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Influence Factors of Powerline Communication by Artificial Intelligence Approach based on Rock Electric Signal

Journal of Electrical Systems

Abstract: - The field of powerline communication (PLC) has been around for more than a century and uses the power line as a means of information transport. Because it utilizes the current system to transfer data using electrical power, it is advantageous because it prevents the need for new installations. The impact of coal and rock electric signals is examined using the established test methodology, taking into account the coal and rock temperature, characteristics, friction, loading speed, and load size. The main findings can be summed up as follows: Depending on the intensity of the electrical signals produced, the change rule of electrical signals in the coal rock rising with temperature can be separated into three stages. The electrical signals produced by the uniaxial compression of coal-rock mass with varying properties have distinctly different amplitudes. The friction between coal and rock can produce electrical impulses. As loading speed increases, the electrical signal that indicates when the coal rock is prepared to fracture tends to get stronger. The information bottleneck perspective is then used to study information theory and artificial intelligence. In conclusion, we go through a few concepts about the deep integration of AI methods with wireless communication networks. The fundamental aspects of AI that are pertinent to various uses have been briefly addressed at the outset of the paper.

Keywords: Powerline communication, Rock Electric Signal, artificial Intelligence, coal-rock mass.

I. Introduction

In recent decades, technical breakthroughs have led to a greater development of modern civilizations. The demand for accessible, sustainable electric energy has been enormous globally. Real device blockage problems have been brought about by the increase in energy consumption and the erratic, non-linear distribution of electrical power. The overstressed state of affairs is exacerbated by the fact that the existing power system lacks essential and persuasive interchanges, examinations, and fault diagnostics, increasing the likelihood of a localized system breakdown brought on by the collapse impact of a single defect [1]. The production of both non-renewable and renewable energy in the twenty-first century has resulted in several new issues, such as energy stockpiling, control network reconciliation, and system stability, all of which have to be addressed as new difficulties.

Compared to other conventional electricity-saving technologies, electric vehicles (EVs) are more relevant due to their ease of use and ability to preserve a pleasant environment according to recent studies. Due to their greater efficiency, especially in urban areas, EVs are expected to see a significant increase in market share as time goes on. For example, initial calculations show that France's 15% electric car convoy will result in a mere 3% increase in energy consumption but a 90% reduction in CO_2 emissions. Utilizing eco-friendly or sustainable energy technologies, the advantages of urban de-carbonization, and the capacity to leverage local energy resources to enhance environmental health are the main points of emphasis of the most recent economic shift.

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These three areas of attention are interconnected. Therefore, renewable energy sources like solar and wind power might incentivize conventional energy producers to cut emissions during peak demand if they are maintained in operation. They enable the efficient integration of intermittent power output by acting as a possible safety net for renewable energy sources (RES) including solar and wind energy. Electric vehicles (EVs) are widely acknowledged as a very efficacious means of curbing petrol consumption, advancing urban decarbonization, and augmenting human welfare. For an apparatus that makes use of the 42–89 kHz frequency band for Powerline communication. The power supply use must not contaminate my communication band with additional noise in the powerline in Figure 1.1.

