Chapter 1
Introduction

1.1 Backgrounds

1.1.1 Basic Introduction to DC-DC Converters

In the current era, environmental problems such as the global warming and the depletion of fossil fuel attract more and more attentions globally, leading to the increasing penetration of renewable energy resources [1, 2]. The inherently fluctuating, intermittent and widely-distributed renewable energy brings challenges to the existing power grid. To ensure the reliable and stable connections between renewable energy resources and existing power grid, DC-DC converters and DC-AC inverters are the key enablers. Several applications of DC-DC converters and DC-AC inverters are shown in Fig. 1.1.

Generally, the topologies of DC-DC converters can be classified into non-isolated and isolated types according to whether there is galvanic isolation, or can be classified into unidirectional and bidirectional types based on the directions of power transfer [3]. In the non-isolated DC-DC converters, conventional Buck, Boost, Buck-Boost, Ćuk and Sepic/Zeta converters have been widely applied in photovoltaic systems [4], LED drivers [5], fuel cell vehicles [6], etc. To enhance the voltage boost ability and relieve the burden of current stress, two or more converters can be connected in a cascaded fashion, which has applications such as smart grids and distributed power systems [2]. Interleaved and multilevel converters, which are also non-isolated DC-DC converters, can be utilized in automotive systems [7], HVDC grids [8], etc.

From the perspective of isolated DC-DC converters, except for the benefits of safety, the galvanic isolation can achieve high voltage gain ratio and provide the possibility of multi-input and multi-output topologies. In the isolated DC-DC converters, flyback, push–pull and forward topologies are commonly applied in low and medium power situations [3]. The most popular isolated DC-DC converters are dual active bridge (DAB) converters, whose applicational fields include electric vehicle charging

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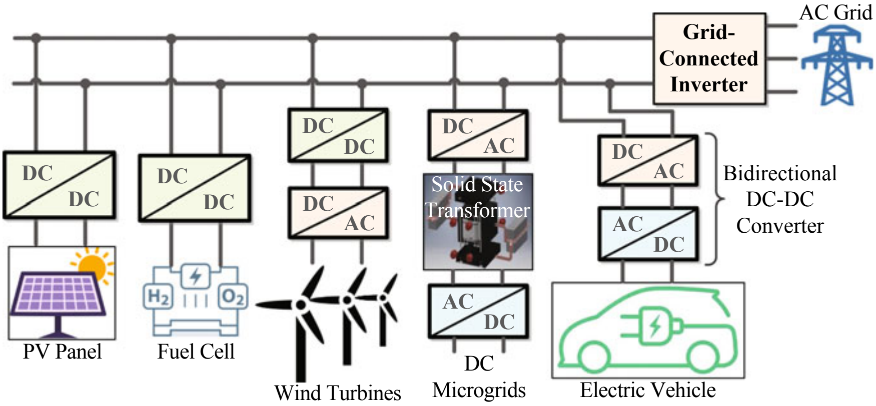

Fig. 1.1 Applications of DC-DC converters and DC-AC inverters

[7], battery storage systems [9], uninterrupted power supply [3], solid-state transformer [10], etc. Recently, DAB converters with resonant tanks such as LC, LLC, CLLC [11] are hot research topics.

1.1.2 Basic Introduction to DC-AC Inverters

To build the connection between the existing AC power grids and the distributed renewable energy sources such as solar energy, wind energy and tidal energy, DC-AC inverters are also playing significant roles, as the applications shown in Fig. 1.1. According to the operation modes, inverters can be classified into stand-alone, grid-connected and bimodal types [12, 13]. From the configuration topology point of view, the grid-connected inverters mainly consist of three types: centralized inverters, string inverters and module inverters, which are suitable for high power, medium power and low power applications [14, 15]. Similar to DC-DC converters, DC-AC inverters are widely used in renewable energy systems, such as solar PV systems [16] and wind farm systems [17, 18]. In addition, Inverters can be used in space applications [19], telecommunication [20], computer systems [21] and traction scenarios [22].

