INTERNATIONAL JOURNAL of SMART GRID
B. Ersöz et al., Vol.12, No.4, December, 2022

Methods of Explainable Artificial Intelligence, Trustworthy Artificial Intelligence and Interpretable Machine Learning in Renewable Energy

Betül Ersöz*, Şeref Sağıroğlu** and Halil İbrahim Bülbül‡ *

*Computer Education and Instructional Technology, Education Faculty, Gazi University Ankara, Türkiye;
**Computer Engineering Department, Engineering Faculty, Gazi University, Ankara, Türkiye,

(betul.ersoz@gazi.edu.tr; ss@gazi.edu.tr; bhalil@gazi.edu.tr)

‡ Corresponding Author; Halil İbrahim Bülbül, Computer Education and Instructional Technology, Gazi Universitesi, Türkiye, Tel: +90 312 202 2069

Fax: +90 0312 223 7569, bhalil@gazi.edu.tr

Received: 11.12.2022 Accepted:30.12.2022

Abstract - In recent years, there has been a significant increase in the use of renewable energy (RE) resources in order to produce cleaner energy. The impact of decisions made by artificial intelligence models on energy efficiency is very important in the transition to these resources. With eXplainable Artificial Intelligence (XAI), various methods have been developed to increase trust, transparency, and decision-making by artificial intelligence models, but more research is needed in this area to enhance confidence in the performance, evaluation, and explanations of these models. The aim of this study is to investigate and analyze how RE systems can benefit from the use of XAI and Trustworthy AI and Interpretable AI, along with considering some criticisms. The results of the study suggest that XAI is a relatively new topic in the field of RE and requires more attention in order to be effectively applied in critical systems to improve trust and transparency.

Keywords - Explainable artificial intelligence, renewable energy, trustworthy artificial intelligence, interpretable machine learning, energy system.

1. Introduction

The use of artificial intelligence (AI) in renewable energy resource applications (such as wind, ocean, solar, geothermal, hydro, hydrogen, and bioenergy energy) is increasing every year due to fast computation, ease of use, and impressive recent results. The eXplainable Artificial Intelligence (XAI) approach helps to develop processes, techniques, and strategies that provide explanations for the recommendations, predictions, and decisions of complex machine learning (ML) systems [1]. XAI stands out as a solution for understanding how AI techniques make decisions and what is happening in the background, or "black box", of these models. In the field of renewable energy (RE) systems, XAI is a new approach and solution for increasing trust in the decisions made by ML algorithms, providing more efficient, confident and low-cost systems with explainability, and finding intelligent solutions to problems.

Today, there are many problems related to energy production, transmission and distribution, including cost, security, safety, efficiency, inconsistency in carbon footprint, etc. due to the large amount of data that energy companies must manage, handle, store, protect or get values for better service, quality and product. AI is being used to increase energy efficiency, manage demand, control system or stability, improve network continuity, reduce energy consumption and cost, improve security, and predict anomalies or detect natural gas leaks [2]. As a result, the use of AI approaches, which has become very popular in recent years thanks to ML and deep learning (DL) algorithms, is also increasing. Energy system applications are further enhanced or supported by smart grids, which are thought to have an ecosystem worth around $15 trillion by 2030, according to a report by Precedence Reserve. The RE market, which is one of the factors enabling the global AI market to be even larger, is estimated to be around $75.82 billion in 2030 and is expected to increase electricity demand in settlements. The growing need for smart energy grids will make AI more effective in the global RE market. Another need for AI in the RE field is the digitalization of energy [3]. With the development of smart technologies, power generation, transmission and distribution have become more efficient and sustainable. Big data and AI are crucial at this point, as these technologies are essential tools for intelligent decision-making in optimizing all services based on data analytics. Data or AI-driven "smart grids" can play a role in supply management by increasing the use of renewable energy sources such as wind and solar power to higher levels [4].

Users often require evidence to ensure that they can trust the reliability of AI's decisions. XAI systems provide users with the reasoning behind their decisions and try to build confidence in AI. XAI makes the "black box" of AI systems transparent and allows the outputs to be more easily interpreted or explained. In contrast to AI systems, XAI systems present their outputs to the users along with the reasons for their decisions.

The purpose of XAI approaches is to help experts understand and explain the decisions and outputs of DL or ML models [5]. In this study, XAI methodology and techniques, Trustworthy AI (TAI) and Interpretable Machine Learning (IML) methods and mechanisms are explained and summarized, and their potentials for use in RE systems are discussed.

