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RESEARCH ARTICLE

Optimization of the Black-Box Arc Models for DC Current Limiting Circuit Breakers Using Levenberg-Marquardt Algorithm

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ABSTRACT The black-box arc model is a tool that facilitates efficient research based on empirical studies in breaker design and analysis. However, its application has primarily focused on the design of ACCBs, with only a few instances of its implementation in the design of low-voltage (LV) DC circuit breakers (DCCBs) using mechanical methods. In DCCBs with non-zero crossing characteristics, several factors need to be considered in the design process. Therefore, it is crucial to have a reliable and accurate DC arc model to effectively apply black-box arc model studies to actual DCCB designs. Especially, DC Current limiting circuit breaker (CLCB), which has fast operation characteristics through its own over current relays (OCR), requires reliable and accurate modeling because minor factors in the topology can contribute significantly to the interrupting performance. This paper presents a study on the characterization and modeling approach for the DC CLCB, which exhibits somewhat different arc voltage characteristics compared to the general Air Circuit Breaker (ACB). The black-box arc model incorporates existing schwarz and kema arc models, and the Levenberg-Marquardt Algorithm (LMA) is employed to optimize the parameters of each model. An efficient parameter optimization method for the CLCB model is proposed, and the characteristics of factors that should be considered in the design are identified. Consequently, the applicability and reliability of the model are verified through a comparative study with the short-circuit test results of the actual DC CLCB.

INDEX TERMS LVDC CLCB, dc arc modeling, black-box arc model, Levenberg-Marquardt algorithm (LMA), parameter optimization.

I. INTRODUCTION

A key characteristic of DC arcs that distinguishes them from AC arcs is the absence of a current zero point. This non-zero crossing feature results in the generation of large breaking energy. Therefore, DCCB employ various topologies and interrupting methods for each voltage class [1], [2], [3], [4], [5], instead of relying solely on mechanical methods to interrupt fault currents. Typically, LV DCCB with small breaking energy use mechanical breakers with the same mechanism as ACCB [6]. While LVDC and ACCBs may share similar structures and mechanisms, the design considerations are distinct and require adaptation and modification to account for DC arc characteristics. For ACCB, the mechanical force and TRV (Transient Recovery Voltage) generated by the asymmetric fault current peak are crucial factors. In contrast, DCCB need to consider a wider range of factors, including mechanical force, fault current rise rate and peak value, as well as TIV (Transient Interruption Voltage) rise rate and size, which can swiftly reduce the fault current [7], [8]. These factors should also be incorporated into the simulation study of the CB. It is essential to conduct the simulation study with realistic arc

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characteristics to ensure effective and efficient application in the actual design.

With the development of various FEM (Finite Element Method) and transient analysis simulation software, many CB researchers and manufacturers are actively conducting arc description simulation studies for effective and reliable CB design. Four main arc simulation techniques are being utilized: physical modeling, black-box modeling, arc resistance calculation, and graphics and diagrams. Physical modeling is a method that describes the physical phenomena of thermal, mechanical, electromagnetic, and fluid arcs using FEM technology [9], [10]. It has the advantage of providing the most realistic representation of arcs. However, there are many difficulties in terms of the reliability and accuracy of analysis.

The black-box modeling and arc resistance calculation method models the arc as a flowing conductor and simply analyzes the current-voltage interaction between the arc and the power system. It is a tool that can verify and analyze the requirements of the CB based on the interaction with the power system when the CB is applied to the grid [11].

Black-box modeling is a method that formulates the arc as a first-order differential equation based on the conductivity and represents the arc based on actual CB performance and data. Therefore, it focuses on the results (voltage/current characteristics) rather than the interrupting process. The ultimate purpose is to predict the behavior of the CB arc in various situations in the power system. The Cassie and Mayr models have been developed [12], [13], and various derived models have been applied. When utilizing each model to describe the CB arc, the value of each lumped parameter should be selected to be as close to the actual arc as possible.

When performing a CB arc description simulation using a black-box arc model, it is crucial to model the values of the lumped parameters that determine the voltage/current waveform of the arc as closely as possible to the actual CB data. This process requires the utilization of a function optimization technique to ensure the reliability and acceptance of the results. Therefore, various methods can be employed to enhance the accuracy of the lumped parameters in the arc model [14]. Functional optimization techniques are evaluated as tools for accurately and reliably finding the optimal solution of arbitrary functions, and they are applied in various fields. the Levenberg-Marquardt Algorithm is the most used method for function optimization to find the optimal solution. The accuracy of the results obtained using this algorithm is also considered reliable [15], [16].

The black-box arc model was originally developed to describe AC arcs, and research has been conducted in various areas where arcs can occur. These include the AC CLCB [17], free air burning arc [18], [19], ACB [20], SF_6 CB [21], [22], research on modifying and developing existing black-box models [23], research on developing new arc models [24], and research on optimizing black-box model parameters [14].

With the recent surge of interest in DC systems, several studies utilizing black-box arc models have been conducted in the DC environment. It has been applied to various fields such as DC arc faults study [25], LV DCCB [26], [27], arc modeling of vacuum interrupters located in the main path of HVDC resonance type breakers [28], and model parameter optimization study [27]. However, simulations to verify the applicability of the black-box arc model developed for conventional AC arc to DC arc description are still lacking, and further research is needed to develop reliable and accurate simulations. In particular, DC arcs without current zero have very different interrupting characteristics depending on the time of the breaker operation, and CLCBs have very fast operation characteristics due to the built-in OCR. Therefore, when performing arc modeling using the black-box arc model, a different modeling approach from the general DC ACB model should be considered.

