a novel addition that goes beyond the scope of many existing studies. The integration of ANN serves to fortify the credibility of the results, offering a more robust validation process and contributing to the methodological innovation in the field of healthcare performance assessment.

The practical implications of the research findings are substantial. The proposed framework not only facilitates the ranking of psychiatric hospitals based on their performance but also provides a nuanced understanding of their strengths and weaknesses across various indicators. This depth of analysis serves as a valuable resource for healthcare authorities, enabling informed decision-making and targeted interventions to enhance the overall effectiveness of psychiatric healthcare which is seamlessly verified by ANN. Lastly, the dedication of the suggested framework to psychiatric hospitals in Tehran adds a contextual richness to the study, acknowledging the significance of local nuances and reinforcing the practical applicability of the research in diverse healthcare settings.

The main findings of this paper are the following:

- We propose a novel performance assessment framework of psychiatric hospitals referring to ergonomics and job satisfaction indicators.
- In case of implementing a DEA model, unlike other studies, an optimal model is used to evaluate the performance.
- Validation of the results achieved from the DEA optimal model is done by applying ANN method additionally.
- We rank psychiatric hospitals based of their performance.
- The strengths and weaknesses of each psychiatric hospital will be determined per concluded indicators.
- Lastly, the dedication of our suggested framework to psychiatric hospitals in Tehran also adds to the essence of the present study.

The structure of this paper is as follows. Section 1 presents an introduction and literature review. In Section 2, the proposed framework is described. In section 3, the numerical results related to the case study are described. Lastly, Section 4 concludes the findings of the paper and offers suggestions for the development of future research.

2. Methodology

The proper performance of health care systems during the Covid-19 pandemic is critical. One of the important parts of these systems are psychiatric hospitals, which due to the negative impact of this pandemic on the mental state of people, the effective performance of these hospitals becomes more important. In this regard, this section presents a new approach to evaluate macro and micro ergonomic indicators and job satisfaction in psychiatric mental hospitals with the DEA method. The steps of this approach can be seen in **Error! Reference source not found.** and are summarized as follows:

Step1: Identifying indicators.

Step2: Designing and distributing a questionnaire

Step3: Calculating Cronbach's alpha to check the Reliability of the questionnaire

Step4: Determining the best DEA model

Step5: Calculating the efficiency score and ranking

Step6: Performing sensitivity analysis by using statistical tests

Step7: Validating the results by Comparing of the results of DEA and ANN methods

To evaluate the performance of psychiatric hospitals based on macro and micro ergonomics and job satisfaction indicators, we first identified the relevant sub-indices by studying the existing literature such as A. Azadeh, Gaeini, Haghighi, and Nasirian (2016). Finally, for micro-ergonomics, "mental power", "physical conditions" and "workplace c" indicators were identified, which examine the impact of work environment conditions, physical conditions and factors related to people's patience, vigilance and concentration on their performance. Also, for macro ergonomics, "human resource management and work culture", "information and communication systems", "teamwork and effective communication", "knowledge, situation assessment and situation analysis" and "specifications of work and equipment" indicators were identified which examine the situation of human resource, information systems, equipment, Colleague interactions, and their impact on the employee performance.

In the following to collect the required data, based on the opinion of experts and by studying the relevant literature, a standard questionnaire including 44 questions was designed and distributed among the employees of psychiatric hospitals. It should be noted that in this questionnaire, a score between 1 and 10 has been assigned to each question. The relevant questionnaire can be seen in **Error! Reference source not found.** After collecting the data, the reliability of the questionnaire was checked by calculating Cronbach's alpha. It should be noted that a value greater than 0.7 is acceptable for Cronbach's alpha (Dörnyei, 2007). After confirming the questionnaire data, in this section we will evaluate the performance of psychiatric hospitals with DEA method. DEA is a non-parametric method for calculating the efficiency of different decision-making units (DMUs), which was first proposed by Charnes, Cooper, and Rhodes (1978). In this study, our DMUs are employees of psychiatric hospitals, and macro and micro ergonomics were considered as input and job satisfaction as output of the problem. In this study, first, we choose the best DEA model by comparing its four models, i.e., input-oriented, output-oriented CCR (Charnes et al., 1978) and input-oriented, output-oriented BCC (Banker, Charnes, & Cooper, 1984). The structure of these models can be seen in **Error! Reference source not found.**. Considering all matters above, we use noise analysis for our study and choose the model with the least sensitivity to the generated noise as the best DEA model. In the following, we calculate the efficiency of psychiatric hospitals based on ergonomics and job satisfaction with the best DEA model, and after ranking them, we determine the best and worst hospitals in performance.

