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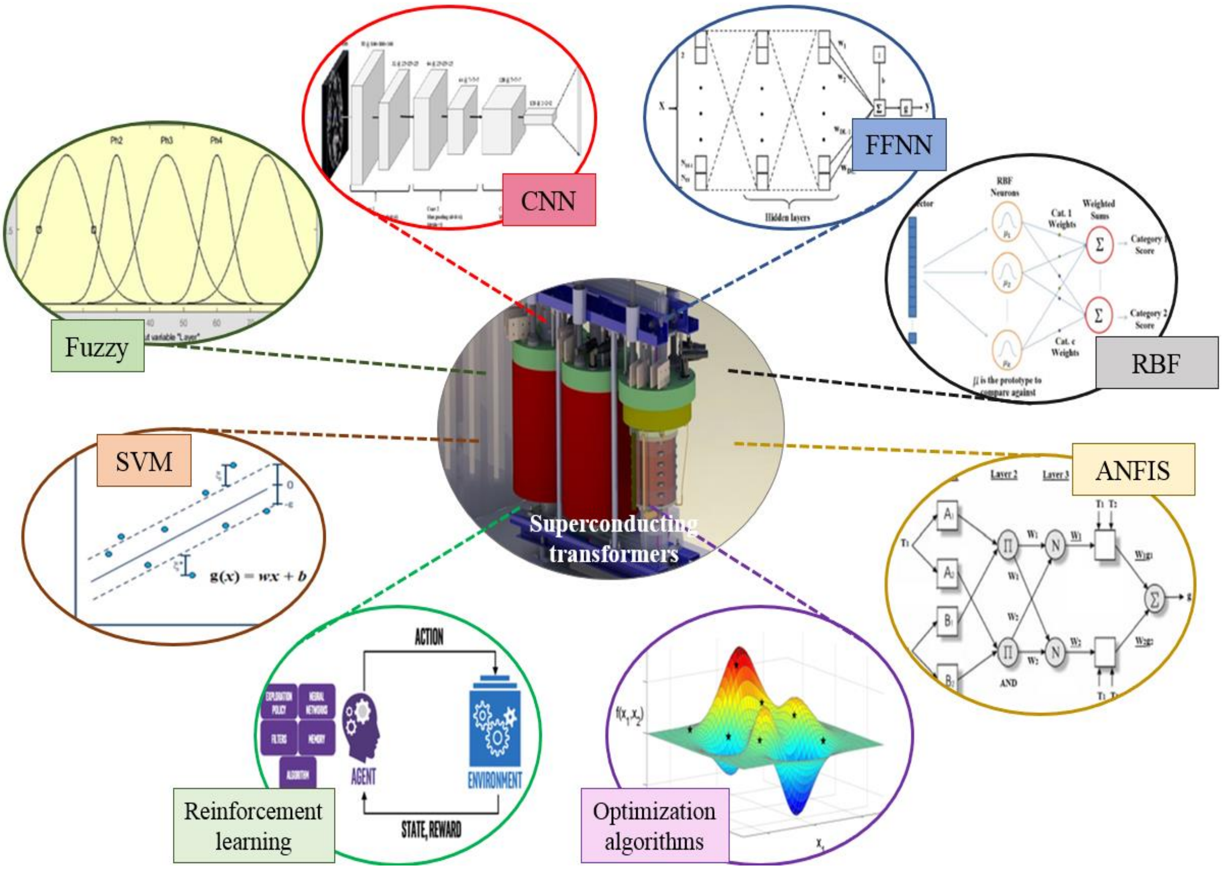

Artificial intelligence for superconducting transformers

How can superconducting transformer technology become smarter in future by using artificial intelligence?

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In this article, we have shared our views on the potential role of artificial intelligence (AI) techniques to effectively address future tasks and issues, related to four distinctive life-cycle phases of superconducting transformers, i.e., design, operation, maintenance / condition monitoring, and asset management stages.