In this paper, a verification study was conducted to assess the applicability of the black-box model for reliable and accurate arc modeling of LV mechanical DC CLCBs. The study utilized the interrupting data and voltage/current waveforms obtained from actual CLCBs. The selection process and validity of each free parameter in the black-box model were analyzed, and a mathematical model of the applied arc model was created to optimize the selected parameters. The mathematical model was implemented in the LMA designed with MATLAB code to enhance the reliability and accuracy of the free parameters by applying a function optimization technique that compares the actual data with the model values. Furthermore, the verification simulation of the Schwarz model and the KEMA model, which are among the most applied black-box models, was conducted and compared. The simulation results demonstrated that both models exhibited good data fitting results when compared to the actual breaker's data. However, there were certain limitations in terms of accurately describing the arc voltage. Consequently, a method for applying the existing black-box arc model to LV DCCB arcing was presented, and the applicability and reliability of the model were confirmed through a comparative study with the short-circuit test results of the actual DC CLCB.

A. COMPARISON OF THE EXISTING LITERATURE ON PARAMETER ESTIMATION

We surveyed various references on parameter estimation of the black box arc model, analyzed the characteristics of the parameter estimation techniques used in each reference, and conducted a comparative analysis with the LMA applied in this paper. In addition, as artificial intelligence (AI) has recently received a lot of attention in various fields, we analyzed the applicability of the neural network concept to the black box arc model.

1) SIMPLEX METHOD FOR FUNCTION MINIMIZATION [35]

In this reference, a new type of arc model of SF_6 CB that is applied to AC was created and parameter optimization was performed. The optimization technique was based on the simplex method as described in reference [36]. Since this method is mainly used to solve linear programming problems where the objective function and constraints are linearly related, this paper proposed a black box arc model for each critical element where the objective function and parameters are linearly related. To briefly explain the optimization principle, the Simplex Method starts with an initial feasible solution and iteratively moves along the edges (or ''simplexes'') of the feasible region to find an optimal solution. The main difference between the LMA and the Simplex Method is that the Simplex Method is suitable for linear programming problems, while the LMA is ideal for curve fitting and nonlinear least squares optimization problems. The schwarz and kema arc models used in this paper are nonlinear least-squares optimization problems, which require the application of the LMA technique.

2) GENETIC ALGORITHMS (GA) [27]

A GA is a population-based metaheuristic optimization technique inspired by the processes of natural selection and evolution. Genetic algorithms can be used to find the best set of parameters for a given model or system. This is especially useful when the model contains complex interactions and has multiple parameters that affect its behavior. Instead of manually tuning these parameters, which can be time-consuming and impractical for complex models, genetic algorithms can be used to automate the process. Therefore, the choice between genetic algorithms and the Levenberg-Marquardt algorithm depends on the nature of the optimization problem and the nature of the objective function. Genetic algorithms are better suited for global optimization and handling complex multimodal environments, while the Levenberg-Marquardt algorithm is better suited for local optimization with smooth and continuous objective functions, especially in nonlinear least squares problems.

3) SYSTEM IDENTIFICATION THEORY [37]

System identification is a branch of research in engineering and control theory that focuses on building mathematical models of dynamic systems based on observed input and output data. These models can be used to predict the behavior of the system and perform various control and optimization tasks. In this reference, the identification toolbox in MATLAB was utilized to perform parameter optimization of a black box arc model, where the goal is to identify the unknown parameters of a system model using measured input and output data (real experimental data). This process involves finding the model parameter values that best match the observed system behavior. While system identification theory is a broad concept that includes the process of building a model from observed data, the LMA is a specific optimization technique used in the context of system identification to estimate the model parameters that best fit the observed data. The algorithm helps refine the parameters of the selected model structure to match the observed system behavior as closely as possible.

4) NEURAL NETWORKS [38], [39]

Refers to artificial neural networks, especially deep learning models, that are very complex and difficult for humans to interpret or understand how they derive at decisions. These networks are called ''black boxes'' because their inner workings are opaque and not easily explained, like a sealed black box that operates without revealing its internal mechanisms. In the sense of the word black box itself, it can be considered a similar concept to the black box arc model, with the difference that the object is a neural network and an arc. Neural networks have recently been applied in various fields, and they are mainly applied and studied to solve highly complex problems such as AI. Therefore, applying neural network theory to the research goal presented in this paper may not be feasible considering the complexity of the model, interpretability, and data requirements. However, it is possible to extend the research to construct optimization algorithms for a set of different types of CBs and to create a wide range of complex selection algorithms that can simultaneously determine the suitability of these breakers in an arbitrary power system.

II. METHODOLOGY

The evaluation of the applicability of black-box arc models, originally designed to model AC arcs, to accurately describe DC CLCB arcs was performed through simulations and related parameter optimization. The following steps were followed for this evaluation. While detailed descriptions of black-box arc models will be provided in the main text, the Schwarz and KEMA black-box arc models were utilized due to their popularity and recognized advantages in representing electric arcs.

A. PARAMETRIC SWEEP METHOD

As part of the process to derive the initial parameter values of the black-box arc model for reliable and accurate parameter optimization, simulations were conducted using the parametric sweep method, which is the most fundamental approach. The simulations yielded reliable results through a comparison between the actual LVDC CLCB interrupting data and the current and voltage waveforms.

1) Among the LVDC CLCB products commercially available and sold by utility provider in Korea, the voltage/current waveforms and data sheets of the products that underwent short-circuit tests were selected. The DC short-circuit test setup used by PT&T, a power testing laboratory of the company, served as a benchmark to model the DC short-circuit test setup for performing short-circuit simulations, based on the specifications of the selected products.
2) The black-box arc model employed the Schwarz and KEMA models, and assumptions were made to predict the range of free parameter values for each model to conduct parameter sweep simulations. The criteria for the free parameters of each model were established

based on various experimental facts and evidence. The parameter sweep values (Schwarz: τ, P, α, β; KEMA: τ_1, P_1, P_2, k_1, k_2, k_3) were selected using the established assumptions.

3) Perform short-circuit test simulations using a DC short-circuit test bed designed based on the selected parameter sweep values to derive parameter values for the black-box arc model.
4) From the results of the parameter sweep simulations, select the proper parameter values that best approximates the actual LV DCCB data and the voltage and current waveforms.
5) Utilize the model parameter values from the selected interrupting curve as the initial parameter values for the Levenberg-Marquardt Algorithm simulation, which aims to optimize the parameters.