In the next step, we will evaluate the effect of each of the indicators on the performance of psychiatric hospitals. For this purpose, we remove each of the indicators and calculate the efficiency of hospitals in their absence with the optimal DEA model. We use statistical tests to compare these results with the primary model where no indicators were removed. If the data distribution meets both the conditions of normality and homogeneity, we use parametric tests (paired T-test) and otherwise non-parametric tests (Wilcoxon test). The null hypothesis tests the equality of the average efficiency score before and after removing each indicator at the 95% confidence level. As a result, if the p-value is less than 0.05, the null hypothesis will be rejected and it can be concluded that the omitted indicator has created a significant change in the average efficiency and has an effect on the performance of psychiatric hospitals. In the following, we will compare the mean efficiency score before and after removing each indicator to identify the weaknesses and strengths of psychiatric hospitals. If the mean has decreased, it can be concluded that the hospitals have a good performance based on the omitted indicator, and if the mean has increased, it can be concluded that the omitted indicator was the weakness of psychiatric hospitals.

Finally, we will validate the results of the DEA model by comparing these results with the results of the ANN method. ANN is a data-driven black box technique inspired by human’s central nervous system (Shahzad, 2022), which is able to use learning algorithms by learning from data (Han, Lee, Lee, & Yoo, 2018). ANNs are generally composed of an input layer and an output layer that are linked by one or more layers of hidden nodes (Torabzadeh, Tavakkoli-Moghaddam, Samieinasab, & Hamid, 2022). One of the most successful possible network architectures introduced by Rumelhart, Hinton, and Williams (1985) is Multilayer Perception (MLP) that utilizes backpropagation algorithm (Flores, 2011). Further details about ANN model can be found in **Error! Reference source not found.** For validation, we first calculate the efficiency of psychiatric hospitals using the ANN method and then calculate the Spearman correlation coefficient between the results of the two DEA and ANN models. It should be said that the large value of this coefficient proves the validity of the DEA model results. The choice of Artificial Neural Networks (ANN), particularly the Multilayer Perceptron (MLP), for validation is grounded in its ability to model complex, non-linear relationships among multiple variables without requiring predefined assumptions about data distribution. While DEA provides relative efficiency scores based on a linear programming framework, it does not capture potential nonlinear interactions or latent patterns within the data. The use of ANN, a widely accepted approach in hospital performance prediction and benchmarking, complements DEA by offering an independent, machine-learning-based validation mechanism. Prior studies have successfully applied ANN in conjunction with DEA to cross-validate healthcare performance metrics, enhancing both the interpretability and reliability of results (Azadeh et al., 2010; Araujo et al., 2018).