Abstract

Artificial intelligence (AI) techniques are currently widely used in different parts of the electrical engineering sector due to their privileges for being used in smarter manufacturing and accurate and efficient operating of electric devices. Power transformers are a vital and expensive asset in the power network, where their consistent and fault-free operation greatly impacts the reliability of the whole system. The superconducting transformer has the potential to fully modernize the power network in the near future with its invincible advantages, including much lighter weight, more compact size, much lower loss, and higher efficiency compared with conventional oil-immersed counterparts. In this article, we have looked into the perspective of using AI for revolutionizing superconducting transformer technology in many aspects related to their design, operation, condition monitoring, maintenance, and asset management. We believe that this article offers a roadmap for what could be and needs to be done in the current decade 2020-2030 to integrate AI into superconducting transformer technology.

Keywords: artificial intelligence, condition monitoring, design development, loss estimation, superconducting transformers

Cryo-electrification which takes advantage of superconductictivity and cryogenic technologies is the viable option for shaping future for addressing the electrification issues in the power network and modern transportation applications

Artificial intelligence is widely used in many engineering fields, yet there is a question mark on what benefit it will bring into superconducting devices, such as superconducting transformer

1. Introduction

Cryo-electrification is a solution that superconducting technology together with cryogenic engineering can offer to assist in resolving the issues in the power network and transportation sector related to global warming, pollution, emission, losses, and achieve the targets in many Net Zero Emission plans [1]. The superconducting transformer is one of the most promising applications for cryo-electrification in power networks since it is much lighter (2 to 3 times), more compact (3 to 5 times), more efficient (up to 5 %), and more over-load tolerable compared with its conventional counterpart [2]. In addition, the environmental footprint of a superconducting transformer is smaller than traditional oil-immersed transformers since superconducting windings need to be immersed in liquid nitrogen (LN2), which is non-toxic and non-hazardous liquid. Therefore, by omitting the oil in this type of transformer, the risks of the explosion caused by the oil over-heating would be completely removed. On the other hand, this will increase the reliability of the superconducting transformers compared to their traditional counterparts. These benefits pave the way for implementing superconducting transformers in high power applications or supplying sensitive loads, replacing them with traditional oil-immersed ones. At the moment, the breakeven of using superconducting transformers is 25 MVA, but with the advancement of tape / wire production technology as well as progress in manufacturing techniques, this power will decrease further in this current decade. Apart from the superconducting tape manufacturing challenge, other challenges have slowed down the evolving process for the superconducting transformer technology, including fault tolerance concerns [3-4], high cost of former production for windings cryostat manufacturing, and efficient cooling system design. Many researchers and companies are working to address the challenges above in order to make the superconducting transformer a viable commercialized component for electric networks and increase its competitiveness against conventional oil-immersed transformers. Most efforts are focused on tape production improvement to reduce its cost and AC loss as well as focusing on some technical or innovative way of manufacturing and assembling transformer parts. Besides these efforts, there have been recent developments in Artificial Intelligence (AI) techniques in electrical engineering, which can be adopted and implemented on superconducting devices. AI techniques can address the challenges that a superconducting transformer is facing and offer some solutions to solve them. The opportunities offered by AI will lead to producing a smart superconducting transformer in this decade.

AI is the intelligence of trained machines and basically refers to resembling human intelligence by a computer. The main target of AI is to perform tasks such as learning, problem-solving, planning, reasoning, and identifying patterns. AI approaches can be divided into two main groups: computational intelligence (CI) and non-computational intelligence [5]. Generally, computational intelligence is a set of nature-inspired computational methodologies and approaches to addressing complex real-world problems which mathematical or traditional modelling may not solve for several reasons: 1) the processes might be too complex for mathematical reasoning, 2) it might contain some uncertainties during the process, or 3) the process might simply be stochastic in nature. Fuzzy logic, artificial neural networks, heuristic algorithms are some of the most well-known categories in CI. On the other hand, non-CI methods are suitable for dealing with high-dimensional data and require manual effort to prepare data for training procedure. Support vector machines, reinforcement learning, Bayesian theorem-based classifier, and data clustering methods fall under this category.