1.2 Problem Descriptions

Due to the increasing proportion of DC-DC converters and DC-AC inverters in both industry and our daily life, their power modules, circuit parameters and modulation schemes have to be carefully studied and optimized from power quality, stability, efficiency, reliability and economic perspectives [16, 23, 24]. In practice, to design and deploy a power electronic system in real-world, the whole process mainly consists of three steps: performance analysis, optimization, and modulation and control.

As exhibits in Fig. 1.2, the conventional methods for performance analysis, optimization and modulation of power converters suffer from some unneglectable problems: time-consuming and inaccurate manual performance analysis, suboptimal optimization and unsatisfactory modulation [25, 26]. Generally, conventional performance analysis suffers from excessive human-dependency, time-consuming and inaccurate problems, traditional optimization approaches suffer from suboptimal problem and heavy computation, and conventional modulation approaches may result in high space and time complexity.

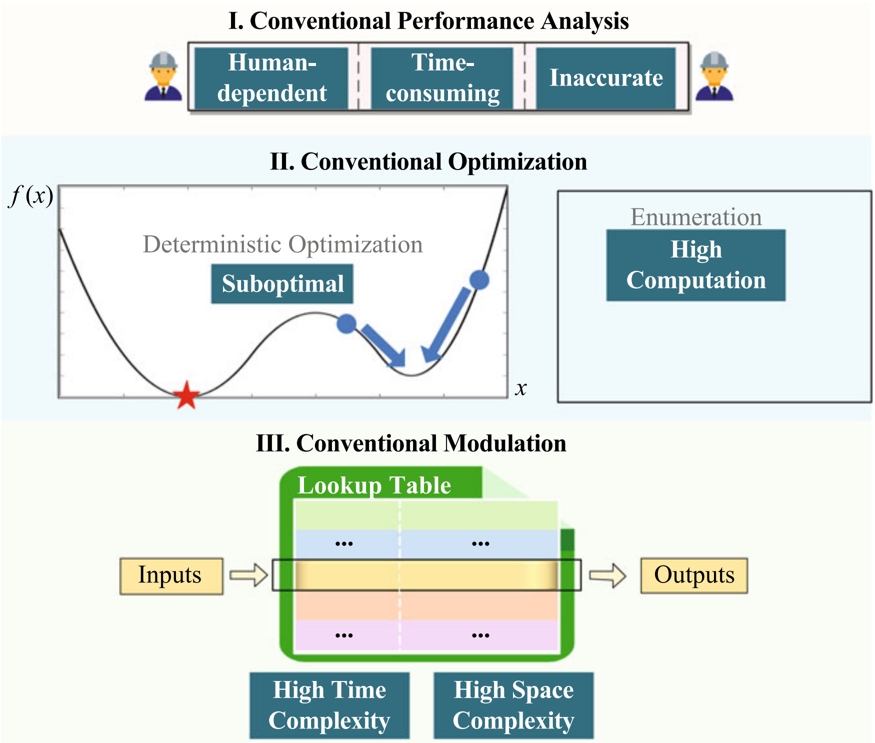

Fig. 1.2 Problems in the conventional approaches for the performance analysis, optimization and modulation for DC-DC converters and DC-AC inverters

1.2.1 Problems in the Human-Dependent Analysis of Performance of Power Converters

In the performance analysis of power converters, most of the existing conventional methods require the fully involvements of engineers and researchers for the mathematical expressions. For example, to obtain the expressions of copper loss and conduction loss of DAB converter, the inductor current has to be analyzed piece by piece for all the operating modes, and the deduced high-order expressions are then squared and integrated to compute the rms value for further computing copper and conduction losses [27]. Lin et al. manually deduces the analytical expressions of the output impedance of symmetrical CLLC-type DAB converter for the stable operation of cascaded power converter systems, where the small-signal model of main circuit reflects high complexity caused by the four resonant inductors and capacitors [28]. Due to the excessive human-dependency, the conventional analysis and deduction of performance of power converters are time-consuming and error prone [29, 30].