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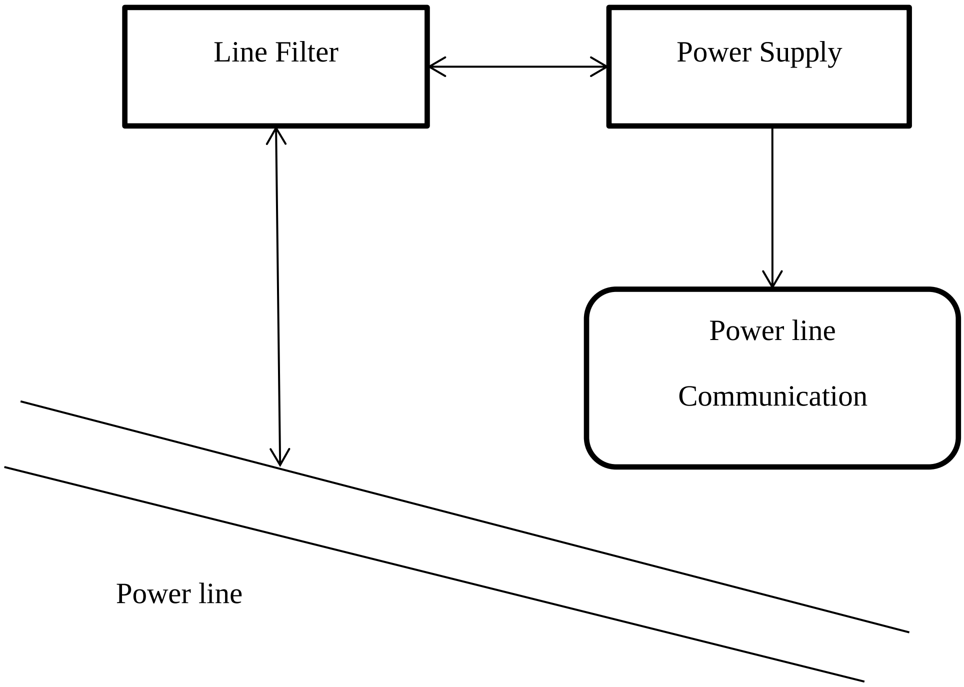

Figure 1.1. Alternating mode power source for Power Line Transmission

Since elastic waves are known to be released from rock mass during the fracturing process of many different types of rocks, which can be caused by geological processes or human action, the acoustic emission (AE) technique can be used to detect a variety of signs associated with the disintegration of rock mass. The formation of rock mass is a type of environmental geology that results from the movement of geological structures and a complex atmospheric setting [2]. It is characterized by a certain mineral composition and structural plane. Mineral compositions and geological features, including joints and tiny cracks, vary between different types of rocks. In a rock fracture, there is deboning and slippage between the minerals, grains, and geological formations. Every AE signal indicates that a portion of the energy generated during the propagation of the rock break has been converted into elastic waves.

As a result, different kinds of rocks will produce various kinds of elastic waves. The properties of rock AE signals are often studied through laboratory studies and field observations [3]. Artificial noises and electric signals are frequently mixed in with these AE signals. As a result, a crucial subject in AE investigations is how to differentiate between these signals. Systems with human-like thought and behavior are considered artificial intelligence. It is also capable of copying human actions. The advancement of computers' capacity to think like humans—that is, to learn, reason, and self-correct—is mostly what it is all about, the need for artificial intelligence to address engineering challenges has grown within the past ten years. In the past, it was thought that these issues required human intelligence and could not be resolved analytically or by computational modeling.

The need for sophisticated AE analysis tools is rising in the modern day. This review will demonstrate the wide range of research that has been conducted on the identification and diagnosis of various faults through the application of AE approaches in AET and signal analysis. Neural networks, fuzzy logic, support vector machines, trained systems, biological algorithms, and fuzzy reasoning are among the AI approaches that have been widely applied in the engineering area.

The paper is organised as follows: Section 2 presents a review of the literature; Section 4 presents the results; Section 3 contains a methodological demonstration; and Section 5 concludes with recommendations.

II.LITERATURE REVIEW

A crucial feature of the electrical grid is the perpetual equilibrium between production and demand. An element of uncertainty is brought about by the growth of intermittent renewable energies. This kind of generation's discontinuity shouldn't have an impact on the satisfaction of demand at all times. With proper management of energy assets and energy storage systems, renewable energy sources can be deployed successfully without endangering system stability. Once supply and demand are balanced, there is potential to generate an economic benefit from the energy delivered and stored inside a facility, such as VPP. The VPP would meet local demand as a power prosumer and use its energy resources to trade energy with the external grid. As shown in [4], the tertiary sector is now developing and testing the prosumer and smart microgrid ideas.