AI methods have been widely used for solving different kinds of problems in electrical engineering, which can definitely be beneficial for the superconducting technology as well

2. General AI functions for electric power devices

Recently, AI methods have been widely used for solving different kinds of problems in electrical engineering. Table 1 summarises the most important AI functions. The main challenge, general solution and AI solution of each function are briefly described.

Table 1: AI functions in electrical engineering

Function	Challenge	General Solution	AI Solution
Supervised modelling and simulation	Practical and experimental tests are expensive, sometimes destructive in nature, and time-consuming.	Computer aided design (CAD) systems.	Despite the high complexity of this process, AI techniques can give us the models by using supervised learning procedure. Huge amount of data is needed, which makes it "data-based" modelling.
Knowledge-based modelling	Developing new electrical equipment or facilities.	Finding effective parameters and variables of the problem and related knowledge to the case.	This type of modelling normally has an "if – then" structure. These models can be made by converting the knowledge to "if – then" rules.
Optimization	In many cases, we have knowledge about the best performance of electrical equipment, but the performance is not suitable enough in practice.	Finding an optimal solution using maximizing or minimizing objective functions from a set of available alternatives given constraints, equalities, or inequalities that the solutions have to fulfil.	The random search feature of some AI techniques makes the whole searching process much faster than conventional trial and error method or even mathematical search method.
Classifications	Determining anomaly, abnormality or different types of faults in the equipment in initial steps.	Discriminating different situations or conditions of the equipment's performance or to monitor and determine a special performance of the equipment.	By using classification methods to develop a more reliable AI-based protection / fault detection system, we can prevent future costly damages.
Clustering	Sometimes we encounter cases with a huge number of data logged from an experiment or model but without any labels. It means that we have no knowledge of what is happening.	Developing unsupervised models.	AI-based clustering methods are the best choices to cluster experimental outputs for developing effective discriminating systems or perhaps protecting systems.
Regression and prediction	Some phenomena in electrical equipment led to gradual changes in them over the lifetime. Complexity of the problem does not allow for easy finding of a mathematical formula or model.	Finding regression models.	AI techniques are able to follow time series phenomena and can easily deal with the complexity of the problem.

3. Potential future applications of AI in the superconducting transformer technology

Here we offer and discuss ideas on involving AI techniques and functions to address some of the challenges that superconducting transformer is facing. In the following lines, these potential solutions that can be implemented in the future are offered and discussed for the first time:

3.1 Tape architecture optimization and material selection

AC loss is one of the important challenges for a superconducting transformer, given that all existing cooling systems are extremely low efficient. Typically for dissipating 1 W out of the cryostat of a superconducting transformer, about

12 to 30 W needs to be consumed in the cooling system, depending on the type and capability of the cryocooler as well as operating temperature. The part of heat load that we can control and manage to reduce is generated by AC loss, and this highly depends on the tape architecture, its material, operating temperature, and winding configuration. On the other hand, all commercial superconducting tapes for high power applications are coated conductor tapes that have a layered architecture with different layers, including a substrate, superconducting, buffers, and stabilizer layers. The size, thickness, and material of these layers drastically affect the superconducting transformer performance during normal operation, and especially during a short circuit fault, as fault current does not flow in the superconducting layer during the course of a fault but flows in other layers depending on their resistivity. In addition, the type and thickness of the materials in different layers of a coated conductor will affect the production cost and total price of the superconducting tape. Therefore, to achieve minimum AC loss and reach a specific fault impedance, one can run an optimization problem using AI techniques with a proper objective function to find the optimal thickness of layers and, consequently, optimal thickness of the tape with the best material composition and minimizing the cost at the same time. Note that this will drastically improve recovery after the fault of a transformer as well, and in fact, recovery performance can be a constraint itself. It is worth noting that this problem would be complicated enough to motivate us to use AI to solve it since there are lots of material candidates such as brass, copper, silver, Hastelloy, stainless steel, sapphire, GdBCO, YBCO, BSCCO, MgB_2, etc., and all these materials have their temperature and magnetic field-dependent parameters. In addition, superconducting materials have a temperature, magnetic field, and carrying current dependent performance. This optimization problem can be a single- or multi-objective problem depends on the complexity and needed precision for the final design.