B. PARAMETERS OPTIMIZATION

This process involves optimizing the parameter values of the black-box arc model derived in step 1) using the parametric sweep method, which is essential for obtaining accurate and reliable results in describing LVDC arcs using the black-box model.

1) The Levenberg-Marquardt Algorithm (LMA), which is widely used in function optimization techniques, was selected for parameter optimization.
2) To utilize the MATLAB code for LMA provided in reference [29], voltage/current equations applicable to the algorithm were established for each black-box arc model. These derived equations were then applied to the LMA code.
3) To optimize the free parameters of each black-box arc model, the interruption data obtained through the short line fault test of utility provider's actual DCCB, which served as the target for the parameter sweep simulation study in step 1), were inputted.
4) Perform the optimization of each parameter value for the Schwarz and KEMA arc models through LMA simulations.
5) Conduct a comparative analysis using the standard error, damping factor (λ) value, and residuals (R^2) between the actual interrupting voltage/current data and the optimized values.

Based on the methodology described above, the DC arc of the LVDC CLCB was described using the black-box arc model. The results of the two models were compared to verify the consistency between the simulations and the actual results. A comparative study was conducted to assess the advantages and disadvantages of each model, leading to the selection of a more suitable black-box model.

III. SIMULATION MODEL DESIGN

A. LVDC TEST BED

To match the simulation results with the actual CB test data, a schematic diagram of the short-circuit test circuit used by Korea utility provider was provided. The short-circuit test circuit is depicted in Fig. 1, and the circuit diagram consists of a short-circuit generator, making switch & back-up breaker, converter transformer, rectifier, primary circuit constant, and secondary circuit constant, respectively. Utilizing the provided schematic diagrams, a test bed model was designed to fulfill the following four requirements, as presented in the literature [30]:

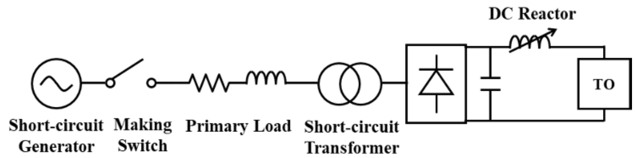

FIGURE 1. DC short-circuit Testbed model. By benchmarking the utility provider's 1.5 kV/100 kA specification short circuit test facility, the parameter values were selected to test the 1.5 kV/60 kA DCCB targeted in this paper.

TABLE 1. Specifications of DC short circuit test-bed model.

Items		Specifications
SCG rated voltage [kV]		18
SCG rated capacity [MVA]		85
SCG short-circuit capacity [MVA]		2000
Transformer ratio [kV]		18.0/1.732
Transformer connections		△/Y
Supply circuit	Resistance R [Ω]	1.067
	Reactance L [Ω]	0.1557
	Reactance L_{dc} [mH]	0.35

1) The DC test bed should be capable of generating high di/dt.
2) It should possess sufficient energy storage capacity.
3) The CB must endure continuous nominal voltage stress during all interrupting phases.

1) The DC voltage withstand capability of the CB must be verified after the interruption.

The maximum specification of the provided short-circuit test circuit model is 1600 V / 100 kA. The parameters of each component of the short-circuit test circuit for the actual LV DC CLCB (1.5 kV/60 kA) test, which was utilized in this paper, were calculated, and selected. Additionally, the DC side time constant of the circuit was measured to be 15 ms.

1) DC SHORT-CIRCUIT GENERATOR

The specifications of the short-circuit generator is shown in Table 1. Based on the provided specifications, the synchronous generator model in Matlab/simulink was used to design a short-circuit generator with the same specifications.

2) MAKING SWITCH & BACK-UP BREAKER

The making switch determines the timing of the voltage/current input to the short-circuit test circuit. In AC short-circuit test circuits, the timing of each phase is crucial for the short-circuit specifications. However, in the case of DC short-circuit test circuits, the making switch simply determines the input timing as the current is rectified by a rectifier. A back-up breaker serves as a safety mechanism for energy dissipation in the event of a sudden circuit accident, failure of the breaker to trip, or successful trip of the breaker. In this paper, the short-circuit test was conducted by operating the two circuit switches in the same sequence as the actual test.

3) LUMPED PARAMETERS OF CIRCUIT IMPEDANCE

The circuit constants of the short-circuit test circuit can be categorized into the primary side (AC side) and the secondary side (DC side) based on the rectifier. Firstly, the primary circuit constant is an integer that determines the DC voltage and current specifications of the secondary side, and it can be selected according to the generator and transformer specifications of the primary side.

The secondary circuit constant comprises an inductor that determines the rate of rise of the DC short-circuit current (di/dt). This can be obtained by conducting a simple transient analysis of the series RL circuit. The di/dt represents the interval immediately after the fault occurs, until the breaker voltage equals or exceeds the system voltage, and the fault current and arc voltage continue to rise. This interval determines the di/dt, and the component values that satisfy requirement 1) mentioned earlier can be derived.

The simulated fault current in the test bed can be calculated using the following Eq. (1).

$$V_{dc} - L\frac{di}{dt} - Ri = 0 \tag{1}$$

i is the fault current, V_{dc} is the DC source, and R is the resistance to the fault point when the fault occurs. Based on circuit theory, if the initial steady-state load current is assumed to be I_N in Eq. (2), the following equation Eq. (2) can be derived.

$$i(t) = \frac{V_{dc}}{R}(1 - e^{\frac{-t}{\tau}}) + I_N e^{\frac{-t}{\tau}} \tag{2}$$

In this case, $\tau = L/R$, which is the time constant of the circuit. From Eq. (2), the fault current value converges to V_{dc}/R as time passes, and there is no interrupting in this section. Based on the mathematical model derived from this section, the inductance and resistance values of the secondary side of the short-circuit test circuit were derived. The parameter values of each component and circuit constant are shown in the following Table 1.