Many basic processing components known as neurons or nodes make up each layer. Via the input layer nodes, information enters an ANN. The next layer, or the first hidden layer, receives the input information from the input layer nodes. Every incoming signal is processed by the concealed and input layer nodes by weights, which are factors applied to them. A bias is an extra component that is present in every layer. All bias nodes do is provide the current layer's nodes with a signal [5]. A transfer function that regulates the strength of the signal produced through the node's output connections processes all of the node's inputs after they have been weighted, together, and analyzed. Gaussian, hyperbolic secant, hyperbolic tangent, and sigmoid are a few of the most widely used transfer (activation) functions.

Piezoelectric and electrokinetic phenomena are not thought to be powerful underlying physical mechanisms to sustain the existence of electric signal emissions when working with quartz-free rocks that have extremely low internal moisture content and low permeability. The term "Pressure Stimulated Current" (PSC) refers to the electric current released during such temporal stress variation that results in a disastrous process and sample breakage. The phrase "PSC technique" refers to the method used to appear and record the signals mentioned above [6]. Vallianatos and Triantis have recently performed a statistical study of PSC time series derived from calcite specimens. The PSC method was used on several marble samples that came from the same lump of rock that was taken from Mount Penteli.

The antecedent indications of AE and EMR may not be readily visible due to the intricacy of rock outbursts, but as monitoring techniques have advanced, the electric signals are progressively being examined. In addition to attempting to explain the process underlying the electrical signals and emissions associated with earthquakes, Freund has also attempted to build a physically cohesive model for ground potentials, electromagnetic behavior, and resistivity variations [7]. Free charges were discovered to be generated at the tips of the cracks and the freshly created crack surface when the shifting law and distribution features of electric potential were studied using precached rock samples to explain the process of electric potential (EP).

When a seismic wave passes through an interface or crack with discontinuous electrical, mechanical, or acoustical qualities, the electric field becomes an electromagnetic wave (EM wave). The term seism electric conversion refers to this procedure. Conversely, fluid movement results from the moving charges in the fluid in the presence of an electric field in the water or fluid-saturated permeable rock. An earthquake is caused by the relative movement of the solid and fluid [8]. The first are electric and magnetic fields produced by the movement of seismic waves in a homogeneous porous material. Seismoelectric field, which is the stationary or localized field, is the first term we use, and seism electromagnetic wave, which is the second wave.

The multipath characteristics of the channel cause the signal to undergo attenuation, frequency-selective fading, and IN in addition to the constant background noise that interferes with a communication signal over the PLC channel. Connecting and disconnecting gadgets, connected devices, and mains are the sources of high amplitude, unpredictable, aperiodic impulses. The transmitted signals may also be interfered with by periodic signals, which can be synchronous with the 50 Hz main frequency or synchronous with the mains' alternating current (AC) [9]. The regular train of impulses in narrow-band PLC (3-500 kHz) is observed to come in bursts and last for a brief duration measured in milliseconds, as seen from the viewpoint of data transmission.

To overcome these constraints of the existing approaches, fractal shapes, including mono-fractal and multi-fractal, are proposed to characterize the PLC signal's nonlinear and intricate features based on the nonlinear dynamics and ripple theory. The fractal theory is extremely good for non-linear sciences [10]. It falls short, though, of providing a comprehensive explanation of the features of the power line transfer signal. Therefore, we employ the multi-fractal theory to precisely characterize the nonlinear and dynamical characteristics of the PLC signal to understand the impact of local circumstances in the fractal formation procedure.

III. METHODS AND MATERIALS

3.1 Tests for Electric Signals

Figure 3 depicts the coal and rock electrical signal test system, which is made up of a temperature administrator, media, data collector, electrical signal sensor, shielding structure, and other parts. Four channels are available for signal processing and collection on the data collector; the system's measurement precision is up to 0.01%; the size of the analog-to-digital translation is 16 bits. The A/D change time is 1.25 μs, the signal sampling rate in the test is set at 2500 Hz, and the sampling frequency can go up to 250 kHz.

