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Topical Review

Artificial intelligence methods for applied superconductivity: material, design, manufacturing, testing, operation, and condition monitoring

Mohammad Yazdani-Asrami[1,*], Alireza Sadeghi[2], Wenjuan Song[1], Ana Madureira[3], João Murta-Pina[4], Antonio Morandi[5] and Michael Parizh[6]

[1] Propulsion, Electrification & Superconductivity Group, James Watt School of Engineering, University of Glasgow, Glasgow G12 8QQ, United Kingdom
[2] Faculty of Electrical Engineering, Shahrood University of Technology, Shahrood, Iran
[3] Interdisciplinary Studies Research Center, Institute of Engineering, P.PORTO, Porto, Portugal
[4] Centre of Technology and Systems/UNINOVA, TecnologiaNOVA School of Science and Technology (FCT NOVA), Quinta da Torre, 2829-516 Caparica, Portugal
[5] Department of Electrical, Electronic, and Information Engineering, University of Bologna, 40136 Bologna, Italy
[6] General Electric Research Niskayuna, New York, United States of America

E-mail: mohammad.yazdani-asrami@glasgow.ac.uk

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Abstract

More than a century after the discovery of superconductors (SCs), numerous studies have been accomplished to take advantage of SCs in physics, power engineering, quantum computing, electronics, communications, aviation, healthcare, and defence-related applications. However, there are still challenges that hinder the full-scale commercialization of SCs, such as the high cost of superconducting wires/tapes, technical issues related to AC losses, the structure of superconducting devices, the complexity and high cost of the cooling systems, the critical temperature, and manufacturing-related issues. In the current century, massive advancements have been achieved in artificial intelligence (AI) techniques by offering disruptive solutions to handle engineering problems. Consequently, AI techniques can be implemented to tackle those challenges facing superconductivity and act as a shortcut towards the full commercialization of SCs and their applications. AI approaches are capable of providing fast, efficient, and accurate solutions for technical, manufacturing, and economic problems with a high level of complexity and nonlinearity in the field of superconductivity. In this paper, the concept of AI and the widely used algorithms are first given. Then a critical topical review is presented for those conducted studies that used AI methods for improvement, design, condition monitoring, fault detection and location of superconducting apparatuses in large-scale power applications, as well as the

[*] Author to whom any correspondence should be addressed.

prediction of critical temperature and the structure of new SCs, and any other related applications. This topical review is presented in three main categories: AI for large-scale superconducting applications, AI for superconducting materials, and AI for the physics of SCs. In addition, the challenges of applying AI techniques to the superconductivity and its applications are given. Finally, future trends on how to integrate AI techniques with superconductivity towards commercialization are discussed.

Keywords: artificial intelligence, big data, deep learning, superconductors, machine learning, optimisation, prediction

(Some figures may appear in colour only in the online journal)

Nomenclature

2D	Two dimensional
3D	Three dimensional
AC	Alternative current
AEDNN	Auto-encoder deep neural network
AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
ARCS	Automated remote-control systems
ASIC	Application-specific integrated circuit
ATHENA	Advanced telescope for high energy astrophysics
B_{C2}	Upper magnetic flux density
BCS	Bardeen–Cooper–Schrieffer
BD	Big data
CGCNN	Crystal graph CNN
CICC	Cable-in-conduit conductor
CMG	Co-axial magnetic gears
CNN	Convolutional neural network
CORC	Conductor on round core
CS	Central solenoid
DC	Direct current
DCS	Dual-capacitor switching
DG	Distributed generator
DL	Deep learning
DS	Data science
DSV	Diameter of spherical volume
DT	Digital twin
DTM	Decision tree model
EBSF	Electron-boson spectral function
ECM	Equivalent circuit model
EDXS	Energy dispersive x-ray spectrometry
EMPS	Electro-magnetic property measurement system
EPC	Electron-phonon coupling
FCC	Future circular colliders
FEM	Finite element method
FPGA	Field-programmable gate array
GA	Genetic algorithm
GBDR	Gradient boost decision tree
GE	General electric
GPR	Gaussian process regression
GPU	Graphics processing unit
GRU	Gated recurrent unit
HEP	High energy physic
HET	Hybrid energy transfer
HSFCL	Hybrid SFCL
HTS	High temperature superconductor
HVDC	High voltage direct current
iCGCNN	Improved crystal graph CNN
IoT	Internet of things
KNN	K-nearest neighbours
LCOE	Levelized cost of energy
LHC	Large hadron collider
LNG	Liquefied natural gas
LSTM	Long short-term memory
LTS	Low temperature superconductor
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MCM	Majorana correlation matrices
MgB_2	Magnesium diboride
ML	Machine Learning
MRI	Magnetic resonance imaging
MSE	Mean squared error
NASA	National Aeronautics and Space Administration
NbTi	Niobium titanium
NIST	Standards and Technology
NLP	Natural language processing
NMR	Nuclear magnetic resonance
NN	Neural Network
NNM	Neural network model
NSE	Nash-sutcliffe efficiency
OPEE	One-particle entanglement eigenvectors
OPES	One-particle entanglement spectra
PHIL	Power hardware in the loop
PID	Proportional integral derivative
PM	Permanent magnets
PSO	Particle swarm optimization
QPS	Quench protection system
R^2	Goodness of fit
RAD	Ionic radii
RBFNN	Radial basis function neural network
RCF	Richer convolutional feature
RL	Reinforcement learning
RML	Reinforcement ML
RMSE	Root mean squared error
RNN	Recurrent neural networks
RPT	Reading periodic table
RQ	Research question
RRR	Residual resistivity ratio
RTS	Room temperature superconductors
RvNN	Recursive neural networks
SC	Superconductor
SFCL	Superconducting fault current limiter

SLA	Superconducting linear acceleration
SLD	Structural lattice distortion
SMES	Superconducting magnetic energy storage
SML	Supervised ML
SQUID	Superconducting quantum interference device
SVM	Support vector machine
SWT	Stationary wavelet transforms
TFIH	Transverse flux induction heating
THD	Total harmonic distortion
TS-LTSM	Temporal sliding long short-term memory
UML	Unsupervised ML
XRD	X-ray diffraction
XRPS	X-ray photoelectron spectroscopy
YBCO	Yttrium barium copper oxide

1. Introduction

SCs and superconducting apparatuses are broadly used in commercial imaging technologies such as MRI, NMR. Superconductivity-based devices are promising options in modern power grids, cryo-electrified aviation units, novel terraqueous transportation vehicles, high energy physic (HEPs), fusion, and many other applications.

1.1. Brief history of superconductivity

In 1911, Onnes found that at temperatures lower than a specific threshold and critical temperature, some materials transit into a whole new state. This was the beginning of the phenomenon that was later called superconductivity [1]. About 20 years after Onnes's discovery, Meissner and Ochsenfeld have found out that the static magnetic flux lines are expelled out of SCs, which was later known as the Meissner–Ochsenfeld effect [2].

In 1935, Fritz and Heinz London have proposed a simple theory for SCs, which explained the Meissner–Ochsenfeld effect [3]. However, their theory could not explain the exact thermoelectric behaviour of SCs. In 1950, Ginzburg and Landau have proposed another theory to bridge the gap of London's theory [4]. In 1957, Bardeen *et al* took advantage of quantum physics to establish their theory, which was called BCS theory [5].

Due to the high cost of cooling units, which provide cryogenic temperatures for early discovered SCs—known as LTS materials—and their extremely low critical magnetic field, the BCS theory was the origin of many efforts to find SCs with higher critical temperatures. Finally, Bednorz and Müller discovered a brand-new type of SCs with a critical temperature of about 30 K with the chemical formulation of $Ba_xLa_{5-x}Cu_5O_{5(3y)}$ [6]. Nowadays, rare-earth barium copper oxide SCs, also called REBCO, are recognised as one of the most promising options for superconducting devices with a critical temperature of around 92 K [7].

In 2001, superconductivity in MgB_2, a long-known compound with two cheap abundant elements, was discovered [8]. More recently, another type of SCs was discovered in 2008 by the Hosono group with a Fe-based structure [9]. A brief timeline of the history of superconductivity is shown in figure 1.

1.2. Applications of SCs and the challenges

Since the appearance of commercially available SCs, much research has been conducted to use SCs in various applications, such as healthcare, transportation, power systems, electronics, communications, HEPs, fusion, defense, and astronavigation. During the last few years, the large-scale applications of superconducting materials in the form of coated conductors, tapes, and wires have gained significant attention in academic research [10, 11]. Figure 2 shows some of the large-scale applications of SCs.

Both LTS and HTS superconducting machines are considered to be used in large power wind turbines with >10 MW power [12]. Superconducting propulsion units in hydrogen-based aircraft with specific power density above 20 kW kg^{-1} are considered for future cryo-electrified aircraft. However, to commercially use these machines in aviation industry, the main challenges are the further reduction of their weight and size to increase the specific power density, manufacturing issues, and AC loss [13–16].

SMES has the potential to be used in future micro- and smart-grids. SMES increases the stability and reliability of power grids in which they are installed. However, their design, control, power density, and cost must be further improved to be competitive with other storage systems [17–22].

SFCLs have been introduced in many types, such as the resistive, saturated iron core, and shielding SFCL, and others. Recently, several commercial transmission-scale 220 kV SFCL had been installed in Russia and Germany [23]. In the near future, SFCLs will be installed not only in power systems but also in cryo-electrified transportation systems [24–28]. The challenges that SFCLs face are AC loss reduction in steady-state, faster quench and recovery time, optimisation of volume, cost, weight, and performance against high impedance faults. In the electric systems of power grids or electric aircraft with SFCLs, an ultra-fast protection system is required to coordinate with the operation of SFCL to cut off the fault circuit in time. Superconducting circuit breakers could accomplish this role and clear the fault. Coordinated operation of SFCLs and superconducting circuit breaker limits interrupts the fault current, and hence increases the protection level of the electric system [29].

HTS transformers are another up-and-coming superconducting apparatuses in large-scale power applications. Superconducting transformers are more compact, lighter, and more efficient than their conventional counterparts. The ability to continuously overload operation without degradation of insulation due to thermal stresses is another advantage of HTS transformers. Fault tolerant HTS transformers operate not only to regulate the voltage level but also to limit the fault current [30–35].

HTS cables, both AC and DC, are used in the transmission/distribution of electrical energy in power grids or stand-alone power systems, with a high current carrying

Figure 1. The timeline for evolving superconductivity: from discovery to the latest efforts.

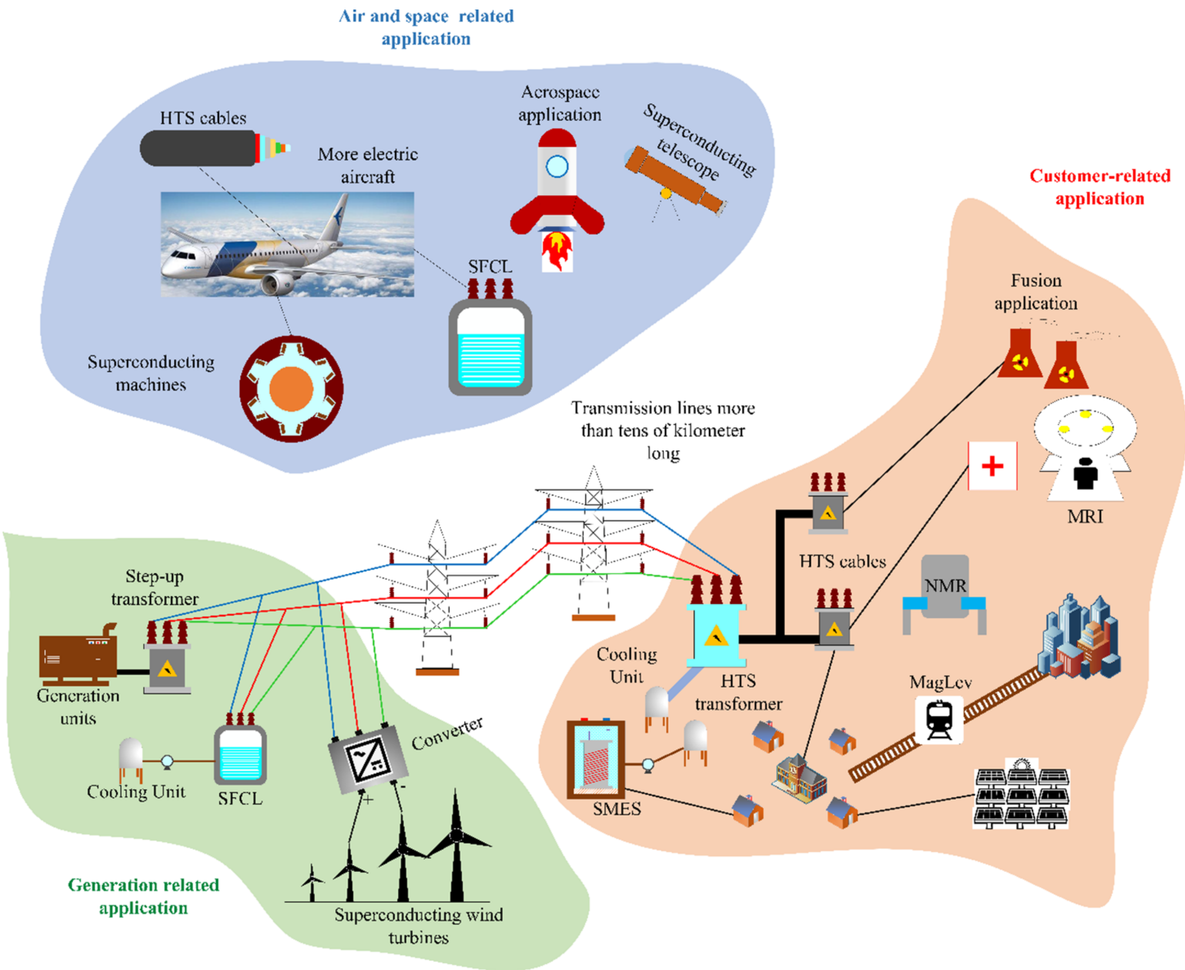

Figure 2. The role of superconductors in the near future in any part of the power systems, aviation industry, fusion, healthcare systems, and space programs.

capability. From the technology point of view, the main challenge is their operation in high voltages and long lengths without efficiency reduction [36–41].

Superconducting magnets are the most commercialised superconducting applications, operating in MRI scanners, fusion applications, and electric machines. They provide high magnetic fields in a much smaller size. However, they face some challenges, such as manufacturing and operation support issues and quench protection in HTS magnets [42–47].

Magnetic levitation, bearing and shielding are other applications of SCs that are used in railways and flywheels. They offer a compact structure and high magnetic field. Recently, many investigations were made on these superconducting devices, along with sharply increasing attention on energy storage units in space programs [48, 49].

Busbar is another potential large-scale application of SCs, often used in the fusion industry and systems, and also in aluminium and chlorine plants. They are capable of carrying an extremely high current in comparison to conventional busbars. Hot spots on the body of the busbars, insulation, and their corrosion issues are known challenges of this technology [50–52].

Superconducting flux pumps are devices that deliver magnetic flux density to a closed superconducting loop, such as coils, magnets, and machines. It is expected that by using them, the problem of high-value heat load generated by current leads is tackled. They have been proposed for many applications, such as magnets in MRI and fusion systems, electric machines and coils. Their main challenges are the need for very accurate control, operation stability, cost of HTS materials, adding extra weight in aviation applications, etc. [53–55].

Superconducting filters are used in telecommunication industry, e.g. mobile communication, radar, and radio astronomy. Due to the low surface resistance of SCs, the quality factor of superconducting filters is way higher than their conventional filters made out of normal metals. On the other hand, these filters come in a more compact size compared to their conventional counterparts. The main challenge of these filters is the stabilization of the cryogenic temperature to enhance the quality performance of the filter. This is normally achieved by design improvements of these filters and recalculating their design parameters [56]. Recently, these filters have been gaining attention for large-scale power applications.

Due to the utilisation of superconducting qubits in superconducting computers, as a new type of application, they have higher performances, longer coherence time, and many other advantages. However, the need for dilution refrigerators to remain at the superconducting state, the need for enhancement in qubit connectivity, and improvements in gate fidelity are issues that must be addressed [57].

The SQUIDs are highly sensitive detectors of magnetic fields. So they are used for the detection of magnetic signals in the human brain, fluctuations of the Earth's magnetic field for earthquake predictions, and in many other fields of science. They are categorized as DC SQUID and radio frequency (RF) SQUID [58].

Superconducting RF cavities are one of the superconducting parts in particle accelerators as, e.g. the LHC. They show lower losses in comparison to copper cavities, as their surface resistance is 10^9–10^{10} times lower than the surface resistance of the latter. Accordingly, they are very suitable for accelerators that demand a continuous wave or long pulse accelerating field of more than a few million volts per meter [59].

Superconducting antennas have higher efficiency in comparison to conventional antennas which results in a higher radiation resistance compared to loss resistance of conventional antenna. Due to the compact size of superconducting antennas compared to conventional ones, it becomes a promising choice for space programs [60].

The Josephson effect is a physical phenomenon that describes the electromagnetic characteristics of SCs. Concerning this phenomenon, an application of SCs was invented, known as the Josephson junction. This is a quantum application in which two SCs are separated by a non-superconducting part, known as a barrier. They are normally used in SQUIDs, superconducting qubits, and digital electronics [61, 62].

Superconducting receivers and superconducting analogue-to-digital converters are the most common applications of SCs in the field of electronics. Low loss and compact structures are the most common properties of these elements [63, 64].

1.3. AI for superconductivity

Broad applications and the commercialization of superconducting technologies require advances in science, unit and system design, manufacturing and maintenance, including superconducting, cryogenic, mechanical and other components. The electromagnetic coupled with thermal characteristics, efficiency, and reliability of the SCs in their applications must be enhanced, while the manufacturing, purchasing, operation, and maintenance costs should be minimised. SCs have to operate at cryogenic temperatures, provided by a cooling system. Cryocoolers are one of the main components in a cooling system, which require high input power and sometimes expensive coolant fluids to provide the desired cryogenic temperature. Often, a cryocooler demands stern vacuum conditions and thermal insulation, which results in cost-inefficiency of SCs in many applications, especially AC ones [65]. Thus, to overcome this issue, it is desirable to increase the critical temperature of commercial SCs and/or to discover new composition of superconducting materials with a much higher critical current at relatively the same temperature range in comparison to currently used SCs. However, for DC applications, the cost of the SCs is the driver. Therefore, the increased critical temperature is not a killing factor for most DC applications. In addition, AI techniques can be applied as predictors and estimators to fasten the discovery procedure of new SCs with higher critical temperatures, as well as supporting the design of cryogenics leading to more adequate and cost-effective ratings. Improving the weight, size, and other geometrical factors of superconducting devices is another challenging issue for future transportation applications. These parameters are affected by the cooling system, and non-superconducting parts. To improve these factors, the design procedure becomes a complex problem with numerous constraints and limitations, and tight manufacturing tolerances. It is time-consuming and sometimes requires an extremely high-performance computer to solve this problem.

Regardless of the increasing attention to HTS tapes, their cost is still higher than what is expected, while the cost of LTS materials is in an acceptable range. For instance, the price of NbTi wire is about 0.8–1 $ kAmp-m^{-1} at 4 K–4 T, while the cost of rare-earth barium copper oxide (REBCO) tapes is around 227–230 $ kAmp-m^{-1}. The cost of bismuth strontium calcium copper oxide (BSCCO) tapes is also about 17.4 $ kAmp-m^{-1} and the cost of copper at room temperature is about $10 kAmp-m^{-1} [66]. This originates in some sophisticated and expensive manufacturing processes and also types of stabilizers and shields used in superconducting wires, tapes, and filaments.

Non-destructive condition monitoring of superconducting devices and monitoring local hot spots along the length of SCs are other hindrances that must be addressed before the massive implementation of HTS materials in industries, and these issues can be addressed using AI techniques. The condition monitoring includes methods of temperature estimation in each period of time, AC loss and other types of loss estimation under different electromagnetic-thermal circumstances, fault detection and location of superconducting devices, critical current weak point detection of superconducting tapes, etc. Condition monitoring approaches are ideally based on real-time techniques.

In addition, AI techniques can be used to improve the design and the efficiency of superconducting devices by optimizing the size, weight, losses, and heat loads. Accordingly, they are vital tools in the field of superconductivity and have been receiving attention during the last few years.

For further illustration of AI technique applications for superconducting devices, a comprehensive example is presented in the following. For this purpose, consider an HTS machine that is used as a propulsion unit of a cryo-electric aircraft. Firstly, there is a need for the reduction of cost, AC loss, and size of the HTS tapes, while the manufacturability, heat capacity, critical current density, and engineering current density of the tape must be increased. To do this, an AI-based optimisation procedure could be conducted while there is also a need for highly smart and intelligent supervision in the assembly line and manufacturing stages of the tape. After finding an optimum structure for HTS tapes with minimum possible defects and critical current weak points, the very next step is to manage the design procedure of the HTS machine. The objective function must be concerned with minimisation of weight, cost, AC loss, field inhomogeneity, while the efficiency, power density, and maximum delivered power must be maximised. There are also numerous trade-offs related to the flight conditions of cryo-electric aircraft, manufacturing process and constraints, cooling system, etc. These considerations and trade-offs, with respect to objective function, make the optimisation problem a highly nonlinear and highly complex one. Regardless of the complexity and nonlinearity of the problem, analysing the characteristics of the HTS machine by means of FEM-based models is a time-consuming problem with high computational cost and burden. Optimisation methods based on AI could help engineers and designers to get to the optimum structure of the machine, while surrogate models could replace the FEM-based methods to increase the calculation speed and reduce the computation burden. After installing the machine, unsupervised condition monitoring methods without human interferences are required to guarantee the safe operation of HTS machines. AI techniques could help and perform as unsupervised operators to monitor the machine against any internal, external, and other types of failures. To do this, AI must be able to discriminate different transients in the power systems of aircraft, make the right choice and send the command to the physical parts and components. In addition, after each flight, the model could be updated based on the operational conditions during the mission and this procedure makes the condition monitoring method specific for the mission and type of aircraft. At the last stage, AI could make a prediction based on historical data, reliability data, and flight data to precisely forecast the maintenance time of HTS machines.

In this paper, we aim to present a topical review on the application of AI techniques in superconductivity. This will help the researchers to understand the previous developments around AI in superconductivity and also the future trends in this regard, and hence follow the path towards future utilisation of AI techniques to address the challenges of superconductivity in the next decade. The paper is written in such a way to provide answers to the following RQs, for the readers.

- RQ1: What is the concept of AI?
- RQ2: What kind of studies using AI techniques were done in superconductivity and its applications?
- RQ3: What are the areas that previous studies in the literature overlooked?
- RQ4: What are the major challenges of superconducting applications and how is AI able to solve them?
- RQ5: How are AI techniques, superconducting applications and manufacturing related to each other in the future?

The rest of the paper is organised as follows: section 2 is dedicated to explain the concept, history, different types, and applications of AI techniques. This section will help the superconductivity community readers to familiarise themselves with AI before getting into other sections. A literature review on conducted studies using AI techniques for superconductivity applications is presented in section 3. Statistical analysis is given based on the review of large-scale, material, and physics-related applications, electronics, and communication, mainly according to the publication date and type of AI. After that, an application-based review study was conducted. The next section focuses on the challenges of applying AI techniques to superconductivity. Finally, future trends are discussed in section 5.

2. Concept of AI

AI is defined as a smart system that evaluates inputs and takes actions to obtain a particular goal. AI is a booming field with many practical applications and active research topics [67]. We look to intelligent software to automate routine labour,

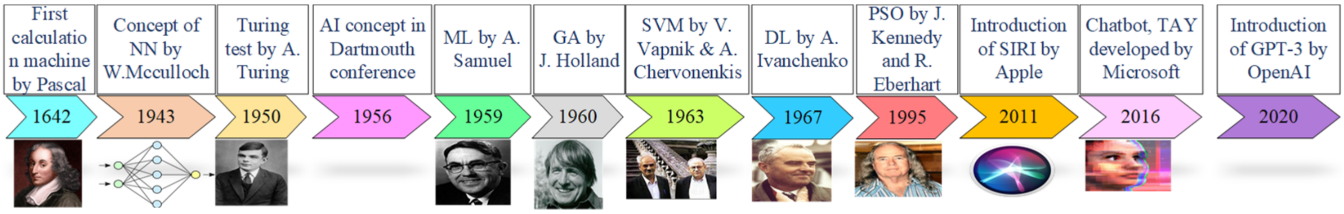

Figure 3. Artificial intelligence historic perspective [81].

understand speech or images, make diagnoses in medicine and support basic scientific research. AI-based systems could be categorised into two groups: software-based systems that act in a virtual world, such as image-processing software, face recognition programs and embeddable in autonomous hardware devices such as robots, cars, aircraft, domestics/smart homes, and Internet-of-Things—IoT—applications).

Discovering the knowledge and making decisions are the most significant characteristics of AI methods by which it tries to transcend the abilities of humans and thus could be used for numerous fields of science and other industries. Nowadays, AI is also used in the engineering world as a shortcut to solve problems, discover new structures and devices, find new materials, manage the systems, and so on. To improve the performance of AI techniques, data is the necessary requirement. Thus, if their performance is improved, they can be used for making automated decisions. For instance, fault and abnormality location and detection in power transformers could be accomplished based on data from the network or system and by training an AI model.

2.1. AI historic perspective

With the advent of computers, an important question emerged, both from a philosophical and a practical point of view: 'Could a computer ever behave intelligently, exhibiting behaviour similar to a human being?'. The idea that technology could one day replicate human logical thinking was advocated by Alan Turing in 1950, when he published the paper 'Can a machine think?' [68]. The term 'AI' was proposed by the scientific community at the Dartmouth Summer Research Project on AI, hosted by John McCarthy and Marvin Minsky, in 1956 [68]. AI was described as the ability of machines to perform certain tasks that require the intelligence showcased by humans. Since then, several definitions and developments have been proposed by the scientific communities.