2. XAI, Trustworthy AI and Interpretable ML

In recent years, deep neural networks that offer multi-layered and more complex operations have been widely used. However, the "black box" nature of these networks can lead to a lack of trust in AI. At this point, XAI provides interpretable, intuitive, and easily understood explanations of the tools, techniques, and algorithms that can produce high-quality AI decisions [6]. The Defense Advanced Research Projects Agency (DARPA) has developed a program for XAI to build AI systems whose learned models and decisions are trusted and understood by users [7]. As the number of important decisions made by machines increases, explainable and interpretable AI become more important. With the help of XAI tools, users can better understand and rely on ML models that make important decisions. Fig. 1 shows the concepts, models, and techniques for XAI approaches.

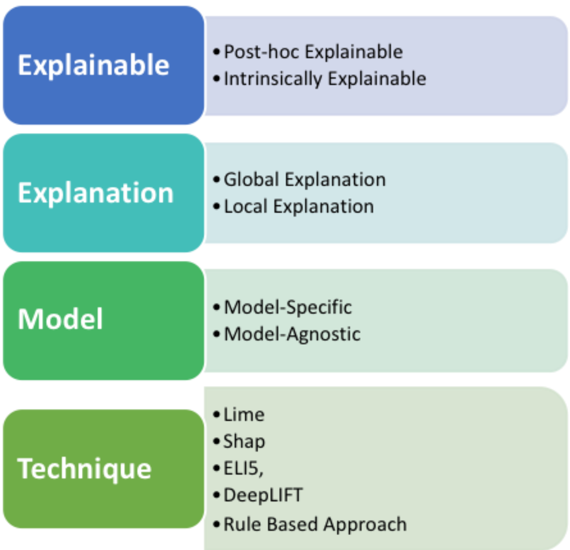

Fig. 1. Concept, model and technique for XAI

DL is the current term for artificial neural networks that use a large number of nonlinear functions. These networks have become extremely popular in recent years because they have achieved significant successes, reaching the level of human performance. Essentially, multiple layers of nonlinear functions learn features of the data at different levels of abstraction between the raw data and the final prediction. There is an inverse relationship between accuracy and interpretability in ML methods. Complex models, such as those used in DL, can provide highly accurate predictions, but they are often difficult to understand or explain, appearing like a "black box" to users. With current advances in ML, it is normal for an ML model to have thousands of parameters, making them much more complex than simple linear regression models. The concept of XAI arises when we ask questions such as "Why?" "When?" and "How?" about the decisions made by ML algorithms. Explainable AI can help us better understand the results of these algorithms and make more informed decisions about their use. Responsible AI is an approach to developing, evaluating, and deploying AI systems in a safe, reliable, and ethical manner. It involves keeping user goals at the center of system design decisions and proactively guiding the development and deployment of AI systems towards more beneficial and equitable outcomes [8]. There are several XAI methods available in the literature, such as LIME, SHAP, Rule-Based Approach, DeepLIFT, ELI5, XGBoost, K-Means, Decision Tree, and others. These methods can be used in a variety of AI models or architectures, such as SVM, LSTM, MLP, DL, RNN, CNN, LightGBM, SOM, Random Forest, Gradient Tree Boosting, and others. The most commonly used XAI methods are LIME and SHAP. LIME is a model-agnostic interpretation method that creates a new dataset of corresponding predictions from an underlying model based on a new observation. SHAP is a model-agnostic interpretation method based on the Shapley value from game theory [9].

2.1. Trustworthy Artificial Intelligence (TAI)

In recent years, there has been a concern about the negative effects that AI could have on humans. It has been shown that in security-critical scenarios, AI can unintentionally cause harm and make unreliable decisions [10]. Therefore, algorithms need to be trustworthy in order to mitigate the risk of misbehavior. The concept of TAI was developed to address this need and contribute to the proper management of risk [11]. In 2019, the principles for reliable AI were discussed under five headings in the "Artificial Intelligence Council Recommendation" by OECD member states. These include "inclusive growth, sustainable development and prosperity," "human-centered values and justice", "transparency and explainability", "resilience, safety and security" and "accountability" [12]. At the international level, there is already consensus on six dimensions of "Trustworthy AI" to address these issues.