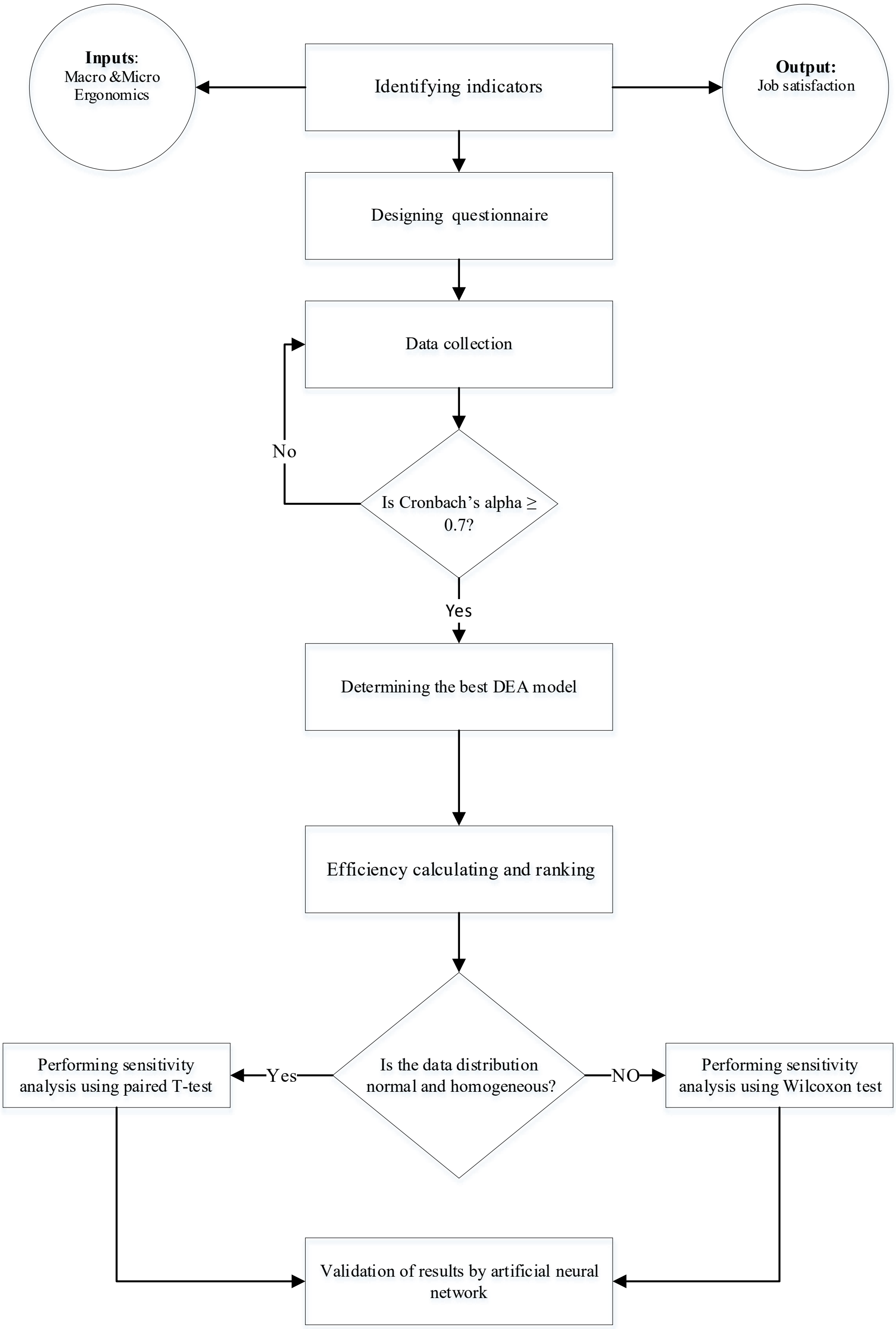

Figure 1. Flowchart of the presented framework

3. Case Study

Since we are studying mental healthcare centers, three psychiatric hospitals in Tehran are considered as a case study in favor of evaluating their performance in terms of macro-ergonomics, micro-ergonomics and job satisfaction indicators. A healthy community is seized through both mental and physical well-being. Paying attention to mental health is a must these days with the various problems caused by the Covid-19 pandemic and the stressful lives in big cities such as Tehran. The case study involves 3 psychiatric hospitals with the highest patient attendance rate in Tehran chosen as a result of their great contribution to the treatment of patients with mental illnesses. Moreover, these hospitals have an important impact on the overall society's mental health, therefore, superior performance is a necessity for their managers. Determining the strengths and weaknesses of each hospital have a huge role in bettering their performance. In the interest of reaching our purpose in evaluating their performance, the DEA and ANN methods fit correctly as we calculate their efficiency score using DEA models and validate the final results with the derived efficiency scores from ANN.

Due to confidentiality agreements with the participating institutions, detailed profiles of the three psychiatric hospitals (e.g., names, bed capacities, or organizational structure) cannot be disclosed. However, all three hospitals are among the most frequented psychiatric centers in Tehran, selected based on their high patient admission rates and significant role in mental health service delivery during the COVID-19 pandemic. The inclusion of these hospitals ensures the data reflects a high-impact and relevant segment of the psychiatric care system in Tehran.

3.1. Designing and Distributing A Questionnaire

In order to collect valid data, a standard questionnaire was designed and distributed among three psychiatric hospitals. The questionnaire was completed by 61 DMUs consisting of 20 staff from the first, 23 staff from the second and 18 staff from the third hospital. In order to answer 44 given questions, they had to assign a number between 1 and 10 based on their agreement. Items in the questionnaire include macro-ergonomics and micro-ergonomics indicators mentioned as the inputs and job satisfaction as the output to of the DEA method evaluate psychiatric hospital's performance from different perspectives.

3.2. Questionnaire's Reliability Test Results

After distributing the questionnaire and collecting data, Cronbach's alpha reliability test is done on the results via SPSS software. According to Cronbach (1951) alpha's value varies from 0 to 1 and the desirable value is close to 1. Our data is acceptable since all the computed values are higher than 0.7. The Cronbach's alpha for mental power, physical condition, workplace condition, human resource management and work culture, information and communication system, teamwork and effective communication, knowledge and situation assessment, specification of work and equipment, job satisfaction are 0.813, 0.887, 0.876, 0.881, 0.896. 0.892, 0.901, 0.898, 0.897 respectively.

3.3. DEA Results

In this section, the performance of psychiatric hospitals is evaluated through DEA method respecting 61 DMUs. In order to do so, first, an optimal DEA model should be chosen among four DEA models used in this study. To the extent of reaching this purpose, 5% noise is inserted into 5% of DMUs to compare CCR input-oriented, CCR output-oriented, BCC input-oriented, and BCC output-oriented DEA models. Hence, a single model that is the least vulnerable to the noise is chosen as the optimal one. Comparison between the results of each model's before and after noise, is done by implementing the Spearmen's correlation test. Outcome with the highest amount is the least sensitive to noise and will be selected as the optimal model. Considering the results, the CCR input-oriented DEA model is the optimal DEA model. Regarding the CCR input-oriented model, the average efficiency score related to performance indicators is calculated for each DMU as shown in Table . Finally, the efficiency score of each psychiatric hospital is calculated through the average efficiency scores seized from the last step. The correlation test results for DEA models based on Spearmen's correlation test are 0.990, 0.994, 0.979, 0.965 for CCR output-oriented , CCR input-oriented, BCC output-oriented, BCC input-oriented.