AI methods include multiple techniques, namely ML techniques with specific examples of DL and RL; automatic reasoning, such as planning, programming, knowledge representation and reasoning, search, and optimisation, and robotics [69].

Since its proposal in the 1950s, AI has evolved from an academic field into a powerful engine of social, technological, and economic change. AI is now the foundation for a wide range of technologies, including web search, smartphone applications, medical diagnostics, voice recognition, and more recently, autonomous vehicles. Several definitions and developments have been proposed in the literature, but it is consensual that the main objective of AI is to provide the systems and their components with characteristics inspired by human intelligence [67]. In this context, developments and contributions have emerged, considered as subareas of AI: ML/DL [70–73], Industrial AI [74], Generalized AI [75], Safety AI [76–79], among others. Figure 3 depicts and identifies some of the most relevant milestones in AI history.

From 1957 to 1974, AI prospered (referred as the first AI age): computer information storage capacity increased with a faster computation speed, and more accessible and cheaper characteristics. ML algorithms improved, and researchers were better at choosing the most appropriate algorithm for their specific problems. Early presentations of problem solvers, such as Joseph Weizenbaum's ELIZA and Newell and Simon's General Problem Solver, showed great promise towards the goals of the interpretation of spoken language and problem-solving, respectively. The period from 1974 to 1980 suffered a drop in government funding, a period known as 'AI Winter' when some criticised progress in the field.

The second age of AI was initiated in 1980 according to outstanding technological advancements: expert systems based on rules, a heuristic form of logical reasoning based on symbols, and an NNs recovery triggered by the appearance of novel algorithms for training.

With the appearance of novel symbolic-reasoning systems based on algorithms, in year 2000, the last age of AI has been started that enabled the capability of solving a specific type of problems called 3SAT and, with another advance called Simultaneous Localization and Mapping, which is a technique for map creation while a robot moves in a specific region. At the beginning of the 2010s, the aforementioned wave had accumulated new powerful momentum with new computational resources and the rise of NN learning from massive data sets. A Stanford vehicle won the Defense Advanced Research Projects Agency (DARPA) Grand Challenge in 2005, driving autonomously for 211 km. In 2011, IBM's Watson won 'Jeopardy!' and Apple introduced the virtual personal assistant Siri. OpenAI introduced, in 2020, the GPT-3, the autoregressive natural language model that uses DL to produce human-like text [74]. Now the age of big data (BD) is initiated, in which mankind has the capacity and capability to collect a vast amount of data and information, which is too difficult to be analysed by any person.

2.2. ML

Arthur Samuel is considered the first researcher that proposed the term ML 'as a subfield of computer science that gives computers the ability to learn without being explicitly

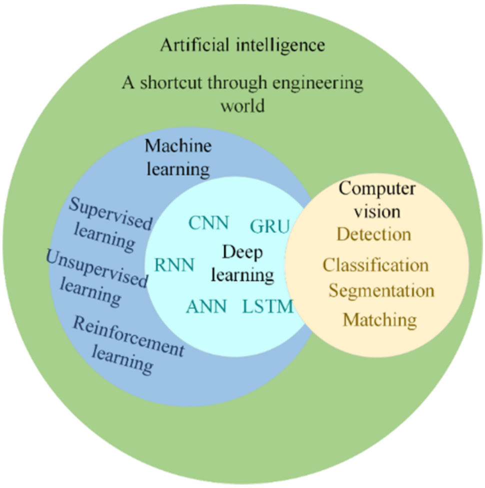

Figure 4. The relationship between AI, ML, DL, and NN, GRU stands for gated recurrent unit (GRU).

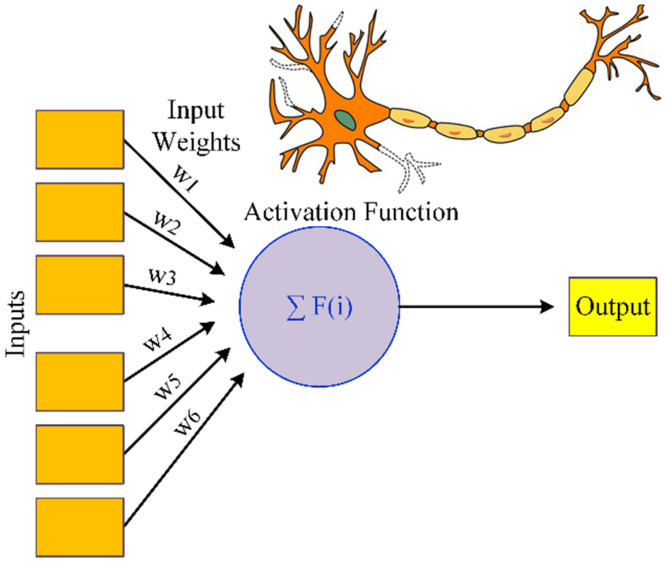

Figure 5. The internal structure of an artificial neural network, which comprised inputs, weights, activation function, and output.

programmed' [80]. The term was introduced, in 1959, in a paper under the IBM Journal of Research and Development dedicated to the use of ML in the game of checkers [80, 81]. An indispensable characteristic of ML is the self-learning concept that is defined as the application of statistical models for the recognition of patterns and empirical information-based performance improvements, without any direct programming commands. ML is responsible for constructing computer programs that is automatically improved based on experiences [71]. ML algorithms observe behaviours or the environment, detect a pattern, make a generalization, and infer an explanation. The resulting probabilistic correlations may predict outcomes with a high degree of accuracy. The output of an ML algorithm is entirely dependent on the data it is exposed to. If the data changes, the result can change. It is possible to solve the same task using different algorithms with different performance (accuracy or speed). Sometimes, to achieve better performance, different ML algorithms can be combined.

It is possible to identify three categories of ML algorithms, which are distinguished by the type of information handled, as mentioned in the literature [70–72]: Supervised Learning (for structured/labelled data); Unsupervised Learning (for unstructured/unlabelled data); and RL (with the aim of maximizing a reward). To clarify some semantic confusion between the terms AI, ML, and DL, figure 4 depicts a representation of the relationship between them. AI is driving the development of machines capable of simulating cognitive abilities. Several AI subfields can be identified in the literature, including search and planning, reasoning and knowledge representation, perception, NLP, and ML [82].

In ML, there are different algorithms (Decision Trees, NNs, KNNs, SVM, and others) to solve problems. DL, or Deep Neural Learning, is a subfield of ML, concerned with algorithms inspired by a structure and function, like the human neural system, called ANNs with multiple layers and other techniques. DL performs well in certain tasks, such as image recognition and NLP [81].

ANNs are simple models of the way the nervous system and the human brain processes information. The basic units are neurons, which are typically organized into layers, as depicted in figure 5. It works by simulating many interconnected processing units that represent conceptual neurons versions. The basic principle under an ANN is a collection of basic elements, generally artificial neurons or perceptrons. They take several binary inputs, $x_1, x_2, \ldots, x_N$ and produce a single binary output if the sum is greater than the activation potential.

If the inputs do not have the same influence, *weights* are assigned to the *inputs, x_i* to allow the model to assign more significance to some *inputs*. The output is 1, if the weighted sum is greater than activation potential or *bias*, according to equation (1):

$$\text{Output} = \Sigma_j w_j x_j + \text{bias}. \tag{1}$$

In practice, this simple form is difficult, due to the abrupt nature of the step function. A modified form was proposed to perform more predictably, and small changes in *weights* and *bias* produce a small variation in *output*. The literature refers to two main modifications [83]:

- The inputs can take any value between 0 and 1, instead of being binary.
- To make the output behave more smoothly for given inputs, $x_1, x_2, \ldots, x_N$, and weights. $w_1, w_2, \ldots, w_N$, and *bias*, using the sigmoid function, equation (2):

$$\text{Output} = 1/\left(1 + \exp\left(-\Sigma_j w_j x_j - \text{bias}\right)\right). \tag{2}$$

The smoothness of the exponential function, or σ, means that small variations in *weights* and *bias* values will produce a small update in the neuron output (the update could be a linear function of variations in weights and bias). In addition to the usual sigmoid function, other nonlinear functions are frequently used, allowing the train of the network with gradient descent, including [83]:

- **ReLU**: Rectified linear unit. This keeps the activation guarded at zero. It is computed using the following function (equation (3)):

$$Z_j = f_j(x_j) = \max(0, x_j) \tag{3}$$

where x_j, the jth input value, and Z_j is its corresponding output value after the ReLU function f.

- **LReLUs (Leaky ReLUs)**—These mitigate the issue of dying ReLUs by introducing a marginally reduced slope ($\sim$0.01) for values of x less than 0. LReLUs do offer successful scenarios, although not always.
- **ELU (Exponential Linear Unit)**—These offer negative values that push the mean unit activations closer to zero, moving the learning process quickly, by moving the nearby gradient to the unit natural gradient.
- **Softmax**—Also referred to as a normalized exponential function, this transforms a set of given real values in the range of (0, 1), such that the combined sum is 1. A softmax function is denoted in equation (4):

$$\sigma(z)_j = e^{z_j} \Big/ \sum_{j=1}^{k} e^{z_j} \qquad \text{for } j = 1, \ldots, K. \tag{4}$$

Different types of ANN can be identified in the literature, varying in complexity. They share the intended goal of imitating the behaviour of the human brain to solve complex problems. The structure of each type of ANN in some way simulate neurons and synapses. However, they differ in terms of complexity, use cases, and structure. Differences also include how neurons are modelled within each type of ANN, and the connections between each node. Other differences include how the data may flow through the ANN, and the density of the nodes.

2.3. DL

DL is considered as an advanced form of ML that makes the experience-based learning of computers possible and causes the computers to conceive the world based on hierarchical concepts [73] and makes use of sophisticated and multi-layered NNs, whereby non-linear transformations of input data and the level of abstraction gradually increases [73]. The term DL arises as the generated models are significantly more complex or deeper than traditional NNs. The term 'deep' is related to the number of hidden layers in the ANNs; traditional ANN just have 2–3 hidden layers, while DL may have around 150 layers.

The architecture of ANN was inspired by the brain, in which signals are transmitted by neurons and synapses. Each input in an ANN neuron is summed up and then an activation function is applied for output determination. Figure 5 shows the internal structure of an ANN with respect to the actual structure of NNs in the body creatures.

Deep ANNs can discover structures, known as learning of features, from unlabelled/unstructured data, such as images (pixel data), documents (text data), or files (audio, video data).

The development of the DL research area was motivated by the limitations of traditional ML algorithms to generalize well. Many ML problems become exceedingly difficult when the number of dimensions in the data is high—the curse of dimensionality. The main differences between ML and DL can be summarised as follows:

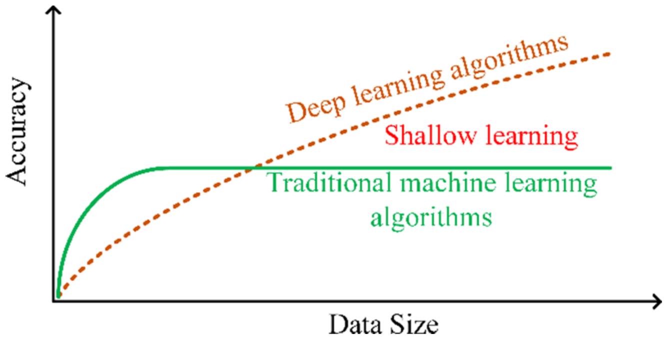

Figure 6. How the accuracy of DL techniques scales with the size of data [83].

- The functionality of an ML is started by a manual feature extraction of data. Then, the extracted features are used to create a model that categorises the objects in the data.
- In ML, feature selection is conducted manually, while in DL feature selection and modelling steps are conducted automatically.
- DL performs 'end-to-end learning' which means if raw data (inputs), and a task to perform (activation function), are given to an ANN, it learns how to do this automatically.
- DL algorithms scale with data, whereas shallow learning converges. Shallow learning refers to ML algorithms that maintain a certain level of performance when you add more examples and training data to the network.
- DL has improved the ability to understand and analyse the characteristics of engineering devices, such as power lines, buried pipes, aircraft, and many others.

This has been made possible with major advances in ML research as well as vast increases in both massive available data and computing power [81]. There are different architectures for DL, such as Unsupervised Pre-trained Networks, CNNs, RNNs, and RvNNs [83, 84].

A vital advantage of the DL approach is performance improvements with respect to increasing the size of data. Figure 6 depicts the performance of traditional ML and DL algorithms with respect to the size of input data [83]. The performance of DL techniques is higher than simple ANN models, however their required time for training is higher than ANN models. Due to the appearance of the massive volume of data, GPU computing, and transfer learning, the training of DL algorithms in the current technological context has become easier and more efficient [84].

2.4. BD and DS

BD describes large, hard-to-manage volumes of data (structured and unstructured) generated in the organizations/devices/processes. BD can be analysed for insights that improve decisions and give confidence for making decisions. Modern computing systems provide the speed, power, and flexibility needed to quickly access massive amounts and types of BD. Although accessing and storing a large amount of information and data for has been around for a long time, the concept of BD was presented by the Gartner Group in 2001 [85].

Most DL algorithms are based on the concept of ANN, and the training of such algorithms has been more efficient and effective with the increasing of data volume and computational resources. With the increase of data volume, the performance of DL models continues to improve. A representation of the behaviour of DL algorithm performance scalability when compared with traditional ML this can be depicted in figure 6.

DS is a field of science that includes algorithms and systems for the sake of knowledge and awareness extraction from computers and models that use data. There are several definitions in the literature considering its recent popularity in mathematics, statistics, computer science, engineering, materials, science, and finance [85, 86]. DS is concentrated on the large data set analysis and also the data generation from different sources. Systems could be trained so that they make decisions while training is a continuous process for them, where the system updates its learning and improves its decision-making capability with more data [85]. DS requires the language and techniques necessary for understanding and dealing with data. It includes the design, collection, assessment, and the interpretation of numerical data, to recognize patterns and other properties of data [86–89].

3. A review on different applications of AI techniques in superconductivity: past and current developments

Before getting to the review section, the aims and methods used to conduct the review must be clarified and explained. Note that papers themed with AI for SCs are reviewed. So, papers that involved superconducting nanowires or any other form of SCs for improvements of AI methods are out of our scope.

To answer these questions, literature on this topic is reviewed, analysed and represented according to the following structure:

(a) Categorization of the papers based on the application.
(b) Highlighting the significant points and findings of the papers at the body of the topical review.
(c) Explaining the shortcomings of each specific study/application.
(d) Identifying the further development needed as a future path of the AI and SCs in each specific study/application.

According to the aforementioned reviewing methodology, the reviewed papers are categorised into three subclasses: large-scale, materials and physics-focused, and electronics-communications.

Among the overall-reviewed papers, above 61% are themed with the application of AI techniques in large-scale superconducting applications; 33% aim at the prediction and estimation of the characteristic of superconducting materials, classified under material and physics-related applications; and only around 5% fall into the scope of the electronics and communications fields. China, South Korea, Japan, the USA, Italy, and the UK contribute the most in the studies to apply AI techniques for SCs. Among them, the majority of the studies under a large-scale subclass focus on the design and improvements of superconducting transformers, machines and fusion systems. By looking at the statistics of the publication shown in figure 7, a sharp tendency to use AI techniques for large-scale superconducting applications is observed during the last decade. About 70% of the publication are dated from 2011 to 2021. Around 82% of the literature has been seen in the last decade, which means that during the last few decades special attention has been drawn on linking superconductivity and AI-techniques.

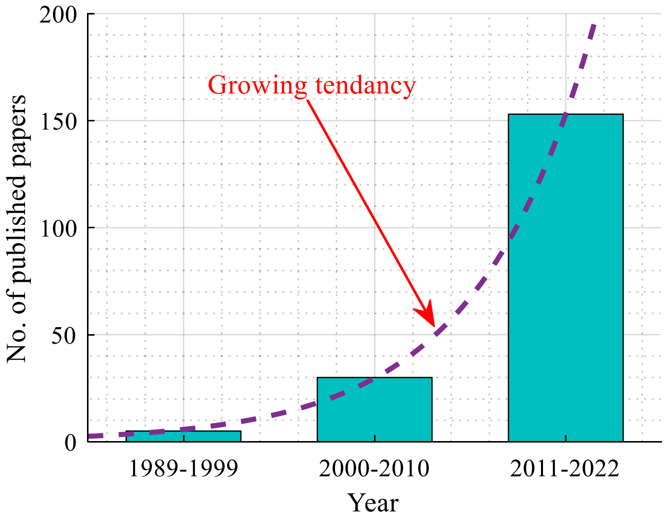

Figure 7. The number of published papers in the literature with respect to all the conducted studies in the last three decades.

This phenomenon can be understood by the remarkable progress not only in the advancement of AI techniques but also the increased funding and investment for large-scale superconducting applications. If materials and physics class are considered, significant attention in recent years is obviously clear. More than 70% of papers on the application of AI for materials and quantum topics were published during the last 4 years. AI was also used in the field of electronics and communications for the sake of design optimisation, control, and modelling. We note insufficient publications related to potentially commercial large-size superconducting devices such as >10 MW generators, >30 MW motors, >1 MVA fault current limiters and transformers, etc.

3.1. AI for large-scale applications

Further advancements and improvements in large-scale superconducting applications are required to make them cost-competitive in power systems and cryo-electrified transportation units.

Optimisations through AI techniques can maximise the efficiency, reliability, and safety of superconducting apparatuses,

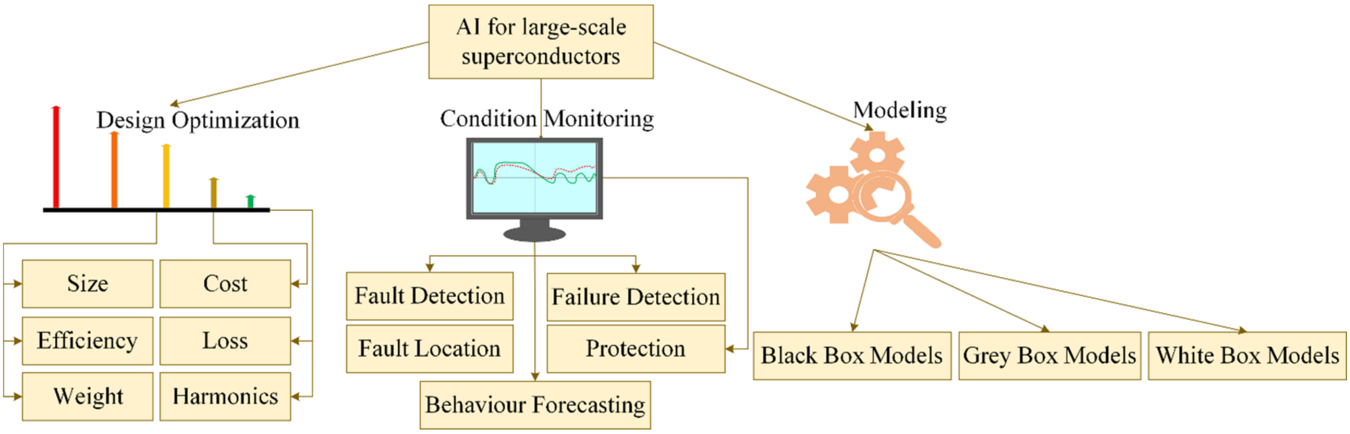

Figure 8. The different goals that AI techniques help to achieve in large-scale applications of superconductors.

while the cost, size, and thermal losses are minimised. Facilitating these improvements is the most significant contribution of AI techniques for SCs. AI algorithms can predict, estimate, and characterise the behaviour of LTS and HTS devices in different operating conditions, such as temperature, field, stress, and so on. Therefore, AI could be used for the characterisation and condition monitoring of devices.

Figure 8 represents the different types of tasks that are accomplished by AI-based techniques in the literature for large-scale superconducting applications. Accordingly, they are categorised into three classes: optimisation, condition monitoring, and modelling. The first class involves with the reduction of operational cost, harmonic effects, weight, and losses in superconducting apparatuses, by means of AI. Usually, each aforementioned factor has its own priority with respect to the application of the superconducting devices and they are prioritised through the optimisation process by applying weights of the different terms to the objective function. As an illustrative example, when one designs a superconducting machine for electric aircraft, the efficiency of aircraft propulsion machines, weight and size are more important factors than cost.

The second class adopts AI to reduce the risk of failures, faults, and burnouts of superconducting devices under abnormalities in the power grid, such as faults, short circuits, overloadings, and over-voltages, among others. AI enables the finding of hot spots in superconducting tapes/wires.

Another use for AI in the large-scale application of SCs is known as black box and grey box modelling. Black box models are the models that are reviewed as inputs and outputs, in which the internal functions that change the inputs to outputs are unrecognisable. On the other hand, grey box models use a combination of the DS and theoretical knowledge to turn inputs into outputs and results. Due to the complex characteristics of SCs under different operation conditions, conventional models tolerate a high computational burden. However, this can be simplified by using AI techniques, and hence superconducting devices could be characterized in a much shorter time, lighter load and acceptable accuracy or even higher accuracy.

3.1.1. AI for superconducting MRI scanners. MRI is one of the most practical instruments to diagnose diseases and tumours. Superconducting MRI systems can provide higher and more homogenous magnetic fields, lower heat, and higher quality images in a compact structure, in comparison to conventional, resistive or PM MRI scanners. In superconducting MRI magnets, main coils are used to generate the desired magnetic field, while shield coils are placed in the structure of the magnet to supress the magnetic field out of the imaging area. Subsequently, many investigations were performed to enhance the efficiency and reduce the manufacturing/purchasing cost [42, 46, 90–95]. AI techniques were used to optimally design superconducting MRI scanners and increase their imaging quality. The most applied methods of AI for gaining an optimal design of MRI are GA and ANN [42, 96–99].

The design and structure improvement of superconducting MRIs were initiated in the last years of the twentieth century [100]. Recently, an ultra-compact, small-bore HTS MRI was proposed in [101]. This MRI provided a high-quality image of an ultra-compact size. The model of this 1.6 T MRI was analysed using FEM in the COMSOL software package. Through a Live-Link of COMSOL and MATLAB, the structure of the magnet was optimised by performing a GA on the design parameters. The aim was to reduce the inhomogeneity produced by the superconducting magnet, and hence to increase the imaging quality, which can be achieved by restructuring the superconducting MRI. The results indicated that inhomogeneity of this type of MRI reached 2.36 ppm in DSV. This number was 3.3 ppm before applying GA optimisation. The 28.5% reduction in inhomogeneity led to better image quality. These results were obtained in the 2D analysis of superconducting MRI, while 3D analysis could hand more precise values.

Many structures were proposed to increase the homogeneity and subsequently the quality of the image. One of them is an open-structure MRI that consists of ferromagnetic and superconducting magnets, as shown in figure 9. This is a research project done by IEE CAS (China). Commercial units used only a tiny volume of magnetic materials for passive shimming [102]. Mechanical forces in magnets, i.e. Lorentz force, should be carefully considered since they can cause

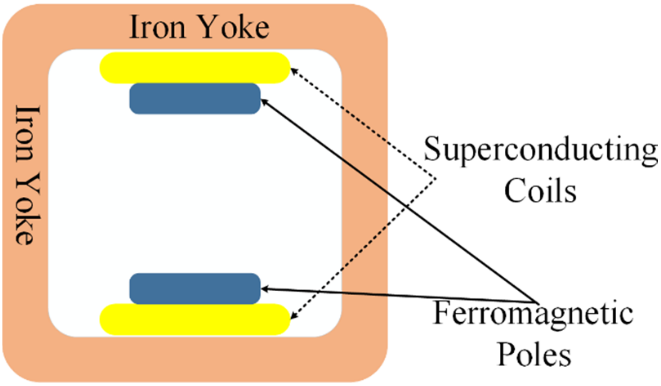

Figure 9. An MRI system using superconducting and ferromagnetic coils [102].

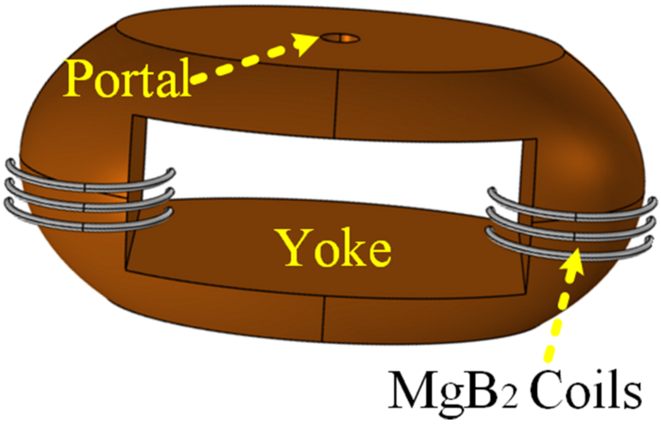

Figure 10. A 3D view of LinacMRI consists of MgB_2-based coils [103].

quenches in superconducting magnets. If the imposed force approaches the maximum tolerable force of superconducting wire/tape, impregation or other components, mechanical energy will be released in the coil and a quench is highly possible. In fact, Lorentz force and inhomogeneity are a function of the structure and the design parameters of the magnets. Thus, an optimisation procedure will address the mechanical issues simultaneously with the inhomogeneity while the size is minimised. Therefore, there is a need for the consideration of applied Lorenz force in the optimisation procedure of a magnet design. By performing this optimisation using GA, 98.33% of inhomogeneity was reduced, while Lorenz force decreased from 40 kN to 0.1 kN, the equivalent of 99.73% reduction. The improvement in inhomogeneity and Lorenz force led to high-quality images, safe operation of the superconducting MRI for patients, and also better performance of the cooling system.

Another type of superconducting MRI is the linear accelerator MRI (LinacMR). As shown in figure 10, this type of MRI has a non-axial superconducting magnet with a 0.5 T magnetic field. To reach a compact structure, a design optimisation based on the PSO algorithm was performed with a cost function concerning the outer surface of the plate pole [103]. The results showed the objective function for five spokes was reduced to 69.76% of the plate pole, and for the nine-spoke case, this value reached 55.55%, which led to a much more compact LinacMR.