B. LOW-VOLTAGE DC CIRCUIT BREAKER MODEL

To verify the accuracy and reliability of the black-box arc model's description of the DC arc, it is important to identify the characteristics of the CB that needs to be modeled and assess how effectively the black-box model, which consists of first-order differential equations based on arc conductivity, can describe the arc in LV DCCBs. Therefore, the DC arc modeling process of the black-box arc model is presented as follows. Firstly, the general characteristics and behavior of LV DC arcs are described to identify the specific characteristics of the LV DC arcs that need to be modeled. Secondly, the purpose and definition of the black-box arc model, along with the principles of arc description characteristics, are explained. The feasibility of the black-box arc model in describing the DC arc is analyzed and presented. Thirdly, the detailed characteristics of the Schwarz and the Kema arc model are described, and the reasons for selecting these two models as tools for LV DC arc description are explained. The fourth section describes the process of selecting the parametric sweep values for each model, which serve as the initial values for the optimization technique. Lastly, for the purpose of comparing the results of the DC applicability verification simulation, the specifications, and voltage/current waveforms of an actual DC CLCB (based on the breaker models used in this simulation) are presented.

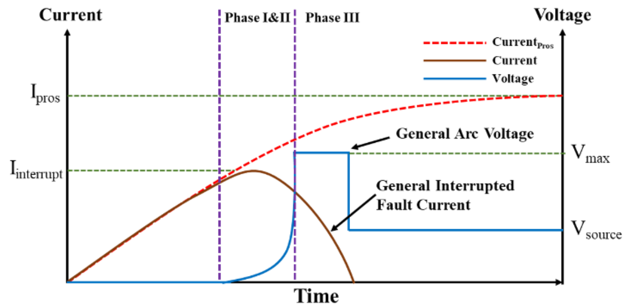

FIGURE 2. Typical waveform of LV DC arc. According to the behavior of the arc in the mechanical DCCB, it is divided into three phases: 1) arc ignition and commutation, 2) arc motion, and 3) arc splitting [6].

1) CHARACTERISTICS OF LV DC ARC

As mentioned in the introduction, low-voltage DC breakers utilize mechanical mechanisms similar to AC breakers for interrupting fault currents. However, the interruption process and sequence for DC, without current zero, are significantly different. Therefore, it is crucial to analyze and understand the characteristics of LVDC arcs thoroughly to accurately and reliably model arc depiction using the black-box arc model. For successful depiction of the LVDC arc using the black-box arc model, it is necessary to satisfy the typical waveform of the LVDC arc shown in Fig. 2. To simplify the interrupting sequence of an LV mechanical DCCB (direct current circuit breaker), the arc generated between the breaker contacts is directed into an arc splitting chamber where it is dispersed and cooled, leading to an increase in arc resistance. As the arc resistance rises, a reverse voltage is generated in the breaker. When this voltage equals or exceeds the grid voltage, the fault current is interrupted.

In reference [6], the arc behavior of this LV mechanical DCCB is analyzed, and the interrupting phase is divided into three stages by studying the arc motion from the time the arc occurs inside the breaker until it is extinguished. The first stage is the arc ignition and commutation stage, where the arc generated at the contact is commuted to the arc runner. The second stage is the arc motion phase, during which the arc moves along the arc runner towards the splitting plate. The third stage is the arc-splitting stage, where the arc is cooled by the splitting plate, causing the arc resistance to rise. As a result, the fault current decreases rapidly, and the arc voltage spikes. While the details of each stage may vary among different mechanical DC breakers, it can be observed that they all go through similar stages to extinguish the arc. The short circuit test results of the actual breaker used in this paper exhibit similar characteristics. Therefore, it is highly important to characterize DC arcs for black-box arc modeling based on actual breaker data.

2) APPLICATION OF BLACK BOX ARC MODEL FOR LVDC ARC

The black-box arc model is a first-order differential equation based on arc conductivity and can be considered as an approximate model derived from experimental results [11]. The black-box arc model has the advantage of representing complex arcing phenomena in a straightforward manner. The simplicity of the calculation process makes it a valuable tool for describing the interaction between the switching arc of a circuit breaker and its power system. The ultimate objective is to establish a specific mathematical model using a black-box model, leveraging voltage and current traces obtained from actual circuit breaker tests. This model can then be used to predict the arcing behavior of the breaker under different circuit conditions. Various derivative models, including the basic models like CASSIE and MAYR, are derived from the first-order differential equation presented in the following Eq. (3).

$$\frac{1}{g}\cdot\frac{dg}{dt}=\frac{1}{T(i,G)}\cdot\frac{ui}{P(i,G)}-1 \tag{3}$$

where:

G: Arc Conductance
u: Arc voltage
i: Arc current
P, T: Black-box model parameters

The differential equation satisfies the law of conservation of energy. As seen from the equation above, the black-box arc model includes parameters represented by P and τ. Since the objective is to provide a simple representation of a complex arc, the various arc phenomena are described by the variables P and τ. P represents the cooling power, which describes the rate at which energy is dissipated from the arc into the surrounding gas or vapor. This cooling effect can occur through mechanisms like heat conduction, radiation, or convective cooling. Cooling power is a crucial parameter in black-box arc models as it influences arc behavior, including arc length, temperature, and ionization level.

τ, on the other hand, represents the arc time constant, which characterizes the response time of an electric arc to changes in arc current or voltage. It can be defined as the time required for the arc voltage to change by a factor of 1/e (approximately 0.37) in response to a step change in current. The arc time constant depends on arc characteristics such as length, temperature, and the gas or vapor surrounding the arc. In general, shorter arcs, higher temperatures, and more ionized gas or vapor result in lower arc time constants. The arc design procedure utilizing the black-box arc model is presented in Fig. 3 and is entirely based on real-world data.