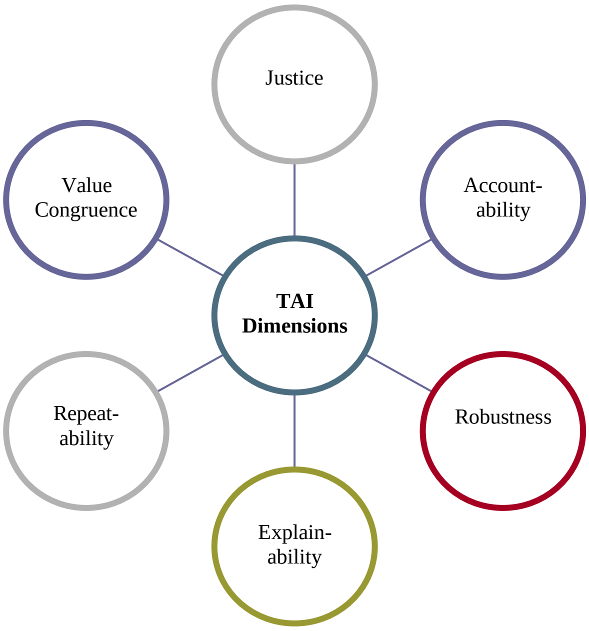

Fig. 2. Dimensions of trustworthy AI

Fig. 2 explains the dimensions of TAI. While justice, accountability, and value congruence represent social responsibility, robustness, repeatability, and explainability pose significant technical challenges. Adopting the principles of TAI will produce beneficial results for society [13]. It is especially important to rely on AI technologies that are actively involved in the effective use of RE resources and to make informed decisions. TAI will greatly contribute to the trustworthiness of algorithms against the risk of misdirection. It is predicted that TAI will be very effective in studies conducted in the fields of data management, the future of professions, innovation, and commercialization. However, it is important that AI is protected from being misled by human manipulation and produces reliable and accurate results. Personal data collected for AI solution should be safely stored and protected, applied equally to all individuals regardless of gender, race, age, or any form of discrimination, and free from prejudices. In order for AI to be auditable and accountable, its negative effects should be quickly noticed and reported, and control should be ensured by intervening in the decisions it makes. As AI is intended to provide the greatest possible benefits, it should be sustainable and capable of contributing to the development of the society in which it [14].

2.2.Interpretable Machine Learning (IML)

Interpretable Machine Learning (IML) is a new approach that aims to provide a promising solution to the problems arising from the uncertainty of complex ML techniques. It focuses on explainable ML models and can be used interchangeably with XAI. However, it can be said that IML is a specific aspect of XAI that focuses on explaining the logic of ML algorithms. The purpose of IML is to validate results rather than to provide an explanation of the inner working principles of ML models. In the event of an unexpected decision, the results should be able to support further justification. IML aims to provide new perspectives on ML problems in order to make fairer and more reliable decisions. The primary task of constructing an interpretable model is to use "white box" techniques, which allow the inner workings of the model to be understood. Interpreting and explaining complex models can be a difficult process, but it is especially important in high-risk decision-making situations where maximum transparency and understanding are necessary for issues of justice and safety [15]. Understanding how ML models influence critical behavior is crucial in various scenarios such as model debugging, AI-human collaboration, and regulatory compliance [16]. The more critical the use scenario, the more interpretability will be required. Fig. 3 introduces the process of covering interpretability features in a model.

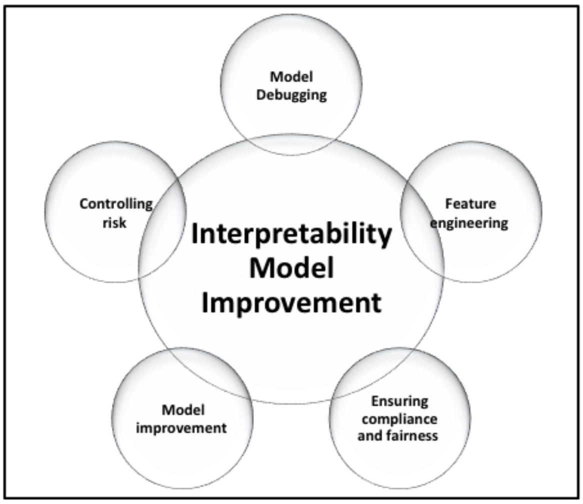

Fig. 3. Interpretability features in model improvement

XAI enables users to understand whether decisions made by machines are reliable and how they are reached. It also expands the decisions made by AI systems and serves as a bridge between humans and machines. XAI is a new approach that provides transparency to users by supporting the interpretability of decision-making mechanisms in investments in RE systems.