Performing such design optimisation can reduce the possibility of quenching for superconducting magnets during their operation. Also, high-quality images obtained by optimised superconducting MRIs can help doctors diagnose diseases and tumours better, faster, and more precisely. However, the cost of cooling units and their impact on the magnetic behaviour of superconducting MRIs could be evaluated in future research. In addition, transient loss/loads, quench protection, and cost analysis are other topics that can be improved by AI optimisations and enhance the techno-economic considerations of superconducting MRIs. Intelligent quench protection for superconducting coils/magnets in MRIs is extremely important as huge energy released during a quench can damage SCs. Therefore, AI-based techniques must be developed to provide intelligent condition monitoring methods for MRI magnets.

3.1.2. Superconducting magnets for fusion and accelerator.

Superconducting magnets are the essential components in the fusion industry and systems [104, 105]. Thus, AI techniques were developed widely to design, monitor, and model the behaviour of SCs in these systems [107–114].

The LHC is one of the world's largest experimental nuclear research facilities, founded on the border of France and Switzerland, at CERN. Studies and investigations carried out at the LHC aim to prove and verify the physical theory known as the Standard Model. In addition, another objective of the LHC is to establish a physical theory about the universe [106]. The LHC consists of many electrical, mechanical, and magnetic components. Among them, superconducting magnets are the most vital and also vulnerable components, and their accurate testing and operation are crucial for experiments that use the LHC. A sample of such a test system is shown in figure 11. Therefore, many responsible teams were formed by many experts, such as related to cryogenics, superconducting materials, control engineering, and even software engineering. The main goal of these teams is to prevent faults, malfunctions, and failures in superconducting magnets and their related systems, such as cooling systems. One of these teams has created a model based on RNN to characterise the electromagnetic behaviour of superconducting magnets. Due to the distributed nature of the data gathered from these magnets, RNN is put to work using a time series of voltage and current to make predictions and assessments of the electromagnetic characteristics of magnets. To gain high accuracy and efficiency out of RNNs, the structure was selected to be either LSTM or GRU. To properly detect malfunctions and failures in superconducting magnets, the regression task is replaced by classification. Accordingly, data in the training and test phases are categorised. Thus, the developed model is capable of predicting some time steps coming in the future. By doing this, the maximum error of prediction is between 5% and 10% [115–117].

Due to the vulnerability of magnets in the LHC against quenches, an QPS was developed based on current signals [118]. The challenging issue for the QPS is that usually the quench detection can be accomplished after the abnormality occurs. Consequently, there is need for very fast protection

Figure 11. Test facilities for testing quadrupole magnet [106].

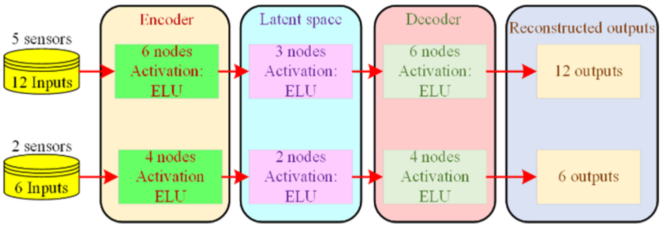

Figure 12. AEDNN for fusion magnet protection in [119].

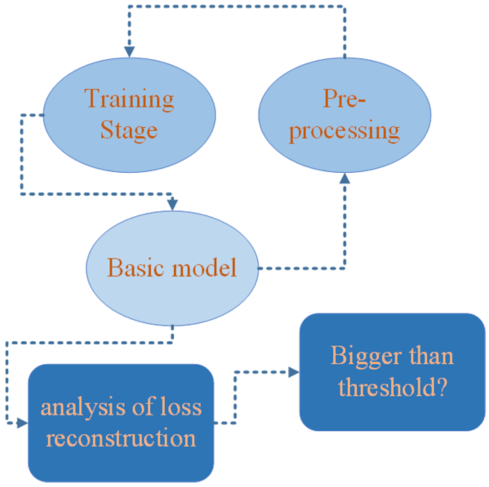

Figure 13. An overview of dynamic learning used in the LHC as a predictor [119].

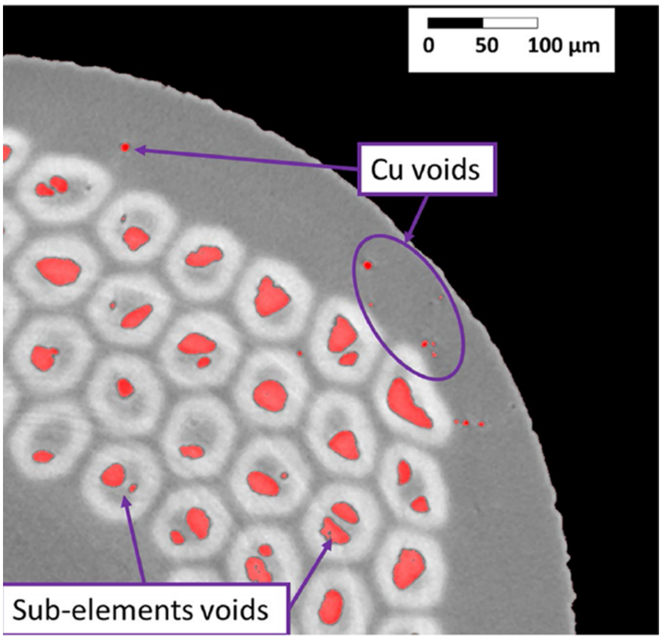

Figure 14. An x-ray micro-tomography presenting the copper voids and other sub-element voids in a Nb_3Sn wire [120].

schemes that are more expensive than slower versions. To meet this challenge, dynamic learning is used, which consists of an Auto-Encoder Deep Neural Network as shown in figure 12. In static learning, firstly input data are trained to build a model. Afterwards, the test data are fed to the built model for estimations and predictions of the output, and comparing the output with target value, i.e. the real output. This of course leads to some error between real output data and estimated one. Due to the sensitivity of the QPS in superconducting magnets, a dynamic learning method must be used instead of a static one. In dynamic learning, the basic model is upgraded every 10 s based on a triggering process. Triggering can change the basic model to operate in a real-time manner, based on the test data. In this method, the weight of the network is updated to be adapted to changes in the main problem. An overview of dynamic learning is shown in figure 13. By doing this, 77% of the quenches were detected about 25 s before its occurrence [119]. This can provide tremendous protection for the superconducting magnets in either the LHC or any other fusion industry. However, the accuracy and prediction timespan can be further improved in the near future by using more advanced DL methods.

Due to the high Bc_2 of Nb_3Sn wires (around 30 T), the critical temperature around 18 K, and the high critical current density of these wires, around 10^6 A cm^{-2}, they are widely applied in superconducting magnets in fusion systems, such as CERN and LHC magnets. So, the condition monitoring of magnets, as a key component, is a vital step towards the safety enhancement of the related projects. To detect copper voids in these wires, x-ray micro-tomography can be applied as a powerful tool along with ML methods. By using such an approach, copper voids and sub-element voids can be detected with high accuracy. The process begins with acquiring some images of Nb_3Sn wires with x-ray micro-tomography. Then, each image pixel is compared with a threshold colour to find voids. As a result, copper voids must be separated from others, which is performed by an ML method. The clustering of ML is based on the well-known *k*-means method. Pixel brightness is implemented here as the input while the type of void is the output [120]. A sample of x-ray micro-tomography is shown in figure 14, which includes copper voids and voids of other sub-elements.

Cryoplants are one of the crucial parts of any large fusion or accelerator superconducting system. To evaluate the behaviour of the cryoplant of the ITER project, a program known as

4 C was developed [121]. This program modelled and simulated thermohydraulic transients. To reduce the simulation time, ANNs were used to split the model of CS into problems with a lower order of complexities. To model the CS with ANN, inputs are the total power of each CS module, and outputs are thermohydraulic parameters, such as pressure, temperature, and mass flow rate.

By implementing the ANN, pulsed heat load induced by CS to liquid helium baths was estimated with an error range between 0.04% and 0.22% [122, 123]. Restructuring the ANN further improved the results. Some parameters of ANNs were changed, such as network topology, activation functions, number and types of inputs and outputs, and training time step, to increase the accuracy. By performing optimisations on these parameters, the ANN model became 500–1000 times faster and about 8% more precise than the un-restructured ANN [124, 125].

CICC is another important part of the superconducting magnets in fusion power plants. Improvement of the structure led to a better operation of the whole power plant. So, ANN could be used as a solution to find the optimum structure of this type of cables, which results in a fast optimisation without any possibility of sticking to local optima. The results of finite element analysis were used as inputs of the training phase for ANN, under the objective function to maximise the generated magnetic field in the pancake, while the temperature of hot spots, mechanical force, and the pancake volume must remain below a limited value. After applying such a model, the calculation time was 90% reduced, whilst the accuracy of the model was about 99.994% [126]. As stated in [127], the stray magnetic field around the International Thermonuclear Experimental Reactor (ITER) tokamak is around 200 mT that could jeopardize the reliability of electrical, electronic, and sensor devices installed around the tokamak device. So, an immune zone for installing the electronic and electric devices must be recognized with the lowest possible magnetic field. This immune zone is a function of the structure of superconducting coils, which could be the outcome of an optimisation problem. Thus, in [127], an NSGA-II optimisation algorithm was used for designing a magnet system with four coils, 1 m side length, 275 mT magnetic field, and homogeneity of 1.05 that is shown in figure 15. For this purpose, the objective function is considered so that the power loss in coil system and the mass of the superconducting tapes are minimized. After the implementation of such an objective function, the optimum design of the coil system was acquired and the next level was modelling the designed coil. Figure 16 shows the distribution of power loss and magnetic field of the coil system after optimal design process. After comparing the result of simulations—based on NSGA-II algorithm—and the experiments, a high level of agreement was observed.

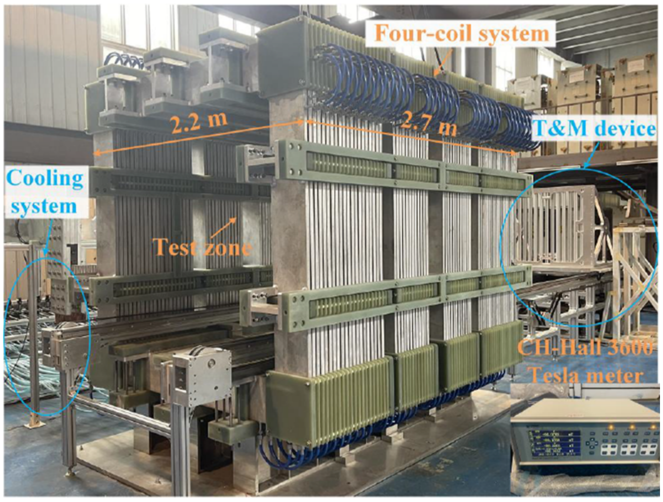

Figure 15. The four-coil system with a 275 mT magnetic field [127].

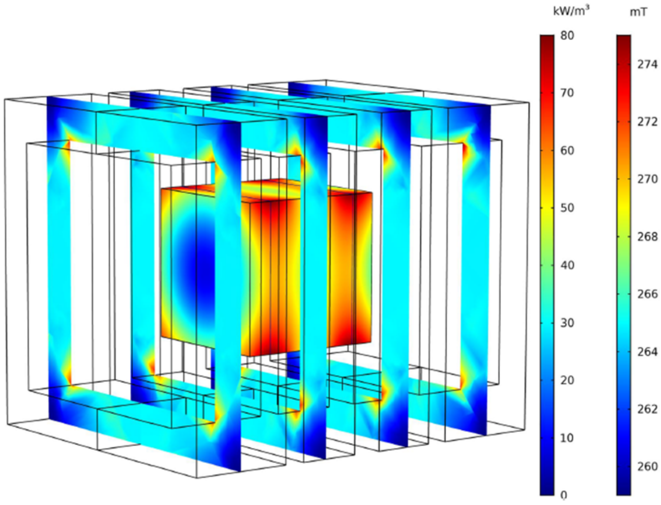

Figure 16. The field and loss distribution of the four-coil system after the design process with NSGA-II [127].

3.1.3. AI for superconducting cables. Superconducting cables are candidates to transmit and distribute electric power in future power grids and cryo-electrified transportation systems. Advantages of the HTS cables include minimised cable resistance, minimized impedance, and compact size. Challenges for the commercialisation of these cables include high manufacturing cost, high thermal loads, requirements for reduction in size and weight, electrical joints, and long HTS cables, among others. They lead to a decrease in the efficiency of the cable, cooling system, and the reliability of both. To tackle these issues, AI techniques have been proposed as a fast and effective solution. Condition monitoring of superconducting cables for analysing their temperature, operation mode, and AC loss is a challenging issue on its own.

Due to the novel structure of the cables, it is almost impossible to simply use those condition monitoring methods developed for conventional power cables. The different structure of coated conductors in comparison to conventional wires and the arrangement of tapes/wires in a novel cable structure makes it crucial to bring in new monitoring procedures for these cables. AI approaches can be used to overcome this problem, as accurate and reliable condition monitoring methods. As a matter of fact, an accurate condition

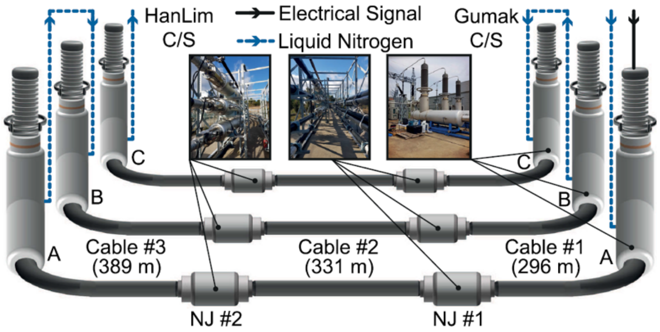

Figure 17. The location of electrical joints in the system of the 154 kV/600 MVA HTS cable [128].

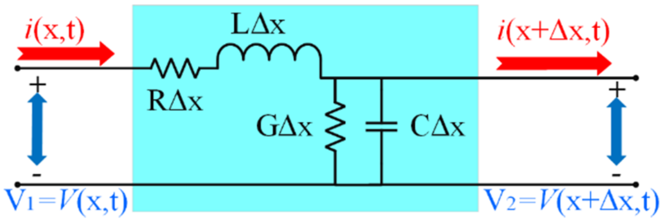

Figure 18. The S-parameter block for condition monitoring of the 22.9 kV HTS cable presented in [129].

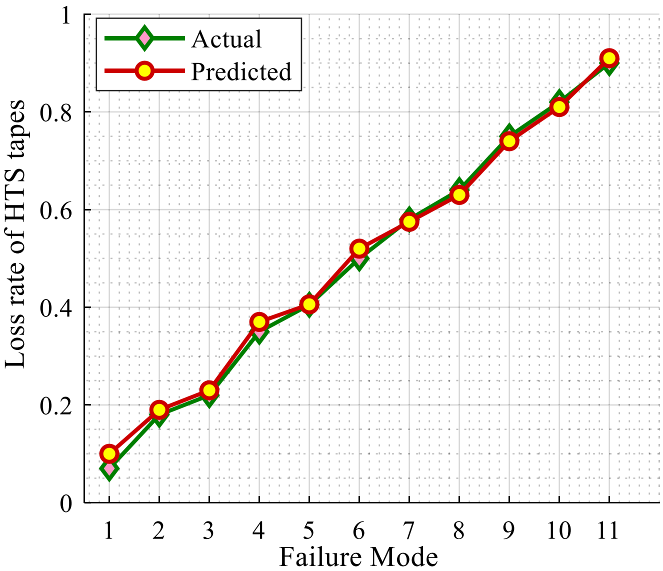

Figure 19. The loss rate of the HTS tapes for fault detection in 22.9 kV HTS cable by machine learning [129].

monitoring method can be used for monitoring the characteristics of superconducting cables under steady state meanwhile it can be used also as a part of the protection system and help the real systems to isolate the faulty cable.

A condition monitoring method using TS-LSTM was proposed in the technology development project [128] for the sake of determining the dielectric and electrical characteristics of a 1 km 154 kV/600 MVA HTS transmission cable as shown in figure 17. TS-LSTM was used to monitor the condition of the joints, which cannot be accomplished with conventional methods due to voltage signal reflections. To do this, firstly the location of joints and terminations in the cable was analysed through time-frequency domain reflectometry. After that, for joint monitoring, the voltage signals were analysed with a chirplet transform operating in the time-frequency domain parallel with TS-LSTM. Thus, by implementing such a model, joints can be analysed and in the case of any failures and faults in these elements, the location of faults on HTS cables is identified. To extract the features of the investigated voltage signal, in each step time, they were divided into sub-signals known as sections (n), which played an important role in gaining the highest possible accuracy of the monitoring procedure. The accuracy of this model reached 99.27% when $n = 3$ while the accuracy for section number of 2 could be just about 89.4%. By applying this method, the reliability of the cable operation was increased by reducing the risk of long-duration faults.

On the other hand, the proposed condition monitoring method could be applied during the test phase of the HTS cable and before implementing in a real power system to improve the lifetime of the cable by monitoring its performance under different circumstances.

The condition monitoring of HTS cables in a real-time manner is a key factor in increasing their reliability and lifetime, and enhancing their performance in the long run. However, no evidence in this paper clarifies if the proposed method is universal enough to apply to all kinds of superconducting cables. In addition, there was no discussion on the suitability of the method to detect any other abnormalities or in any other location apart from joints.

Another approach for condition monitoring of superconducting cables is to use ML methods to train a system that could discriminate faulty conditions from normal ones. To implement such a model, an S-parameter block can be used to represent a magnetic signature in both transient and steady-state conditions as an index for fault detection [129]. The S-parameter block of a 22.9 kV HTS cable based on a lumped model is shown in figure 18 as a two-port linear time-invariant network system. In this figure R, L, C, and G represent resistance, inductance, capacitance, and the conductance of the understudied cable, per unit length, respectively. To perform fault detection, firstly, the electromagnetic characteristics of a cable are experimentally acquired. Afterwards, the S-parameter model is built based on the experimental data. Finally, an ML method is applied to predict the type of fault, based on the magnetic signature. The ML method gains the multiple linear regression of the voltage and current waveform of the normal operation mode of the cable and compares other voltage and current signals with that. By doing this, series faults can be identified and characterized, based on the loss rate of HTS tapes. A loss rate model shows an average accuracy of 98.06%, as can be seen in figure 19.

AI techniques can also assist in monitoring over-voltage in any HTS cable during operation in a power grid. To do this, a PSO-SVM-based approach is an effective option to recognize the lightning and the internal overvoltages in a 110 kV HTS cable [130]. Firstly, the signals of over-voltage were acquired by highly sensitive sensors at the grounding tap of transformer

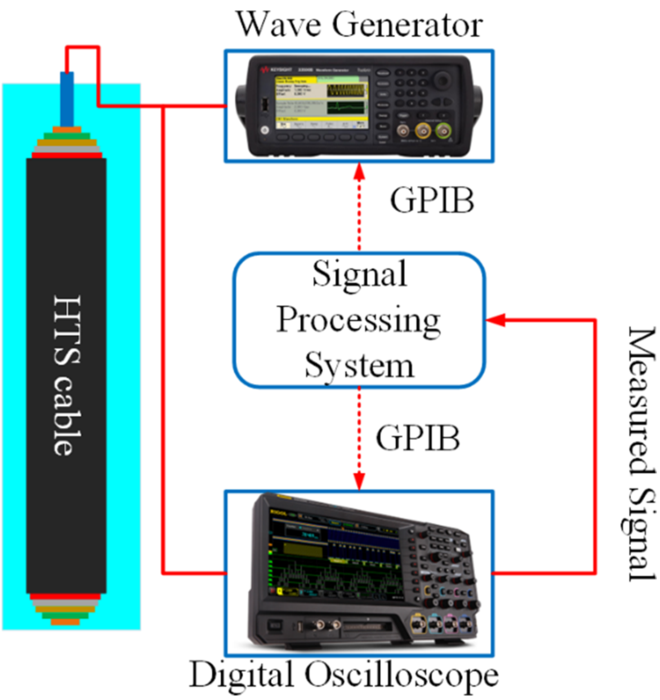

Figure 20. The experimental setup in a 110 kV AC HTS cable that feeds the input data to an ANN model for fault detection [131].

bushing. After that, a hierarchical pattern recognizing structure used the PSO-SVM as the classifier to extract the features of different types of over-voltage. The accuracy of this approach was above 90.4% [131]. The error might be further reduced by applying NNs to the model and the accuracy may even reach above 99%. This can be conducted by using a measurement and test system, as shown in figure 20 [131].

The role of AI-based approaches in the condition monitoring and fault detection of superconducting cables becomes more significant, compared to conventional methods. Although most of these studies aimed to perform an estimation procedure, there is a lack of online or even real-time monitoring methods that predict short-term future conditions of the cable. These types of models, if successfully built, would be able to predict the behaviour of a cable with respect to the parameters of the power systems, such as voltage, current, frequency, and even loading. By implementing a prediction-based model, a proper protection setting could be adjusted for HTS cables. This protection can isolate the cable when the predictions imply the high probability of cable burnout. Note that conventional relay-based protection is incapable of predicting a fault before it occurs.

A discriminative method of fault detection for a 33 kV/202 MVA/5 km distribution cable was proposed in [132]. This method uses two kinds of feature extraction techniques, SWTs and two AI-based approaches, ANN and SVM. A method was proposed for the identification of internal faults from external faults and other transient events in power systems such as load switching. Internal faults refer to any fault that occurs within the HTS cable, while other faults are categorised as external faults and have origins outside the cable. First, the three-phase voltage and current signals were received and SWT was used to decompose the signals. The next step was the feature extraction of samples to feed them into the binary classification. The binary classification was conducted with ANN and SVM. Results showed that both methods achieved high accuracy around 99.6%, while ANN had an outstanding action time (i.e., less than 1.5 ms) which was 430% faster than SVM. The high accuracy and fast response time of the proposed ANN-based method made it an excellent choice for protecting the HTS cables not only in power systems but also in future electric aircraft. However, it was not discussed whether this model was adoptable for any other structure of the HTS cables upon some modifications based on other cables.

Making high-current cables out of the superconducting tapes can usually be accomplished by three methods: manual winding, acceptable for technology Demo only, device-assisted winding, and fully automatic winding. By performing each one of these methods, the distribution of a critical current is different. Winding methods also impact the quality of the cable and could increase the possibility of weak points and burnout during the operation of the cable. To avoid this, an AI-based technique with three steps was presented in [133] to analyse the quality of winding in a CORC cable. The first step was data preparation based on video of winding process and turning them into a couple of image samples. After that, all image samples were binirized as ground truth for the training phase. However, the amount of data at this stage was not appropriate to train a system with high accuracy. Thus, the data set must be enlarged to increase the stability and accuracy of the trained model.

This was done by flipping the images or by rotating them 90 degrees, clockwise. In the second step, an RCF network was used to detect the quality of winding, based on the input data. This model is accomplished in five steps. The first step is a modified residual NN, ResNet50, consisting of bottleneck models with a 1×1 kernel size and a 1×21 channel, consisting of convolutional layers. By applying the input images to the network, the output is a series of grayscale images, which are converted again into a series of binary images with two parts. The white part was the predicted interval of the cable and the black part was the background of the image. These black-white images could have noises and holes that make the detection procedure inaccurate. To overcome this issue, in the third step of the detection procedure, the output images were post-processed to increase the accuracy of detection.

Since the first application of HTS cables, specifically the triaxial type, uniformity of current distribution in superconducting layers is always a very complicated fabrication task. To achieve such uniformity, the preliminary structure of the cable should be adjusted. This procedure could be analysed as an optimisation problem and can be solved by using AI techniques [134]. To solve such an optimisation problem, many constraints and limitations are imposed on the feasible domains, such as maximum irreversible strain and maximum tolerable Lorentz force for HTS tapes. The total AC loss of the cable can be considered in the optimisation algorithm and should be minimised [135]. The reliability of the designed HTS cable is another constraint [136]. Another

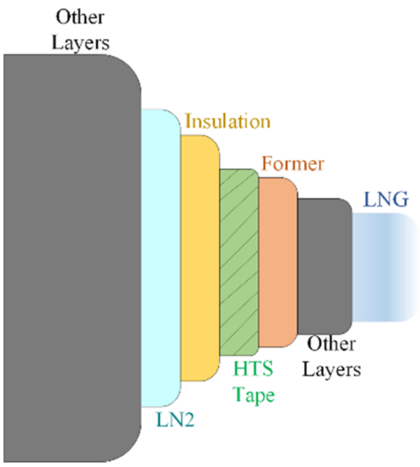

Figure 21. The structure of a hybrid-HTS cable for transmitting electrical energy and LNG simultaneously [139].

imposed constraint is related to mechanical load considerations, such as stress, strain, torsion, and twisting, among others, which could also reduce the feasible domain to essentially find the optimal solution faster [137, 138]. The optimum structure of the cable could have some of the following results. One of them is that the size and the weight of the cable are reduced. This can fit them for future electric ships and aircraft. Another consequence of design optimisation is that the value of AC loss is reduced. This results in an enhancement in the total efficiency of the cable where less heat load is imposed to the related cooling system and results in a lower operational cost. These optimisation techniques, for reducing the size, weight, and cost of superconducting cables, can be used to assist the design procedure of HTS cables. For instance, recently, a novel concept was presented for HTS cables, such as HET [139]. HET implies the simultaneous transmission of different types of energy. An HTS cable can transmit not only electrical energy but also LNG as shown in figure 21. In this figure, the main electrical structure of the cable is shown. In addition, other parts related to the LNG transmission are shown with '*Other Layers*'. A PSO optimisation problem was carried out on a 500 kV/2 kA/1 GW AC HTS cable to improve the design parameters of the cable with HET capability [139]. The objective of this optimisation was to maximise the current sharing uniformity in different superconducting layers by applying changes in twisting angles and twisting directions of HTS tapes, while maximum and minimum applicable angle and assigned total current limit the feasible domain [139]. Finally, the values for twisting pitch length, magnetic fields, critical currents, and the structure of the cable were optimised. Indeed, the optimised structure of the depicted cable has 445 mW m^{-1} of AC loss, about 15%–20% less than the non-optimised structure.