> To achieve minimum AC loss and reach a specific fault impedance, one can run an optimization problem using AI techniques with a proper objective function to find the optimal architecture of superconducting tapes

3.2 Optimal design of superconducting transformer

Existing superconducting transformers are mostly designed and built based on a conventional transformer benchmark design, and they usually have core-type structure no matter if they are three-phase or single-phase. In addition, practical difficulties and obstacles around characterizing superconducting material parameters push the designers towards more technical approaches, based on trial and error as well as rule of thumb. Using AI techniques, one can set an optimization problem based on geometrical parameters of the transformer parts and physical, electrical, thermal, and electromagnetic parameters of its materials to optimally design a superconducting transformer based on different objective functions. Depending on different applications, objective functions can vary from minimum cost, size, mass, or weight, loss, to maximum efficiency, in order to achieve and satisfy constraints related to a specific level of loss in windings, core, and cooling system, a specific fault impedance, a specific recovery performance after fault, a specific voltage regulation, a specific cost margin, etc. Using new multi-objective AI techniques, it also would be possible simultaneously to solve several objective functions together to satisfy many different constraints at the same time. Everything in a superconducting transformer including shape, type, material, and size of its core, winding configuration, number of winding layers, number of turns in a layer, height of winding, size and material of flux diverter, tape / wire material, and cryostat size can be calculated using AI techniques / models as the output of an optimization problem.

3.3 Additive manufacturing

Additive manufacturing (AM), also known as 3D printing, is a transformative approach to the industrial production of transformers that enables the creation of lighter, custom-designed, more flexible and stronger parts, finally lead to more rapid prototyping and manufacturing. AM uses highly accurate data CAD software or sophisticated 3D object scanners to direct hardware to deploy material, layer upon layer, in precise geometric shapes. AM, together with AI, can revolutionize superconducting transformer manufacturing and prototyping in insulation processing, winding former design and production, soft magnetic core manufacturing, and cryostat design and manufacturing. The distance between turns, the shape of groves, and its pitch angle for carving on the winding former can be an output of an optimization problem using AI techniques. The thickness of insulation material on the surface of a tape in winding can be the output of a regression or optimization problem, and it can directly be linked to a 3D printer to place it on the surface of the tape. The utilization of AI to design a cryostat for a superconducting transformer will be highly beneficial. We can get the minimum size to decrease the production cost, and eventually, using combined AM-AI will reduce material waste as the process can be precisely controlled. The importance and cost of this waste will be quite significant when it comes to large cryostats for three-phase transformers. In addition, AI combined with 3D printing technologies could increase the precision of a 3D printer performance by reducing the potential risk of error and facilitating automated production. It is highly needed in the manufacturing of highly accurate and sensitive devices such as superconductors superconducting transformers. Using AI techniques, we would be able to evaluate and precisely process a large number of data logged from many different sensors allocated in the 3D printer during the printing process. This will further improve the print success rate and will reduce its printing time.

> A model for the transformer AC loss can be developed based on the AI regression function, which can be used for the real-time calculation of the AC losses of the superconducting transformer continuously over its lifetime

3.4 Online loss prediction

The most commonly used accurate way of measuring AC loss for superconducting devices is the electrical method. Usually, it needs a lock-in amplifier for a fine measurement, but this equipment does not exist on-site where the superconducting transformer will be installed in a crowded and compact substation. The most common offline way of AC loss evaluation is finite element modelling. But this approach is computationally very exhaustive and cannot be implemented in real-time, especially when we consider the nonlinear characteristic of a transformer core. Thus, we would need an ultra-accurate real-time approach to estimate the AC loss of a transformer to log the data and monitor and indicate the condition of the winding. If not caused by input variation, any change in AC loss can reflect an internal fault or anomaly in the transformer. AC loss variation will affect thermal management of the superconducting transformer, increase the chance of developing a hotspot in the winding, and change the remaining lifetime of insulation, locally. Therefore, it is crucial to accurately predict AC loss by measuring the input to the transformer, i.e., network or load current, as it is highly desirable to not assemble any other instrument in or out of the transformer itself. For this purpose, a model for the tape, winding, and transformer AC loss can be developed based on the regression function of AI, and later it can be used in real-time mode to calculate AC loss of the superconducting transformer continuously over its lifetime. It is worth noting that AC loss of winding can be modelled using AI techniques, but all other types of loss, including core loss and stray losses, can be modelled for normal operating conditions or transients. One easy way can be using a simple finite element-based model to produce a sufficient amount of input data for the AI-based models. This can be done during the design stage of a transformer.