In this study, the term "optimal DEA model" refers to the DEA formulation that demonstrates the highest stability and reliability under noisy data conditions. To identify this model, we compared four conventional DEA variants (CCR input-oriented, CCR output-oriented, BCC input-oriented, BCC output-oriented) by injecting random noise into the dataset and evaluating the change in DMU rankings using Spearman's correlation. The CCR input-oriented model showed the highest resistance to noise (Spearman coefficient = 0.994), and was thus selected as the optimal model for our analysis.

Table 1. Efficiency for each DMU

DMU No.	efficiency	DMU No.	efficiency	DMU No.	efficiency
1	0.992	22	0.881	43	0.990
2	0.971	23	0.897	44	1
3	0.932	24	0.958	45	1
4	0.993	25	0.992	46	0.957
5	0.957	26	0.921	47	1
6	0.902	27	1	48	0.885
7	1	28	1	49	0.958
8	0.884	29	1	50	1
9	1	30	1	51	0.931
10	0.971	31	0.992	52	1
11	0.973	32	1	53	0.983
12	0.898	33	0.932	54	1
13	0.980	34	0.932	55	0.947
14	0.933	35	1	56	1
15	0.880	36	1	57	0.994
16	1	37	0.978	58	0.933
17	0.920	38	0.978	59	0.972
18	0.937	39	1	60	0.944
19	0.983	40	0.915	61	0.969
20	0.971	41	1		
21	0.984	42	0.896		

Figure 2 illustrates the average efficiency scores of the three psychiatric hospitals as calculated using the optimal CCR input-oriented DEA model. Hospital 3 achieved the highest efficiency score (0.971), followed closely by Hospital 2 (0.967), while Hospital 1 scored the lowest (0.953). The visual comparison highlights performance disparities and supports the ranking derived from the DEA analysis.

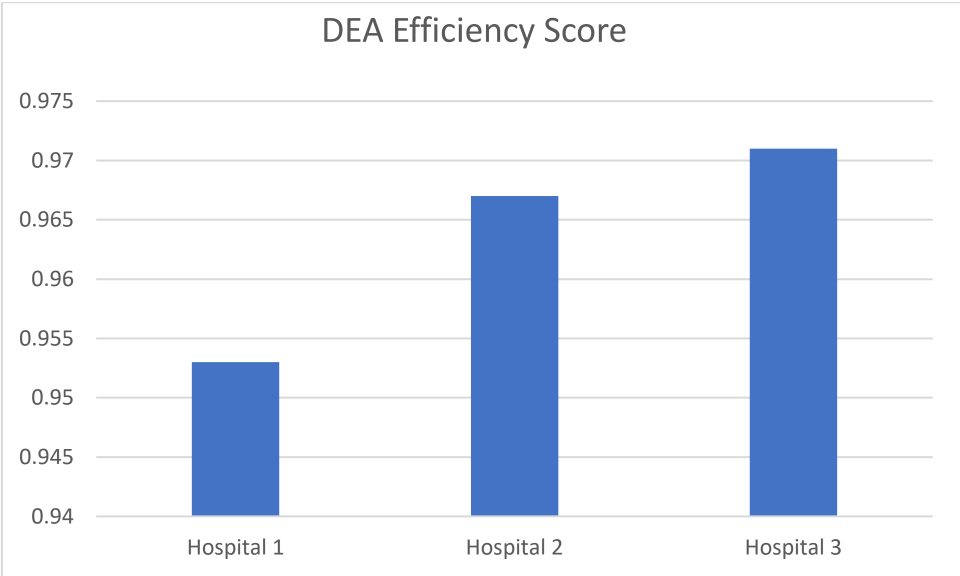

Figure 2. Comparative DEA efficiency scores of psychiatric hospitals

3.4. Sensitivity Analysis Results

As stated in methodology section, sensitivity analysis is applied in order to demonstrate the performance of psychiatric hospitals in the matter of macro-ergonomics and micro-ergonomics factors. To do so, the impact of each input indicator on the performance is determined by neglecting one indicator at a time. Then the efficiency score after their absence is calculated with the optimal DEA model and compared with previous results before the elimination. But before that, we have to check whether the data distribution is parametric or not. For this, Normality of the data is figured by Shapiro-Wilk test. In addition, the value of homogeneity is assessed using one-way ANOVA test. Both statistical tests for normality and homogeneity are implemented using SPSS software which resulted in values presented Table . Indicators with p-value of these tests higher than 0.05 are parametric, in which Next, the paired t-test is used for parametric distributions. Otherwise, the Wilcoxon test is employed for non-parametric ones. For this reason, if the data distribution is not normal, their homogeneity has not been investigated, similar to our results mentioned in Table . Related results are shown in Table . Lastly, the average efficiency score after the elimination of each indicator for all the hospitals is reported in Table .