Fig. 4 illustrates an example of the demonstration of XAI methods in the transformation of renewable energy. There are various techniques and principles that enable ML models to be explained and understood through XAI. Aiming to facilitate the use of ML techniques, XAI is expected to be effective in the control and management of energy resources obtained through RE applications. DL and ML models are often referred to as "black box" because their inner workings are not easily understood. XAI aims to provide transparency to experts in this field, allowing for a better understanding or evaluation of the results of XAI techniques. However, it is necessary to improve explainable DL and ML models. Assessing, evaluating, and explaining the performance of XAI techniques often requires domain experts and is specific to the problem at hand.

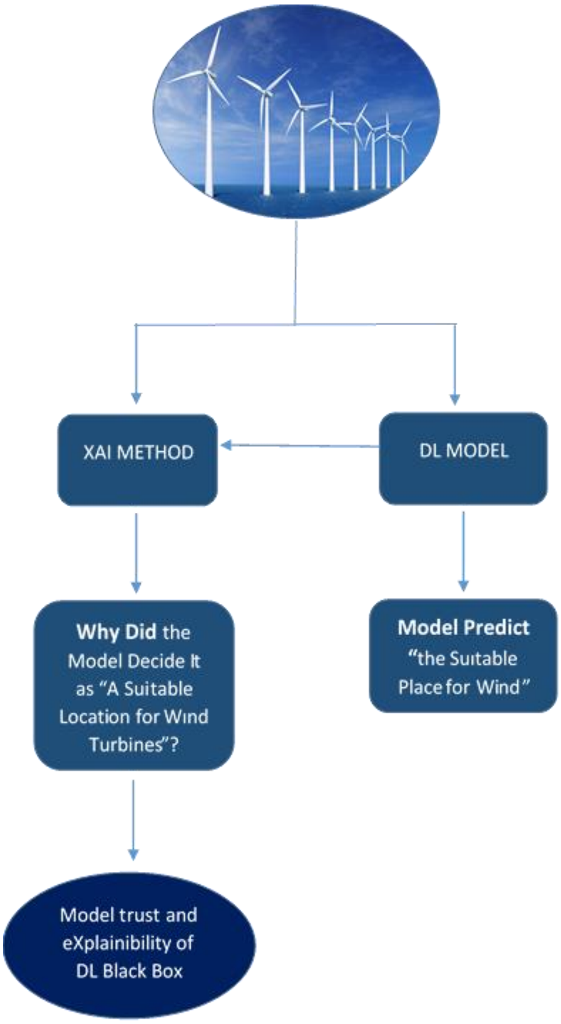

Fig. 4. XAI for RE transformation

XAI has been applied in renewable energy systems to improve energy management and efficiency. It has been a rapidly growing area of research, with the goal of transparently visualizing its solutions for renewable energy systems. Table 1 presents a categorized list of some studies on AI and XAI approaches in this field.

Fig. 5 depicts ratio of studies and citations related to XAI in recent years. As can be seen, studies on XAI have increased considerably. Although studies on renewable energy are still considered a new field of study, XAI appears to be effective in various fields. Table 2 shows the categorization of a total of 4909 studies related to XAI over the past nearly 20 years. According to data obtained from the Web of Science (WoS), more studies have been conducted in the computer field. However, it can be seen that studies in other scientific fields are increasing every year.

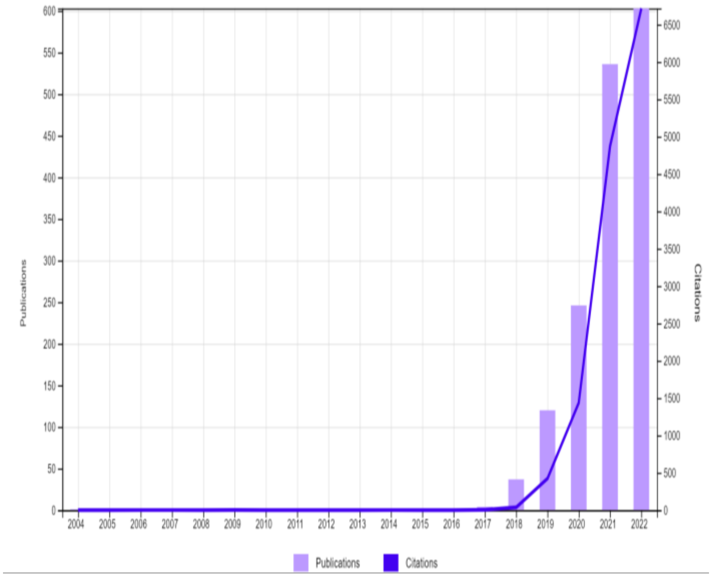

Fig. 5. XAI studies (based on WoS)