3.1.4. AI for SMES. Implementing energy storage devices in power grids increases their stability and reliability [140–142]. SMES stores energy through a superconducting coil/magnet, and also by integrating power converters, a cooling system, transformer and a fast solid-state switch. The weight, size, and cost of these components can affect the total structure, efficiency, and final price of the energy-storing procedure in SMES. Thus, an optimisation problem can be conducted to find the optimal values of design parameters. By optimising these parameters, the power density and efficiency could be increased, while losses, cost, size, and weight can be significantly reduced [143].

To optimally design SMES, AI techniques presented a fast and accurate solution for optimisation problems [144, 145]. In addition, they were capable of estimating any magneto-mechanical characteristics of SMES based on acquired data such as maximum applied force to the superconducting coil, the maximum magnetic field of SMES, and mechanical characteristics of HTS tapes used in SMES, among others.

To optimise the structure of SMES, the size or/and the cost of the device could be set as the objective function(s), while AC loss, the stored energy, and the stray magnetic field could be defined as constraints [146–148]. This leads to an SMES with higher power density and higher energy storage capabilities. Power density is an important factor when the SMES is designed for applications such as microgrids, cryo-electrified aviation systems, and space.

There are many AI-based algorithms to find the optimum design parameters. Among those, GA and simulated annealing (SA) are commonly used [149–151]. It is worth noting that the SA is an optimization algorithm that is adapted based on the slow cooling of metals where atoms inside the metal lose their lattice defect density by reducing their movements.

Due to the rapid increase in penetration of DG and the uncertainty regarding their capability in providing the demanded load at all times, SMES could be used as a vital component in smart-grids with DGs. To optimally operate of SMES in future modern smart grids, constraints and uncertainties of DG must be also taken into consideration during the design stage. In such grids, SMES can inject a high amount of power into the power system at a short time, which will benefit the suppression of around 20% of fluctuations in the grid caused by overloading and other abnormalities [152].

Mechanical constraints also affect the optimum structure of SMES. These mechanical issues can include hoop and radial stresses or any other kind of stress, strain, and mechanical deformation of superconducting tapes, considering mechanical stresses in the design stage of SMES are vital, due to the possibility of establishing weak points and hot spots caused by mechanical issues. These may lead to burnout of SC and also SMES malfunction [153–155].

If SMES is optimally designed, the stability of the grid can be remarkably enhanced when it experiences events such as overloading, generation unit disposal, frequency oscillations, and even faults and over-voltages. However, the majority of studies have focused on the design optimisation of SMES itself. Therefore, some new studies on the design optimisation of SMES concerning system parameters need to be conducted to improve the reliability, stability, and even protection of the power grid.

To model SMES, there are multiple options on the table, such as ECMs, FEM, and analytical models. FEM offers high accuracy but with a high computation burden, which makes it a non-real-time approach. ECMs also offer acceptable accuracy and lower simulation time if compared with FEM. However, ECMs have issues in defining some mechanical and thermal constraints. Finally, there are analytical methods with a geometry-dependent accuracy and computation speed.

To overcome previous challenges in modelling the SMES, ANNs are one of the most convenient approaches to model and characterise the behaviour of such devices without any complexity of computation, e.g., for the calculating magnetic field. Usually, ANN-based approaches consist of a training phase, in which the system is trained with respect to the inputs and outputs, and a test phase that can be used for the sake of prediction and estimation of the behaviour of SMES [156]. By applying ANN to estimate the magnetic field and AC loss of a 150 kJ SMES, a high accuracy, e.g. with an error of 0.1%–3.7% can be achieved. In this process, the inputs are operating current and load parameters, while the output is AC loss. Also, the supervised training is used to increase the accuracy of the model, which was reduced due to the highly non-linear relation between current and AC loss [156].

Due to the high speed and accuracy of the ANN-based models, they are implementable in a real-time manner. This makes the online condition monitoring of SMES available when operating in a grid or cryo-electrified transportation system. However, there is a lack of a complete model for SMES that can predict magnetic, electric, mechanical, and even thermal behaviours of SMES, under different conditions of the grid.

So far, AI methods are applied to relatively small technology demonstration units. Potentially commercial units with energy above 10 MJ and deliverable power above 3 MW will require different AI approaches. Depending on the purpose, SMES optimization will use different constraints and weight functions. For example, 5–10 MJ, 1–5 MW micro-SMES for support of critical loads have relatively few discharges on the order of 10 a year. These units will be optimized with size, cost, minimized lead losses. Larger SMES units were proposed for the line stabilization. These units experience frequent charge/discharge cycles and AC loss optimization is one of the design drivers.

To increase the stability, reliability, and safety of power systems, including wind farms, SMES units were proposed as they are efficient, and optimum control is a critical concern. The Archimedes optimisation algorithm is a novel AI-based optimisation method that was used in [157] for determining the operating condition and parameters of the proportional integral (PI) controller of an SMES. By doing this, under different grid conditions, the charging and discharging of SMES would be regulated and as a result, grid stability increases. The SMES is installed at the load side while a wind farm delivers the power to the load. For this purpose, the objective function is selected so that the difference between the required active/reactive power of the grid and the delivered active/reactive power by SMES is minimised. GA and PSO algorithms were also used for the sake of comparison with the proposed Archimedes optimisation algorithm. By doing this and under a 400 ms line to ground fault, 80% of terminal voltage drop is reduced in comparison to when GA method is used and 800% of voltage drop is reduced in comparison to the situation that no SMES is implemented. A line-to-line to ground fault was also tested and the results showed the superiority of the proposed Archimedes optimisation method. The PI controller of SMES units could be also adjusted based on the NNs. For this purpose, an enhanced block-sparse adaptive Bayesian algorithm (EBSABA) is presented in [158] to control the PI parameters of a 10 MW/20 MJ SMES. By using such a method, the output power of the wind farm is smoothened. As a result of simulation of 23-bus power system with two wind farms and 100 MVA base power, while the EBSABA is applied to the PI controller of wind farms, more than 10% of the farm output power is smoothened in comparison to the situation where EBSABA is not applied to the PI controller.

3.1.5. AI for superconducting machines and transformers. Significant advances in technology and manufacturing are required to enable commercialisation of superconducting machines. Among these requirements is the increase of magnetic field in the excitation area between rotor and stator, the increase of the power density, reduction in size and weight, efficient cryogenic system with the minimized use of liquid cryogens, improved system reliability with minimized maintenance, a long system operation period of over ten years, and the availability of the operation of superconducting components over 99% of the time, which have higher priorities. AI techniques are powerful tools to deal with the challenges related to optimisation as well as condition monitoring [159–163].

Rotating machines including motors and generators are the most common types of electrical machine. However, there are other types of electrical machines where AI can optimise their structure and operation conditions, for instance, superconducting transformers [164] and linear HTS machines [165]. Generally speaking, rotating machines consist of two major components. One of the components, typically called a rotor, practically generates a DC magnetic field that varies in space. In generators, the stator converts mechanical energy to electric energy. In motors, AC currents in the stator cause the rotor rotation vs the stator. The low-loss DC component may use either LTS or HTS superconducting winding. The high level of AC loss (especially the eddy loss) in superconducting armature windings remains an unsolved challenge for high-speed superconducting motors [166]. It was shown that the stator may benefit from operation at a higher temperature despite the penalty in SC cost.

Relatively high cost of cryogenic vessel and other components of the superconducting rotating machines cause only large-size machines to be commercially competitive with conventional units. For generators, only units with output power not below 10 MW are expected to be competitive. The motor power should be above 3 MW for competitive superconducting units [167].

Cost is a vital factor in designing superconducting machines. While the capital cost for superconducting machines is generally higher than for the mature conventional devices, the lifecycle cost promises to be competitive. Their cost could be minimised by conducting an optimum restructuring process on some parts in machines. One of these candidate parts for being optimised is the excitation system, which is responsible for magnetic field generation. In superconducting machines, the excitation system could be either composed of superconducting tapes/wires, resistive or PTs. In the case of designing a machine with a superconducting excitation system, there are multiple trade-offs. Although minimising the size and number of coils in it would make the cost to be minimised, minimization alone has significant limits [167, 168]. Cooling consideration is another factor that can highly impact the total cost and weight of the machine. For instance, due to the lower cost of first generation (1G), bismuth-based HTS tapes compared with second generation (2G), REBCO-based tapes, at temperatures near 20 K, 1G are the best economic option in AC. However, as a matter of fact, NbTi version is the only DC architecture that can compete with conventional motors and generators in terms of cost. However, the AC regime may be different, depending on different AC loss components [168, 169]. However, the cooling cost of the required cryogenics to provide such a low temperature would be significant, which must be considered in the cost evaluation stage. As a result, temperature could be assessed in future research as an effective factor on the cost of superconducting machines and the total power density of the energy unit (i.e., the total weight of the machine plus cooling system must be considered) [170].

Superconducting machines were proposed and studied for wind turbines to convert the mechanical energy of the wind to electrical energy, as a green energy solution. The EcoSwing project aims to deliver a 3 MW HTS generator, and the generator has operated on a tower for about 4 months. Previously, the related research and investigations about the design of superconducting machine happened in Japan, 1990s–2000s, and the coils of the machine consisted of NbTi SCs operating at 1.8 K [171]. There are limitations for such applications, which can change the structure of the machine and consequently its cost [172, 173].

The efficiency and power density of superconducting machines are two important design factors. Power density is the ratio of generated/consumed power of the machine to its weight (kW kg^{-1}). So, by minimising the weight and the size of the machine, its power density increases. GA is usually used for dealing with the challenges of power density and efficiency increase in superconducting machines. Armature windings, stator iron yoke, and field windings are the most susceptible parts to minimise the weight and the size of the machine. By performing an optimisation based on the size and weight reduction of a 200 kW/220 V/250 rpm nonsalient magnetic-cored superconducting synchronous machine using the GA method [174], volume and weight was reduced around 28% and 36%, respectively, in comparison to the size and weight of the un-optimised machine. The efficiency of the machine with the optimum design was 1.15% more than the preliminary non-optimised design. Consequently, the power density was 156% increased, which is quite significant for a machine with 200 kW power.

In [171], a sensitivity analysis was performed to find the optimal solution of a 74.7 MW/10 kV LTS generator composed of NbTi wires. Multiple objective functions were defined in this study with different constraints and aimed to solve them by performing a sensitivity analysis on the parameters of GA and SA algorithms. However, these changes did not make a significant improvement in the power density and efficiency of the machine. The range of changes was between 0.3% and 0.7% for the specific power of the machine. In fact, the authors compared GA and SA algorithms, and show that the two approaches converge. Within such constraints, there is not much room for optimization.

The power density of a superconducting machine is critically important in electric aircraft applications, as the low weight of the propulsion system is quite vital for flying at a longer distance [175]. For the superconducting machines proposed in aerospace applications, specific mass of the cooling system is another factor to be considered and minimised. It is defined as the ratio of the weight of the cooling system to its cooling power, and is shown based on kg kW^{-1}. When designing a cryo-electric aircraft, this factor must be taken into consideration. As shown in [176], depending on the operating temperature, the cooling system is responsible for 24%–90% of the total mass of the whole system of a 50 kW superconducting machine designed for aviation purposes. Near the 20 K operational temperature of the machine, most of the total mass belongs to the cooling system. Meanwhile, when the temperature approaches 77 K, the mass of the cooling system, especially the cryocooler, is significantly reduced. These results seem about right for low power machines; however, in future aviation applications superconducting machines with power in the MW range are required to achieve the reported values for mass and weight. This great finding should certainly be considered in the design procedure of an electric aircraft. As reported in [176], for low-power 50 kW machine, the best operating temperature was 66 K, which led to a 0.6 kW kg^{-1} overall power density (cooling system included); whilst for a 1 MW machine, the overall power density can be up to 6 kW kg^{-1}, at 50 K. A schematic of the understudied machine is shown in figure 22 [176]. The research considering the aircraft limitations could accelerate the implementation of SCs in electric aircraft and commercialisation. AI techniques demonstrate their effectiveness in the development around superconducting devices in aviation technology.

Harmonics are an inevitable part of a system with power electronic devices. They have destructive impacts on the equipment such as generating a higher loss, producing more heat load, and reducing its life span. Superconducting machines are normally subjected to harmonics either in the current or voltage. Harmonics increase the amount of AC loss in superconducting machines, lowering the efficiency of the cooling system, exposing the superconducting tapes/wires to extra heating, and many other devastating consequences. To avoid such harm to superconducting machines, they should be optimally restructured considering harmonic constraints [177]. The PSO algorithm was implemented on a 50 kW superconducting synchronous generator to optimally design it to reduce the THD of the output voltage [178, 179]. This optimisation in the design of the machine by PSO algorithms has led to a THD reduction of 13.5%–5.8% in comparison to the

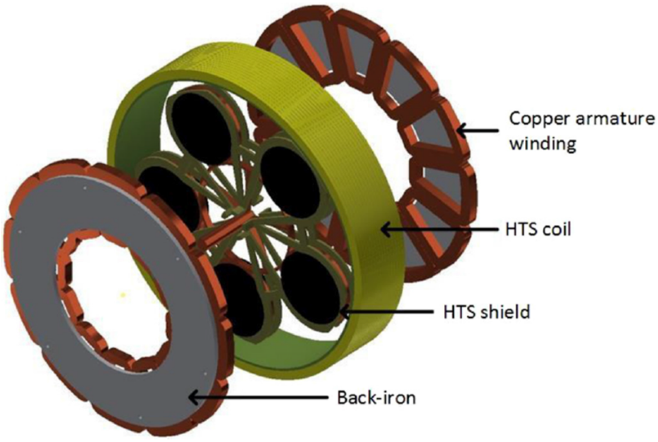

Figure 22. A 3D schematic of the 50 kW superconducting machine designed for aviation purposes [173].

preliminary design. Thus, the THD of the air gap magnetic flux density of the machine varied from 21.64% to 9.65%. The values of THD are significantly reduced, however, there may be room for further reduction using a new type of meta-heuristic optimisation algorithms.

Investigations on THD reduction with AI algorithms have not been accomplished for other types of superconducting machines, such as induction homopolar DC and PM machines. This could be an excellent opportunity for further investigations, knowing that homopolar DC machines and high-speed induction machines are attracting attention recently.

The main issue with superconducting transformers is their heat load mainly coming from AC losses in superconducting windings carrying AC current with harmonics, heat leakage of cryosts, heat load of current leads, etc, particularly for high power transformers [180]. The unavoidable significant AC losses make LTS transformers not commercially-competitive if technically feasible. The heat load causes the rise of the conductor temperature and imposes extra cooling power on the cooling unit. So, loss must be minimised to increase the techno-economic advantages of the superconducting transformers [181]. Electromagnetic and Lorentz forces are other challenging parameters that should be taken into account to achieve a better performance out of HTS transformers.

GA and SA are two common AI techniques to optimise the AC loss while thermomechanical limits are considered [182]. Performing these optimisation methods on a 315 kVA, 20/0.4 kV HTS transformer caused the reduction of AC loss, the heat load of the cooling unit, the increase of the lifetime of the transformer, the decrease of the possibility of mechanical damage in tapes, and the increase of the efficiency of the cooling system and transformer by size reduction. As a consequence of this, AC loss is reduced according to different scenarios between 20% and 85% and the mechanical force varies between 120.3 N and 272.6 N concerning the preliminary design of the transformer.

Some novel ideas about the utilisation of AI techniques for modernising superconducting transformer technology were discussed in [183]. The stated ideas can be considered as a roadmap for making changes in transformer manufacturing, and also apply to other superconducting applications such as machines, SFCLs, and cables. One of the ideas published in [183] was using additive manufacturing along with AI to completely eliminate the old manufacturing process of tapes, insulations, and other components of transformers and make them way lighter, cheaper, and more environmentally friendly. Online loss prediction of superconducting transformers is achievable with the help of AI techniques. To do this, a meta-heuristic model of transformers needs to be built based on regression techniques.

After verifying the model, it can be used as a package to predict values of AC loss, online and in real-time. Real-time monitoring of superconducting transformers can be realized by AI. As a matter of fact, the monitoring of superconducting transformer can be done for hotspot finding, fault location and detection, as well as finding any other anomalies in windings.

Another type of superconducting transformer is used when there is a need to supply a large current to other superconducting devices. Under such circumstances, the sample current passing through the conductor is reduced. To address this issue, a controllable sample current was proposed based on the PID control strategy. RBFNN was used to adjust the control parameters of PID. As a result, a self-learned adaptive algorithm is available that adjusts the control parameters of the current loop. The structure of such a method is shown in figure 23 [184].

Superconducting tapes/wires, well known for their high current carrying capability, are the beating hearts of any superconducting apparatus including machines and transformers. In fact, they are the most expensive part of machines and also the origin of the AC loss heat loads. The peculiar non-linear characteristics of SCs and large width-to-thickness ratio are the main reasons for the heavy computational load of the models. There have been also some investigations on the superconducting tapes/wires with respect to the limitations which are imposed by superconducting machines. The goal of these studies is to prepare and analyse tapes and wires for the sake of being used in superconducting machines [185, 186].

The imposition of elliptical magnetic fields on HTS tapes is one major limitation for HTS machines. These fields have two elements, one as a pure AC field, and the other one as a rotating field purely out of phase. These fields impose a new-shaped AC loss. The AC loss values were predicted using ANN to speed up the model of the HTS rotating machine [187]. It took a few milliseconds for an ANN to predict the AC loss of superconducting round filaments superconducting tapes with an average error of 3%. In this model, inputs were the properties of a superconducting filament, dimensions of the SC, external magnetic field, and transport current while the output was AC loss. The estimated values were also validated with respect to the results of FEM-based software, COMSOL [187]. However, the lack of real-time analysis of the proposed model is completely tangible. The model should be implemented in parallel with an FEM or ECM model to be verified.

Superconducting motors, as a promising technology for propulsion of future electric aircraft, are subjected to current and voltage harmonics and inter-harmonics caused by power electronic drive systems. This can significantly increase the

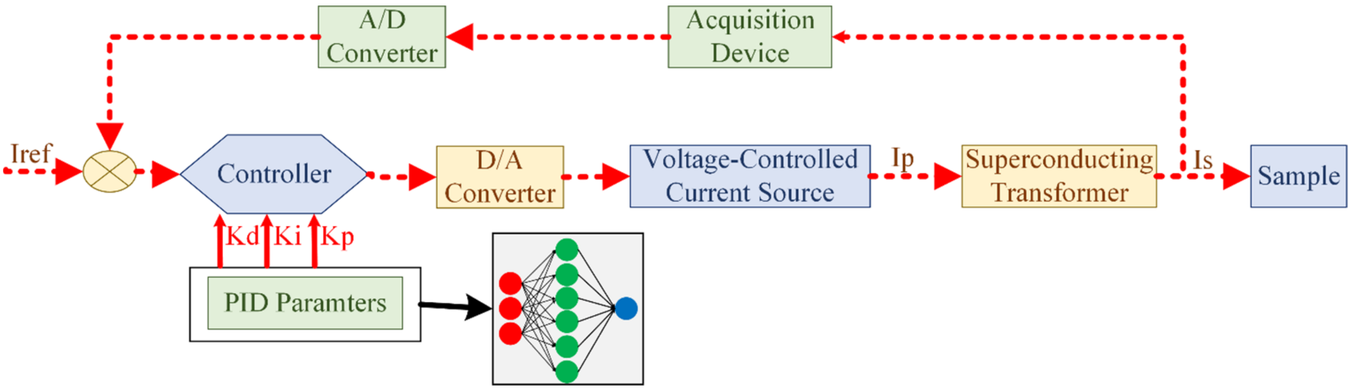

Figure 23. The self-learned adaptive algorithm for PID controller [184].

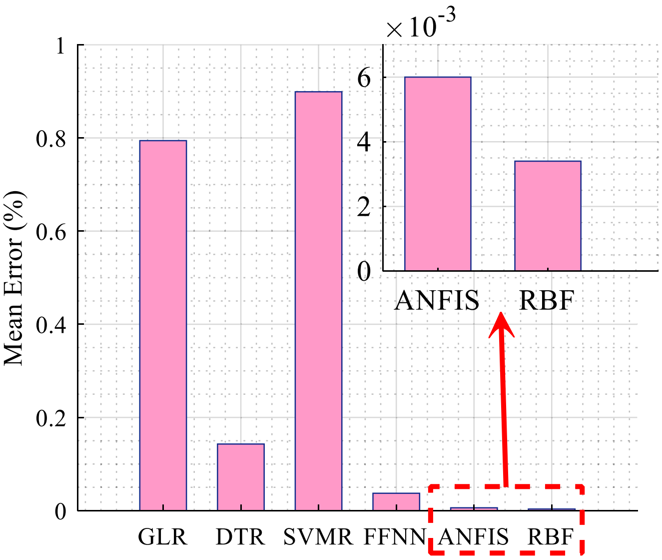

Figure 24. The mean error of AC loss prediction in superconducting tapes under harmonic conditions [188].

AC loss and jeopardise the proper function of the cooling system. Therefore there is a need for a fast model to calculate the AC loss of the tapes, under harmonic distortions. AI approaches are the fastest option to calculate AC loss, for example, NNs, SVMs, and generalised linear regressions, can predict the AC loss of superconducting tapes with high accuracy [188]. These methods were applied to a YBCO tape, manufactured by SuperPower to predict AC loss under different currents. The amplitude, phase angle, and THD of current harmonics acted as inputs of the models [188]. Among the aforementioned methods, RBFNNs has the highest accuracy; however, the mean errors for each method are shown in figure 24. By a precise prediction of AC loss under harmonic conditions, proper sizing for the cooling system could be selected in the design stage. The next step is to verify the real-time performance of AI techniques in a stand-alone grid, e.g., in the electric system of an airplane.

3.1.6. AI for SFCLs. Due to the automatic phase transition of SCs, and the high resistivity of SCs in the normal state, SCs are used to fabricate a limiting component for suppressing fault currents, called SFCL. As a matter of fact, unlike other superconducting apparatuses, SFCLs are used in the power grids for their intrisic phase transition behavior [189]. SFCLs can improve the stability and the reliability of the grid to which SFCL is connected with [190]. AI techniques, especially SVM, GA, and ANN, were used to improve the design optimisation of SFCLs [191–193].

As mentioned before, the pecular non-linear characteristic of superconducting tapes leads to a long simulation time and a massive computation burden [194]. To avoid long computation, AI is used to present a fast empirical model. Empirical models are based on observation and do not use theory to get the results. The main idea in such models is to observe how an output of a system behaves with respect to variations of inputs. This model characterised the thermomagnetic, electromechanical, and other behaviours of an SFCL [195]. Another application of the empirical models is to help the condition monitoring process of SFCLs. The accuracy of these approaches reached between 96.5% and 99.3% for modelling the magnetic-thermal characteristics of a 22.9 kV/630 A SFCL used in the power grid of South Korea. Cooling units of the same SFCL were modelled using AI techniques with an accuracy range between 98.75% and 99.97% [196, 197].

HSFCL is composed of two resistances (R_u and R_d), a superconducting inductance (L_{SC}), a high-speed controlled switch (S_{hs}), and a metal oxide surge arrester (MOSA) (R_{MOA}), as shown in figure 25. Resistance and inductance limit any power frequency fault current while MOSA restricts the induced lightning and switching over-voltages. Design of an HSFCL was optimised in [198]. The objective was to increase the fault current limitation capability of HSFCL by optimizing its geometrical parameters such as winding height, winding thickness, and iron core parameters, among others. The amplitude of the fault current is 36.77% reduced in comparison to the preliminary design of HSFCL, through applying optimised parameters to the model.

Most of the AI-based models are concerned with the behaviour of the SFCL in transient states. However, the AC loss and thermal loads in a normal state must also be taken into consideration.

Under the steady-state of the grid, harmonics are one of the reasons for AC loss increase, which could result in SFCL malfunction. In a transient state, optimisation of the structure

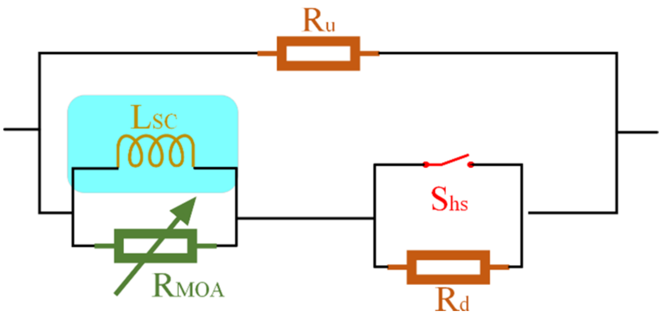

Figure 25. The structure of the hybrid-SFCL, introduced in [198].

can be affected by the fault and grid parameters, such as fault resistance, ground resistance, location and duration of fault, or power factor of the grid during faults, among others. The impact of these terms on the optimal design of SFCLs has not been studied yet. Therefore, the fault behaviour of a grid with a SFCL can be characterised and promoted, by designing an SFCL with optimum parameters using AI techniques.

3.1.7. AI techniques for magnetic levitation. Contact-free levitation has been investigated for a long time, especially for rail transit systems. Superconducting materials are promising options that can realize the MagLev concept. To acquire an excellent performance out of superconducting MagLev, it went through a design optimisation procedure for the structure using AI approaches [199, 200]. AI approaches are provided to control strategies for HTS MagLevs as well [201].

HTS MagLevs consist of superconducting bulk material, HTS electromegnets, and PMs. To maximise the levitation force, and cost reduction, an optimisation is performed using GA [202] considering maximum allowable cross-sections as constraints. As a matter of fact, the price of the MagLev is minimised during optimisation while the aim is to maintain the maximum levitation force at the operational level. Cost is reduced by decreasing the utilisation of SCs. To do this, geometrical parameters of the MagLev system are chosen as optimisation variables. By accomplishing this optimisation, the levitation force is increased by 30.7%, while the cross-section is one-sixth of the maximum allowable value [202, 203]. If cost is considered as the objective function, it can be 25.3% decreased while the levitation force is still way higher than the minimum allowable force [204]. In fact, both cost and volume can be considered as objective functions. This leads to a multi-objective optimisation, which results in a high computational burden and time. To address this issue, an equivalent permeability model can be used. Using such a model on a D5 levitation bearing reduces the simulation time by 91.95% and changes it from more than a day to a couple of minutes. After the optimisation, 16.2% and 22.4% of the volumes of HTS material and PM are reduced, respectively. As a consequence of volume reduction, the cost is 16.6% decreased [205].