Apart from the problems of heavy manpower burden, conventional human-dependent performance analysis suffers from inaccurate problems. To derive the mathematical expressions for the targeted optimization objective, many approximations will be taken for the sake of analytical convenience. For instance, [23] only adopts the zeroth and first order terms in Fourier expansion for the simplicity of impedance analysis. Besides, [31] assumes ideal models of power switches and neglectable magnetizing current. All these approximations for analytical convenience undermine the precision of deduced expressions and thus potentially lead to low design accuracy.

1.2.2 Problems in the Optimization of Power Converters

After deducing the analytical formulas for the performance of converters, optimization is conducted to achieve better operating performance. The conventional optimization approaches of power converters are based on enumerations or deterministic optimization algorithms, which suffer from the drawbacks of large computation and suboptimal designs [32, 33]. The enumeration-based approach tries out all possible design cases, so its computational burden for computer is extremely heavy, while the design cycle is an important factor to be considered. As shown in Fig. 1.2 [34], enumeration-based approaches for the optimization of DC-DC converters may require infeasible computational time especially when the dimension of design parameters is high or when the design parameters are continuous with infinite possible values.

As for the deterministic optimization approaches such as sequential unconstrained minimization, augmented Lagrangian and Newton–Raphson, their optimization results highly depend on the selected initial iteration points and the predetermined convergence threshold, as plotted in the left-side of Fig. 1.2. Both improper initial iteration point and inadequate convergence threshold will lead to unsatisfactory local optima [35]. With deterministic approaches, the optimality of design may be nontrivially undermined with a high possibility. Busquets-Monge et al. [36] reveals the suboptimal problems of some commonly used deterministic algorithms in the optimization of boost power factor correction converter.

1.2.3 Problems in the Modulation of Power Converters

To realize the real-time modulation for power converters, there are mainly two approaches: through online computation of deduced expressions or through searching a stored lookup table. For instance, [37] adopts lookup table to realize online triple phase shift modulation of DAB converter, in which the implemented lookup table stores the optimal modulation parameters for different operating situations. Zhou and Wang [38] utilizes deduced formulas to realize real-time space vector modulation (SVM).

Generally, the space and time complexity of the real-time modulation are always considered, both of which are favoured to be as low as possible. It has to be admitted that the conventional lookup-table-based and expression-based modulation schemes are easy to implement, but they suffer from either high space complexity or unacceptable time complexity. According to Tang [37], the storage size of lookup table exponentially rises with the increasing of stored variables, and the exploding storage size will nontrivially slow down the query speed of lookup table, as shown in the bottom of Fig. 1.2. Compared to lookup tables, expression-based modulation approaches have low space complexity, but the time complexity might be unacceptable due to the non-linearity of the expressions required to be solved in real-time [39]. Apart from that, the deduction process for the expression-based modulation approaches also suffers from tedious and overwhelming human-dependency.

1.3 Basic Introduction to Artificial Intelligence Algorithms

To overcome the aforementioned problems in the analysis, optimization and modulation of power converters, three AI tools can be applied: neural networks, evolutionary algorithms and fuzzy inference systems, which are introduced one by one as the followings.

1.3.1 Neural Networks

Neural network (NN), which lies at the heart of recent popular deep learning algorithms, is a parallel-structured computational graph mimicking the flexible connections of biological neurons in brain [40]. As shown in Fig. 1.3, the general structure of NN consists of input layer, hidden layers and output layer, which are responsible for obtaining inputs, learning underlying behaviors and predicting outputs. Artificial neurons in NN connect with one another through adjustable weights and biases and non-linear activation functions. Being beneficial from its high non-linearity and easily adjustable structure, NN can learn any complex and nonlinear relationships between design variables and objectives with arbitrary precision, so it has better fitting accuracy compared with other regression techniques such as ridge regression, Bayesian regression and support vector regression [41].