Fig. 6 includes the number of studies related to AI and renewable energy. There have been a total of 1943 publications on Artificial Intelligence and renewable energy in the past 30 years. The increase in the number of publications and citation rates every year also indicates that energy systems in this area need the support of AI. AI is a very important technology for managing decentralized networks, as it makes the transformation of RE more efficient and its use is increasing. Data is the source that feeds AI systems.

The energy efficiency of RE systems can be improved through the collaborative and effective use of explainable AI and the integration of decisions made by ML algorithms. This can only work effectively if experts understand the background of AI, perceive the learning mechanism, and apply different methods and techniques in XAI models. In recent years, the number of electricity generation facilities has increased significantly thanks to RE resources such as solar and wind. Intelligent generation can respond to consumption [17].

Smart grids create various application areas that direct RE sources and enable them to be more effective. The evaluation and analysis of producer, storage, consumer, and distribution data over the network offered by AI models is very important for the formation of control mechanisms. However, XAI models and techniques are used to improve systems to solve the causes of crucial situations, such as the misdirection of energy resources, and are also necessary for developing more transparent AI applications for future developments.

Table 1. Categorizations for AI and XAI studies in RE systems

Studies		Purpose	Content	Model/Architecture
[18]	Artificial Intelligence (AI)	AI assistance predictive maintenance for RE systems	Developed an AI model based on a deep learning algorithm, specifically convolutional neural network (CNN), utilizing the labeled endoscope image dataset	CNN
[19]		Hybrid AI method for RE	Hybrid AI optimal method to improve the efficiency of energy management in a smart grid for the optimal management of RECs.	MPC Algorithm
[20]		The Geothermal AI for geothermal exploration	Remote Sensing (RS), ML and AI have potential in managing the challenges of geothermal exploration.	ML
[21]	eXplainable Artificial Intelligence (XAI)	XAI for RE	Explainability of RE-driven Membrane Desalination System using Evaporative Cooler	LIME
[22]		XAI driven net-zero carbon roadmap	Offshore wind energy and the offshore wind speed dataset was collected through remote sensing.	VAE and t-SNE
[23]		XAI for energy consumption prediction.	Energy Consumption Forecasting Models	LSTM, MAE and MSE
[24]		Explainable Fault Detection Systems	eXplainable Fault Detection Systems (XFDS) for incipient faults in PV panels.	Irradiance-based three diode model (IB3DM)
[25]		XAI for building energy performance	Alternative approach to classify a building's EPC label using artificial neural network	ANN models and SHapley Additive exPlaination (SHAP)
[26]		Day-ahead Load Forecasting using XAI	Artificial Intelligence (AI), Information and Communication Technology (ICT), and the Internet of Things (IoT) for a better forecasting using XAI tool.	SHAP
[27]		Neural network interpretability for forecasting of aggregated renewable generation.	For solar generation forecasting the global feature importance and local feature contributions are examined.	Integrated Gradients, Expected Gradients and DeepLIFT
[28]		Electrical Load Forecasting Utilizing XAI Tool on Norwegian Residential Buildings	Experienced power market and system professionals can be integrated into developing the data-driven approach.	LSTM and SHAP

Table 2. Categorization XAI studies based on Web of Science (WoS)

Web of Science Categories	Record Count	Category in %
Computer Science Artificial Intelligence	1245	44.133
Computer Science Theory Methods	572	20.276
Computer Science Information Systems	527	18.681
Engineering Electrical Electronic	500	17.724
Computer Science Interdisciplinary Applications	443	15.704
Computer Science Software Engineering	190	6.735
Telecommunications	159	5.636
Medical Informatics	118	4.183
Computer Science Cybernetics	96	3.403
Materials Science Multidisciplinary	92	3.261
Physics Applied	88	3.119
Engineering Biomedical / Multidisciplinary	87	3.084
Imaging Science Photographic Technology	85	3.013