3.5 Transformer surrogate model

The common way of modelling a superconducting transformer is using a model based on the finite element method, usually in software packages like COMSOL. It is an accurate approach but computationally slow and costly. The other ways are equivalent circuit modelling and analytical modelling. These methods are faster but less accurate compared with the finite element modelling approach. In addition, modelling results, even if obtained by the finite element modelling approach, need to be in good agreement with experimental results. The built model must be able to analyse the behaviour of the transformer for many different conditions offline and possibly real-time. An advantageous method free from the computational burden and cost of the finite element method but with a similar range of accuracy uses surrogate models based on many multilayer neural networks. These neural networks model the behaviour of a superconducting transformer and can be solved thousand times faster compared to similar finite element-based models. Another point is that the prepared model can easily be used to study many different behaviours of transformers and not only its loss, but most finite element models need to be purpose-built.

> Hotspot and critical current weak points of superconducting winding can be estimated using the clustering functions of AI, then a properly architectured and well-trained ANN should be able to do the job

3.6 Hotspot and critical current weak point detection

One of the biggest challenges in developing most large-scale superconducting power devices is the establishment of a hotspot in the superconducting tape / coil / winding. The reason for the occurrence of a hotspot is not very clear and depends on the type of superconducting device, operating condition, superconducting tape architecture, and resistivity of the stabilizer material. Generally speaking, using a stabilizer material such as copper with very steep resistivity versus temperature curve can easily establish a hotspot in the transformer windings, especially in a high current regime such as during an external short circuit [3-4]. The use of materials such as brass helps lower the chance of a hotspot development along with the tape. In addition, the hotspot shows a similar / close behaviour of the tape to when a critical current weak point exists in there. Usually, a hotspot can be easily established around critical current weak points along the length of the winding. The conventional way for detecting it is by having many voltages taps along the length of windings. A more recent way of finding them is using fibre optic sensors such as fibre Bragg grating (FBG) sensor. But using FBG sensors in a transformer means adding an extra element around winding turns, which will increase the complexity of the winding assembly process and will change the heat transfer performance of LN2 around the winding. In addition, from reliability point of view, it would be more desirable to find the hotspot and weak point using the current and voltage signal of the transformer. For achieving this, a set sufficient amount of experimental data on critical current measurement of an intentionally damaged tape would be of great help. As this problem should be categorized under classification and clustering functions of AI, then a proper well-trained ANN together with a support vector machine (SVM) or wavelet transform (WT) should be able to do the job.

> Lead: AI can help to detect the fault in a superconducting transformer, which can be treated as a classification problem - for that purpose, some samples of healthy winding at different current and frequency levels are needed.

3.7 Fault detection and condition monitoring

Condition monitoring of superconducting transformers is another critical area where AI can offer some solutions / opportunities. As superconducting tapes and windings in this type of transformers are very sensitive and brittle, avoiding any destructive transient or fault is highly important. In case of high current severe faults, current flows in stabilizer and it can naturally protect the superconducting layer. In addition, by choosing a proper stabilizer, sufficient conductor thickness and operating at subcooled temperature, a higher level of fault tolerance can be achieved [3-4]. But in the case of an internal turn-to-turn fault, the transformer current usually would not drastically change. Therefore, detecting this fault, based on current amplitude protection would not be possible. On the other hand, this type of internal turn-to-turn fault usually happens at a very low number of turns and is quite destructive over time since it can establish a hotspot in the location of the fault and cause circulation current in the winding that can further burn the tape / winding. AI can help to detect the fault in a superconducting transformer as a classification problem. For this purpose, some samples of healthy winding at different current and frequency levels are needed. These samples can be used later to be compared with faulty winding signals.