Five types of NNs were implemented in [206] to anticipate the magnetic levitation and guide forces based on 3720 data. These five types of NNs are RBF NN, DNN, CNN, RNN, and LSTM. The aforementioned force was estimated by applying these methods. The error of the force calculation according to different methods is tabulated in table 1. The parameters of this table are expressed in equations (5)–(8):

Table 1. Comparison of different NNs for estimation of the MagLev guiding forces.

	Test			
NN	R^2	MSE	RMSE	MAPE
RBF	0.9763	518.49	22.770	60.232
DNN	0.9992	20.145	4.488	8.135
CNN	0.9981	42.167	6.493	12.112
RNN	0.9916	102.604	10.129	30.620
LSTM	0.9984	17.820	4.221	11.934

$$\mathrm{RMSE} = \sqrt{\sum_{k=1}^{N} \frac{(A_k - F_k)^2}{N}} \tag{5}$$

$$R^2 = \frac{\sum_{k=1}^{N} (A_k - \bar{A})(F_k - \bar{F})}{\sqrt{\sum_{k=1}^{N} (A_k - \bar{A})^2 \sum_{k=1}^{N} (F_k - \bar{F})^2}} \tag{6}$$

$$\mathrm{MSE} = \sum_{k=1}^{N} \frac{(A_k - F_k)^2}{N} \tag{7}$$

$$\mathrm{MAPE} = \frac{100}{N} \times \sum_{k=1}^{N} \left| \frac{A_k - F_k}{A_k} \right| \tag{8}$$

where, N is the number of data, A_k is the value of real experimental data, F_k is the value of the forecasted data, $\bar{A}$ is the mean of experimental data, and $\bar{F}$ is the mean of forecasted data.

3.1.8. Other applications of SCs combined with AI. SCs are used in other applications that are less noted by researchers, or are less widespread. In these applications, AI techniques were adopted for optimising structure [207–213], monitoring the condition of a device, and estimating characteristics [214–216]. This section provides an overview of the conducted studies in less investigated applications of SCs, such as special issues in aviation [217] and fusion [218–222].

Passing a high-frequency current through an inductive coil is the basic operation of induction heating. As a matter of fact, induction heating is used in many fields, such as furnaces, welding, brazing, sealing, heat treatment, and plastic processing. TFIH are more commercially conventional than longitudinal flux induction heating, due to the lower frequency and higher efficiency. However, inhomogeneity of the temperature distribution remains a main challenge for conduction heating. By optimising the superconducting coil geometry, this issue can be tackled. Although the restructuring process is a complicated and highly nonlinear problem to solve, ANN and GA can be used to simplify it. The problem consists of two parts: magnetic parts, which are concerned with the calculation of the magnetic field generated by eddy current, while the

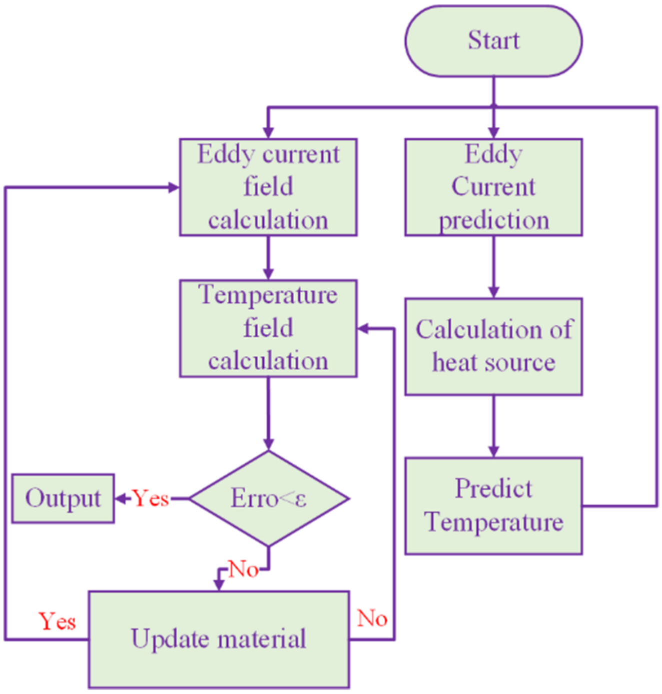

Figure 26. The procedure of using coupled GA and FEM to model temperature of a coil in a superconducting induction heating system [223].

second one is related to the computation of temperature distribution. In the first part, ANN inputs are the wall width of the inductor, the distance of the calculation point from the central line of the inductor, while the output is the absolute value of eddy current. In the thermal part of the problem, inputs are the heat source, the geometry of the elements, and the direction of moving, while output is the temperature. The next step is to link ANN and FEM, to gain the exact distribution of temperature. To optimise the structure of the superconducting coil, GA was applied to solve the optimisation problem, shown in figure 26 [223]. A maximum of 1%–8% error was obtained using ANN. Also, the number of computations by FEM was reduced to seven after design variables were chosen by GA. However, the values of error can be further decreased by the utilisation of novel structures of ANN, i.e., CNN, and RNN as well as increasing the input data.

AC induction heating is largely used in the metallurgical industry to preheat metal billets before hot working. In conventional AC heaters the billet is exposed to the AC field produced by a water-cooled copper coil. The efficiency of the process was around 90% for magnetic metals, whereas for nonmagnetic materials like aluminum, copper, or brass the efficiency drastically dropped at about 50% [224].

DC induction heating methods enabled by superconduting technology have been proposed, and recently introduced at the practical level [225, 226]. In DC induction heating, the billet was forced to rotate inside a transverse DC magnetic field produced without losses by superconducting coils, thus reaching an overall efficiency above 90%. Temperature homogeneity and heating time were influenced by the profile of the applied DC field profile. Hence, the coil's shape must be optimised to obtain suitable performance of the heating process. In [227] a split saddle coil for optimal induction heating was designed. The layout was obtained by first calculating the field profile needed to produce required uniformity of final temperature distribution inside the billet and then applying GA for determining the optimum current distribution suitable to produce the required field profile. Temperature inhomogeneity was decreased to 2.5% with the optimised coil, compared to 17.6% obtained using a uniform field, fulfilling the requirements of the subsequent extrusion process.

High field LTS magnets are used as EMPS for accurately measuring magnetic fields and other magnetic properties in low temperatures and high fields. GA is used to optimise the size and the structure of the magnet, which is usually fabricated by NbTi wires. The optimisation is also limited by some constraints, such as the necessity of a larger central field than 5 T, field homogeneity lower than 1%, and the necessity of the operational current lower than 70% of the critical current [228, 229]. After the optimisation process, the maximum hot spot temperature during a quench was reduced by 15.5% and the quench voltage was reduced by 45.46%. This led to lower applied quench energy to the magnet and, as a result, the magnet was well protected [230, 231].

The space mission of ATHENA mission will start its space program in 2028. The magnetic diverter of ATHENA is made of superconducting magnets, which have a maximum magnetic field 0.74 T and 2.1 kJ stored energy. To meet the requirements of launch, a GA was used to optimise the mass, size, and total current. The variables of this optimisation are coil size, distance from the field, and magnetomotive force. Accordingly, the mass of the coil with MgB_2 wires and ancillaries was 114 kg, while the mass of winding with REBCO and its ancillaries was 76 kg [232]. However, the mass of ancillaries had not gone through the optimisation and maybe it could also be reduced.

SLA systems, shown in figure 27, are proposed as a solution to the melted pellet in fusion reactors. To reach the plasma core, SLA includes an HTS film and has 5 km s^{-1} speed. The acceleration performance of the SLA can be increased by using a multi-objective GA optimisation. The first-level objective function of such optimisation is to maximise the velocity of the pellet for a homogenous current profile while the structure is optimised by weight and size reductions. The second level objective function concerns minimizing the HTS filaments. After optimisation, it turns out that the velocity of acceleration is highly increased by the enhancement of the length of HTS filaments and coil [233].

Quenching is a phenomenon that may happen in many superconducting applications. Quenching can cause damages to the superconducting device and threaten the stability of the system in which the latter is implemented. To have a fast and predictive quench, CNN-LSTM is a popular choice instead of using the conventional quench detection method. The first phase is to gather a large number of data and divide them into three sets, i.e. training, validation, and test sets. The first one is used to train the system, the validation set is used to apply adjustments and modifications, and the test set is prepared to examine the generalisation ability of the model. For

Figure 27. Superconducting linear accelerator system with a detailed look to different components [112].

quench detection, time series of voltage signal is selected as input of the model. This is due to the different characteristics of voltage during steady-state and quench-state. However, to avoid low accuracy or inaccurate feature selection, voltages of more than 5 μV cm^{-1} were extracted among the training data and removed from the training process. This data were used to train, validate, and test the model. As a result of this, any quenches can be detected in a time between 1.3 and 2.8 s after the occurrence [234].

By the fast detection of quenching in any superconducting device, proper protection decisions could be made to protect it. This is crucial, especially for some applications of SCs, like cryo-electrified transportation systems, fusion applications, and military and space programs. However, there is a need for improvements not only in speed but also in the accuracy of methods. There are many considerations to make, such as the impact of geometry on results, detection of false signals due to malfunctions, and the stability of the system connected to the superconducting device.

DCS protection was proposed as a method of protection against quenches for high energy density magnets and is shown in figure 28. To gain better protection by DCS, its design and structure were optimised using a GA. R_{p2}, C, R_C, R_{EE}, shown in the previous figure, and the frequency of switching were optimisation parameters. By performing a GA-based optimisation according to figure 29, the quench load of the system decreased between 15.31% and 17% [235].

Flywheels are new types of energy storage units using superconducting materials and magnetic bearings to store electrical energy. Through the optimisation of their structure, the stored energy in a flywheel can be maximised. The physical parameters of the rim, the type of materials used in the flywheel, and its size, are three parameters that play a role in maximising the stored energy. By applying a PSO algorithm to this problem, the density of the stored energy and also the maximum velocity increased by 12.3% and 5.98% compared with the flywheel when no optimisation was conducted on the structure. A schematic of such a flywheel is shown in figure 30 [236].

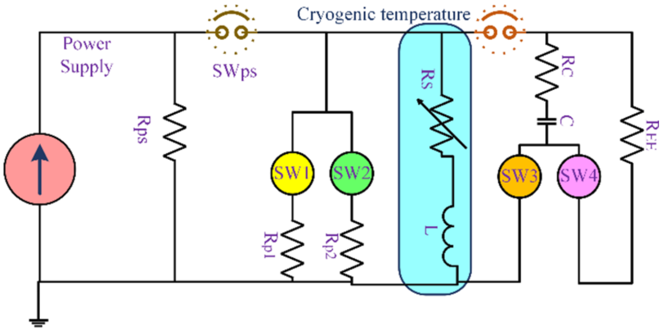

Figure 28. The dual-capacitor protection circuit for protecting high energy magnets against abnormalities [235].

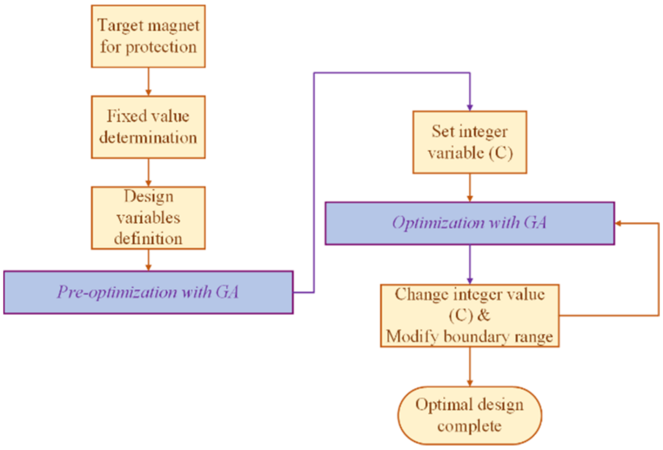

Figure 29. The performance procedure of a dual-capacitor switching system for magnet quench protection [230].

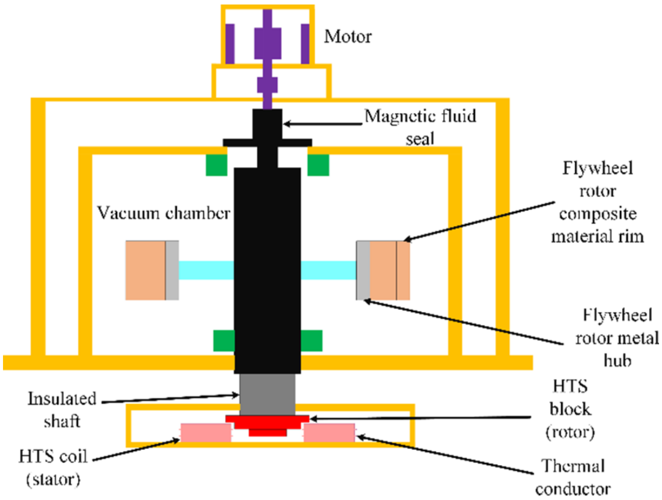

Figure 30. 2D schematic of a superconducting flywheel [236].

Flux pumps are used to generate magnetic fields in circuits like magnets without any physical connection. Similar to other superconducting applications, they are investigated experimentally or based on simulations. Usually, FEM is used to model the characteristics of flux pumps and simultaneously evaluate all their design parameters, which is quite time-consuming. To avoid this, a simulation approach based on AI

Table 2. A comparison of the accuracy and error indices of the different ML methods used in [234] to gain the best performance in modelling of the flux pump.

Method	RMSE	MAE	MAPE	NSE
NNM	58.56	39.73	9447.38	0.975268
GPR	2.68	1.25	0.0684	0.999949
SVM	3.07	1.51	0.0743	0.999936
DTM	79.07	49.28	0.5356	0.957424
KNN	60.40	35.74	0.5627	0.975355

techniques was proposed in [237]. This model takes advantage of ML methods to analyse the correlation of circuit voltage with the design parameters of a rotary flux pump. These parameters include the frequency response, air gap and the width of the superconducting tape. For the sake of comparison, four indices were studied, i.e. SE, RMSE, maximum absolute error (MAE), and MAPE. Multiple types of ML approaches have been analysed for the aforementioned inputs and output, such as the neural network model, GPR model, SVM model, DTM, KNN model. A summary of the results of these ML methods is shown in table 2.

To evaluate the critical current distribution of superconducting tapes, several methods are proposed, such as experimental analyses or FEM-based models. However, they are not capable of being used in real-time for online condition monitoring systems. Performing this type of condition monitoring AI-based model is an excellent choice. In [238] an ANN-based estimator is developed to characterise the critical current density of three types of 2G HTS tapes including SuperOx, SuperPower, and SuNAM. The magnitude and angle of the magnetic field and the temperature are the inputs of ANN while the output is the value of the critical current. The conducted estimation is compared with the resulting values by a fit function in MATLAB, known as '*Scatterred Interpolant*'.

The estimated values of critical current has R^2 value from 0.99942 to 0.99999, for different HTS tapes Another important finding of this paper is that the ANN-based estimator outperforms the fit-based estimator in large amount of data, higher than 10^6. With such a number of data, ANN-based estimator has around 1 s computation time while this value for fit-based estimation is around 3 s. Another application of AI-based models for SCs was studied in [239] as a method of quench and hotspot detection in superconducting apparatuses. Two classification techniques based on the ML method in parallel with a discrete wavelet transform (DWT) were used to extract the features of hot spots in superconducting devices. DWT was used to convert the experimental data into the feature vector, while ML-based methods are used to extract the features of hot spots from the translated data. The selected and analysed features were mean absolute value, root mean square, standard deviation, variance, variance third-order, average amplitude change, average power, and skewness. By considering these features, the quenches were detected with only 3 out of 63 samples misclassified.

Magnetic gears are increasingly used in the industrial world and are replacing mechanical gears. These electromagnetic devices have an extremely low acoustic noise, free maintenance, and protection against overload. Recently, HTS materials have been used in these types of gears to increase their flux leakage and torque. CMGs are one of the many types, which is proposed in [240] as a dual-flux-modulator CMG for an HTS-based magnetic gear. The dual-flux modulator is composed of iron and added to the conventional structure of CMGs. In this structure, the segments are specified with slots are un-even, which means they have different sizes. The rest gear consists of two rotors, inner and outer, the outer rotor consists of 17 pairs of PMs. Four pairs of PMs are also implemented in inner rotor and at last, there is a stationary part consisting of ferromagnetic and non-ferromagnetic materials. The GA has been used in this reference to enhance the magnetic performance of the proposed CMG by variations of the thickness of PMs at the inner and outer rotors. By applying the GA optimisation algorithm, the torque is about 190% increased, while the weight of the PMs are 48% reduced and at last the torque density of the proposed CMG also increases, which is due to the fact that the volume of the CMG remains constant during optimization.

The value of the critical current in superconducting tapes varies with respect to many factors, among which temperature, magnetic flux density, strain value, and tape properties are important considerations. Also, the maximum applied stress to the HTS tapes is a function of temperature, strain value, and type of tapes. Usually, the exact value of critical current/stress is obtained by some basic polynomial fitting methods. However, fitting methods cannot be used to consider all aforementioned parameters and the interdependencies among them. To overcome this issue, a novel method was proposed in [241] based on ANFIS to estimate the value of critical current/stress of different types of 2G YBCO HTS tapes while the interdependencies of the electromechanical factors impacting critical current/stress are considered for all kinds of 2G HTS tapes. The inputs for critical current estimation were temperature, magnetic flux density, strain, width and thickness of tapes while the output was the normalised critical current value. The magnetic flux density was removed from inputs when stress was estimated and the same system was used to stress estimation procedure. Three clustering methods were used to increase the accuracy of train and test phases and to choose the most accurate method, the fastest method, and a method with both acceptable accuracy and computation time. This has led to an estimation of critical current with the maximum R^2 value of 0.92 and 0.047 RMSE value, while the fastest method requires 628 ms computation time. These values for stress estimation are 0.989 as R^2, 41.988 as RMSE, and 689 ms as the computation time. The model is also capable of performing appropriately when the test data are out of the training range with 0.95 as R^2, 0.019 as RMSE. However, following concerns better discussed in the future to increase the efficiency of the proposed method:

- Further reduction of computation time, which needs high-performance computation resources.
- Make the estimation real-time.
- To increase the comprehensiveness of the model, try to consider more inputs related to the geometry and properties of

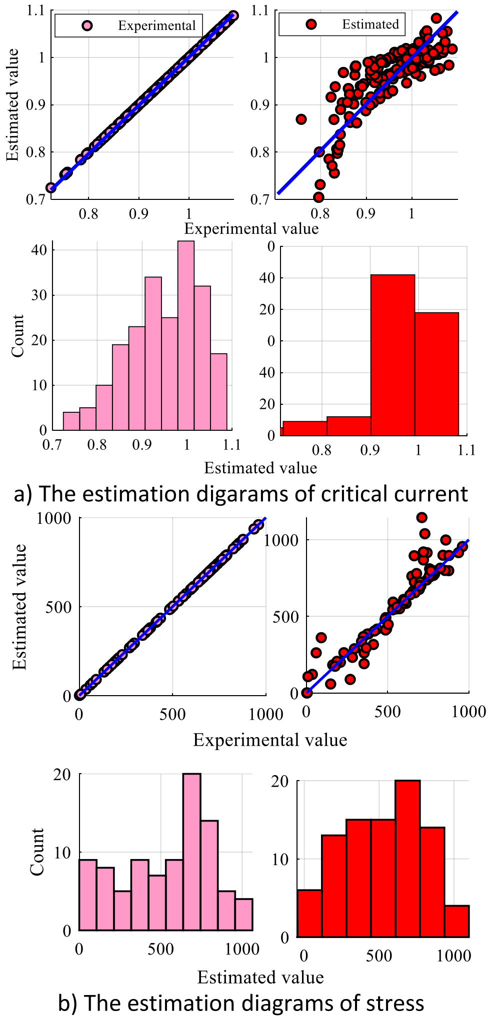

Figure 31. Critical current/stress estimation of 2G HTS tapes using the ANFIS method while interdependencies are considered.

the tape, such as thickness of sublayers in HTS tapes, manufacturing process type, etc.

The test results of the critical current and stress estimation of the 2G HTS tapes are shown in figures 31(a) and (b), respectively.

Manufacturing cost is one of the most significant cost components of SCs that impacts the final cost of tapes and wires. By optimising the available manufacturing approaches, the marketability of SCs would be enhanced. For this purpose, the ML-based method was used in [242] to produce REBCO tapes with higher level of marketability and lower cost. The data were acquired by drop-on-demand inkjet printing of the REBCO precursor. The variables of ML model are average voltage, average pulse length, percentage of ‘Amine’ compositions, average drop volume, drop pitch, line pitch, number of drops, and total volume deposited. A total of 231 samples were gathered, which was initiated by using decision tree-based training methods that fit more to occasions that lower the amount of data available. The model can predict two parameters, number of drops and total volume deposited and is also capable of showing the impact of each variable on these

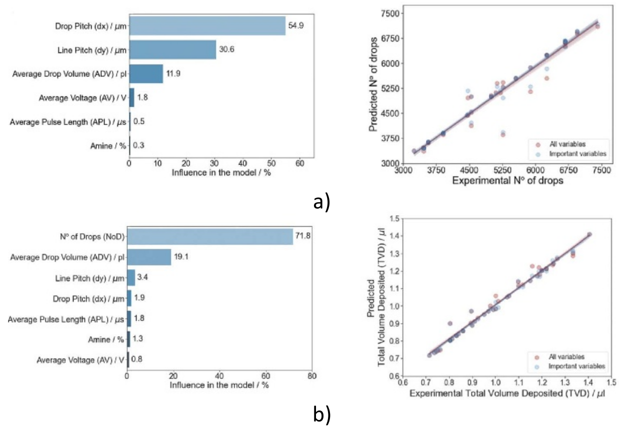

Figure 32. The results of ML model to predict (a) the number of drops on the tape surface, and (b) total volume deposited on the surface of the tape.

parameters. The results of such estimation for the number of drops and total volume deposited are shown in figure 32.

HTS bulk SCs have a low mechanical strength and if any crack exists in their body, under a high magnetic field and due to Lorentz force, this crack would be propagated and thus would result in deterioration of HTS bulk. In [243], a GA method was used to minimise the error between the real location and the assumed location of crack based on magnetic field distribution. By implantation of such a model, the real location of crack could be identified with a high value of accuracy as shown in [243]. However, it was not mentioned how this method could be applied for an online and real-time crack detection system for sensitive applications.

3.2. Material properties of SCs

The increase of the critical temperature in SCs is an interesting topic that has been under research since their discovery. Recently, a new concept was presented as RTSs. These new types operate near 293 K; however, they still require a high pressure to remain in the superconducting state in the range of a million bars [244–252]. To increase the critical temperature of superconducting materials, multiple scenarios have been introduced. The first is to chemically restructure the HTS and RTS materials, to find new SCs with higher critical temperatures at lower pressure. This solution requires numerous tests and experimentation to synthesise different compounds and new materials, which is time-consuming and expensive. The other scenario is to investigate the electromagnetic, mechanical, and chemical characteristics of existing SCs. This scenario also demands massive funding and time investment, to show a path to RTS. Also, another scenario expresses a procedure of finding SCs with critical temperatures the same as currently known SCs while the critical current is higher. Once again, AI techniques can provide their efficient performance to avoid huge computation burdens and costly experiments. These techniques can be applied to predict electromagnetic, mechanical, physical, and chemical behaviour of SCs, in an ultra-fast manner [254–258]. In fact, a

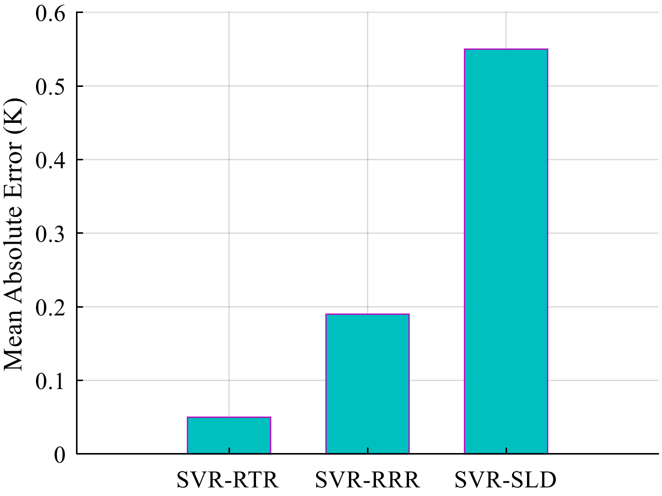

Figure 33. Accuracy of different methods for predicting the critical temperature of MgB_2 [253].

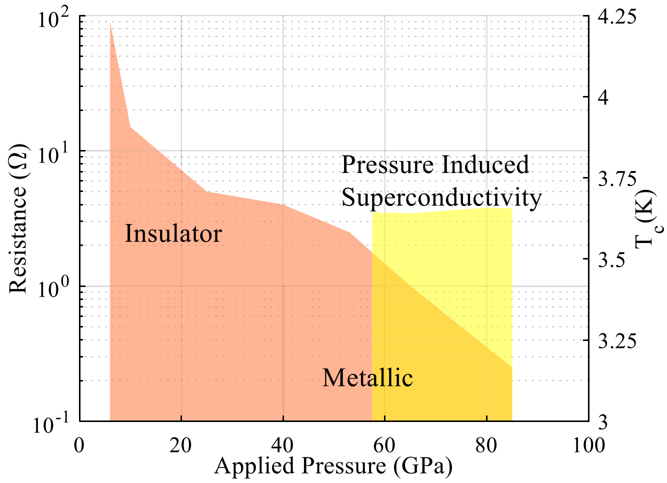

Figure 34. The correlation between pressure, critical temperature, and resistance in $AgIn_5Se_8$ [279].

data bank of electromagnetic, mechanical, physical, and chemical properties of existing materials and SCs has been established to provide an opportunity to use AI techniques to analyse them and predict the critical temperature and properties of any new compounds. As a consequence of this, many researchers have taken advantage of AI techniques to forecast the structure and characteristics of novel SCs [259–273].