In case of considering all the hospitals, according to the results shown in Table , the indicators' computed p-values of the statistical tests for the following factors are less than 0.05 after removing each, meaning that they are effective and can be engaged in the performance assessment process, these indicators include mental power, physical conditions, workplace conditions, human resource management and work culture, information and communication systems, knowledge situation assessment and situation analysis, specification of work and equipment. In contrast, after eliminating the teamwork and effective communication indicator, the p-value of the statistical tests are more than 0.05, indicating that this factor is not effective on hospitals' performance and is not suitable to be considered in the process of performance evaluation.

Subsequently, comparison between the mean efficiency score before and after removing each indicator in determines strengths and weaknesses of the psychiatric hospitals. If the value is positive, representing a decrease in the average efficiency score, its indicator is considered as a strength, because of their good effect on the hospitals' performance. On contrary, the opposite applies for negative values, stating an increase in the efficiency score of that particular indicator, followed by an undesirable effect in the psychiatric hospitals' performance. Moreover, hospitals should consider improving these factors in order to reach a better performance state.

For all the hospitals, referring to table 3, Physical conditions and Information and communication systems are concluded as weaknesses of the psychiatric hospitals and need improvement. In contrast mental power, workplace conditions, human resource management and work culture, teamwork and effective communication, knowledge situation assessment and situation analysis, specification of work and equipment indicators are considered as their strengths by having an appropriate effect on the performance.

Table 2. Statistical test results for all the hospitals

Omitted Indicators	p-value (normality)	p-value (homogeneity)
none	0.00000	-
Mental power	0.00003	-
Physical conditions	0.00000	-
Workplace conditions	0.00020	-
Human resource management and work culture	0.00045	-
Information and communication systems	0.00000	-
Teamwork and effective communication	0.00000	-
Knowledge situation assessment and situation analysis	0.00006	-
Specification of work and equipment	0.00002	-

Table 3. Results of the sensitivity analysis

Omitted indicators	μ_1-μ_2	Hypothesis test	p-value
Mental power	0.002697917	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.01332
Physical conditions	-0.005283474	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00005
Workplace conditions	0.022467998	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00000
Human resource management and work culture	0.008736361	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.01576
Information and communication systems	-0.004987837	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.02256
Teamwork and effective communication	0.000665733	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.44417
Knowledge situation assessment and situation analysis	0.01009193	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00000
Specification of work and equipment	0.002309142	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.03198

Table 4. Results of average efficiency calculation

Omitted indicator	Average efficiency
none	0.96392
Mental power	0.96123
Physical conditions	0.96921
Workplace conditions	0.94146
Human resource management and work culture	0.95519
Information and communication systems	0.96891
Teamwork and effective communication	0.96326
Knowledge situation assessment and situation analysis	0.95383
Specification of work and equipment	0.96162

As the next step, in table 5 each of the hospitals are observed separately and their efficiency score before and after the absence of considered indicators is calculated and presented. Then the results of the statistical tests for normality and homogeneity that has been done for each of the psychiatric hospitals is presented in table 6.

Table 5. Average efficiency score for each hospital

	Hospital No.		
	1	2	3
none	0.953957	0.967161	0.970864
Mental power	0.958025	0.967058	0.957333
Physical conditions	0.962069	0.976569	0.967734
Workplace conditions	0.91712	0.946653	0.961857
Human resource management and work culture	0.942309	0.949269	0.977061
Information and communication systems	0.964523	0.963657	0.980505
Teamwork and effective communication	0.961656	0.960548	0.968504
Knowledge situation assessment and situation analysis	0.945021	0.953136	0.964513
Specification of work and equipment	0.952913	0.971041	0.959241

Table 6. Results of statistical tests for each of the hospitals

Omitted indicators	p-value (normality)		
	Hospital 1	Hospital 2	Hospital 3
none	0.04018	0.00022	0.00668
Mental power	0.02582	0.00040	0.03977
Physical conditions	0.02323	0.00001	0.00663
Workplace conditions	0.37908	0.00354	0.01113
Human resource management and work culture	0.45818	0.06590	0.00301
Information and communication systems	0.03981	0.00087	0.00331
Teamwork and effective communication	0.00554	0.00112	0.00589
Knowledge situation assessment and situation analysis	0.09838	0.00017	0.05606
Specification of work and equipment	0.04184	0.00013	0.07052
	p-value (homogeneity)		
none	-	-	-
Mental power	-	-	-
Physical conditions	-	-	-
Workplace conditions	0.240	-	-
Human resource management and work culture	0.463	0.732	-
Information and communication systems	-	-	-
Teamwork and effective communication	-	-	-
Knowledge situation assessment and situation analysis	0.817	-	0.957
Specification of work and equipment	-	-	0.902