Chemistry Multidisciplinary	77	2.730
Operations Research Management Science	74	2.623
Multidisciplinary Sciences	73	2.588
Logic	71	2.517
Automation Control Systems	68	2.410
Computer Science Hardware Architecture	63	2.233
Mathematics Applied	63	2.233
Mathematical Computational Biology	57	2.021
Instruments Instrumentation	56	1.985
Medicine General Internal	53	1.879
Neurosciences	52	1.843
Showing 25 out of 175 entries		

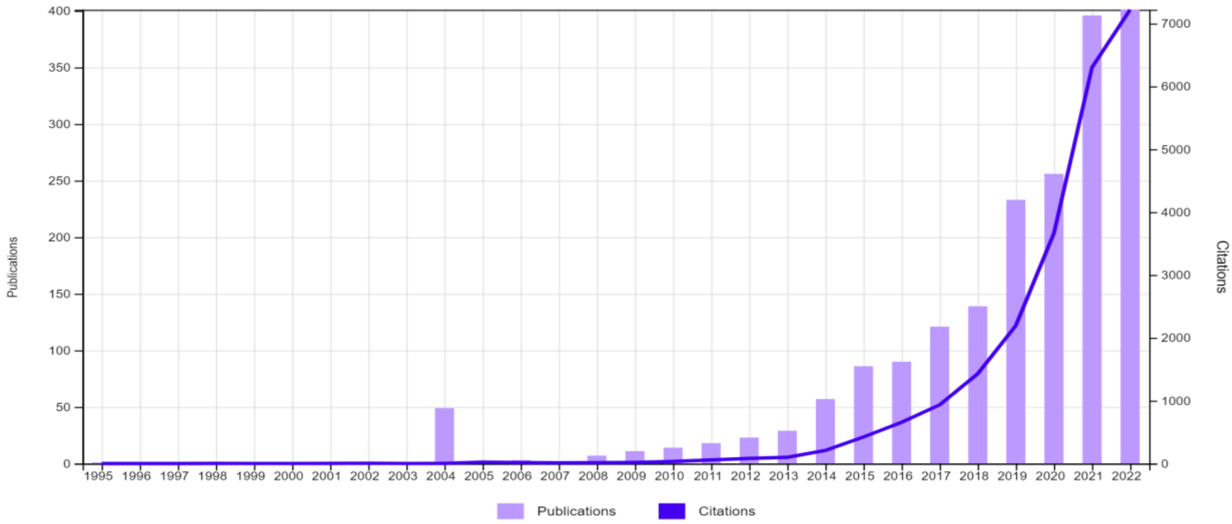

Fig. 6. AI and RE studies (WoS)

3. Results and Discussions

RE systems are critical systems because of being a part of energy power and systems and supported by Information and communications technology. As indicated in [29], AI technologies are used in almost all RE systems today. It is also well known that these systems are always under cyber-attack so they require more attention and protection all the time.

Recently, these systems are covering many smart systems, components, software, hardware, implementations and applications. Big data, cyber security, privacy, IoT, AI, metaverse, data science or digital twin are recent topics used and applied for analysis in RE systems. These are mostly used for improving RE systems' performance, quality, security and services with the help of AI models. XAI, IAI and TAI approaches aim to create confidence, trust and transparency in the results presented by decision-making models. The problems faced today are unable to explain in details of the decisions. With the help of these approaches, one can increase the model confidence index in applications by ensuring that the predictions made by explainable or interpreterable models used for AI processes can be explained to users or system operators with confidence.

Even if a few examples were given in this article, there have been many AI applications in RE systems. In this context, XAI techniques can be also applied for these applications. When the literature has been reviewed, there have been some criticisms about these issues as well.

The use of AI in RE systems has the potential to improve energy efficiency, manage and predict demand, improve network continuity, reduce energy consumption, understand users' behaviors, predict violations in cyber security and privacy, etc.

However, the black box nature of many AI models can lead to a lack of trust in their decision-making, modelling, prediction or control issues. Aforementioned, XAI aims to provide transparency and explanations for the decisions made by AI systems, increasing trust in their reliability and usefulness. IML focuses on explaining the logic behind AI models and validating their results. TAI also helps to ensure that AI systems are developed, evaluated, and deployed in a safe, reliable, and ethical manner.

- More research and development on XAI, IAI and TAI approaches are needed to improve the explainability and interpretability of AI models in RE systems and other fields.
- Ensuring and making AI systems transparent, trustable, efficient, reliable, and accountable might help to get more benefit from their fascinating features.
- Most of the published research on XAI has been in the field of computer science and engineering, with relatively less focus on electrical and electronic engineering and RE systems.