In the current literatures, three types of NN are commonly adopted, namely feedforward NN (FNN), recurrent NN (RNN) and convolutional NN (CNN) [42], the standard structures of which are shown in Fig. 1.3. FNN passes the information in only one direction, from inputs to hidden layers and then to outputs. CNN utilizes convolutional and pooling layers to handle image-like data, so CNN is widely used in image recognition, object detection, and video detection [43]. Different from FNN which does not have cycles or loops in the network, RNN utilizes loops to recurrently feed the historical information to the current output, exhibiting temporal dynamic behaviors. RNN is proficient in handling time-series data, so is widely used in time series prediction, natural language processing, voice detection, and control [44].

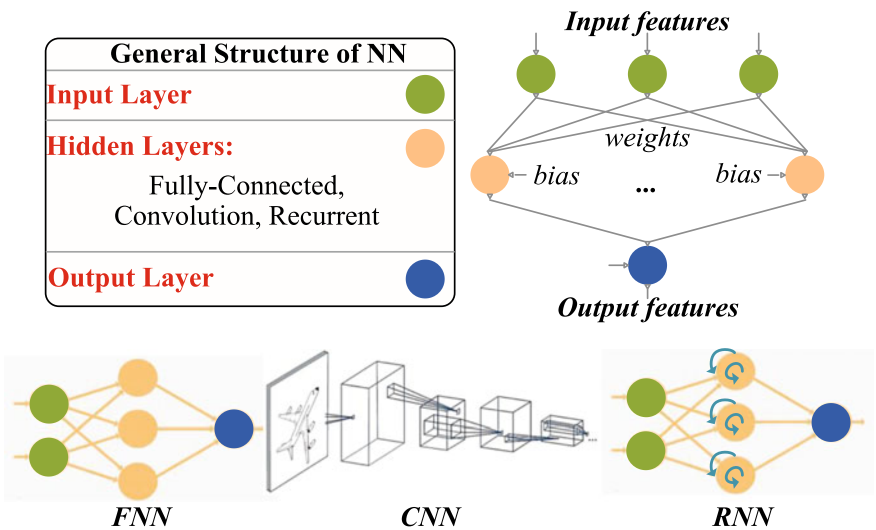

Fig. 1.3 General structure of NN and three types of commonly seen networks (FNN, CNN and RNN)

1.3.2 Evolutionary Algorithms

Evolutionary algorithms (EAs) are stochastic optimization techniques, which are derived from biological phenomenon or physical processes [45]. For example, genetic algorithm (GA) imitates the environmental selection in nature [46]. Particle swarm optimization (PSO) is derived from the social behaviors of bird flocks [47]. Ant colony optimization (ACO) simulates the information tracking behavior of ants to find the optimal solutions [48]. The key characteristics of EAs are that better individuals have larger chances of survival and reproduction, while worse individuals can still survive and reproduce, because of which the solutions can maintain good diversity while still can converge to optimum. Among the three EAs, PSO algorithm is suitable for continuous optimization, ACO specializes in solving discrete optimization problems, and GA performs the best in mixed-integer optimization [45].

According to the number of design objectives to be optimized, EAs are divided into single-objective and multi-objective algorithms [49]. The common steps of EAs shown in Fig. 1.4 are discussed as follows. Firstly, the hyperparameters and states of algorithms are initialized, and the fitness or objective functions of individuals are then evaluated. Subsequently, individuals will be selected to generate new solutions according to the values of fitness or objective functions, and better ones stand larger chance of survival. Afterwards, new solutions are compared to original ones and get updated. This process repeats until the stopping criterions have been met.