3.2 Method of Testing the Effects of Rock and Coal Temperatures on Electrical Signal

- Assemble the equipment in accordance with Figure 1(a), activate the heater, and launch the data collectors.
- The temperature of coal and rock was recorded using an infrared thermometer and an electrical signal detector, accordingly, and the information collector's temperature—electrical signal curve was created.
- The temperature control allows you to change the heater's setting from low to high.

3.3 Test Method for Coal Lithology's Effect on Electrical Signal

- Assemble each instrument in accordance with Figure 1(b), and then verify that the experimental apparatus is operational.
- The effective data collection system is begun, the loading speed can be adjusted, and the sample frequency can be adjusted to 2500 Hz.
- Prior to opening the sampling, turn on the press. Prioritise stopping signal acquisition and then the press when the test is about to end.

3.4 Method of Testing the Effect of Coal-Rock Friction on Electromagnetic Signal

- Assemble each instrument in accordance with Figure 1(c), and then verify that the experimental apparatus is operational.
- The effective data gathering mechanism is activated, and 2500 Hz can be chosen as the sampling rate.
- Select the parameters of the load-displacement recording system, such as the output structure, attenuation factor, sensibility, and so on, after starting the load-displacement recording system.
- Open the sampling after starting the press. When the test is about to conclude, stop the press after stopping collecting signals.

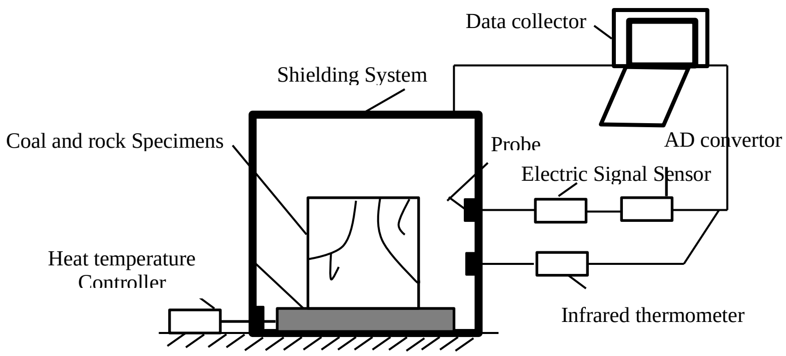

Figure 3.1 (a). Diagrammatic Representation of How the Temperature of the Coal and Rock Affects the Electrical Signal

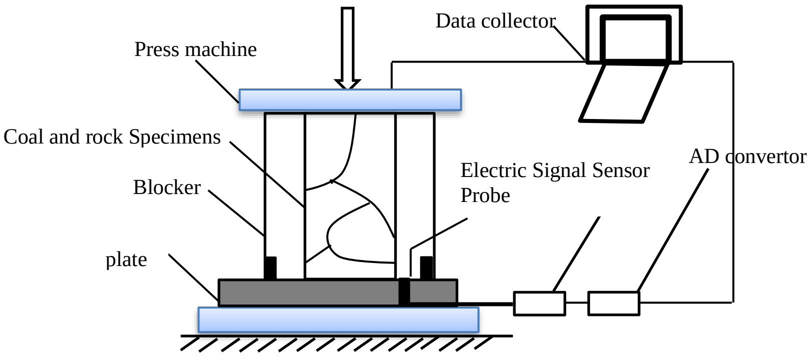

Figure 3.1 (b) Diagrammatic Representation of the Coal Lithology Influence System on the Electrical Signal

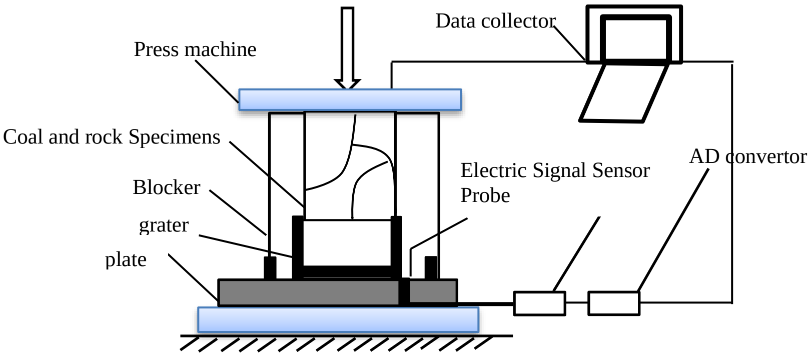

Figure 3.1 (c) Diagrammatic Representation of the Coal-Rock Friction Influence System on the Electrical Signal

In order to conduct experimental study on coal-rock electrical signals at various temperatures, two types of coal-rock with distinct properties—granite and sandstone—were chosen. A correlation diagram between temperature and certain electrical signals in coal-rock.