3.2.1. SVR-based investigations. Hydrogen as the lightest element turns into a solid metal state under massive pressure [274]. The solid metal hydrogen is one of the possible SCs with a high critical temperature [274]. However, the hydrogen is a dielectric at pressures lower than 342 GPa. Therefore, many elements were proposed to be combined with hydrogen to form SCs at low pressure. GA was used simultaneously with first-principles density functional theory to estimate a new structure for boron hydrides with low enthalpy and high pressure. This results in the discovery of a new crystal structure for H-based SCs with BH_2 formulation. The new material became an SC when the pressure reached 50–250 Gpa. The predicted critical temperature of this structure was 28.18–37.31 K at 250 Gpa [275].

Due to the low fabrication cost, high current density in low temperatures, and long coherence length, MgB_2 wires are gaining massive attention. MgB_2 SCs can be used in superconducting machines and cables in future aircrafts. Thus, their critical temperature is a vital parameter that is adjustable by the insertion of some other materials. To acquire the transition temperature of MgB_2 many methods were proposed. Among them, an GA-SVR-based model can be applied which uses room temperature resistivity, RRR, and SLD as inputs, and the output of this model is the transition temperature of the material. This results in an accurate estimation of the transition temperature, which is shown in figure 33 [253, 276, 277].

Data-driven models are used for the estimation, prediction, and characterisation of different types of SCs. They can speed up the procedure of investigations and analyses of the new and present SCs. For instance, in [278] a prediction software was presented which predicted the critical temperature of SCs based on their chemical formulation.

One of the materials that operate as an SC under high pressure is $AgIn_5Se_8$. The chemical behaviour of the single crystals of this material can be evaluated by different methods, such as XRD, EDXS, and XRPS. By performing these approaches and gaining the resistivity of a sample using diamond anvil cell, a data-driven model was established. The results of such analysis show that $AgIn_5Se_8$ transits from the insulation region to metal in 24.8 GPa and from metal region to superconducting state at 52.5 GPa. The maximum critical temperature observed for this material is 3.8 K [279]. The characteristic of the $AgIn_5Se_8$ is shown in figure 34. The same procedure was also conducted for $PbBi_2Te_4$ in [280, 281].

To approximately determine the critical temperature of high-temperature SCs, multiple algebraic formulations are also provided. They normally use different chemical and physical properties, like pressure, doping parameters, and number of valences, among others. However, these methods and formulations cannot satisfy the accuracy needed for finding new SCs. Thus, to gain the most possible accuracy AI techniques can replace these formulations [282, 283].

One way is the combination of support vector regression, PSO, and rough set theory (RST). RST is a preprocessing step that analyses data before the estimation process is initiated. RST categorises the data into two classes, overestimated and underestimated values. By doing this, a weight is dedicated to each set of data and this results in more accurate predictions. After applying RST, the data are inserted as inputs and outputs to a PSO-SVR prediction package. In this step, predictions are conducted in two phases, training and tests. To compare the prediction results, two indices were used, such as MAE and RMSE. If RST is not applied to the PSO-SVR-based prediction procedure, MAE is 14.8% higher in comparison to the computed value by the aforementioned algebraic equation, and this value for RMSE is about 8.4% higher. Surprisingly, by application of RST, MAE of prediction is 4.22% reduced and RMSE is also 12.99% reduced when compared to

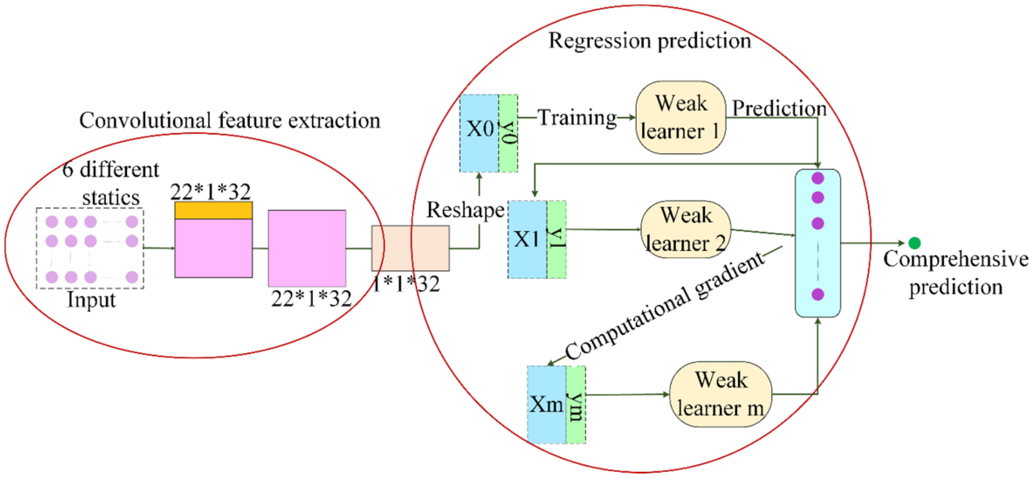

Figure 35. A decision tree-based convolution neural network for transition temperature prediction of superconductors [303].

the values for equation-based calculations. It is worth noting that the reported results are the mean values in [284], which include the estimation of different SCs, such as $YBa_2Cu_3O_{6.92}$, $HgBa_2CuO_{4.15}$, and $RuSr_2GdCu_2O_8$, among others.

Electric connectivity index and valence energy-level connectivity index are two important factors that can increase the accuracy of critical temperature predictions. If they are considered for MgB_2 and at the same time, an SVR-PSO-based prediction procedure is carried out, T_C can be predicted precisely. The average accuracy of such a prediction is about 83.22% while this value for ML models was 45.01% [285, 286]. SVM was also used for the sake of predictions and estimations in Fe-based SCs, which took advantage of the lattice parameters. By using SVM, a 98.65% accuracy was gained for the training phase and a 99.42% accuracy for the test phase [287].

3.2.2. A review on CALYPSO. PSO is used to predict the structure of materials. This has led to the fabrication of a new software package known as Crystal structure AnaLYsis by Particle Swarm Optimization (CALYPSO), which stands for crystal structure analysis by PSO. Therefore, numerous efforts and investigations were conducted using this package to predict the crystal structure of SCs and estimate their critical temperature [288–299]. Many SCs were studied by this package including rare-earth metal hydrides, alkaline earth metal hydrides, transition metal hydrides, boron group hydrides, tetragon hydrides, pnictogen hydrides, and noble gas hydrides. As a matter of fact, CALYPSO is one of the major methods to predict the properties of hydrogen-based SCs [290]. CALYPSO was used in [300] as a prediction tool for yttrium hydrides, such as YH_4 and YH_6. These two compounds are stable at a pressure of around 150 GPa. Under such high pressure, these compounds have a critical temperature of around 84–95 K and at the 120 GPa, these values reach 251–264 K. This proves that CALYPSO also has an appropriate performance in lower pressures. The same has been predicted for CS_2 in high pressures using CALYPSO in [301].

3.2.3. Estimation of critical temperature by NN. NNs are another powerful tool for the sake of estimating and predicting the critical temperature and microstructure of SCs [302]. In [303], an GBDR-based CNN was adapted to classify the materials into three superconducting groups, cuprates, Fe-based, and others. First, the features of the structures of SCs were extracted using the element property of materials based on CNN. In the next step, the prediction model was improved by implementing GBDR into conventional CNN. Lastly, the test phase was initiated and critical temperatures were predicted. Figure 35 represents the used GBDR-based CNN for the sake of predictions. The results show that the accuracy of the normal CNN model is about 83.1% while by implementing GBDR in the model, the accuracy reaches 93.7%. NNs have numerous different types, which can be used as prediction techniques. Among all these types, CGCNN and its iCGCNN were designed especially for the sake of predicting and estimating the properties of materials and their crystals. They were also used as predictors of the thermodynamic stability of inorganic SCs. Thermodynamic stability is defined as the difference between the formation energy of a compound and the lowest energy of a linear combination of phases corresponding to that composition [304]. By applying CGCNN and iCGCNN to $ThCr_2Si_2$ and Li_2O_2 SCs, the results show that iCGCNN has a 20% higher accuracy in comparison to CGCNN. The iCGCNN also found more superconducting compounds than CGCNN [282]. This shows the high capability of the iCGCNN approach not only for estimating the characteristics of the existing SCs but also for exploring new SCs.

Atomic vectors are another approach to identify the relationship between atoms and the surrounding environment of the atom. This approach combined with NN can be used to predict the critical temperature of SCs. Firstly, there is a need for a dataset containing different properties of materials. After that, an atom-environment pair must be generated for each possible compound.

The environment has two properties: the number of target atoms of the material and the number of different atoms in the residue. The procedure of atomic vector generation is shown

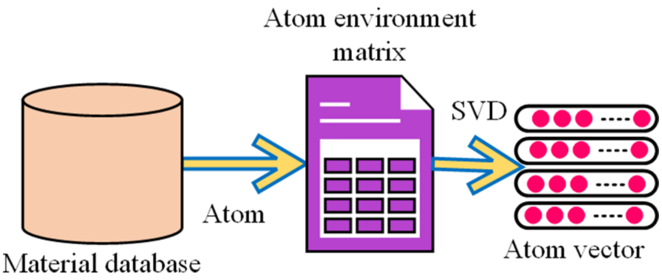

Figure 36. Generating process for atomic vector of materials [305].

in figure 36. By applying an atomic vector to a CNN-LSTM, a high accuracy prediction of about 90% was reported. This means that the accuracy of CNN-LTSM is 4.17% higher than the LSTM predictor, while this value of the CNN predictor is 34.38% [305]. To take advantage of ML methods for the prediction of the critical temperature [273], more than 34 000 data are gathered in the SuperCon database. They are divided into two subclasses, i.e., SCs with T_C higher than 10 K, and those with a critical temperature lower than 10 K. AFLOW Online Repositories can also be put to work to increase the accuracy of the predictions by ML methods. Lastly, Inorganic Crystallographic Structure Database is another data bank that shares information about newly discovered SCs [306]. By applying an ML-based estimation to these data, an accuracy of about 93% was achieved. It is worth mentioning that 85% of data in the SuperCon database are SCs while 15% of them are non-SCs [307]. Using data sets is a common approach to predict the structure and the critical temperature of SCs. However, this data could consist of some duplicated information. Duplications reduce the accuracy of the predictions and estimations. So, they must be removed to increase the precision of predictions [308].

3.2.4. ML and DL-based methods. ML methods are classified into three groups, namely SML, UML, and RML. SML types require human intervention for the sake of classification and pattern recognition. UML, however, can perform this task without human intervention. RML trains intelligent agents to take actions and decisions for a system. Normally, SML is used to prediction critical temperature and structure of SCs. An SML is applied to a deformed one-dimensional topological SC in [309] to identify the existence of Majorana zero mode. McMillan formulation and Allen and Dynes theory are the two most commonly used analytical methods to predict the critical temperature of SCs.

By using ML methods these approaches can be improved. By applying ML to Allen and Dynes theory, surprisingly, recently discovered SCs with an EPC higher than two-dimensions, neither follow the Allen and Dynes theory nor the ML model. This shows that new indicators are needed to predict the characteristics of new SCs [310].

Many structural improvements can be made in ML to increase the accuracy of its prediction to discover new SCs and their properties. One of them is the application of GPR, which is a kernel-based nonparametric probabilistic model. An GPR-based ML algorithm was used to predict the transition temperature of SCs, including Bi2223, where four process parameters were chosen, namely the amounts of bismuth and oxygen, sintering time, and sintering temperature. As a consequence, an accuracy between 88% and 98% was achieved [311]. Fe-based SCs are another type of SCs whose critical temperature could be estimated using GPR. By implementing such a model for Fe-based SCs, 99.99% accuracy was reported. The accuracy of the GPR-based model in comparison to the NN-based model was also 5.981% higher [312]. Hybrid intelligent computation methods, which consist of PSO and SVR, were used to predict the properties of Fe-based SCs. To do this, tetragonal to orthorhombic lattice structural transformation or RAD as descriptors were used. Consequently, the obtained prediction accuracy was between 86.37% and 98.97% [313]. These results show that the algorithm achieves a better performance when RAD is designated as a descriptor.

There are also other considerations and properties that were used as inputs to predict the critical temperature of SCs, known as descriptors [314]. These can include the average atomic mass of a compound, the average number of electrons in an unfilled shell, the average ground state atomic magnetic moments, and the maximum difference of electronegativity. By applying these descriptors to an ML-based prediction package for 2500 data, the critical temperature was estimated with an accuracy 92% [315].

To find a strong correlation between lattice parameters and the value of critical temperature in Fe-based SCs, an ML approach was adopted. The gathering data were divided into four classes, namely 11, 111, 122, and 1111 Fe-based SCs. Each of these has a specific degree of discreteness and a nonlinear relationship, which are known as the lattice parameters of these classes. Thus, the lattice parameters of each group were selected as inputs to the ML and the output was a critical temperature. An accuracy between 89.42% and 91.29% was obtained for SCs including $SmFeAsO_{0.93}F_{0.07}$, LiFeP, FeSe, NaFeAs, and others [316]. These indicate that dividing the Fe-based SCs into subclasses can increase the prediction accuracy. A method was proposed as RPT, which adopted the DL approach to identify new SCs [317]. This model can read periodic tables even better than an expert. Computers can recognise the data and all their chemical properties while humans have a limited capacity for this at a time. The concept of RPT is shown in figure 37. The relative positions of the elements on the table can be learned by the convolutional layers, which is due to the utilisation of the same local weights to the whole periodic table [317]. By applying this method to the SuperCon database [318], 95% accuracy in the prediction of SCs was achieved. However, the main finding of the RPT method was the discovery of new SCs, which were never reported in SuperCon. These materials were $CaBi_2$ and $Hf_{0.05}Nb_{0.2}V_2Zr_{0.3}$ [317].

Critical currents at specific cryogenic environment and pressure is one of the most importance parameters for SCs, which are a function of vortex dynamics and its interaction with nonsuperconducting defects. During the manufacturing and operation process, the critical current value of SCs can be changed and deteriorated. An optimisation procedure using AI

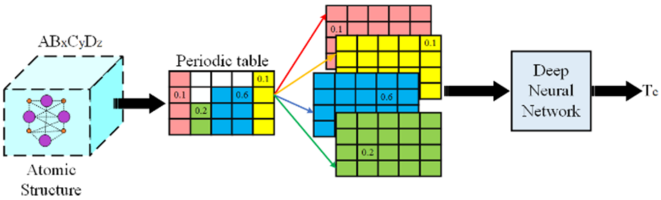

Figure 37. The procedure of reading periodic tables by deep learning [316].

techniques can be helpful to predict the critical current at any condition. In fact, the mathematical approaches could also be used; however, the approaches must be chosen that are adaptive with changes in the geometry of the problem, such as the Nelder–Mead method. It is worth mentioning that the objective is to maximise the critical current by the optimisation of pinning centres. PSO, pattern search, adaptive pattern search, and Nelder–Mead algorithms were candidates for solving such problems [318].

3.3. AI for physics of SCs

AI techniques are adopted to solve the issues around the link between quantum mechanics and SCs, mainly for predictions, curve fitting, and speeding up calculations [319].

Theories that describe the origin of SCs are mostly based on quantum mechanics, such as the BCS theory and Ginzburg–Landau theory. Many classical intuitions are controversial in quantum mechanics.

As a matter of fact, numerous novel concepts are defined and proved in this branch of physics. In quantum mechanics, the physical system is supposed to be a black box, which contains preparation and measurement to show the probabilities of experiments as outcomes. In fact, the time evolution of such a system has a stochastic nature and can be explained by the Schrödinger equation. Here, the quantum trajectory is defined as the time evolution with the stochastic nature of the wave function. The knowledge on this wave function is extractable using quantum filters. A variety of physical parameters of the filters need to be identified by AI techniques, such as RNN [320].

BCS theory is unable to elucidate the origin of superconductivity for materials with strong EPC. This has been solved for normal metals by Midgal. Eliashberg has used the Midgal's method and proposed a modification to BCS theory. This means that Eliashberg proposed a model to originate the superconductivity in materials with strong EPC. The collaboration between fermions and bosons has a massive impact on the superconductivity of such materials. Many researchers have tried to discover a bosonic mode in such SCs, to gain higher T_C. One of the obstacles to such achievement is the calculation of (EBSF) and to address this, supervised and UML methods were applied. The results showed that the proposed methods could precisely predict EBSF with an accuracy above 99.9% [321]. Much research has been conducted to analyse the static properties of in-gap bound states for single and multiple quantum dots. The main aspects of two quantum dots are related to the ground state configuration, which can

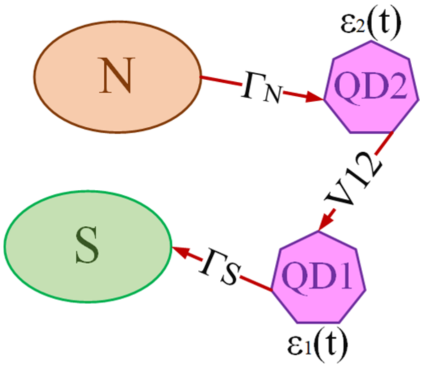

Figure 38. The structure of N-DQD-S [322].

alter the even–odd parity and zero-biased conductance with a honeycomb structure. The accomplishment of the on-dot and inter-dot electron pairing is achievable through many arrangements of two quantum dots. One of them is S-DQD-S and the other possibility is N-DQD-S, where DQD stands for double quantum dots. N-DQD-S is shown in figure 38. The value of zero-biased conductance is calculated by solving differential equations and ML is helpful for such problems. By applying this method, high accuracy of conductance prediction (around 98.7%) was obtained [322].

According to the BCS theory, many physical and subatomic interactions, including isotope mass, the interaction of electrons and phonons, and the formation of Cooper pairs, could have an impact on the critical temperature of an SC. Some properties could affect the EPC constant, which is listed in table 3. These properties can be extracted by using ML methods [323]. Properties for various pairing symmetries of spin-polarised local density of states can be extracted using DL methods. To do this, a different Hamiltonian model should be built first' after that a fitting on experimental data or the first principal calculation could present the parameters of such a model, and, at last, the data can be fed to deep NNs for the purpose of training [324]. The ability to create multicentre bonds in allotropes and borides, and an electron deficiency of boron, makes this element interesting for SCs. A swarm intelligence-based ML was used to predict the boron phase with a 24 atom cubic unit cell at ambient pressure [299]. The noisy voltage signals are produced by weak measurements of a superconducting qubit. These noisy voltages are weakly related to the qubit state. Detection and monitoring of these signals were conducted using LSTM-NN, which was trained with experimental data and compensates for the delays and correlations [325].

Defect densities play an important role in the occurrence of the mixed state of SCs. Studying these densities experimentally could be highly expensive and very time-consuming. So, to tackle these challenges,a simulation approaches are proposed. Normally, simulations take advantage of thermally coupled time-dependent Ginzburg–Landau equations to characterize the vortex penetration of a superconducting film under an increasing magnetic field. However, ANNs can be used as estimators for predicting defect densities. To do this, the magnetization and free energy density of various defects densities

Table 3. Effective properties on electron-phonon coupling constant, which can be extracted using ML techniques [323].

Priority	Properties
1	Hall coefficient
2	Electron-phonon coupling constant
3	Work function
4	Melting temperature
5	Atomic volume
6	Effective U
7	Bulk modulus
8	Ionization potential
9	Debye temperature
10	Electrical conductivity
11	Magnetic susceptibility
12	Specific heat
13	Ionic mass
14	Thermal conductivity

were considered as inputs of ANN and the vortex penetration was the output. This led to a model with 93% accuracy [326].

DL is a useful technique to analyse the topological phase transition of SCs. Various types of information are proposed to be used as input of a DL-based model, namely MCMs, OPES, and OPEEs. The impact of the data on the form of matrices or tensors originating from MCM on the transition point is obvious. There are three important spatially dependent quantities in OPEEs, which are intensity, phase of particle, and the phase of the whole components. By taking these considerations, DL can be used as an effective method to analyse the topological phase transition of SCs [327].

SCs have some other applications related to communications and electronics. AI techniques have been applied to these applications. They have been used for resonant control systems of superconducting radiofrequency cavities [328] and their fault classifications [329], design modification of superconducting antennas [330, 331], computing new tongues for superconducting logic [332], optimizing superconducting digital circuits [333], damage detection in SQUIDs and modelling them [334–337].

4. Challenges to apply AI techniques in superconductivity

In this section, the following points will be discussed in detail:

- AI-related manufacturing and operation experience from other industries. Helpful approaches and techniques are discussed.
- The objective of AI: to minimise the production and operation costs, and maximise the yield of superconducting devices.
- Requirements for data collection and assessment: consistency and integrity of data, reasonably minimised data set, avoiding excessive/overlapping data, cyber-security and other factors.

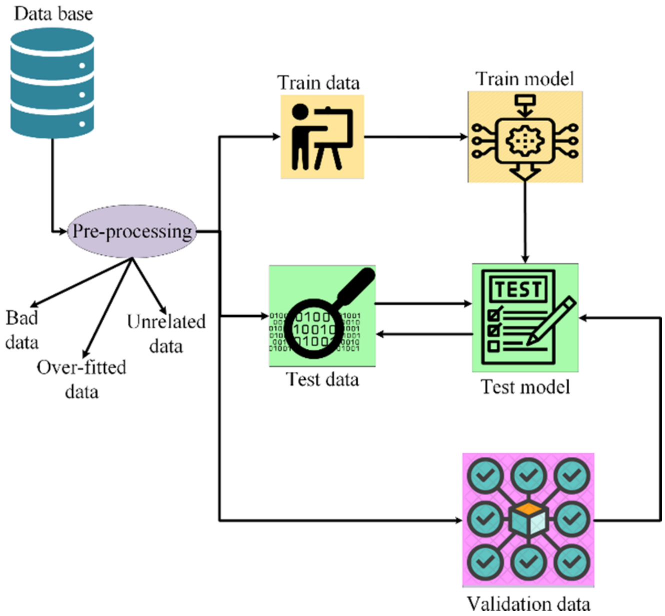

Figure 39. The impact of the pre-processing of the data on the training and test-phase results and accuracy.

- Collect system data beyond superconducting components for future improvement of both superconducting unit(s) and the whole system. Evaluate system interactions.
- Approaches to minimise biased conclusions: 'False positives' and 'False negatives'.

4.1. Data generation and management

The input data for AI techniques must be re-organised, and those over-fitted, bad, and unrelated data must be removed. Over-fitted data specify multiple values of outputs for a specific series of inputs. Over-fitted data could result in false estimation of the outputs and should be firstly identified and removed. Bad data originates errors and failures in operation of the measurement units, sensors, and their wiring. This means that the aforementioned devices report the false input value of voltage, current, frequency, and temperature, to model and this data is gathered and used for AI techniques. Bad data could also be a result of cyber-attackers that try to inject false numbers and unreal data into the system. There are many methods, known as pre-processing methods, that locate, detect and remove tbad data among all data sets. Usually, these pre-processing methods are AI-based methods that can discriminate between bad data and over-fitted ones, which again shows the capability of AI methods. This can be seen in figure 39.

This can increase the reliability, accuracy, and stability of the solutions resulting from AI techniques. For instance, when an AI-based system is trained to compute AC loss in superconducting tapes/wires, one should notice that for an assigned value of current, magnetic field, and harmonic just one specific value of AC loss exists [338]. Therefore, if for one series of inputs more than one output exists, the data must be refined so that the over-fitted data is removed.

Also, there is common mistake among researchers that increasing the amount of data must improve the results of AI techniques, but it is not necessarily correct. However, the amaount of of data is an important factor, and data sets must have other properties, such as variety, non-over-fitted characteristics, non-bias distribution, data quality, etc., to result in high accuracy during test and training processes.

Data sets must be selected so that they cover the whole domain of possible changes while over-fitted data must be avoided. Usually data is gathered through some experiments and tests on real apparatuses or through some simulations based on exact and reliable models. The correctness of the predicted/estimated values by AI highly depends on the accuracy of the input data, as well. Thus, before implementing any data set to the AI-based predictors, the accuracy of the data or even simulation/test procedure must be verified [338]. All of this translates into the need for advanced (fast & accurate) model-based calculation tools as well as innovative testing approaches for SCs apparatuses that must be massively used to create the conditions for reliable AI training and exploitation.

In the coming future, SCs are going to be installed in power systems, cryo-electrified applications, fusion industry, and many other applications. Preserving the data against cyber-attackers is an important challenge when AI is going to be merged by superconducting technology [339]. There is another challenge of AI technique in the case of '*unseen data*'. Suppose that an AI model is used in a superconducting machine to discriminate between the faulty conditions from normal ones by analysing the voltage and current signals. This means that any condition in the system would be classified as one of these two states. Now consider that a third condition occurs, which is neither a fault nor the steady state, such as the switching of a capacitor or low-frequency oscillations. Under such circumstances, it is highly possible that AI model considers this condition as a fault and makes some protective decisions, rather than asking for more information. This is the main difference between artificial and human intelligence. Usually, humans declare that they '*do not know*' the right decision and ask for help or more details [340].

4.2. Integration of AI with cloud computation

The internet has caused many changes in the way of life of human beings, one of these changes was approaching from parallel computing by multiple computers to grid computation through internet. The concept of grid computation has been also changed with further improvements in internet infrastructures to a whole-new concept known as cloud/internet computing. By the implementation of AI techniques into the superconducting applications, there is a high opportunity to perform all computations and simulations through the internet/cloud, instead of doing them on the personal computers. However, cloud computation has some challenges, the most significant one is data security through the internet, while another important challenge is a delay in the receiving data due to interruptions of the internet. In some applications of SCs, like those used in fusion or future transportation applications, this delay in receiving data could be catastrophic [341].