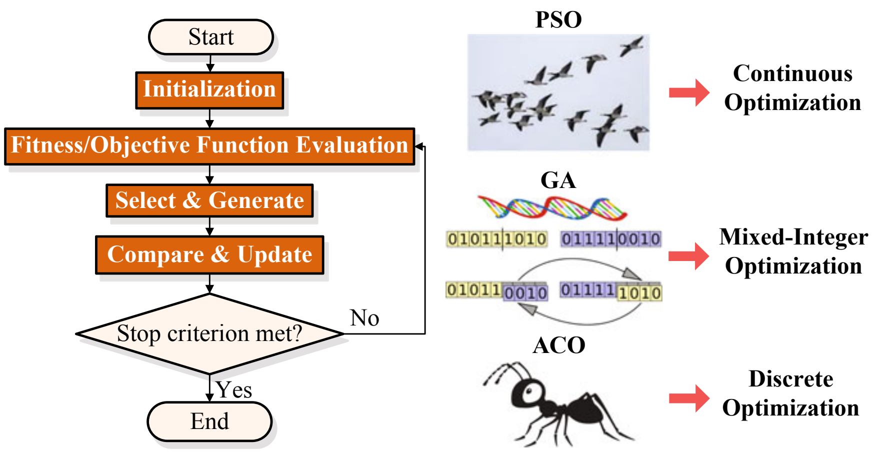

Fig. 1.4 Common process of EA and three popular algorithms (PSO, GA, ACO)

1.3.3 Fuzzy Inference System

Taking advantage of fuzzy set theory, fuzzy inference system (FIS) can properly interpret the ambiguity and fuzziness of real-world data. FIS transfers the usual crisp value (0 or 1) to a degree of truth (continuous between 0 and 1), which provides human-like logic that enables intermediate degrees other than true or false [50, 51]. According to the type of its output function, FIS is classified into Mamdani and Sugeno types [52], which are shown in Fig. 1.5.

The output function of Mamdani FIS belongs to fuzzy membership functions, and a typical Mamdani FIS contains four steps: fuzzification, fuzzy inference, fuzzy rules congregation and defuzzification. Fuzzification step computes the membership degree of input variables belonging to each fuzzy linguistic set. Fuzzy inference evaluates fuzzy rules. The results of all fuzzy rules are congregated and defuzzified to calculate the outputs. Mamdani FIS can be implemented in both multiple input and single output (MISO) system and multiple input and multiple output (MIMO) system [52]. Compared to Mamdani FIS whose outputs are fuzzy membership functions, Sugeno FIS has no fuzzy membership in its output, and it only utilizes crisp functions as the output functions. Sugeno FIS computes its final output through the mathematical combinations of crisp values and rule firing strength, which is different from the defuzzification step in Mamdani FIS. Sugeno FIS possesses more flexibility than Mamdani FIS, but it can only be used MISO system. If the fuzzy membership functions and rules of FIS are properly tuned, the whole system will successfully track desired behaviors (regression) or correctly classify the data (classification).

1.4 Applications of Artificial Intelligence Algorithms in DC-DC Converters and DC-AC Inverters

The briefly introduced neural networks, evolutionary algorithms and fuzzy inference systems have many fascinating advantages in mitigating the possible problems of conventional approaches. These algorithms have been widely applied in DC-DC converters and DC-AC inverters, as listed in Fig. 1.6.