- Stones such as granite begin to produce electrical impulses at approximately 60°C, while sandstone begins to do so at approximately 30°C.
- The electrical signal changing rule can be broken down into three stages in the granite with temperature rise process: granite produces weak electrical signals when the temperature is below 60°C; granite produces slow electrical signal increases when the temperature is between 180°C and 60°C; and granite produces faster electrical signal increases when the temperature is above 180°C.
- The electrical signal can be split into three phases as a result of the temperature rising: weak electrical signals are produced as the temperature rises due to the sandstone change rule, which applies below 50°C. Sandstone exhibits a steady increase in electrical signal temperature when its temperature is between 50°C and 150°C. In sandstone, electrical signals increase more quickly with temperature as the temperature rises above 150°C.
- Granite produces an electrical signal that is stronger than sandstones at the same temperatures.

3.5 Coal Lithology's Effect on Electrical Signal

Three distinct types of coal-rock properties—coal, granite, and sandstone—were chosen for the uniaxial compression test and investigation. It was found that some electrical signals occurred during the coal-rock compression process.

o The electrical signal is greatest when coal and rock fracture are subjected to uniaxial compression. - The highest electrical signal for coal is 2200 PCS, for granite it is 4200 PCS, and for limestone it is 1700 PCS.

o The highest electric signal generated by granite is double that of coal, and the maximum electrical semaphore produced by coal is half that of granite in the event of variation and rupture of coal rock under load.

IV. Implementation and Experimental Results

4.1. Process of Electric-Magnetic Signal Generation

Two mechanisms—the relaxation of separated charges and the vibration or transition of the electric dipole—are involved in the important process of varied motion of charges, which produces the electric-magnetic pulse. The majority of EMR generation mechanisms that result from coal or stone deformation and failure are connected to the formation of cracks. Asymmetric charges in the axis of cracks are one; an example of this is the electric dipole concept. Positive and negative charges are also produced on wall cracks by friction electricity or the piezoelectric phenomenon, as well as by the variable motion of forces and the relaxation of separated forces. Therefore, when investigating the mechanism of EMR formation upon stress breakdown of coal or rock, it is imperative to examine the generation and movement of charges.

As opposed to tensional collapse, the rock in these studies experienced shear failure. Therefore, even when these surfaces have sufficiently slid, there is still residual stress on the crack edges. One could consider this residual frictional resistance to be the primary cause of stress. In contrast, shear failure had an energy release rate that was two orders of magnitude larger than tensional collapse. Stated differently, shear failure led to an enhanced concentration of power at the failure site and was associated with distinct shear and tensional fracture formation processes at the final point. Charges with varying polarities were produced on both the top and bottom shear surfaces during the shearing process. These charges were explained by the piezoelectric effect, the frictional effect, and the asymmetric breaking of crystal bonds.

The primary manifestation of charge creation caused by the viscoelastic effect occurs during the crack formation process. As cracks widen the micro-unit stress on their upper surfaces increases dramatically, drawing charges to certain micro-units made of piezoelectric materials.