The p-values obtained from the comparison of mean efficiency score before and after the elimination of each factor for hospital 1 are shown in Table . The specification of work and equipment is the only indicator that can't be engaged in evaluating hospital 1's performance since it's p-value of the statistical test is higher than 0.05 stating their ineffectiveness on the performance. On the other hand, mental power, physical conditions, workplace conditions, human resource management and work culture, information and communication systems, teamwork and effective communication and knowledge situation assessment and situation analysis indicators are effective on the performance of hospital 1 by having the p-value less than 0.05. In terms of Studying the comparison of mean efficiency scores, Table shows that workplace conditions, human resource management and work culture, knowledge situation assessment and situation analysis and the Specification of work and equipment with positive value, are hospital 1's strengths showing that hospital 1 has a good performance based on these indicators. But mental power, physical conditions, information and communication systems and teamwork and effective communication are considered as hospital 1's weaknesses as a result of the increase in the average efficiency score.

Table 7. Results of the sensitivity analysis for hospital 1

Omitted indicators	$\mu_1 - \mu_2$	Hypothesis test	p-value
Mental power	-0.004068	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.01886
Physical conditions	-0.008112	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00086
Workplace conditions	0.036837	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00003
Human resource management and work culture	0.011648	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00629
Information and communication systems	-0.010566	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00098
Teamwork and effective communication	-0.007699	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00022
Knowledge situation assessment and situation analysis	0.008936	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00002
Specification of work and equipment	0.001044	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.17971

Referring to Table 8 regarding hospital 2's data and the comparison of indicators before and after each of their elimination, the obtained p-value of mental power is higher than 0.05, so as mentioned before it's not appropriate to use this indicator in the performance evaluation process because of its ineffectiveness on the efficiency score of hospital 2. In contrast, the rest of the factors are effective in the process proved by their calculated p-value less than 0.05. As presented in table 8 for two factors in hospital 2, the mean efficiency score has been increased by removing them. These factors, physical conditions and specification of work and equipment, are treated as weaknesses for hospital 2 in case of its performance. The other ones with positive mean efficiency difference, mental power, workplace conditions, human resource management and work culture, information and communication systems, teamwork and effective communication and knowledge situation assessment and situation analysis, are strengths in hospital 2, through causing a decrease in the average efficiency score in their absence.

Table 8. Results of the sensitivity analysis for hospital 2

Omitted indicators	$\mu_1 - \mu_2$	Hypothesis test	p-value
Mental power	0.000103	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.59611
Physical conditions	-0.00941	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00082
Workplace conditions	0.020508	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00335
Human resource management and work culture	0.017891	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00535
Information and communication systems	0.003504	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.03251
Teamwork and effective communication	0.006613	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.01860
Knowledge situation assessment and situation analysis	0.014025	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00506
Specification of work and equipment	-0.00388	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00503

Table 9 contains the computed p-values concluded from the comparison of the factors before and after their absence for hospital 3. Since the p-value results for all the indicators including mental power, physical conditions, workplace conditions, human resource management and work culture, information and communication systems, teamwork and effective communication, knowledge situation assessment and situation analysis, specification of work and equipment are lower than 0.05, they can be used as the effective factors in order to assess the hospital 3's performance. By observing Table 9 and the negative difference made in the mean efficiency score for human resource management and work culture as well as information and communication systems factors, these two weaknesses are introduced, showing the need of improvement in order to achieve a good performance in hospital 3. However, positive values in mean efficiency comparison for indicators such as mental power, physical conditions, workplace conditions, teamwork and effective communication, knowledge situation assessment and situation analysis and at last specification of work and equipment shows strengths regarding hospital 3. Stating that hospital 3 has a desirable performance towards the mentioned indicators.

Table 9. Results of the sensitivity analysis for hospital 3

Omitted indicators	$\mu_1 - \mu_2$	Hypothesis test	p-value
Mental power	0.013531	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00023
Physical conditions	0.003131	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.02728
Workplace conditions	0.009007	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.02771
Human resource management and work culture	-0.0062	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00283
Information and communication systems	-0.00964	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00901
Teamwork and effective communication	0.00236	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.01796
Knowledge situation assessment and situation analysis	0.006351	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.03260
Specification of work and equipment	0.011623	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	0.00000

The sensitivity analysis results indicate whether each input indicator positively or negatively contributes to hospital performance. Specifically, if the average efficiency score decreases after an indicator is removed, it implies that the indicator was a strength, contributing positively to performance. Conversely, if the average efficiency increases, the indicator was a weakness, possibly reflecting inefficiencies in that area.