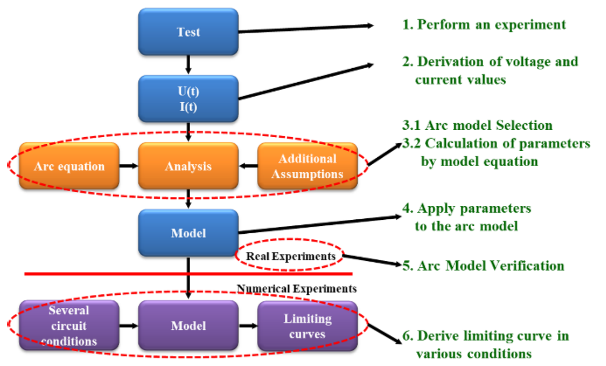

FIGURE 3. Overall application procedure of Black-box arc model to LVDC arc design. Black box arc model can be designed based on actual experimental results, and a suitable model and reliable parameter selection process are very important.

3) SCHWARZ ARC MODEL

In this paper, an LVDC arc applicability verification study is conducted using two existing black-box models. The first model under investigation is the Schwarz model. The DC arc applicability verification study of the Schwarz model has been previously conducted in the existing literature [26]. This study aimed to examine the behavior of LVDC arc description for each free parameter through the parametric sweep method, and it has been found that the Schwarz model possesses sufficient capability to represent the LVDC arc. Among various derivatives of the black-box arc model, the Schwarz arc model stands as the most widely used model [31]. It offers the advantage of effectively representing both the large and small current sections of the arc and can be expressed by the following Eq. (4). The Schwarz arc model involves a total of four free parameters (τ, P, α, β), allowing for the selection of appropriate parameter values to describe the arc. For implementation, the Schwarz arc model utilizes the blockset [32] provided by Delft University of Technology and is applied to the power system using the Differential Equation Editor (DEE) tool in Matlab/Simulink. The model incorporates two inputs (arc voltage, CB_trip), four free parameters, and an initial value for the arc conductivity.

$$\frac{1}{g}\cdot\frac{dg}{dt}=\frac{1}{\tau_0 g^{\alpha}}\cdot(\frac{gu^2}{P_0 g^{\beta}}-1) \tag{4}$$

where:

τ_0: Arc time constant
α: Exponential components of conductance of $\tau(g)$
P_0: Cooling power
β: Exponential components of conductance of $P(g)$

4) KEMA ARC MODEL

The second model selected is the KEMA arc model. The reason for selecting this model is that, as mentioned in the previous section on LVDC arc characteristics, the arc of LV DCCB is extinguished in a total of three stages. Therefore, it was determined that the entire arc extinguishing process would be better described by utilizing an expression that consists of three first-order differential equations, such as the Kema arc model, instead of a single arc conductivity, where the electric arc generated during the entire interrupting process is divided into sections and the total arc conductivity is calculated as the sum of the arc conductivity of each section. The Kema arc model can be expressed as Eq. (5)-(9), which consists of 6 parameters (3 free parameters, 3 constant CB parameters).

$$\frac{dg_1}{dt} = \frac{1}{\tau_1 P_1} g_1^{\lambda_1} u_1^2 - \frac{1}{\tau_1} g_1 \tag{5}$$

$$\frac{dg_2}{dt} = \frac{1}{\tau_2 P_2} g_2^{\lambda_2} u_2^2 - \frac{1}{\tau_2} g_2 \tag{6}$$

$$\frac{dg_3}{dt} = \frac{1}{\tau_3 P_3} g_3^{\lambda_3} u_3^2 - \frac{1}{\tau_3} g_3 \tag{7}$$

$$\frac{1}{g} = \frac{1}{g_1} + \frac{1}{g_2} + \frac{1}{g_3} \tag{8}$$

$$u = u_1 + u_2 + u_3 \tag{9}$$

Same as the Schwarz model, the Kema model also utilizes the blockset developed by Delft University of Technology. The Kema model consists of a total of 8 inputs, each of which is determined based on the above equations of the Kema arc model. These inputs represent the conductivity applied to the power grid circuit. Apart from the three free parameters, which can be adjusted according to the simulation requirements, the Kema arc model includes three constant CB parameters. These constant parameters are associated with the actual design parameters of the breaker and remain unchanged throughout all simulations. The values of k_1, k_2, and k_3 can be defined using the following Eq. (10). The constant CB parameters are derived by combining cooling power and arc time constant values for each interval, and their selection is performed randomly based on the actual interrupting graph of the DC CLCB.

$$k_1 = \frac{\tau_1}{\tau_2},\ k_2 = \frac{\tau_2}{\tau_3},\ k_3 = \frac{P_2}{P_3} \tag{10}$$

5) THE SELECTION OF PARAMETER SWEEPS VALUES

To achieve fast and accurate results using the parameter sweep method, it is crucial to appropriately select the parameter sweep values. Generally, the selection of parameter sweep values should be based on identifying the characteristics of each applied model and conducting a precise analysis of the behavior and characteristics of the individual free parameters. The characteristics of the Schwarz model parameters can be found in the previous study [26]. The parameters τ and α determine the peak current and interrupting time of the arc, while the cooling parameter P determines the peak voltage value, and the parameter β determines the rise rate of voltage. For the Schwarz model, the sweep values for each free parameter are selected based on the simple following assumptions:

1) τ: In general, τ is set to 0.8 ms or lower, considering the arc time constant in the air insulation of DC condition.
2) α, β: α and β represent variables that contribute to the arc time constant equation in the Schwarz model, and their values are chosen between 0 and 2, relying on general simulation experience and references.
3) P: The selection of P is determined by considering the voltage and current waveforms of the actual interrupting curve. In the Schwarz model, the cooling power (P) is chosen to be 10 MW or lower, considering the parameter β that needs to be considered.

TABLE 2. Parameter sweep values of schwarz & kema arc model.