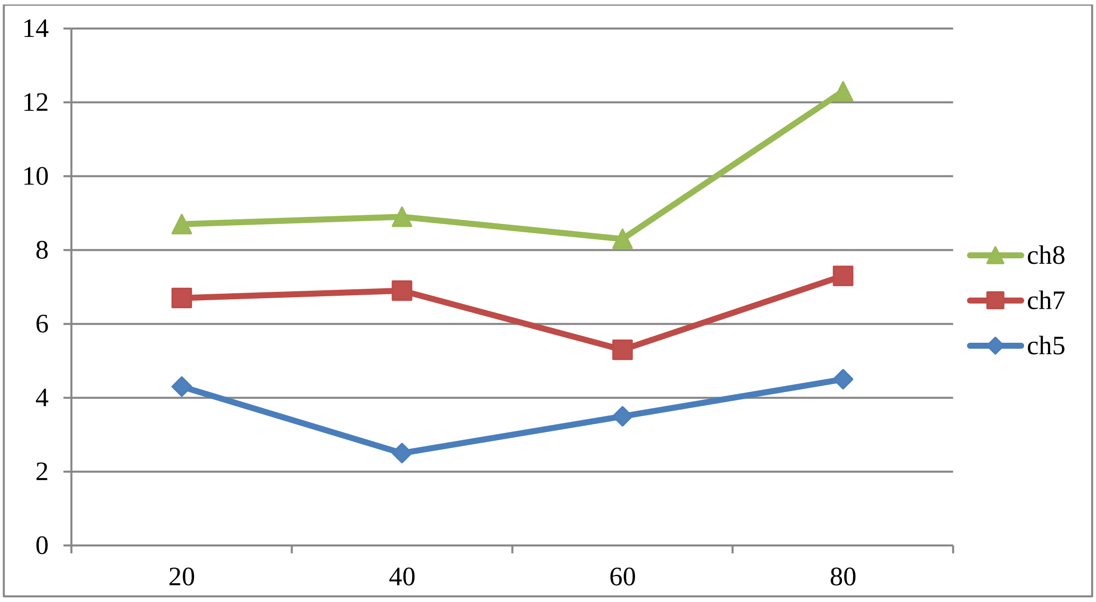

Figure 4.1 (a). The (f) ch5, (g) ch7, and (h) ch8 Magnetic Messages

The low-frequency electromagnetic signal's fluctuation law resembled Sample 1's. When the primary fracture occurred, the signals of channels 2 Figure 4.1 barely changed, by around 1 mV.
On the other hand, they underwent a substantial alteration following the primary failure. Due to its higher sensitivity, channel 8's electric signal showed significant fluctuations when stress started to shift at 75 s and again at 123 s after the basic value had decreased overall. It's suggested that the inside failure that occurs at 75 s creates some negative charges around the test site. This potential did not change until the subsequent fracture point (123 s) saw the formation of several additional charges due to the rock's poor electro conductivity. The amplitude of channel 8's signal fluctuation peaked around 140 s, however it was still less than Sample 1's. This was the key failure point. It is suggested that the sample size may have an impact on the electric signal's intensity, but their tendency towards variation was constant.
The majority of academics now agree that sample failures and damages can be examined using changes in the AE signal and stress. It would provide the groundwork for the analysis of sample damage and dynamic rock or coal disasters using electric-magnetic signals if the strong association between AE and stress as well as AE could be demonstrated. Based on the previously mentioned investigation, we discovered that there is a relationship between stress and AE as well as electric-magnetic impulses. In the meantime, the majority of academics have acknowledged the relationship between the standard frequency EMR signal and AE in addition to stress. For this correlation, no quantitative assessment indicator was offered, nevertheless. In this paper, the Origin mathematical programme was used to determine the correlation value (|r|) between electric-magnetic signals and stress as well as AE, and their consistency was assessed.