For instance, the removal of "Information and Communication Systems" led to an increase in average efficiency, suggesting that hospitals struggled with IT infrastructure, data flow, or internal communication systems—factors that impaired overall performance. Similarly, the "Physical Conditions" indicator was also identified as a weakness, potentially reflecting poor ergonomic design or suboptimal physical work environments. On the other hand, indicators such as "Workplace Conditions" and "Knowledge, Situation Assessment, and Situation Analysis" caused efficiency to drop when removed, indicating that hospitals generally performed well in those areas and relied on them for effective functioning.This interpretation provides hospital administrators with a clearer understanding of which areas require improvement, and which should be maintained or enhanced.

3.5. Validation of The Results

Eventually, in order to validate the results of the DEA model, the efficiency score of the DMUs is calculated through ANN algorithm and then is compared to the efficiency score obtained from the DEA method. The ANN method is widely used for predicting values by learning algorithms. MLP networks are frequently utilized among ANN's many networks. The MLP network is implemented by SPSS software to train ANN, using the obtained efficiency scores and the input parameters of DEA (macro ergonomics and micro ergonomics indicators) as the input layer for ANN and the DEA output parameter (job satisfaction) as the ANN's output layer. In this study, the data set in partitioned into 70% training data, 20% test data and 10% holdout data so that we can assess the final ANN results. With mentioned assumptions, ANN is trained and the relations among considered factors are estimated. Then the statistical mean error of the output is also calculated to make sure the results are appropriate. Ultimately, by the calculated efficiency score of the psychiatric hospitals via MLP network, the Spearman correlation test is applied via SPSS software to compare the final results of the two algorithms. The value range close to +1 achieved from this statistical test, verifies a strong correlation (Solutions, 2016). According to the detailed results in appendix E determining our computed correlation value equaling 0.716, a strong relation between the results of DEA and ANN methods is approved and the used DEA model is recognized as valid. While the Spearman correlation (0.716) indicates a strong positive relationship between DEA and ANN results, we further explored the similarities and differences at the DMU level to gain a more nuanced understanding. In general, high-performing DMUs in DEA were similarly rated by ANN, confirming overall consistency in identifying efficient units. However, some discrepancies were observed for mid-range performers. For instance, DMU #26 showed relatively lower efficiency in DEA but scored higher in ANN, possibly due to ANN's ability to model complex, non-linear interactions between ergonomics and job satisfaction indicators. These differences suggest that while DEA is effective for benchmarking based on relative efficiency, ANN may better capture latent patterns or nonlinear relationships. Thus, using both methods provides a more holistic performance assessment. The DEA model offers interpretability and input/output sensitivity, while ANN enhances predictive insight. Together, they form a robust hybrid approach for evaluating healthcare performance in complex systems such as psychiatric hospitals.

4. Discussion and Managerial Insights

Recently, scholars have become increasingly interested in the organizational performance of Psychiatric hospitals. These hospitals now face new jobs and organizational challenges as a result of restricted budgets and considerable reorganization. A hospital is required to boost productivity despite financial constraints, recruit highly skilled staff, and promote health in addition to provide high-quality healthcare services. Several models have been developed to evaluate a hospital's performance, but many of them only take into account a small number of variables and are therefore prone to giving inaccurate or unsatisfactory results. According to the literature, running a hospital has several facets and frequently reveals the difficulties hospital doctors encounter or unresolved concerns, such as problems with organizational climate, organizational structure, communication, and management. The performance of the hospital, or its capacity to serve patients successfully, is more crucial than cost control, which presents a difficulty for a system that prioritizes cost reduction. Equally crucial is that a hospital serve as a setting for the formation of groups with similar beliefs. According to research, involving employees in the decision-making process greatly reduces the risk of staff members developing a pessimistic outlook on the company. Hospital administrators should pay close attention to any actions that make it easier for doctors to participate in choices about how a department or hospital is organized. It is also important to mention that information and knowledge management is unquestionably crucial for healthcare businesses. Scientific sources claim that the clinic director and the hospital administration have different approaches to managing information and knowledge. Because healthcare workers are educated to attend to and put patients' needs first, the majority of issues in the industry come in this area.

This study is discernable in a sense that evaluates the performance of psychiatric hospitals based on macro and micro ergonomics and job satisfaction indicators during the Covid-19 pandemic through the DEA method. Unlike other studies, in this study, we first determined the optimal DEA model and then evaluated the performance of hospitals. In this article, in addition to ranking the hospitals in the case study, we analyzed the impact of each indicator on their performance and identified their strengths and weaknesses, which have a significant impact on improving the performance of hospitals. Another distinguishing feature of this study is the validation of DEA's optimal model with the MLP-ANN algorithm to ensure the results.
The results of this study on three psychiatric hospitals in Tehran show that the indicators of Information and communication systems and Physical conditions are the weak points of two of the three investigated hospitals, and in general, psychiatric hospitals perform poorly regarding these two indicators. In other words, the physical conditions of the hospital employees as well as the status of the information systems and information circulation in these hospitals are not suitable and have a negative effect on the performance of the employees. Therefore, hospital managers should pay proper attention to these indicators and prioritize them in their programs to improve hospital performance. It is also interesting to note that the performance of all three investigated hospitals has been very suitable for the two indicators of workplace conditions and knowledge, situation assessment and situation analysis. Therefore, managers need to maintain this strong performance based on these indicators. Finally, it should be mentioned that among these three hospitals, hospital 1 has 4 weaknesses (Mental power, Physical conditions, Information and communication systems, and Teamwork and effective communication) and due to the fact that the Specification of work and equipment indicator did not affect the performance of hospital 1, this hospital has a good performance with respect to only 3 indicators, and it is necessary for the managers to improve the performance of this hospital as soon as possible and have a comprehensive plan for it.