Model	Parameter	Sweep value
Schwarz	τ [ms]	0.36, 0.38, 0.4, 0.42, 0.44
	P [MW]	6, 6.5, 7, 7.5, 8
	α	0.1, 0.11, 0.12, 0.13, 0.14
	β	0.7, 0.75, 0.8, 0.85, 0.9
Kema	τ_1 [ms]	0.5, 0.55, 0.6, 0.65, 0.7
	P_1 [MW]	9, 10, 11, 12, 13
	P_2 [MW]	1, 1.5, 2, 2.5, 3

Next, the sweep values for the three free parameters of the Kema arc model and the three k factors were determined based on the following assumptions, considering the three-step interrupting process of the DC breaker:

1) τ_1: Similar to the Schwarz model, τ_1 was set to 0.8 ms or lower to account for air insulation.
2) P_1: Considering the three stages of the DCCB, the cooling power of the first and second stages of the CLCB is very high, so it was set to 10 MW or higher.
3) P_2: P_2 was selected as 1.5 MW based on the black-box arc model study of DC HSCB [27].
4) k_1: This parameter represents the relationship between the arc time constant of phase 1 and phase 2, and it was chosen as 0.25 considering the very fast initial voltage rise speed of DC CLCB.
5) k_2: This parameter represents the relationship between the arc time constant of phase 2 and phase 3, and it was selected as 0.8 to reflect the characteristic that the arc voltage quickly reaches the peak value and remains at a similar level until it is interrupt.
6) k_3: Due to the arc characteristics of the DCCB, a significant amount of arc energy is dissipated at the moment of interrupting, and k_3 was chosen as 0.33 to reflect this characteristic.

For the Kema arc model, the reference design value of the k factor for the DC CLCB was not determined, so it was arbitrarily selected based on the results obtained during the parametric sweep simulation. The values shown in Table 2 represent the closest values to the selected ones among the performed parametric sweeps.

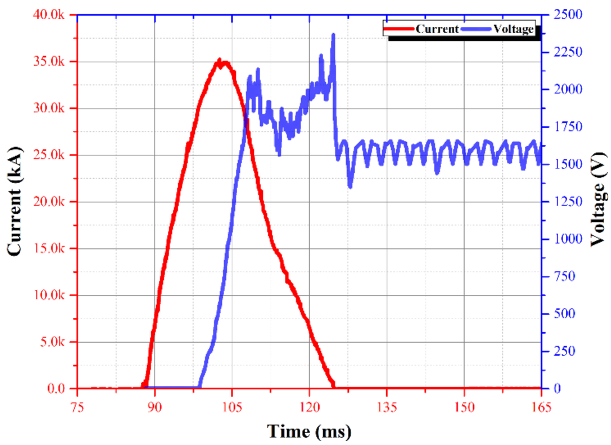

FIGURE 4. Current and Voltage waveform of actual DC CLCB. Actual interrupting waveform of a 1.5 kV/4kA/60 kA DC CLCB, showing the interruption at 35 kA peak with fast operation due to internal self OCR.

6) ACTUAL LOW-VOLTAGE DC CIRCUIT BREAKER

The arc modeling simulation conducted in this paper was based on the short-circuit test results of actual breaker products, utilizing the breaker short-circuit test experimental results and data provided by Korea utility provider, a domestic heavy electrical equipment company. The specific breaker used for the test is an LV DC CLCB rated at 1.5 kV / 4 kA. This product has the advantage of a faster interrupting speed compared to general ACB (Air Circuit Breaker) and is capable of interrupting fault currents of up to 60 kA. The voltage and current results obtained from the short-circuit test of the actual breaker are depicted in Fig. 4. The waveform represents the system where a short-circuit current is applied while the breaker is engaged, and the fault current is detected by the relay integrated within the breaker itself.

C. FUNCTION OPTIMIZATION TECHNIQUE

Functional optimization techniques are used in many fields, such as imaging technology, video identification, and control, leading to the utilization of various methods. Multiple function optimization techniques and artificial intelligence algorithms (AI) have been employed to optimize the parameters of the black-box arc model [14], [27]. In general, the least-squares method is the technique used to optimize the function of observations and model values. Simply put, it can be explained as a method to determine the parameter values of the model such that the sum of the squared errors of the residuals between the observed and model values is minimized. This is demonstrated in the following Eq. (11)

$$\sum_{i=1}^{n} r_i^2 = \sum_{i=1}^{n} (yi - f(xi))^2 \tag{11}$$

The least squares methods can be categorized into linear and nonlinear techniques based on the nature of the relationship between the model and the parameter values. In the case of the black-box arc model utilized in this paper, it is evident that the relationship between the model and the parameters is nonlinear. Consequently, for parameter optimization to

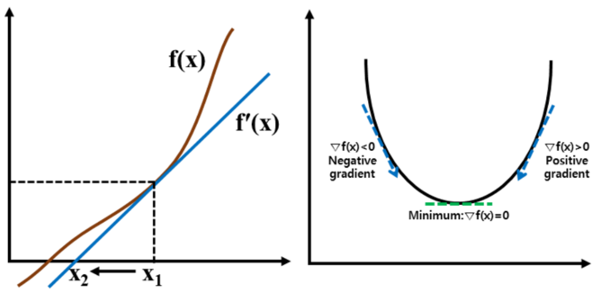

FIGURE 5. The principle of GNM (right) and GDM (left). GNM has the disadvantage of not producing an accurate solution when the initial value is far from the solution, while GDM takes longer as the solution gets closer.

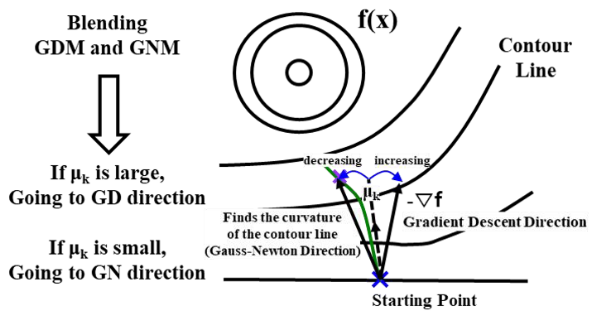

FIGURE 6. Overview of LMA principle. Combining GDM and GNM.

approximate the actual observations and model values [29], a nonlinear least-squares method should be employed.