Here are some criticisms:

- There have been relatively few XAI applications developed for RE systems, despite the increasing use of AI in these systems.
- The success rates of available XAI models in RE systems may not yet be fully satisfactory.
- Even if XAI techniques have gained popularity in recent years, they may not yet be widely used in RE systems, more work needs to be done to make it viable for critical and industrial usage.
- Standardization and efficiency improvements may be needed to ensure that ML algorithms can be interpreted and trusted for use more in RE systems.
- The development of AI technologies integrated with RE systems, following the principles of XAI, can help to increase the efficiency and performance of these systems and facilitate their wider adoption across various fields.
- XAI is particularly important in the field of RE systems, where it can be used to improve the efficiency and reliability of these systems by providing more transparent and interpretable or explainable decision-making mechanisms. This helps to increase trust in AI systems, which is critical in high-risk situations where decisions made by machines can have significant consequences.
- There have been almost 2000 publications on RE and AI applications according to WoS index, but there are limited XAI applications available.
- The success rates of available XAI applications in RE systems are initially good, but there is a need for improvement in various applications.
- Explainable AI can be a new and exciting approach for developing knowledge discovery within AI models, particularly in addressing the black-boxes nature of many AI models.

Finally, it can be concluded that XAI has the potential to significantly improve the use of AI in various fields including RE systems, by making these systems more transparent, interpretable and trustable afterwards.

REFERENCES

[1] M. Ridley, "Explainable Artificial Intelligence (XAI)," Information Technology and Libraries, vol. 41, no. 2, 2022.

[2] Entes, "The Role of Artificial Intelligence in the Energy Sector of the Future," 2021. [Online]. Available: https://www.entes.com.tr/gelecegin-enerji-sektorunde-yapay-zekanin-rolu/.(last accessed on 29/11/2022)

[3] D. Taşbaşı, "Artificial intelligence in the renewable energy industry will exceed $75 billion," https://temizenerji.org/, 2022. (last accessed on 15/12/2022)

[4] IRENA, Future Energy Systems Need Clear AI Boundaries, 2020. [Online]. Available: https://www.irena.org/news/expertinsights/2020/Dec/Future-Energy-Systems-Need-Clear-AI-Boundaries. (last accessed on 24/12/2017)

[5] A. Singh, S. Sengupta, and V. Lakshminarayanan, "Explainable deep learning models in medical image analysis," Journal of Imaging, vol. 6, no. 6, p. 52, 2020.

[6] A. Das and P. Rad, "Opportunities and challenges in explainable artificial intelligence (xai): A survey," arXiv preprint arXiv:2006.11371, 2020.

[7] D. Gunning and D. Aha, "DARPA's explainable artificial intelligence (XAI) program," AI magazine, vol. 40, no. 2, pp. 44-58, 2019.

[8] Microsoft, "Concept Responsible AI," 2022. [Online]. Available: https://learn.microsoft.com/tr-tr/azure/machine-learning/concept-responsible-ai. (last accessed on 25/12/2022)

[9] V. Margot, "A Brief Overview of Methods to Explain AI (XAI)," https://towardsdatascience.com/a-brief-overview-of-methods-to-explain-ai-xai-fe0d2a7b05d6. (last accessed on 29/11/2022).

[10] H. Liu, Y. Wang, W. Fan, X. Liu, Y. Li, S. Jain, Y. Liu, A. K. Jain, and J. Tang, "Trustworthy ai: A computational perspective," ACM Transactions on Intelligent Systems and Technology, vol. 14, no. 1, pp. 1-59, 2022.

[11] S. Thiebes, S. Lins, and A. Sunyaev, "Trustworthy artificial intelligence," Electronic Markets, vol. 31, no. 2, pp. 447-464, 2021/06/01 2021, doi: 10.1007/s12525-020-00441-4.

[12] N. Singil, "Artificial Intelligence and Human Rights," Public and Private International Law Bulletin, vol. 42, no. 1, pp. 121-158, 2022.

[13] A. Kizrak, "Trustworthy AI," Medium, 2020. [Online]. Available:https://ayyucekizrak.medium.com/a%C3%A7%C4%B1klanabilir-sorumlu-ve-g%C3%BCvenilir-yapay-zeka-bece897c5ea9. (last accessed on 01/11/2022)

[14] G. Yilmaz, "European Code Of Ethics On The Use Of Artificial Intelligence In Jurisdictions," Marmara University European Community Institute Journal of European Studies, vol. 28, no. 1, pp. 27-55, 2020.