4.3. Implementation of AI techniques in existing systems

Most of the currently used superconducting devices are designed so that no AI-based controller, estimator, detector is considered to be implemented. Therefore, by drastically increasing in utilization of AI for SCs, these devices must be designed so that sensors, computing resources, and other required tools fit into new designs.

4.4. The increase of computation burden along with the increment of data sets

Learning-based AI techniques can be used in the future to model the characteristicd of the SCs or fault diagnosis of the superconducting devices. Dynamic learning (a type of ML in which data is fed to the AI system in an online and dynamic manner and the system would use them to train itself in each period of time) can be used to adapt the learning phase with the changes of new input data and increase accuracy. However, this large amount of data could jeopardise the ultra-fast aspect of the surrogate and predictive models by increasing their computation burden. Predictive models are used to predict the characteristics of a specific type of SC or superconducting device under certain circumstances. For instance, they can predict the critical temperature and critical current of a composite of materials under a specific pressure. On the other hand, surrogate models are used to simulate the outcome of a complicated system by means of observation and data rather than exact formulations. For instance, it is possible to design a surrogate model for magnet design optimization. To overcome this issue, the AI-based systems should be designed so that the old and unused data or repetitive ones removed to keep the computation speed high.

4.5. Biased estimation of algorithms with respect to the fed data

AI techniques could also experience another abnormality during their test phase, known as biased estimation. For instance, consider an ML method that is trained to predict the AC loss, critical current, or other values for different 1G and 2G HTS tapes, under different fields, temperature, strain, etc. Suppose that 10 types of 1G and 2G HTS tapes are selected for this purpose, while temperature, field, and strain vary in the range of 4.2–80 K, 0–19 T, and 0%–1.5%, respectively. If most of the trained data relate to temperature range of 20–60 K while the field and strain vary through their whole range, the estimation of the desired parameter in 20–60 K is highly accurate, while out of that range the prediction is deemed inaccuracies. This phenomenon is known as biased estimation and to avoid this, data sets must be homogenous and uniformly cover and distribute over the whole range of inputs. To avoid the biased decisions, three procedures are proposed [342]. The first type of procedure occurs before feeding data into the learning system, which is known as pre-processing. This can be accomplished by means of assigning a weight to each group of data or using a probabilistic fairness-aware framework. The second group is referred to as the in-processing methods, which means that during training, fairness of data is improved. Usually, this is accomplished by reformulating the classification problem or by training on latent target labels [343]. The next level is post-processing of the model and data when the learning is complete. This can be done either by changing the model's internals, known as the white box approach, or by changing its estimations and predictions, known as the black box approach [342]. Another classification for managing the data to avoid bias is presented in [340], which are substantiate assumptions, vet training data, bias evaluation, data production monitoring, creation of supportive processes, and creating feedback loops.

4.6. Model integrity and stability challenges

Most of the AI techniques, such as GA, PSO, ANN, ML, SVM, etc., works based on stochastic probability functions and thus suffer some levels of uncertainty in reporting results [343]. For instance, if one optimally designs a superconducting machine with GA and reduces 10% of its weight, there is a chance that if the optimisation is done another time, the result be slightly different from the earlier reported one. However, sometimes due to the ultra-complicated nature of the optimization/estimation problem, this instability of the solution could result in an inaccurate or infeasible solution. To prevent any instability in the report, and to get rid of such uncertainty, the optimisation procedure must be conducted multiple times, e.g. more than 100 times, and then, the mean objective value of the 100 runs must be reported as the final results.

4.7. Lack of familiarity among researchers in superconductivity community

Usually, researchers in the field of applied superconductivity tend to use conventional modelling methods and their efforts are concentrated in improving the performance of these conventional approaches. For instance, to model a superconducting tape, usually either analytical methods or FEMs are used and researchers try to make improvements in the computation speed and accuracy of these methods. However, AI techniques can be a great solution, as they simultaneously offer the same accuracy as FEMs together with almost computational speed of simple analytical approaches. On the other hand, most researchers in the superconductivity community might not be familiar with AI techniques, at the same level of their expertise in mathematical and physical-based models. Therefore, when they decide to implement an AI-based method for addressing a challenge in the field of superconductivity, they may need to consult with AI experts to find the most suitable techniques depending on the type of challenge and topology of data. This is due to the fact that, if the chosen AI technique does not have an appropriate harmony with the nature of the problem, we might end up facing inaccurate results or results with higher errors compared with FEMs. However, one needs to pay attention to this point that this error could be because the AI technique was chosen as a wrong match with the nature of problem in the first place, and therefore, simply comparing those results with FEMs is not a fair comparison [344]. In addition, each of the AI-based techniques has its own controlling parameters and their setting has a significant impact on the final results in the output. Therefore, the suggestion is consulting with AI experts, however the trouble is that many AI experts has no idea about the challenges in superconductivity and nature of the SCs therefore, either a common language is needed or a better one to personally get familiar with the nature of the AI-based techniques.

4.8. Lack of a common data base for using AI in superconductivity

AI methods that use data to predict failure estimate the characteristics, solve complex design problems, or to detect and locate faults and hotspots. Thus, data is the beating heart of AI-based methods and without it, no AI model or estimator exist. This is one of the major hindrances in using AI-based techniques in superconducting apparatuses. To overcome this problem, researchers make tests and gather experimental data and with this data, the AI model can be organised. Usually, the low budget hinders conducting numerous studies and tests under different circumstances. As a result, an organised AI model is highly possible to be limited to test conditions and out of that range of data, the probability of accuracy drastically reduces. Establishing an open access data bank in which the test and experimental data of different superconducting devices are gathered is highly beneficial. Although there are databases such as those of National Institute of Standards and Technology [345] and IEEE council on superconductivity [346], and what is presented [347] that share some data about SCs and their applications, many other types of data cannot be found in this databases, which is due to the fact that for profit, companies will not disclose proprietary manufacturing and operation data.

Emerging laboratory-distributed, co-simulation and testing is also a beneficial approach to be pursued [348]. Furthermore, the increasing penetration of PHIL testing, whereby real hardware is submitted to a wide range of actual operating conditions by means of power systems emulated by power amplifiers, is opening new perspectives in this regard. Establishing more in particular, in PHIL testing, the full voltage and current experienced by of power superconducting apparatus in real grid operation are reproduced by means of power amplifiers [349]. PHIL systems allow production of a large amount of data, by reproducing multiple operating scenarios, including contingencies and faults, without using long and costly in-field installations. An open access data bank in which the test and experimental data of different superconducting devices are gathered is highly beneficial.

4.9. Challenges of sensors to receive the data needed for AI techniques

Sensors are one of the main parts of AI-based condition monitoring, modelling, forecasting, and design as they are the source of inputs. The better performance they show, the higher accuracy and speed AI-based models can have. However, the sensors themselves face some challenges. The first challenge is related to the calibration of sensors to increase the accuracy of the measured data and somehow make it error free. For sensitive applications of SCs, like those used in the aerospace or fusion industry ,this calibration plays a significant role in reducing the risk of failure in devices and the whole system. The selection of an improper zero reference could cause inaccurate data to be processed by AI [332]. The second consideration relates to the proper function of the sensors under different thermal and electrical conditions. This is an important consideration for sensors used in cryogenic temperatures for SCs. The best way to avoid the de-calibration of sensors is to calibrate them periodically [350]. Robustness with respect to ambient conditions and immunity to electromagnetic interference is also of paramount importance as SC devices are to be used in harsh and power-dense operating environments (e.g., electric aircraft or ships). Another challenge for sensors is the quality of the received data. This means how to organise the data in a way that it is interpretable for AI techniques. BD management is also another consideration in this level of sensor consideration. This means that all the BD must be received by sensors or there is a need for another AI technique to refine the data. This data, received by sensors, could also experience electromagnetic interferences and this necessitates the use of another AI technique for the sake of pre-processing of data and de-noising them [351]. Lastly, there are also considerations about the cost of sensors. Their cost usually consists of three components: the purchasing cost, the implantation cost, and the communication cost of sensors. The first component is affected by the accuracy of the sensor, type of sensor, its performance under hazard environments, and its speed. The second component of cost is related to the procedure of implementation of sensors. Finally, the type of data transmission by sensor is a highly important factor. The data could be transferred through Wi-Fi, ZigBee, and Bluetooth [352].

The cost of data acquisition comprises components that can be categorized in system specification cost, system setup cost, software development cost, system test and calibration cost, and the cost of required hardware. System specification cost deals with the demanded properties that one data acquisition system (DAS) must have to fulfil the requirements of the application. System setup cost is related to the cost that must be paid to engineers, specialists, or technicians for installing the DAS. The cost of purchasing and licencing the required software is another important and significant cost of DAS. There are other costs, such as cost of sensors, communication lines, etc that also contain their calibration cost.

5. Future trends in AI for superconductivity

5.1. A critical review on the application of AI in superconductivity: manufacturing perspective

5.1.1. AI for prediction of new superconducting materials. The prediction of the structure and properties of new SCs were conducted extensively through AI techniques, such as NNs, PSO, or ML, among others. These approaches could estimate the critical temperature, mechanical properties, critical current, and index values with appropriate accuracy. However, there are still challenges to address in future. Although most of the proposed estimation/prediction techniques are based on datasets like SuperCon, with valid information about SCs, there is a lack of reports that firstly suggest a compound as an SC and then verify the superconductivity of the discovered material by experimental analyses. This results in an uncertainty of predictions of new SCs. Another gap is the lack of standards to validate the proposed methods. There is some research that claims that they have presented a method consisting of novel classifications of material properties and new AI approaches with high accuracy. This has raised some questions. Firstly, some works have proved the proper functions of their approaches with less than 100 data, some with data around 1000, and some others with data more than 10 000. The question is: how much data can express the proper function of an approach? Then, a second question comes into play, which is: if a method is approved with high accuracy for a specific type of SCs, for instance, Fe-based, is it applicable for other types? Or was it valid just for that specific type? This means that a universal model capable of being used for any type of SCs is needed.

5.1.2. AI for design and condition monitoring of superconducting devices. According to figure 8, AI has been used in large-scale applications of SCs for three general purposes: design optimization, condition monitoring, and AI-based modelling. Although numerous papers have been published under these categories, there are issues in these papers that are better to deal with. Usually, most of the authors have claimed that they have used AI to design a superconducting apparatus with a lower cost, size, weight, and maybe AC loss. The first issue in these studies is related to a correct formulation and definition of the objective function and problem constraints. Often, a simple single-objective minimization fitness function is designed, whose constraints also do not reflectthe real practical issues in superconducting device production/manufacturing. For instance, if one just considers the size or the volume of the SCs as an objective function of a minimization problem with some magneto-electrical constraints, the optimised device might not be capable of operating appropriately under really sophisticated conditions of operation, or the device may not be consistent with available components or manufacturing practices. The authors believe that there are more complicated practical trade-offs than some simple electromagnetic or thermo-mechanical constraints for a simple single-objective fitness function, which are used in papers published in the literature. For example, there are many other concerns rather than simply size, volume, loss, and efficiency when designing a superconducting apparatus for terrestrial and stand-alone power applications, which must be taken into account. For example, constraints related to the interaction of superconducting components with the system components are often neglected. The designed device must be capable of enduring transients, faults, and other abnormalities that may originate either inside or outside of the superconducting unit. Another question is: if the size or volume is reduced, how does the reliability and safety of the designed devices change? With the reduction of size and volume, many manufacturing issues may come into play and the resultant dimensions may be infeasible to achieve due to manufacturing tolerances and limitations. The solution is to formulise these limitations and trade-offs for the sake of gaining a highly reliable, manufacturable, and efficient device with strict effective constraints coming from technical and manufacturing issues.

Most of the reviewed papers in section 3.1, claimed that cost, loss, or weight of a superconducting device is optimised. There are two types of issues with these studies. The first one is related to the way results were presented; as they did not present any characteristics of their device before implementing the optimisation technique to show how effective optimisation were, or if it is worth applying such a sophisticated procedure to gain better performance. There is not enough evidence in the published papers to assure us that what the computer came up with as the optimal solution will finally be found after production or in some cases after manufacturing will satisfy the requirements (as discussed in the previous paragraph). The second issue is that most of these studies claimed reducing the cost of superconducting devices with the reduction of the size of the superconducting parts without mentioning the impact of the type of cost. For instance, the cost of a superconducting device may be interpreted as initial purchasing cost, cooling cost, operation cost, maintenance cost, or total ownership cost. The purchasing cost is a function of the size and the volume of the superconducting parts and the type of SC, as at the moment the SC price significantly contributes to the high initial purchasing price of a superconducting device. Given that if a paper reported some tens of a percent cost reduction achieved by a design construction optimization, this may look very significant; however, if we consider total ownership cost of a superconducting device, the effect of initial purchasing price would be smoother in that and, therefore, going through the hassle of using AI for a sophisticated optimisation problem may not look effective enough. In fact, when total ownership cost is considered, other components of cost, such as cooling and maintenance costs would be as important as initial price, and therefore their values would need to go under an optimisation process too. Therefore, there is a need for formulating other components of cost and participating them in optimisation procedures.

The second application of AI in large-scale is the condition monitoring of different superconducting devices. There are some questions to be dealt with in this application, the first question is: how many computational resources are needed to gain an ultra-fast and accurate condition monitoring and how could these computational resources impact the manufacturing process, total size, reliability, and final cost of the device. Another significant challenge is to find a condition monitoring method that is able to differ from all types of faults, abnormalities, quenches, local hotspots, and transients and make proper modifications in the design and manufacturing practices. As a matter of fact, the consistency is a challenging issue in condition monitoring applications of AI techniques.

Each application of SCs has its own real-world requirements, constraints, and a range of standard sizing. Our aim is to address how AI techniques can satisfy these requirements, while the constraints are fulfilled for real-size devices rather than laboratory-size demonstrators.

In MRIs and NMRs, usually two main considerations were taken into account with the help of AI techniques, volume reduction of superconducting coils and field homogeneity maximization. These considerations were formulated with many simplifications. while this is not the case in the real world of manufacturing and engineering. Suppose that one has designed a superconducting magnet with a 1 ppm homogeneity in the DSV border and have validated the design with FEM-based or analytical models. In the real world, there are impurities in superconducting tapes/wires, imperfections, machining accuracy, cold shrinking of the magnet frame, tolerances in manufacturing line, and non-uniformities in the distribution of critical current density. These parameters could result in a whole different value, homogeneity, and stability of the magnetic field, which impacts the performance of the NMRs and MRIs. Although shimming methods have been proposed to overcome the issues related to homogeneity, the implementation, manufacturing, and optimum sizing of shimming coils is a complex problem with many variables. Also, as a matter of fact, considering such simplifications in the design procedure of the magnets of MRI and NMR causes a huge difference between the results of simulations and experimental ones. However, imposing these concerns on conventional simulations and design procedures makes them extremely complex and sometimes infeasible to solve. Thus, to solve such complex problems, AI techniques can be trained as a shortcut, which could hand us similarities between results of simulations and results of tests in the real world. To take advantage of AI techniques at this level, first, simulations are conducted without using any AI method to design a magnet with a high level of homogeneity. After, the magnet is manufactured and the real field and homogeneity are acquired and their differences is calculated and fed to an AI technique to change the simulations. Thus, without exact modelling of the impurities, defects, and other manufacturing issues, their impact could be inserted into the models, which may cause an error in modelling and simulations. Electromagnetic forces and mechanical stresses that are imposed onto the coils during the operation of the MRIs and NMRs are other challenges, which can be handled by AI in two manners: firstly AI can be used to estimate their disturbance at the whole body of the coil and predict the locations with the highest forces and stresses. On the other hand, AI is also applicable for stress and force reductions by varying design parameters. A design optimisation problem can also include all types of coils used in MRIs and NMRs, rather than just main coils. This problem can optimally design the main coils, shimming coils, radio-frequency coils, and even current leads and cooling systems. This means that a whole-system design optimisation (WSDO) is extremely necessary for having an MRI/NMR system that operates at the minimum possible loss, minimum required cooling power, maximum stability, and maximum homogeneity. Usually, WSDO is a very complex problem. AI techniques could be also applied here to reduce the computation time of the optimum solution. WSDO may increase the reliability, stability, protection level, and availability of the system, while most of the trade-offs are taken into account. Real-time condition monitoring of the magnets and their cooling system is another role of AI in MRI and NMR industry. The most significant goal of condition monitoring in these magnets is to protect the system against quenches. Real-time methods can reduce the risk of failures in magnets by a fast response and highly accurate AI technique. This is done by training an AI-based system (usually DL) with possible inputs of voltage, current, temperature, vibration, and magnetic field signals. AI can do much more than that by generating a predictive model that would predict the condition of the magnet in a coming time span to protect it before quenches are even happening. At last, AI is also applicable for the sake of determining the safety zones around the magnets, as discussed in [353]. All these efforts must be conducted to lead the researchers and engineers to the MRIs with 1–3 T magnetic field and 1–10 ppm homogeneity and also NMRs in the range of 500–1200 MHz [46, 354].

SFCLs are one of the large-scale superconducting power apparatuses that are promising to become commercialised in future, if more utility companies invest in it, meanwhile a few devices were implemented in the grid already [355]. AI can be used for SFCLs to establish a surrogate model or to optimally locate their installation sites in power systems, however, there are other concerns that must be considered. In the near future, SFCLs are going to be used in HVDC systems with voltage levels higher than 100 kV. Selection of the proper type of dielectrics and their thickness is a challenge for SFCLs, which can be dealt with as an optimisation problem. One of the trade-offs of this optimisation is that the massive temperature imposed by the fault current could reduce the lifetime of dielectrics. Choosing the appropriate dielectric and estimating the lifetime of this dielectric is better solved by AI rather than costly experiments and simulations with high computational burden. To do this, the thickness and the type of dielectric material are varied to change the maximum temperature of the SFCL. After that, the maximum temperature is fed as input to an AI model to hand us the loss of life of dielectrics. Therefore, not only the optimisation method with variable of thickness and material type could be solved by AI but also the loss of life of the dielectrics is estimable using AI methods. This is the case, especially when HVDC systems are connected to the renewable energy resources that increase the short circuit level of the grid. Meanwhile for airborne and marine applications, SFCL weight is the more important issue than insulations. In these applications, weight is minimised by considering multiple trade-offs, such as fault current limitation constraints, the possibility of tape/wire burnout, and operation temperature.

Usually long HTS cables face more challenges, due to the temperature increase along the length of these cables, and cooling issues. Previously published AI-based papers have dedicated their efforts mostly to the design optimisation of the cable, and offline fault locations. However, there are more concerns about these cables to be considered if commercialization is the target. One of them is to locate the optimal placement of the pumping stations, which must be dealt as a thermal, hydraulic, mechanical, and electromagnetic problem with many trade-offs and constraints. This optimisation must be conducted to avoid the high number of pumps, which could significantly increase the cost of whole system and reduce its reliability. The design of other elements of the HTS/LTS cables could be merged by the design procedure of the cables to increase the system integrity. These elements are current leads, terminations, busbars, cooling systems, and cooling pipes. Cable design must be conducted with respect to the application of the HTS cable, which includes terrestrial, airborne, and naval applications. Usually, the cables used in terrestrial applications, have a GW-range power, 20–200 kV voltage, and if installed in HVDC systems have a length of more than 100 km while an airborne cable has a MW range of power with a voltage of maximum 20 kV and a length lower than 10 m.

Many papers have dedicated their efforts to reduce the initial purchasing cost of superconducting machines, optimizing their design, and reducing their losses. However, there are more to be considered when using AI for superconducting machines and transformers. The first challenge is the reduction of the LCOE rather than the initial cost. This can be reduced by increasing the reliability, reducing the operation and monitoring costs. Fault location, fault detection, and condition monitoring of the superconducting machines are other issues that AI could present a solution. Dielectric/impregnation goodness test, winding quality of the coils, core weight and cryostat weight reduction are other complicated problems that are to be handled by AI techniques. Another important issue is the fact that many studies have been conducted to analyse the superconducting machines/transformers under a specific structure or condition, while their characteristics are better discussed in a systematic way. This means that with the help of AI, a comprehensive analysis is conductive to analyse the performance of the superconducting machine and its auxiliary accessories in a complete and complex system with many elements, various transients, and varying power factor. For instance, optimizing the machine construction is important but what would be the benefit of having a slightly lighter active part that has a very heavy cryostat? Therefore, system optimisation is a key research step for the future. Future superconducting machines will operate at the MW and kV scale, while transformers are economic for powers higher than 25 MVA. In addition, for aviation applications, the specific power density of superconducting rotating machines must be higher than 16–20 kW kg^{-1} [356, 357].

Superconducting magnets, superconducting CICC cables, and superconducting busbars are used as main components at the most of the fusion systems. AI techniques have potential to be applied in these components and at the whole body of the fusion systems to control, estimate, predict, and even design the related components [358, 359]. The main requirement here is to protect the whole system against any kind of abnormities and breakdowns, especially the magnets of fusion systems. To satisfy such a goal, there are many considerations to make, such as fast and even real-time quench detection and location, mechanical stress reduction of the coils and magnets, suppression of the radiation impacts on the superconducting devices, and protecting the cooling system. Most AI-based efforts in fusion systems are conducted to deal with these problems and challenges, with special attention to quench phenomenon.

However, more accurate, real-time, and predictive AI techniques are needed to increase the performance of the system. Also, AI techniques must be applied so that the whole fusion systems come into play to improve the efficiency rather than just considering cryogenic and superconducting parts for this purpose.

SMES systems based on low-temperature SCs are an established power-intensive storage technology. In-grid installation of SMES systems with power rating up to 10 MW for the protection of critical industrial load have already existed for more than 20 years [22]. Despite complete and fully qualified systems having been developed, LTS-SMES technology has failed to find market penetration due to the high cost (capital and operational) related to liquid helium. Beside the high cost, liquid helium also implies complicated management, supply (also facing shortage concerns), maintenance and safety (overpressure and explosion risk in the case of quench), which make its use in the grid or industry systems unviable. Improvements of SMES prototypes based on first-generation HTS materials (Bi2223/Ag conductor) and cryogen-free cooling (not using liquid helium) at 20 K has been obtained with the successful development of 800 kJ demonstrator [360]. However, the high cost of practical 1G-HTS conductors (requiring high silver content) does not offer prospects for commercial development of this SMES technology. Possible alternatives based on the use of MgB_2 (and industrial SC with intermediate electro-thermal performance compared to LTS and HTS), now under investigation [361] are also nontrivial due to the reduced electro-thermal performance of this SC. A drastic improvement in SMES technology, able to create a breakthrough increase in both technical and economic attractivenesses, has become viable today with the advent of 2G-HTS materials. These can operate at a high magnetic field at drastically increased temperature in the range of 20 K–40 K (and beyond), creating breakthrough improvement in cost and efficiency of the system and opening completely new perspectives in SMES technology. Substantial research is still needed, however, to contain the AC loss of the coil during charge/discharge at a level compatible with appropriate efficiency and continuous operation in realistic functioning regimes. This will require the investigation of innovative solutions concerning the layout of the coil, the architecture of the conductors (including multi-filamentary configuration), and the selection of the magnetic field and the temperature levels allowing the best break-even between heat losses, cooling power, and conductor usage. An optimisation-oriented design, assisted by AI, and a modular approach is of paramount importance for successful SMES technology. The development of a quench-detection system immune to false triggering during fast ramping is another innovation that can be enabled by AI for arriving at a robust and correctly operating SMES system.

Magnetic levitation trains can integrate either low- or high -temperature SCs and can be designed for high-speed, long range, or low-speed, urban range. A Japanese LTS high-speed maglev train, the Yamanashi test line, based on electrodynamic suspension (EDS) with superconducting coils has achieved a world record of more than 600 km h^{-1}, levitating 10 cm above the tracks [362]. In EDS, levitating forces are due to the interaction of superconducting magnets on the vehicle and inducing coils on the guide way, which requires enough speed for levitation (around 100 km h^{-1}), and therefore wheels are also needed. In Brazil [363] and China, HTS low-speed MagLevs have been developed based on purely SML, i.e., obtained through the interaction of HTS bulks and PMs [364]. EDS MagLevs require massive investments in dedicated transportation infrastructure, and no expected market opportunity (due to, e.g., competition with other transportation systems) and associated economic viability are expected in the medium term, as was the case for the Yamanashi train. Yet, prospects for the opportunity of low-speed MagLev, in urban routes, have been considered in the literature, due to their lower vibrations and noise, and lower maintenance, when compared to conventional systems. Despite the fact that they use PMs all along the guide way, with a relevant impact on the cost of the system, investments of around 30% of the required for implementing a subway are foreseen by the authors of the Brazilian maglev. SML MagLevs use linear induction motors for developing thrust forces, where the armature may be onboard to avoid implementing coils [365] that would be switched by sectors, all along the guide way. Therefore, energy storage means, namely batteries, also need to be onboard, as well as dedicated power converters to charge them at stations, while the train is stopped. These batteries need to supply the linear motor (although only tenths of kWh have been reported for Cobra, the Brazilian MagLev, to travel between stations 200 m apart), but also all ancillary systems, as air conditioning, which can be several orders above the energy required for the motor [366]. The technical and economic optimization of SML MagLevs is thus a multi-objective problem where AI provides powerful tools for its solution. Design parameters include the configuration of magnets on the line, the geometry, arrangement and cooling temperature of the HTS bulks, the capacity and mass of the batteries, the power of the charging systems on the stations, and the cryogenic technology, among others, subjected to restrictions as the minimum required energy between stations or the headway (time between consecutive departures from a station).

5.1.3. AI for manufacturing and operation of superconducting apparatuses. At this stage, many papers have presented AI techniques as a useful option that find the solutions for some theoretical problems, mostly at an academic level. However, AI can offer much more than that and can be used to find solutions for many unsolved manufacturing and production problems of superconducting tapes/wires and apparatuses or as a real-time solution for monitoring and detecting abnormalities, quenches, and faults in real operational regimes. Local hot spot detection of superconducting tapes/wires, fault detection of superconducting cables, quench prediction of superconducting magnets, and condition monitoring of superconducting machines are the best examples of these tasks. For instance, quench detection in superconducting magnets could be identified by importing the voltage, temperature, current, temperature and vibration signals as inputs to an AI-based model. The model receives these inputs and can digest the normal conditions from quenches. AI can also be used as predictive-models to forecast any incoming quench, fault, failure, etc before they are capable of jeopardizing the superconducting elements.