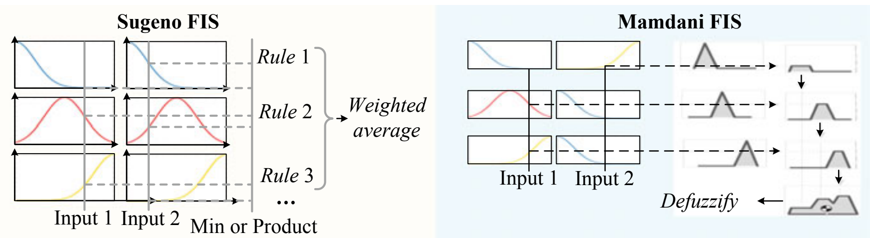

Fig. 1.5 Sugeno FIS and Mamdani FIS

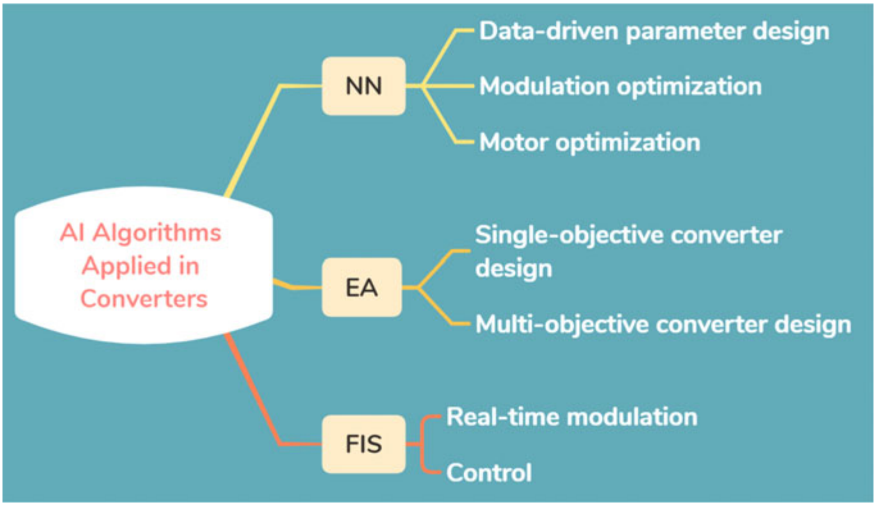

Fig. 1.6 Applications of NN, EA and FIS in DC-DC converters and DC-AC inverters

1.4.1 Applications of Neural Networks

NN has strong capability in memorization and generalization attributable to the adjustable weights, non-linear activation functions and extendible network structures. If sufficient performance data such as efficiency, current stress and reliability is provided, NN can be trained to automatically learn the underlying mathematical expressions, serving as accurate data-driven models to substitute time-consuming human-dependent performance analysis [53, 54]. Utilizing NN, the drawbacks of heavy manpower burden and inaccurate performance analysis in conventional human-dependent approaches can be largely relieved.

NN has been widely adopted in parameter design, modulation strategy optimization and motor optimization [53, 55, 56]. For instance, in [53], neural network (NN) is trained with simulation results to act as the surrogate model for component lifetime consumption for reliability-oriented parameter design. Moreover, in [55], extreme learning machine is adopted to replace traditional model deduction of ripple, harmonics and transient response of permanent magnetic synchronous linear motors to achieve optimal design of permanent magnetic motor. Kazmierkowski et al. [56] utilizes NN to realize adaptive selective harmonic elimination for cascaded multilevel inverters with varying DC sources. NN serves as the model predictive controller for modular multilevel DC-DC converters in [57]. In [58] with regards to SVM for voltage-fed inverter induction motor drive, neural network learns the switching time of reference vectors, reduces the required online computation and raises the frequency limit. In the fault diagnosis of multilevel modular converter, a convolutional neural network is used and achieves high accuracy, with a good noise tolerant ability [59].

1.4.2 Applications of Evolutionary Algorithms

From the descriptions in Sect. 1.2.2, conventional optimization techniques generally suffer from suboptimal design results and high computation problems. To alleviate the problems of conventional optimization techniques, EAs can be used. EAs are stochastic and meta-heuristic searching methods, the characteristics of which ensure their searching performance independent of gradient information and initial iteration points. With EAs, the globally optimal design can be reliably guaranteed with low computational burden [45]. As discussed in the configuration design of a three-phase wound core transformer [33], the better optimization results and faster speed of GA and differential evolution compared with deterministic optimization are shown. Another advantage of EAs is that they require no rigid mathematical deduction as deterministic optimizations, and the algorithms are easy for implementation.