3.8 Cooling system optimization

Another potential application for AI is the optimal design of the cooling system for superconducting transformers. Imagine we know a range of winding heat load and a range of possible leakage heat load, and we have a range for heat transfer coefficient, pressure and pressure drop, and LN2 flow rate as well as capability curve of several different types of cryocoolers. We can set and run an optimization problem with different scenarios to optimally calculate all the above-mentioned parameters and find the number and type of cold heads, optimal pressure and flow rate. This can be done to have the minimum cost or the maximum efficiency in the cooling system. It is worth noting that at the moment, this process is done by using lots of thermodynamic equations and mostly based on one's technical knowledge rather than a purely theoretical approach. Therefore, the final estimation of heat load and heat leakage is usually drastically far away from the real values, which can be measured after the installation of the transformer. Thus, at the moment cryogenic cooling system designer considers a huge safety margin for their estimation, which further causes extra cost and complexity.

3.9 Asset management

An adequate asset management scheme should consist of accurate failure analysis, its frequency and risk of occurrence, and absolute evaluation of their socio-economic impact to reduce downtime and maximize asset availability. Consistent and reliable information on the condition assessment is the key to design a suitable asset management program. However, condition monitoring of superconducting transformers is still under development. The existing methods use direct and indirect means to detect incipient faults that may be generated due to various electrical and thermal anomalies. Due to the lack of behavioural knowledge, risk evaluation and asset management of superconducting transformers is very challenging at the moment. However, significant efforts are in place to transform the available knowledge into a well-defined framework. It is also an opportune moment for the application of AI technologies for such purposes in a cost-effective, cheaper, intuitive, and instantaneous manner.

> Promising artificial intelligence techniques and data-driven modelling can be adopted to turn superconducting transformer into a smarter device

4. Proposed AI techniques for solving superconducting transformer problems

With the advancement of AI technologies, many methodologies are now available to address superconducting transformer issues based on the appropriate problem definition. In our opinion, AI methods should be categorized based on the end goal of a user, such as problem-solving, reasoning, executing logical action, and / or learning. Using this definition, following AI methods may have a greater scope in the application of superconducting transformers.

4.1 Computional intelligence methods

4.1.1 Fuzzy logic

The emergence of the fuzzy system stems from the notion that machines must have the ability to represent inexact data and knowledge using mathematical theories to explain uncertainty. In contrast with Boolean logic, fuzzy logic uses truth-values of variables to explain events. These values can be a real number between 0 and 1. Fuzzy logic is usually used whenever the introduction of an exact mathematical formulation is difficult or complex for solving a problem [6]. Therefore, knowledge-based modelling (mentioned in 2.2) can be done by fuzzy logic. Online loss estimation (mentioned in 3.4) and fault detection and condition monitoring (mentioned in 3.6) is the superconducting transformer challenges, which can be addressed by fuzzy logic in future. Evidently, the use of fuzzy systems for asset management of superconducting transformers is possible if a sufficient knowledge base is available to explain their behavioural dynamics due to operational anomalies.

> Most of the real-time fault detection and condition monitoring problems can be addressed by using deep learning-based ANNs

4.1.2 Artificial neural networks

Artificial neural networks (ANNs) are the most common classifiers for data and pattern recognition in engineering problems. These classifiers are designed based on and by resembling a human's neural network and, in other words, they have similar action and function to human neural network [7].

Feedforward neural network (FFNN), radial basis function neural network (RBFNN), and probabilistic neural network (PNN) are well-known ANNs that are widely used for developing supervised models and solving classification problems. In addition, most of the mentioned applications in Section 3 can be addressed by ANNs. In some cases, we want to use fuzzy logic capabilities, but there is not enough knowledge about the nature of the problem. Therefore, in such cases, an adaptive neuro-fuzzy inference system (ANFIS) is proposed to solve the problem [8].