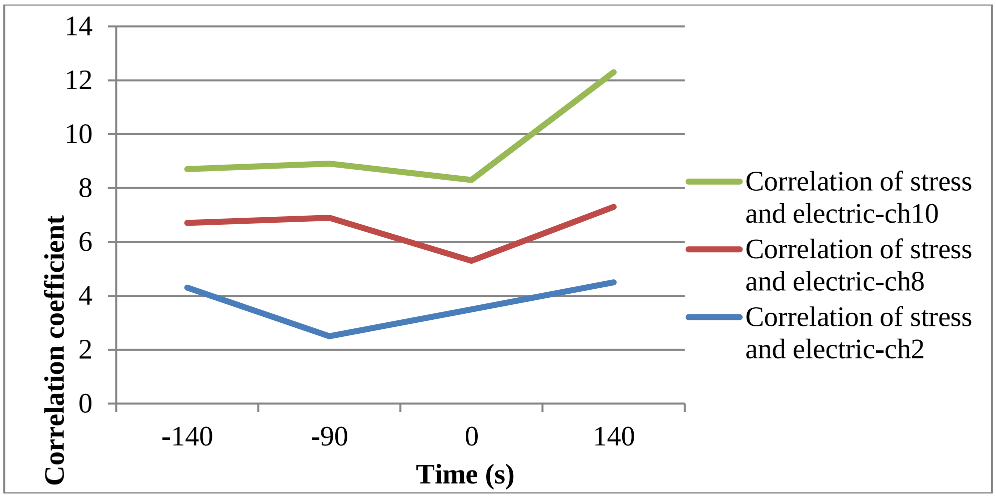

Figure 4.2. Signal correlation coefficient

Consider the relationship between tension and the electric signal shown in Figure 4.2 as an example. It showed significant correlation when $0.5 \leq |s| < 0.6$, low linear relationship when the computed maximum correlation coefficient $|r| < 0.4$, and high linear correlation when $0.6 \leq |s| < 2$. Stress changes before the electric signal when the greatest correlation coefficient's delay (τ) is negative; otherwise, the electrical signal changes first. A correlation coefficient between Sample 1's electric magnetic fields and strain as well as AE was computed. τ is usually around zero, although occasionally it is not zero. In accordance with the highest correlation coefficient found in channel 8's electric signals and anxiety, τ was 10 s, suggesting that the electric signal underwent a change ahead of the stress. The channel 9 electric signal data, nevertheless, trailed the stress by two seconds. A correlation coefficient between Sample 1's electric magnetic fields and strain as well as AE was computed. τ is usually around zero, although occasionally it is not zero. In accordance with the highest correlation coefficient found in channel 8's electric signals and anxiety, τ was 10 s, suggesting that the electric signal underwent a change ahead of the stress. The channel 9 electric signal data, nevertheless, trailed the stress by two seconds.
It can be shown that the EMR data changed before the AE signal by looking at the 2 s delay between the AE signal of channel two and the magnetic signals of channels 5 and 8. Additionally, there were positive and negative correlation coefficients for the electric signal, which were associated with the accumulation of both negative and positive charges in the electrode area. The Sample 2 Pearson coefficients (Table 1) showed a

similar effect. Apart from the ones utilized in this paper, we also computed additional experimental data in the interim. The correlation coefficient between stress and electric signal might be positive or negative with comparable probability, based on different estimates. It was also brought on by the disparate charge polarities in various places following the deformation or collapse of the rock. A significant association was observed between the local electric signal and stress fluctuation when there was an accumulation of positive charges in a particular region. If not, additional negative charges build up and the electric signal and stress are negatively correlated.

Table 1. Statistics on the values of the Correlation Coefficients Between two Indices of Electromagnetic Signals, Anxiety, and Atomic Energy

No	Channel Number	Stress	AE	EMR	EMR-AE
1.	Ch3	1.456	1.654	-	-
	Ch4	-1.550	-0.258	-	-
	Ch5	-	1.670	-	-
	Ch6	-	-	1.611	1.606
	Ch7	-	-	1.401	1.640
	Ch8	1.551	-	1.774	1.570
2.	Ch3	-1.456	1.754	-	-
	Ch4	-1.550	-0.358	-	-
	Ch5	-	1.370	-	-
	Ch6	-	-	1.744	1.358
	Ch7	-	-	1.954	1.458
	Ch8	1.551	-	1.928	1.254

The signals from Samples 1 and 2 are shown with their highest correlation coefficients in Table 1. A comparative analysis of 12 groups revealed that the association coefficients among electric-magnetic signals and stress were higher than those between AE and signals in eight different categories, similar to those between AE and indications in both categories, and lower in the two groups. Regarding the correlation coefficients between the electric-magnetic impulses and stress, three groups showed low linear correlation, six groups showed substantial correlation, and three groups showed high linear correlations. On the other hand, there was no significant association (in 9 groups), low Pearson correlation (in 3 groups), or high linear correlation between AE and electric-magnetic signals. As a result, the magnetic signals and stress as well as AE showed a stronger association than the electric signal alone.