1) PURPOSE OF THE FUNCTION OPTIMIZATION TECHNIQUE

The black-box arc model comprises a first-order differential equation based on the conductivity, as mentioned earlier. It reflects the arc current and voltage characteristics through the free parameters of the model. By complying with the law of energy conservation, which states that the generated arc energy and dissipated arc energy are conserved, the conductivity of the arc can be adjusted by modifying the parameter values of cooling power and arc time constant. Increasing the cooling power and reducing the arc time constant leads to a faster decrease in conductivity, resulting in the dissipation of the arc. Consequently, parameter values of the black-box model can effectively describe the occurrence of DC arcs. Therefore, parameter optimization must be performed for black-box arc modeling. There are several methods available for function optimization, but in this paper, the LMA, which is a well-known approach for solving nonlinear least-squares problems, is employed to tackle the parameter optimization problem of the black-box arc model where the relationship between the parameters and the model is nonlinear. In addition, LMA is particularly specialized for solving local optimization problems and are well suited for problems where the objective function is relatively smooth and there are no multiple global optima, such as the BB model.

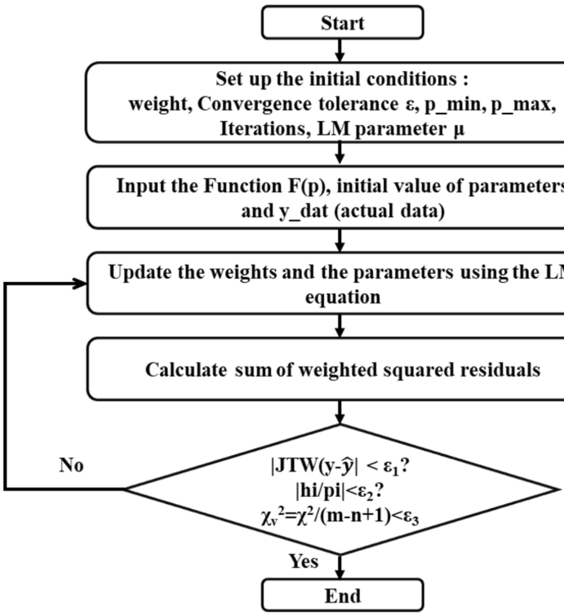

FIGURE 7. Application procedure of LMA to LV dc arc parameter optimization. Based on the initial parameter value selected based on the parametric sweep method, the LM parameter μ is updated every iteration to derive the optimal solution.

2) LEVENBERG-MARQUARDT ALGORITHM (LMA)

As mentioned earlier, the Levenberg-Marquardt Algorithm (LMA) is the most widely employed method in non-linear function optimization techniques. It combines the Gauss-Newton method (GNM) and the Gradient Descent method (GDM), leveraging their respective strengths and compensating for their shortcomings. The principles of these two methods can be easily understood by referring to Fig. 5.

In essence, LMA acts as a gradient descent method when the solution is far away, and as it approaches the solution, it switches to the Gauss-Newton method to refine the solution and an overview is shown in Fig. 6. As shown in the figure, the LMA starts from an arbitrary starting point and iteratively optimizes a function f(x) to find its solution. The GDM finds the solution in the direction perpendicular to the contour line of f(x), while the GNM finds the curvature of the contour line and derives the solution by finding a point on the curvature. Since the LMA parameter μ_k changes with each iteration, the GDM method is more effective at finding the solution quickly when the solution is far from the objective function, while the GNM method is more effective when the solution is close to the objective function since the slope of the contour line is close to zero and GDM takes longer to derive the solution. In summary, GDM exhibits the drawback of slower convergence speed when it is close to the solution, while GNM may fail to find a solution when it is far from the actual solution. Therefore, it determines the proximity between the calculated value and the target value and increases the LM parameter μ_k if the proximity increases, and decreases μ_k if the proximity decreases, and performs function optimization.

The expressions for these three methods are as follows:

$$P_{k+1} = P_k - 2\lambda_k J_r^T(p_k)r(p_k), \ k \geq 0 \tag{12}$$

$$P_{k+1} = P_k - (J_r^T J_r)^{-1} J_r^T r(p_k), \ k \geq 0 \tag{13}$$

$$P_{k+1} = P_k - (J_r^T J_r + \mu_k diag(J_r^T J_r))^{-1} J_r^T r(p_k), \ k \geq 0 \tag{14}$$

The observations can be denoted as (x_i, y_i), the model parameters as $p = (p_1, p_2, \ldots, p_m)$, the model as $y=f(x,p)$, and the residual as $r_i(p) = y_i\text{-}f(x_i,p)$. Additionally, J_r represents $J_r(P_k)$, which indicates the value of the Jacobian matrix of $r_i(p)$ at P_k. The GNM, GDM, and LMA relationships can be more easily understood by utilizing the above equation, which is explained in more detail below. First, equation (12) represents the GDM method. GDM is a method that finds the solution (the singular point that minimizes the error function) by moving in the opposite direction relative to the gradient λ_k, but with a step size proportional to the size of the gradient. The GNM, on the other hand, considers both the gradient and the curvature of the function to find the solution (in the expression, $J_r^T J_r$ stands for the Hessian of the quadratic derivative and represents the curvature of the function). In other words, it determines the step size to move as (the magnitude of the gradient)/(the magnitude of the curvature), so even if the gradient is large, if the curvature is large (if the gradient changes rapidly), it moves a little, and if the curvature is small (if the gradient changes little), it moves a little more to find the minima. Therefore, the GNM has the advantage of finding the solution much more accurately and quickly than GDM. However, that method requires the calculation of the inverse matrix of ($J_r^T J_r$). Therefore, if ($J_r^T J_r$) is close to a singular matrix (a matrix whose inverse does not exist), the computed inverse may be numerically unstable, causing the solution to diverge. Comparing the GNM with the (LMA) in this Eq. (14), LMA is an improvement over GNM by introducing a constant multiple u_k of the identity matrix to $J_r^T J_r$. This addition reduces the risk of divergence and enhances the stability of the solution. The constant u_k is referred to as the damping factor, which behaves similarly to GNM when it is small and akin to the gradient descent method when it is large. From the formula, if $\mu \rightarrow \infty$, $(J_r^T J_r + \mu_k)^{-1} \rightarrow 1/\mu_k$, so as μ gets larger, the LMA becomes similar to the GDM with a step size of $1/\mu$. However, in LMA, the damping factor u_k is not a fixed value but varies at each iteration. It takes on a small value if the present value is converging steadily (GNM) and a large value if the solution is not being found effectively (GDM). Depending on the method of calculating this damping factor, LMA can be implemented in different ways. Detailed descriptions of these models can be found in various references [33], [34].