ANNs are the best responses towards problem-solving, forecasting, and often reasoning tasks pertinent to asset management. They find abundant application in behavioural forecasting of transformers following well-defined fault interpretation algorithms. They can also be used in predicting the overall behaviour of superconducting transformers by exploring the hidden relationships between seemingly unrelated electrical and thermal parameters. Advancement in the design, construction, and operation of superconducting transformers may often require the execution of various monitoring and assessment tasks simultaneously. These can often assist the asset managers / engineers to improve their diagnostic precision and action plans. The emergence of deep learning strategies is equally profitable. It can learn

from unstructured and unlabelled data to either make enhancements in the current system of reasoning and forecasting or create a new system altogether. Nevertheless, continuous and reliable data is the sole capital investment in these AI technologies and thus have a wider scope of application in asset management of superconducting transformers given the current nature of their condition assessment tests.
A general model of deep learning methods contains two main parts: feature extraction and a fully connected network. The feature extraction part includes convolution and pooling layers which work by some special filters. Usually, filters include some parameters that are adjusted during training, but in order to speed up the training, pre-trained filters are used to design ANN. These methods have been recently widely used in different topics of engineering, especially in electrical engineering [9-10]. Deep feedforward neural network (DFFNN), long short-term memory (LSTM), deep belief network (DBN) and convolutional neural network (CNN) are the most used deep networks in the literature. Most of the real-time fault detection and condition monitoring problems can be addressed by using deep learning-based ANNs.

> Optimization algorithms can optimize the performance of ANNs, which later can be used for solving and optimizing the engineering problems of superconducting transformer

4.1.3 Heuristic optimization techniques

Heuristic optimization techniques that are so-called meta-heuristic algorithms are divided into two main groups: evolutionary-based algorithms and swarm-based algorithms. Genetic algorithm (GA) and harmony search (HS) are the famous evolutionary algorithms and particle swarm optimization (PSO), gravitational search algorithm, simulated annealing algorithm, grey wolf algorithm, bees algorithm, and cuckoo algorithm use swarm-based searching techniques to find optimum points in the search space [11]. In many cases, we tend to find optimum parameters for a transformer, and sometimes we want to have optimum design [12]. Also, optimization algorithms can optimize the performance of ANNs that are suitable and a good choice for solving superconducting transformer problems such as tape size and material design, optimal design of superconducting transformer and additive manufacturing (sections 3.1 to 3.3). As the name suggests, these are seemingly intelligent strategies that can enhance the performance of any heuristic algorithm developed for typical tasks such as fault classification and diagnosis. These algorithms are primarily based on the need for search and optimization of parameters that can clearly define a problem and suggest a solution. Although, the application of such strategies on superconducting transformers would initially require the design of some standard benchmarks that can clearly define the solution requirements.

4.2 Non-computational intelligence methods

4.2.1 Support vector machine

SVM is basically a collection of a set of hyper-planes in high dimensional space. SVM maps input data to a higher dimension to increase the separability of features between classes or data space [8]. It could be used both for regression and classification problems such as AC loss prediction, hotspot and critical current weak point detections, internal fault detection, and condition monitoring of superconducting transformers. SVM works well when the dimensional space is huge, the margin between classes is clear, and the number of samples is lower than the number of dimensions. Unlikely, SVM is not a good choice when data sets are large, and data are noisy.

4.2.2 Reinforcement learning

Some superconducting transformer problems such as online loss estimation and condition monitoring need to follow signals for finding new events and learn themselves by new data from an environment. Reinforcement learning is the best choice for solving such problems, which can be categorized into three main groups: associative reinforcement learning, deep reinforcement learning, and inverse reinforcement learning [13]. Reinforcement learning works with a small amount of data, can be implemented for real-time tasks, used for sequences of actions and can perform better than supervised learning but can never learn a completely new approach to solve the problem.