Recently, EAs have been increasingly applied in the design of DC-DC converters and inverters. For instance, in [34], simulated annealing algorithm has been adopted to optimize the parameter values of DC-DC converter. Considering the infinite possible combinations of varying parameter values, PSO algorithm is adopted in [10] to achieve stability, acceptable efficiency and robust voltage conversion gain of DC-DC converter cascading with a Buck converter. In the series–parallel RLC filter automatic synthesis, GA is applied for the optimal filter topology design [60]. If multiple optimization objectives are considered simultaneously, the multi-objective evolutionary algorithms can be used. For example, the efficiency, reliability and cost of distributed maximum power point tracking converter [61] are optimized by non-dominated sorting genetic algorithm—II (NSGA-II). With the output LC filter as design parameters [62], holistic performance of DC-DC converter is realized via NSGA-II, with the simultaneous considerations of reliability, volume, and cut-off frequency. Furthermore, by tuning the frequency, current density, magnetic influx, transformer topology and material, and type of power switches, the weight, cost and power loss of isolated DC-DC converter are minimized altogether through NSGA-II [42].

1.4.3 Applications of Fuzzy Inference Systems

To solve the problems of high space and time complexity of conventional lookup-table-based approaches and formula-based approaches for real-time modulation, FIS can be utilized. Compared with the conventional online modulation approaches, the time and space complexity of FIS is independent of data size, and a carefully-tuned FIS always requires low storage size and has fast computation speed [63, 64]. Apart from its superior algorithm complexity, FIS has other appealing advantages such as easy implementation, good linguistic interpretability, and satisfactory generalization capability [51].

Being beneficial from all of its merits, FIS has been widely implemented in the real-time modulation for power converters. For instance, in the maximum power point tracking of the boost-converter-supplied PV system [8], the fuzzy inference controller, substituting the conventional PID controllers, manifests strong robustness against the fluctuations of parameters, loads, and supply voltage. In terms of SVM for a two-level inverter [65], adaptive network-based FIS has been used, which has realized smaller harmonic distortions than conventional formula-based SVM. Li has proposed a FIS-based modulation scheme for current-stress-minimized triple phase shift modulation for isolated DAB converter [66] under varying operating power and voltage. In [67], the network-based FIS approach offers extremely fast dynamic response with high accuracy, and effectively controls the injected power and maintains the stringent voltage, current, and frequency conditions. Saroha et al. [68] presents an adaptive network-based FIS controller for the unbalanced voltage compensation in a low-voltage microgrid with multiple voltage source converters.

1.5 Arrangement of This Book

Being inspired by the outstanding performance of AI algorithms, this book aims at exploring the applications of AI algorithms in the design and modulation of DC-DC converters and DC-AC inverters. The rest of this book is organized as follows. In Chap. 2, to overcome the under-optimization problem and promote the performance of the emerging double-sided cooling power module, a multi-objective design methodology considering thermal and mechanical performance is proposed. In Chap. 3, a novel coevolving archived-based multi-objective algorithm is proposed, based on which the output LC filter in Buck converter can be flexibly designed to meet requirements in various applications while maintaining outstanding comprehensive performance. Chapter 4 introduces an artificial-intelligence-based design approach for the circuit parameters of power converters, which utilizes the integration of simulation, NN and EA to realize a high-level automation in performance analysis and optimization. Aiming at the optimization of the total power loss in the LCLC resonant converter for the space travelling-wave tube amplifier applications, an efficiency-oriented two-stage optimal design methodology has been proposed. In Chap. 5, for hybrid AC/DC microgrid applications, an AI-based (GA + PSO) two-stage optimal design methodology for high-efficiency CLLC resonant converters has been proposed. Chapter 6 proposed an AI system to minimize the current stress of DAB converter under triple phase shift modulation, in which simulation and NN are integrated to realize data-driven current stress analysis, PSO algorithm is used to search for optimal modulation parameters, and FIS is applied online for satisfactory real-time modulation. In Chap. 7, a systemic co-design methodology is proposed for the overall optimization of the air-cooling SiC inverter from the perspectives of thermal, electrical and mechanical performance. In the end, the conclusion is summarized in Chap. 8.

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