[15] S. Das, N. Agarwal, D. Venugopal, F. T. Sheldon, and S. Shiva, "Taxonomy and Survey of Interpretable Machine Learning Method," in 2020 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 670-677, 1-4 Dec. 2020, doi: 10.1109/SSCI47803.2020.9308404.

[16] Microsoft, "How to Machine Learning Interpretability," https://learn.microsoft.com/en-us/azure/machine-learning/v1/how-to-machine-learning-interpretability-automl. (last accessed on 16/12/2022).

[17] M. Langer, D. Oster, T. Speith, H. Hermanns, L. Kästner, E. Schmidt, A. Sesing, and K. Baum, "What do we want from Explainable Artificial Intelligence (XAI)? – A stakeholder perspective on XAI and a conceptual model guiding interdisciplinary XAI research," Artificial Intelligence, vol. 296, p. 103473, 2021/07/01/ 2021, doi: https://doi.org/10.1016/j.artint.2021.103473.

[18] W. Shin, J. Han, and W. Rhee, "AI-assistance for predictive maintenance of renewable energy systems," Energy, vol. 221, p. 119775, 2021.

[19] F. Conte, F. D'Antoni, G. Natrella, and M. Merone, "A new hybrid AI optimal management method for renewable energy communities," Energy and AI, vol. 10, p. 100197, 2022.

[20] J. Moraga, H. S. Duzgun, M. Cavur, and H. Soydan, "The Geothermal Artificial Intelligence for geothermal exploration," Renewable Energy, vol. 192, pp. 134-149, 2022/06/01/ 2022, doi: https://doi.org/10.1016/j.renene.2022.04.113.

[21] H. Salem, I. M. El-Hasnony, A. Kabeel, E. M. El-Said, and O. M. Elzeki, "Deep Learning model and Classification Explainability of Renewable energy-driven Membrane Desalination System using Evaporative Cooler," Alexandria Engineering Journal, vol. 61, no. 12, pp. 10007-10024, 2022.

[22] S. Heo, J. Ko, S. Kim, C. Jeong, S. Hwangbo, and C. Yoo, "Explainable AI-driven net-zero carbon roadmap for petrochemical industry considering stochastic scenarios of remotely sensed offshore wind energy," Journal of Cleaner Production, p. 134793, 2022.

[23] T. Sim, S. Choi, Y. Kim, S. H. Youn, D.-J. Jang, and S. LeeC.-J. Chun, "eXplainable AI (XAI)-Based Input Variable Selection Methodology for Forecasting Energy Consumption," Electronics, vol. 11, no. 18, p. 2947, 2022.

[24] S. Sairam, S. Seshadhri, G. Marafioti, S. Srinivasan, G. Mathisen, and K. Bekiroglu, "Edge-based Explainable Fault Detection Systems for photovoltaic panels on edge nodes," Renewable Energy, vol. 185, pp. 1425-1440, 2022.

[25] T. Tsoka, X. Ye, Y. Chen, D. Gong, and X. Xia, "Explainable artificial intelligence for building energy performance certificate labelling classification," Journal of Cleaner Production, vol. 355, p. 131626, 2022.

[26] D. A. Bolstad, U. Cali, M. Kuzlu, and U. Halden, "Day-ahead Load Forecasting using Explainable Artificial Intelligence," in 2022 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), pp. 1-5, 24-28 April 2022, doi: 10.1109/ISGT50606.2022.9817538.

[27] Y. Lu, I. Murzakhanov, and S. Chatzivasileiadis, "Neural network interpretability for forecasting of aggregated renewable generation," in 2021 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), pp. 282-288, 25-28 Oct. 2021, doi: 10.1109/SmartGridComm51999.2021.9631993.

[28] E. Henriksen, U. Halden, M. Kuzlu, and U. Cali, "Electrical Load Forecasting Utilizing an Explainable Artificial Intelligence (XAI) Tool on Norwegian Residential Buildings," in 2022 International Conference on Smart Energy Systems and Technologies (SEST), pp. 1-6, 5-7 Sept. 2022, doi: 10.1109/SEST53650.2022.9898500.

[29] J. T. Dellosa and E. C. Palconit, "Artificial Intelligence (AI) in Renewable Energy Systems: A Condensed Review of its Applications and Techniques," in 2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), pp. 1-6, 2021.