4.2.3 Bayesian theorem-based classifier

One of the most well-known probabilistic classifiers is the Naive Bayes classifier, which is based on the Bayes theorem [7]. It makes by posterior probability, which is directly related to probability available before the observation of the identity and its likelihood. A Bayesian classifier, which can be used for condition monitoring of superconducting transformer, is a good choice when the distribution of data is based on the normal distribution. Naive Bayes classifier is so simple to implement, works with a small number of data and is so fast and suitable for real-time regression. On the other hand, it does not show promising performance for nonlinear classification problems.

4.2.4 Data clustering methods

In some cases, the knowledge about the variations of transformer performance does not exist, but we can extract and sample these variations [14]. In such cases, clustering methods are the best choice, and they can be categorized into 5 main groups: partitioning methods, hierarchical clustering, fuzzy clustering, density-based clustering, and model-based clustering. The hotspot and critical current weak point detections, internal fault detection, and condition monitoring of superconducting transformer are some examples. Clustering is the best choice for large data, can simplify the classification step and helps to find the intra-class relation between data. But it is not suitable for noisy data.

> L3: Although accurate future prediction is next to an impossible, yet better understanding of AI technologies can significantly improve the quality of superconducting devices

Conclusion

In this paper, potential opportunities and solutions that artificial intelligence (AI) techniques and approaches can offer for resolving technical issues related to superconducting transformer were explained and discussed, including optimal design of tape, winding, and transformer construction, smart condition monitoring techniques, hotspot detection, smart asset management, smart manufacturing, and etc. A range of potential AI tools for being used in superconducting transformer design, development and analysis were introduced, including fuzzy method, artificial neural network, swarm-based optimization, support vector machine, etc. These tools can be used for performing four main functions of AI, including regression, optimization, clustering, and classification. It is worth noting that most of the discussed cases and methods in this paper can be implemented for any large-scale superconducting power devices.

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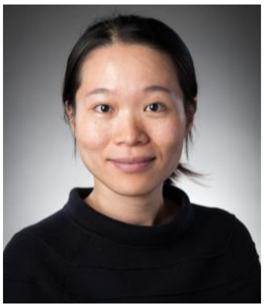
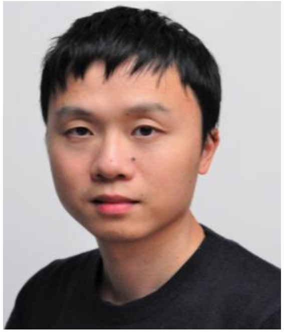


Min Zhang received her PhD from the University of Cambridge in Engineering. Before that, she received bachelor and master's degrees from Tsinghua University in Electrical Engineering. Dr Zhang spent a year as Junior Research Fellow at Newnham College, Cambridge and then joined the University of Bath as a lecturer. She joined the University of Strathclyde as Reader in 2018 and is currently a Research Fellow of the Royal Academy of Engineering. She is a member of IEEE (MIEEE). Dr Zhang's research focuses on the application of high-temperature superconductors in power system transmission, renewable generation and electric transportation.

Sruti Chakraborty holds a Ph.D. degree in Chemical Engineering from Malaviya National Institute of Technology, India. She is the co-founder of an innovative and global tech start-up SeetaLabs. She works on developing low-cost solutions for risk management and failure mitigation in industrial assets. Her research interest includes condition monitoring, alternative dielectric fluids, nonlinear control systems, and particularly machine learning.



Weijia Yuan received his PhD from the University of Cambridge in 2010. He then became both a research associate in the Engineering Department and a junior research fellow at Wolfson College, both at the University of Cambridge from 2010 to 2011. Dr Yuan joined the University of Bath as a Lecturer / Assistant Professor in 2011, where he was later promoted to Reader / Associate Professor in 2016. He joined the University of Strathclyde as a Professor in 2018. He is a senior member of IEEE (SMIEEE). He is now head of the applied superconductivity laboratory (SuperStrath), and leading research on energy storage, fault current limiters, machines and power transmission lines. He has been working closely with industry partners on all electric propulsion for future electric aircraft, designing a fully superconducting system for aerospace application. His work also involves renewable energy integration and power system stability using energy storage systems.