5.1.4. AI for reducting the number of test for acceptance of manufactured devices. Each superconducting apparatus consists of many components with different kinds of materials. To gain the best performance of superconducting devices, each one of these components must be tested separately to gain an acceptance to be used in superconducting devices, for example in MRI applications. Testing them is a time-consuming and complicated procedure, which requires a huge effort and also might be destructive to the device. AI can play a significant role at this stage of manufacturing in two manners. AI can manage these tests on its own without any need for an external human-based operator. On the other hand, AI can be also used to intelligently choose the components that need to be tested (based on possible defects sensed by it in production line) and also as a feedback loop to improve the manufacturing process. However, there is a need for improvements in AI techniques to make them available for such applications.

5.1.5. The capability of AI methods to deal with quenches, from manufacturing to operation. In the literature, some efforts were carried out to establish an AI-based approach for detecting quenching and protecting the magnets to reduce the risk of failures or damage. However, not all quenches are operational condition-originated. Quench can originate in some inherent parameters of superconducting wires/tapes during assembly process, or as a consequence of some errors in the manufacturing process in the production line, or as a result of unexpected interactions with the system components. AI is used here to back track these quenches by finding the patterns among those magnets, which already failed or were faced with quenches, and revise the superconducting component design accordingly. The failures in the manufacturing process could be diagnosed and removed to increase the reliability and quality of the magnet and coil production. This is also valid for defects and voids in the main body of SCs. Many of the defects are due to manufacturing problems. Therefore, by accessing a highly accurate AI-based pattern recognition method, the reasons for quenches, defects, voids, and other types of imperfections in the manufacturing process of superconducting tapes/wires could be detected.

5.1.6. The role of AI in cost reduction of superconducting devices. One of the most important issues that must be considered during the design procedure is the LCOE, which is defined as the total cost of the device over the MWh characteristic of the device over its lifetime. Most of the related design papers tried to reduce the initial purchasing cost of the superconducting devices rather than total ownership cost or even LCOE [367]. However, LCOE reduction could increase the competitiveness of superconducting devices with respect to their conventional counterparts. It should be mentioned that the total price of any superconducting device consists of following components [367]:

5.1.6.1. Initial cost. This cost is related to the purchasing of the superconducting device, cooling system, and auxiliary services like transportation and installation. To reduce this cost, it is often to reduce the volume of superconducting parts as one of the most expensive components in any superconducting device. After that, the cooling system must be optimised with respect to present trade-offs that result in a cooling system with minimum cooling stages and adjusted cooling power.

5.1.6.2. Maintenance cost. Each superconducting device needs to be repaired at a specific period of time. This can be conducted at a planned time, known as preventive maintenance, or could be conducted during failures and errors of the device. The cost of purchasing the required components of the superconducting device, the salary that must be paid to the technician team, and the cost of the unavailability of the device. Usually this cost is reduced by increasing the time spans in which maintenance is needed.

5.1.6.3. Cost of operation. Regardless of the type of superconducting devices, they have a cost known as operation cost, which originates in the required cooling power, electrical power, engineer's salary, cryogenic fluid cost, and many other components. As a matter of fact, some of these costs are constant and cannot be reduced, while some of these costs could be reduced, such as cooling power cost.

5.1.6.4. Protection, monitoring, and testing costs. The finance needed for purchasing, installation, implementation, and maintenance of the protection system could be accounted for as protection cost. The level of protection and the type of the protection system are two important factors that impact this cost. The reduction of this cost has many system-level consequences, which is out of the scope of this paper.

To monitor the superconducting devices, sometimes many sensors and logging systems are needed. These sensing systems also have wiring and could induce a thermal heat load to the cooling system and reduce the efficiency of the devices. In addition, the extra wiring requirement can often be translated to extra space and size increment, thus lower specific power density. As a result, monitoring cost is considered as a significant cost for SCs, which must be minimised by reduction the number of sensors and the optimal sensor placements.

In addition, many components in a superconducting device would need to be tested before either application or before the final release to costomers. Some of the testing procedures would need full-scale testing of a component, and therefore, it imposes another element of cost for the final device.

5.1.6.5. Redundancy and reliability cost. Usually SCs are selected as the main parts of a system, which need back-up units and extra redundant devices to increase the reliability of the system. Due to the high cost of superconducting devices, conventional counterparts are selected as their reserve units. The cost of these units is another component that must be taken into consideration.

Reducting each one of the aforementioned costs results in a significant reduction in the LCOE and, therefore, increases the competitiveness of the superconducting devices over conventional counterparts. However, such a reduction process is a highly nonlinear problem with many limitations, constraints, and trade-offs along with a high level of complexity. AI techniques can be used to solve this nonlinear and complex problem. First, swarm-based optimisation methods can be used to reduce the initial cost of superconducting devices by minimising the volume of used superconducting tapes and wires. This optimisation should be linked to AC loss, manufacturing-related issues, maximum temperature, etc. These AI methods can be also used to predict the maintenance time of superconducting devices to reduce the risk of failures in these devices. Operation cost can be minimised by using intelligent systems that make decisions, control, and manage the superconducting devices, instead of using human operators. By doing this, the risk of human failure is reduced, which could affect the operating cost of superconducting devices. The reduction of condition monitoring cost is another challenge that AI strategies could deal with. Lastly, cost manufacturing process, assembly line, etc are other possible applications of AI methods.

5.1.7. Reduction of manufacturing tolerances by means of AI methods. The design and manufacturing of superconducting devices is a highly sensitive procedure and any change in the size of the designed device could end up being a whole different manufactured device, based on its thermomechanical and electromagnetic characteristics. For instance, in superconducting transformers incapable manufacturing tolerance may lead to higher loss, and in superconducting machines, it may lead to eccentric faults. Conventional manufacturing processes always have some tolerance to produce the devices, even sometimes unacceptable. However, AI can be used here to produce all devices of the same size with minimised tolerance, especially when combined with transformative additive manufacturing methods. With additive manufacturing, accuracy of dimensions, low tolerance, and low waste would be guaranteed by using many sensors in the 3D printer. However, logging many data points in real-time from those many sensors is exhaustive, and analysing them in real-time is impossible except by using DL and other AI approaches. This can lead to highly efficient design procedures and help engineers to have the same characteristics with what was estimated.

Due to unavoidable manufacturing tolerances in MRI, the as-built magnets have a non-uniformity of several hundred ppm. In addition, effects of a magnetic environment such as metal beams or passive shielding of the room must be compensated for. The shimming system is used to reduce the non-homogeneity to the necessary level of 10 ppm. The over-design of the shimming system is counter-productive: the oversized shims may occupy expensive space in the system and increase interaction with other components. Statistical analysis of the manufacturing tolerances and environment, regression and prediction, and classification methods may be applied.

5.1.8. The capability of AI for defect recognition of SCs at the manufacturing stage. In quality assurance of a manufactured device/product many parameters are involved. Controlling these parameters surely has an impact of the quality of manufactured SC or superconducting devices. When the number of input parameters are low, perhaps simple mathematical fitting methods will help to understand the impact of input parameters on the manufacturing output. However, if the number of inputs increases or the interdependencies of the inputs are complex, then the mathematical fitting methods have no use anymore. This is where AI techniques can play a role in finding patterns among the output of manufacturing lines, by regression-related input and output parameters, and also consider all interdependencies as well. In addition, AI techniques can bring one more brilliant benefit for the manufacturing process, and that is finding the priority of impact for input parameters on the output of manufacturing/production line. In other words, it can help manufacturers to know which input parameters are really affecting the quality of their manufactured objects.

5.1.9. The role of AI to establish multi-physical surrogate models for technician and manufacturing-line personnel. Although FE models are an excellent choice for academic research because of their high level of accuracy in simulations, which is comparable with experimental results, they are difficult to deal with and slow to be used at any level apart from design level, for instance, manufacturing and operational levels, by engineers and technicians. AI-based surrogate models seem to be a better option for this level of integrity with industry. Engineers and technicians could use them and with only changing the desired parameters, the results of the changes in design factors and characteristics are accessible. If using surrogate models, engineers and technicians would not need to be familiar with the full construction, topology, and components of the under-studied system. Therefore, there is no need for an age-long model establishing procedures conducted by FEMs, however, the multi-physical characteristics of FEMs make them popular options among engineers and researchers. To gain multi-physical characteristics for surrogate models, AI methods, such as ML, ANFIS, NNs, and SVM, can be used. By applying them, temperature, magnetic field, current, voltage, strain, stress, etc could be set as inputs and outputs could be design factors, characteristic of device, and many other parameters. In addition, data coming from sensors in the production line and manufacturing process can be feedbacked to this model in real-time to keep it up-to-date.

5.1.10. Insulation goodness for coil, winding, magnets, and cables during the manufacturing process, by AI. Insulation is one of the most important parts of any superconducting device, and therefore, part of the manufacturing process. The quality of the insulated devices needs to be approved under different circumstances before the device is built. While AI can be used to test the quality and goodness of the insulation, during the manufacturing process with the help of some pattern recognition and image processing. A picture can be selected as the highest insulation goodness of any superconducting device, and when each sample is manufactured and an image is taken from it, the picture can be decomposed to some data and be compared with the basic picture to show the insulation goodness. The findings of such an image-processing approach can be used to correct the insulating process in the manufacturing procedure [368–371].

5.1.11. Quality assurance. The AI method can be used to increase the quality of manufactured superconducting devices, known as quality assurance. This means that with the help of some AI-based techniques like ML the parameters, which cause the quality reduction of a superconducting device, the appearance of defects in superconducting tapes, and generation of local hot spots in tapes/wires could be diagnosed and removed to increase the quality of superconducting devices, increasing their reliability and lifetime. These parameters could be some impurities in raw materials, or some failures and unbalanced settings of manufacturing machinery, or even some human-based mistakes in the basic design or production process.

5.1.12. Preventive maintenance. Preventive maintenance is defined as a routine check-up and maintenance of any electrical/mechanical device before any costly and unplanned repair is needed. Usually, these are calculated based on some formulations, such as mean time before failures, mean time to failures, and mean time to maintenance. These old methods are usually used for simple devices or some basic processes. Using them for complicated systems like superconducting devices, which contain many subsystems requires a huge computation. AI techniques can be used here to predict the maintenance time of the device. To do this, the lifetime historical data of the device is needed along with some electrothermal properties of the device at each time step. By feeding them into the AI techniques as inputs, the preventive maintenance time could result in the output. As a result, the computation time is highly reduced and the accuracy of the results is extremely increased.

5.1.13. AI for finding manufacturing margins. Another issue that not only in superconductivity but also in other industries can be solved by using AI techniques is manufacturing margin. This factor is defined as the difference between sales and the total variable cost of goods sold. This factor is affected by many parameters, such as the value of the supply of other manufacturers and demand of the costomers. The price of raw materials, net profit, sale earnings, and merchandise cost are other factors that affect the manufacturing margin. Finding the exact value of manufacturing margin for sophisticated devices like superconducting apparatuses is a bit of a difficult task through conventional methods, however, AI systems can be trained so that it gains all the aforementioned effective parameters as inputs, and finds the hidden pattern of interdependencies among them, and finally hand us manufacturing margin as output.

5.1.14. ARCSs. In the coming future, AI techniques may help the emergence of the ARCSs into superconductivity. These systems will be able to detect quenches in superconducting magnet systems, faults and abnormalities in power applications of SCs and failures in other superconducting components. After that an ARCS must be capable of differing false alarms from signals, which indicates the real failures and faults. The next level is that ARCS must make a protective decision independently and automatically to reduce the risk of damage to the superconducting apparatuses. These decisions could isolate the faulty component, restricting the system/-grid in which the superconducting device is implemented, or any other protective decision. Lastly, ARCS must apply the decision to protect the device. All of this must be done automatically and without any human interferences.

5.1.15. Cost of data acquisition. Data is acquired by mean of sensors that are among the most expensive part of the intelligent systems. The high number of sensors results in a higher quality and quantity of data, however, this increases the cost of the whole superconducting system. Thus, the number and the location of sensors must be minimised so that their cost be as minimal as possible. However, we do not wish to lose any valuable data, therefore a trade-off problem exists here, which is a good candidate for AI techniques to be implemented in. AI can perform such minimization of sensor numbers by locating the points in which sensors must be installed. FCCs are one example of this which would need many superconducting magnets. All of these magnets require a sensitive quench analysis, condition monitoring, and fault location methods. Therefore, thousands of sensors and wiring is needed and as a result of this cost of data acquisition rapidly increases. Thus, AI can be applied in FCCs to minimise the number of sensors, optimise their location, and maximise their accuracy.

5.1.16. Lessons to learn from other industries. AI techniques have been used for a longer time in other industries and fields of research, such as power grids, gas-oil systems, automation, power electronics, medicine and healthcare, agriculture industry, and security rather than superconductivity. For instance, in power systems, AI has been used to control the power generation units, predict the future demanded electrical power, optimum location finding of devices, state estimation, performing the power flow, and designing the electromechanical devices. Due to these efforts not only in power systems but also in other industries, many experiments have been acquired and many novel structures, methods, and design algorithms have been established. The lessons learned in other industries are applicable to SCs. Design procedures of conventional machines, cables, and transformers can be applied to superconducting versions of these devices with some justifications. This is also valid for fault detection, condition monitoring methods, protection issues, and many other methods.

5.1.17. The systematic analysis of the superconducting devices. Most of the papers that have used AI techniques for superconducting technology have focused on devices rather than their systematic role. AI can help us to recognise how much impurity is allowed in SCs to result in the desired magnetic field distribution. How do these impurities affect the field, temperature, and the volume of the coils and magnet? SCs are currently used in fusion systems [372, 373] which contain many electrical, magnetic, cryogenic, and mechanical devices as their subsystem. The impact of these non-superconducting devices on the characteristics of the optimised superconducting apparatus is to be identified by using AI techniques. On the other hand, in fusion systems, radiation is an important effect that can re-characterise the behaviour of superconducting magnets, while no design optimisation or condition monitoring investigations has been accomplished with respect to the impact of the radiation. In fact, like other industries, superconducting devices must be analysed in the whole-system level and under more realistic considerations. These systems could be bulk power grids, stand-alone power grids of electric aircraft and ships, the micro-grids with their specific constraints, and many other systems.

5.1.18. Hardware implementation. So far, we have discussed the application of AI for SCs, the challenges of superconducting devices, challenges of AI, and their future trends, types, investigated studies, and many other points and there is one more discussion to make which is the answer to the following query: suppose that one has selected the required AI technique, has purchased a superconducting device, has identified the role of AI (especially ANN, ML, and DL), purchased the sensors, and has installed them at the required site, still there is a need for hardware implementations. There is FPGA, GPU, ASIC, Raspberry pi, etc. to implement an AI technique. Among them, FPGAs and GPUs are more commonly used, while others still need further improvements. GPUs require the highest level of programming skills, while the implementation time of the ASICs are the highest among hardware. ASICs also have the highest energy efficiencies, while GPUs are the lowest ones and ASICs have a higher cost in comparison to other hardware. The important point is that GPUs operate in the software level, while two others are at the hardware level. Lastly, many frameworks were reported for this hardware such as [374]:

- DeepBurning
- DNNWEAVER
- Caffeinated FPGAs
- FPDeep
- fpgaConvNet
- Field Programmable DNN.

5.2. Future developments

As discussed in section 3, the utilization of AI techniques in superconducting applications has already started and is receiving dramatically increasing attention. AI methods, such as ML and DL approaches, can create a shift from traditional model-based design and can be employed to find new solutions for existing scientific and technological challenges in superconductivity and to make superconducting applications more competitive against conventional options. Therefore, we believe AI has a key role in the future for superconductivity in the following areas:

- Assisting SC science for finding new materials with higher critical temperature/current and/or improving the intrinsic performance (critical temperature and upper critical field) of existing ones.
- Designing practical SCs tapes, wires and assembled conductors with optimised performance (engineering current density, pinning and in-field behaviour, AC loss, mechanical strength, uniformity and stability) and reducing cost through improving manufacturing and production lines performances.
- Setting up advanced manufacturing process, also by enabling the use of the latest machinery and additive manufacturing, to produce improved and cost-effective superconducting apparatus and systems.
- Introducing a system approach for effective integration and of different components (SC elements, cooling and vacuum systems, electrical insulation, among others) obtaining improved overall performance and reduced capital and operating costs.
- Implementing lifelong and intelligent condition monitoring of SC apparatus and system for detecting contingencies and for optimizing operation via real-time communication with the hosting system (also managed by AI methods).
- Based on the conducted studies in the materials field of superconductivity, MgB_2 is one of the promising SCs and it is expected that by some modifications or doping, their critical temperature and critical current increase. On the other hand, lattice parameters are other important factors that could be initiated in critical temperature increase. However, to be more specific, the main question is: what is the aim in searching for new SCs? The increase of critical temperature? To increase the critical current? To reduce the manufacturing cost? To reduce losses? Therefore, there are many different considerations that lead to different target materials.

While the first applications were mostly focused the design optimisation of devices and improvements in available materials, new AI trends will be more holistic approach and will have a dramatic impact at the level of the system integration and management and play an important role also in the dissemination of superconducting-based technologies. Together with the advent of IoT, AI enables whole new paradigms throughout the operation lifecycle of those technologies, also assisting the decision-making process for adopting, in particular, high-investment, large-scale systems.

The massification of low-cost sensors and the availability of a large offer of communication technologies support the application of data-driven-based AI methodologies, where DL, in particular, emerges, fed by real-time operational information that can be used for various purposes.

This is the concept of DT, 'a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision-making' [375]. Among others, the digital twinning of superconducting devices and systems is foreseen to enable the following major advances [376]:

- Real-time accurate monitoring and prediction of the performance of superconducting devices obtained by DL models is fed by actual, currently acquired, operational data. To achieve this , DL must be able to handle data from multiple sensors, monitoring the condition of the former (e.g., detecting hotspots and critical current weak points or equipment failures) while continuously updating the complex underlying models with new data, as the system dynamic evolves throughout the lifecycle of the device. It is stressed that physical-based FEM models cannot be used for real-time prediction due to the long execution time required. Nevertheless, hybrid models can be implemented on the virtual twin where the solution for a given operating condition is obtained by regression on a set of pre-calculated FEM solutions.
- Predicting faults or malfunctions in advance, thus allowing for taking maintenance or corrective actions. This is obtained by real-time comparison of measured data with the predicted data of the DT running in parallel. Information can be extracted from possible mismatches that can be due, for example, to internal faults, ageing of components or the need for maintenance and corrective action can be taken timely.
- Assessing compatibility of the required set-point of the hosting system with the current state and the safe operation of the SC apparatus. A bidirectional interaction is needed between the power hosting system controller and the DT to cope with the case where the requested set-point cannot be satisfied due to incompatibility with its current state (this may be, for example, the case when an increase in power is required in a superconducting transformer or cable that is already operating at too high an I/Ic ratio). DT will allow to run a what-if analysis, simulating the reaction of the system to the event, thus allowing to define rescheduling or appropriate mitigation measures in advance.
- DTs are also envisaged to support decision-making processes, associated with the high investments required by superconducting-based technologies (as related to fusion or power grid devices). DT can be integrated and interact with other models and twins, allowing simulation of the behaviour of the devices, and assessing operational scenarios and the economics of the technology throughout its lifecycle, and even beyond.

DTs can be used in all lifecycle steps of superconducting devices, including design, production, and service. In each of these steps, DTs play different roles. At the design stage, DTs are used to improve the design factors of the superconducting device and overcome the problems and difficulties during the design procedure. In the manufacturing stage, DTs can be used, especially on the assembly line, to manufacture a device exactly as it was designed. In fact, DTs are used at this stage for the sake of as-built and as-designed homogenization. DTs can be applied to many manufacturing systems, such as supporting autonomous production systems. They can be used to improve the manufacturing throughput, which is defined as the required time for a device to be manufactured from raw materials. In fact, with the application of the DTs, a real-time condition monitoring is accessible to detect the failures and imperfections of the produced device during the manufacturing process. Lastly, at the service stage DTs are used to monitor the characteristics and behaviour of superconducting apparatuses [377]. At the moment, some industries use DTs to improve their manufacturing, assembly line, designs, and performance of their devices and tools. NASA, GE, Airbus, Northrop Grumman, and Boeing have used DTs for aircraft maintenance, safety analyses of their aircraft, malfunctions predictions, and decision optimisation for assembly lines [378–380]. In electrical energy generation, GE has used DTs to revolutionise the future of wind farms by continuously gathering data to minimise the required maintenance, increase the reliability of wind power plants, and lastly significantly improve the generated power by wind turbines. Siemens has also created a DT for the Finish power system to help them manage the planning, operation, protection, and maintenance of their entire power system. DTs are also used in automotive, oil, gas, healthcare, agriculture, and many other industries [377, 380–383]. As discussed in [377], the aerospace industry is the most appropriate industry for DTs with an acceptable value of funding. This is the same industry in which SCs are going to be applied as cryo-electric transportation airborne systems. It is highly possible to use DTs for electric aircraft and spacecraft to protect these precious devices. This could be an excellent opportunity to consider many trade-offs during design procedures, service life, maintenance, and condition monitoring of SCs used in aircraft. Also, lessons learned from the application of DTs into power systems could be useful for the sake of using the DTs for power superconducting apparatuses.

Quantum computation has revolutionised many engineering sciences and technologies. AI techniques, especially machine and DL methods, can also further improved by using quantum computation. This can increase the accuracy and speed of the learning procedure, especially for ultra-complex and nonlinear characteristics. Thus, with advancements in the field of quantum computation and their integration with AI-based approaches, an eye-catching improvement is predicted in accuracy and speed of the AI techniques [384]. This can be a great opportunity for superconductivity, aerospace, etc.

In 2020, a new concept has been established in the AI field, known as no-code AI. This means that the AI platform is organised so that all users without any special expertise in AI coding can drag and drop data into the platform to gain a high accuracy model [385]. This can be very helpful in the field of SCs and the researchers can create their own special models with the highest and fastest characterisation. The main advantages of such AI platform is their fast computation time, as well as the low cost of hiring data scientists for projects.

Lastly, it should be mentioned that relatively new ML methods and NNs were introduced that are dedicated to problems with a supervised learning nature, while these specific types of ML can be informed about the physical nature of the data by using partial differential equations. Thus, in future, these physics-informed NNs could be used for modelling, design, and condition monitoring of superconducting devices under different electrical, magnetic, thermal, mechanical, and hydraulic conditions [386].

6. Concluding remarks

The last few years have been called the age of AI. This specific field of science has entered into all aspects of human life, such as managing airplanes, controlling power systems, social communication, healthcare systems, and many more. SCs, like any other field of science, have been investigated with the help of AI techniques, recently. These techniques have been used for many purposes in superconductivity and its related applications. This paper has provided a critical topical review on the application of AI in superconductivity. The most important contributions of this paper are shown below:

- A short review of AI concepts, categories, history and developments.
- A review is conducted on the existing state of the art of applying AI in different superconducting applications and materials.
- Challenges that AI methods face being used in superconducting apparatuses and materials are discussed.
- A critical review is also presented in a form of discussion showing how AI must be applied to enhance the efficiency and reliability of superconducting devices and their manufacturing processes.
- Finally, future trends and developments are suggested and discussed for using AI techniques in the field of applied superconductivity.

From what has been reviewed, we note that most of the previous works and investigations are focused on tackling the design optimisation problems of superconducting devices, such as those in large-scale power and material applications or communication systems. Usually, these types of problems are too complex to be solved by mathematical methods. The most useful algorithms for design optimisation of superconducting devices are GA, PSO, and some other metaheuristic algorithms.

On the other hand, AI is used to build models for SCs based on DS rather than formulations and theory. These models reduce the computation time and may increase the accuracy of the results. However, the main goal of using AI models is to present a real-time characterization of superconducting apparatuses. There is also another way to take advantage of AI in superconductivity, namely for condition monitoring. This term refers to continuously analysing the receiving signals of superconducting devices and by a combination of these signals and AI methods, the working condition of the device can be understood. These signals could be voltage, current, AC loss, or magnetic field, among others. Condition monitoring issues include, but are not limited to, fault location, fault detection, and fault discrimination in superconducting devices. Condition monitoring can also be used as a quench detection procedure in magnets. The aim of using AI is here to make the monitoring as fast as possible to make it real-time. ANNs, ML, and DL are the most used methods for the sake of condition monitoring and database models.

There is another application for AI in superconductivity known as critical temperature estimation of new materials. In this application, AI is used as an estimator or predictor to find the structure of new SCs with a glance at the invention of room-temperature SCs at low pressures. If room temperature SCs come into play, their cooling cost will be drastically reduced.

So far, the main applications of AI in superconductivity was firstly the critical temperature prediction of new SCs, controlling and modelling the superconducting magnets of fusion systems, electrothermal characteristic estimation of YBCO tapes, basic, superconducting machine design, and fault detection in HTS cables. Other methods and applications require further improvements and justifications.

We have discussed the challenges and obstacles that restrict the application of AI into the superconductivity technology. These challenges are explained and categorised into nine groups. By addressing these challenges in future, AI will benefit from a high level of the technology readiness level (TRL) in applied superconductivity.

Besides, we have also discussed a critical review and future trends for integrating AI technology with superconductivity, which is followed by a series of questions, in the aspects of design, condition monitoring, reducing cost, etc.

According to what was explained above, AI techniques show great advantages in addressing the existing challenges that face the applied superconductivity and SC materials in increasing their TRL. By following future trends, AI could play a more outstanding role in the field of applied superconductivity and SC materials.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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ORCID iDs

Mohammad Yazdani-Asrami https://orcid.org/0000-0002-7691-3485
Ana Madureira https://orcid.org/0000-0002-0264-4710
João Murta-Pina https://orcid.org/0000-0002-9283-8497
Antonio Morandi https://orcid.org/0000-0002-1845-4006
Michael Parizh https://orcid.org/0000-0002-2737-8578

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