5. Conclusion

This study aimed to evaluate the performance of psychiatric hospitals based on micro and macro ergonomic and job satisfaction indicators during Covid-19 pandemic. At first, by reviewing the available literature, we identified ergonomic sub-indices and by using them, we designed a standard questionnaire and distributed it among the psychiatric hospital staff. Then, we checked the reliability of the questionnaire by calculating Cronbach's alpha. The value of this alpha for all indicators was above 0.7 and the questionnaire had a good reliability. Afterwards, the input-oriented CCR model was selected as the optimal DEA model through noise analysis. Then we calculated the efficiency of each of the DMUs with the optimal DEA model and as the final results, it was derived that hospitals 3 and 1, respectively, have the best and worst performance, based on macro and micro ergonomics and job satisfaction indicators. Additionally, in the sensitivity analysis section, we investigated the impact of each indicator on the performance of the psychiatric hospitals with statistical tests. The results showed that Teamwork and effective communication indicator does not have much effect on the performance of hospitals. It was also found that in general, the indicators of Physical conditions and Information and communication systems are the weak points of the performance of the psychiatric hospitals. While the performance of these hospitals regarding the indicators of mental power, workplace conditions, human resource management and work culture, teamwork and effective communication, knowledge situation assessment and situation analysis, specification of work and equipment is completely appropriate. Ultimately, the results of the optimal DEA model were compared with the results of the MLP-ANN method through Spearman's correlation test, and the results showed the validity of the optimal DEA model by having a strong correlation. This study is one of pioneers that evaluates the performance of psychiatric hospitals in terms of micro and macro ergonomics and job satisfaction indicators during the Covid-19 pandemic period. For future research, the DEA method can be used in a fuzzy environment or further investigation can be implemented on the impact of other indicators such as HSE, resilience engineering indicators, etc. on the performance of the psychiatric hospitals.

5.1 Managerial and Policy Implications

The findings of this study provide clear and actionable insights for hospital administrators and healthcare policymakers. First, the identification of “Information and Communication Systems” and “Physical Conditions” as consistent weaknesses across hospitals signals the urgent need for targeted investments in digital infrastructure and ergonomic work environments. Improving communication flow, access to patient data, and overall system usability can directly impact staff performance and patient care. Second, the strengths identified—such as workplace conditions and knowledge-based decision-making—should be maintained and integrated into staff development programs. These areas can be reinforced through continued training, inclusive management practices, and recognition systems to sustain high performance.Third, the DEA framework used in this study can serve as a diagnostic tool for continuous performance evaluation. Hospital managers can use the same indicators periodically to identify emerging gaps and monitor the effectiveness of interventions. Lastly, in the context of pandemic resilience, these findings emphasize the need for adaptive infrastructure that supports both employee well-being and operational efficiency under crisis conditions. Policymakers should consider these dimensions when designing funding mechanisms, setting operational standards, and regulating psychiatric hospital systems.

5.2 Limitations and Future Directions

Despite the contributions of this study, several limitations should be acknowledged. First, the dataset comprises responses from only 61 employees across three psychiatric hospitals in Tehran. While these hospitals were selected based on patient volume and societal impact, the sample size and geographic scope may limit the generalizability of the findings to broader national or international contexts. Second, although macro and micro ergonomics and job satisfaction were comprehensively considered, other relevant factors—such as resilience engineering indicators, health-safety-environment (HSE) variables, and cultural dynamics—were not included and may influence hospital performance. Third, while ANN enhances validation through non-linear modeling, its "black-box" nature limits interpretability compared to the more transparent DEA approach. Future research should consider expanding the sample size, incorporating more diverse hospital types, and integrating additional explanatory variables for a more comprehensive evaluation framework.

Declarations

The authors declare that they have no conflict of interest. In addition, this article does not contain any studies with human participants or animals performed by the author. The undersigned authors declare that this manuscript is original, has not been published before, and is not currently being considered for publication elsewhere.

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Zahra Hamdi and Fateme Ataei contributed equally to the conceptualization, data collection, and development of the research methodology. Zahra Mohammadnazari supervised the research process, contributed to the validation strategy, and led the manuscript editing and review as the corresponding author. Fariborz Jolai provided methodological guidance and critical revisions of the manuscript for intellectual content. All authors read and approved the final manuscript.

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