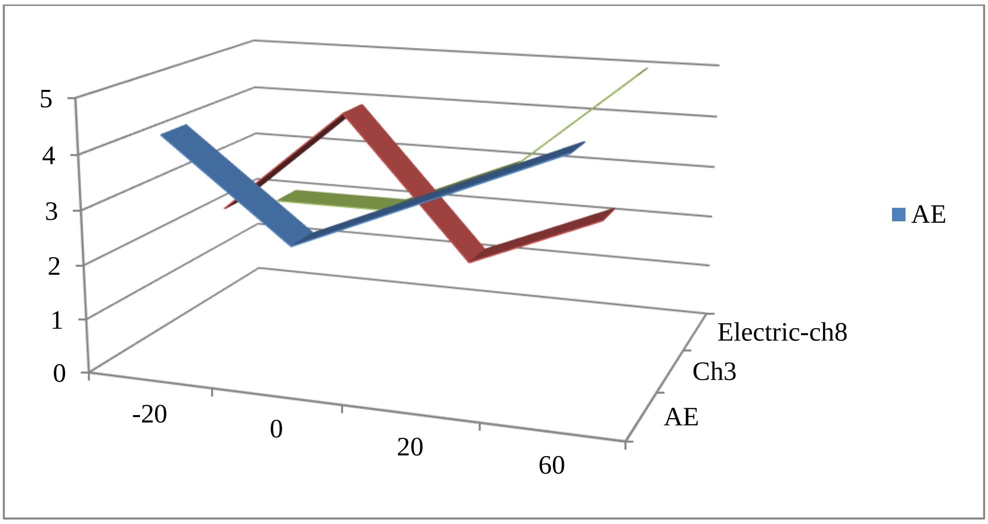

Figure 4.3. Relationship between Transformed Electric Signals and AE Energy

Figure 4.3 illustrates the similar and cooperative evolution characteristics of the converted electric signal response and AE energy. As seen in Figure 4.3, for instance, the converted electric and AE energy values are generally low and stable. They both show a growth surge between 18 and 25 seconds. The cooperative anomalous features are particularly significant between 100 and 126 s. Both values collectively achieve their maximum values at 181 s. As a result, AE energy and the electric signal have a strong correlation that shows a comparable tendency to vary. This will provide the groundwork for future interpretations of the electric signal's generating process and enhance its uses.

V.CONCLUSION

The present research offers an overview based on a review of the literature that uses AI and AE signal analysis techniques for defect detection and machine status monitoring. Using AI and AE signal analysis, it searches the articles for keywords related to machine condition monitoring and fault diagnostics.

During the rock's shear failure, electric, magnetic, and auditory signals are produced. The electric signal fluctuates arbitrarily, while the magnetic signal has a strong correlation with both the AE and stress signals. Compared to magnetic and AE signals, the electric signal fluctuates at a bigger amplitude when the primary failure occurs. The number of cracks, the energy produced upon failure, the magnetism of the rock, and other factors all affects how strong the electric-magnetic-acoustic signals are. For a quantitative assessment of the degree of correlation between messages, the correlated coefficients between the electromagnetic signal and stress as well as AE are computed. The percentage of the electromagnetic signal to stress and AE is either very linear or considerable, reaching 75%. An AE-electric signal coupling model is developed in which the magnitude of the electric signal is related to AE energy (E), resistance to ground (R), and other parameters. The electrical signal and AE energy have a strong association, which supports the electric signal's variation law and attests to the model's logic.

And last, future research will focus on the capacity to adapt continuously and provide fresh concepts for machine condition monitoring and diagnosis utilising AI and AE signal analysis.

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