Consequently, this paper focuses on optimizing the parameter values of the black-box arc model using LMA. The implementation of LMA was carried out using the Matlab code provided in reference [29]. Utilizing this tool, the optimization of each model parameter was performed by repeating the procedure depicted in Fig. 7. Following the procedure shown in that figure, the initial values of the parameters required to activate the LMA were first determined, and the objective function F(p), which was derived by analyzing the DEE of the black-box arc model in the next chapter, was inserted into the matlab code. The initial values of each black-box arc model parameter were entered as the values derived using the parametric sweep method. Then, according to the LMA logic structure, the parameter optimization was performed by repeating the procedure until the value of the calculated residuals was below the value of ε (convergence tolerance). The meaning and values of each initial parameter are as follows. Weight represents the inverse of the standard measurement errors (*1/(y_dat′·y_dat)*), ε is the convergence tolerance (ε_1 (for gradient) = $1e^{-3}$, ε_2 (for parameters) = $1e^{-3}$, ε_3 (for residuals) = $1e^{-1}$, ε_4 (for L-M step) = $1e^{-1}$), P_min and P_max (according to initial value of input parameters) are the max and min values of the calculated parameter values, respectively, the number of iterations (10· number of parameters), and μ_k is the LM parameter ($1e^{-2}$). In this paper, starting from the initial value of the L-M parameter, the error between the actual data value and the calculated value is compared with ε_4, and if the error is in the direction of increasing, the L-M parameter is increased to find the solution in the GDM method, and if it is in the direction of decreasing, it is divided by the reduction factor to approach the GNM method.

3) ANALYSIS OF DEE FOR SCHWARZ BLACK-BOX ARC MODEL

To compare the results of each model with the actual data, it is necessary to create separate model equations. Thus, an analysis was conducted on the algorithm of the black-box arc model employed to implement equations that can be associated with the LMA Matlab code. As mentioned earlier, the black-box arc model block-set was implemented using DEE in Matlab Simulink to align with the characteristics of the first-order differential equations defined in each model.

Since the seven black-box arc model equations in the block-set adhere to the same principle but with different inputs and parameters, this chapter will focus on the analysis based on the Schwarz model equation applied in this thesis. DEE comprises initial values x_0 = $\log x_0$, dx/dt, and y. The input variables are arc voltage and CB_Trip, and if the arc conductivity value x_1 changes by the differential equation of dx/dt according to the arc voltage, the value of x_1 will be output as y.

The 1/g· dg/dt of the Schwarz arc model can be represented as d(lng)/dt, and when this expression is formulated as dx/dt in the DEE, we have x=lng. Consequently, we observe that exp(x)=g and verify that the expression has been correctly implemented. The input value *u(1)* corresponds to the arc voltage, while u(2) represents the CB_Trip value, which can be either 0 or 1. Thus, we can observe that the expression functions based on the CB_Trip value. x_0 serves as the initial value of x_1 and represents the initial conductivity value when the model is executed. The arc conductivity, which changes according to the real-time input arc voltage, enters the input port of the controlled current source through the output formula, thereby impacting the system.

4) APPLICATION OF LMA FOR SCHWARZ ARC MODEL PARAMETER OPTIMIZATION

The Levenberg-Marquardt Algorithm (LMA) provided in reference [29] requires a model equation (black-box arc model) that incorporates actual observations (breaker short-circuit test results) and parameters to utilize the Matlab code. Regarding the actual observations, data values were extracted from the graph of the actual short-circuit test results using the GETDATA program mentioned earlier. These extracted data values were processed into matrix form to be applied to the code. Now, it is necessary to create a model equation to optimize the parameter values. The model equation was developed based on the following simplified assumptions. Ideally, the equations should be constructed to mimic the actual simulation model precisely. However, implementing such complex equations would be impractical and challenging.

Initially, the model to be implemented was established by analyzing the transient state of a simple DC R (dynamic)-L (di/dt determination) series circuit. By defining g(t) as the implementation expression of the DC power source E and the black-box arc model, the following expression can be derived.

$$\frac{i(t)}{g(t)} + L\frac{di(t)}{dt} = E \tag{15}$$

Applying circuit theory, we can create a current Eq. (18).

$$i(t) = i_s(t) + i_t(t),\ \ i_s(t) = Eg(t),\ \ i_t(t) = Ae^{st} \tag{16}$$

Solving the first-order differential equation here, we get the following arc current and voltage expressions.

$$i(t) = Eg(t) - Eg(t)e^{-\frac{1}{Lg(t)}t} \tag{17}$$

$$U(t) = \frac{i}{g(t)} = E - Ee^{-\frac{1}{Lg(t)}t} \tag{18}$$

As a result, by applying the arc model expression in the above section to g(t), we can derive the arc voltage and current expression of the DC short circuit, and the derived expression can be implemented as a matlab function code and applied to the LMA.

5) APPLICATION OF LMA FOR KEMA ARC MODEL PARAMETER OPTIMIZATION

It is organized in the same format as the schwarz arc model, and since the kema model consists of three equations, the initial value x_0 consists of three equations, and the arc voltage u(1) consists of the sum of three equations. In addition, there are 8 inputs (arc voltage, CB_Trip, τ_1, τ_2, τ_3, P_1, P_2, P_3), and the model equations are implemented in the same sequence as the schwarz arc model calculated earlier.

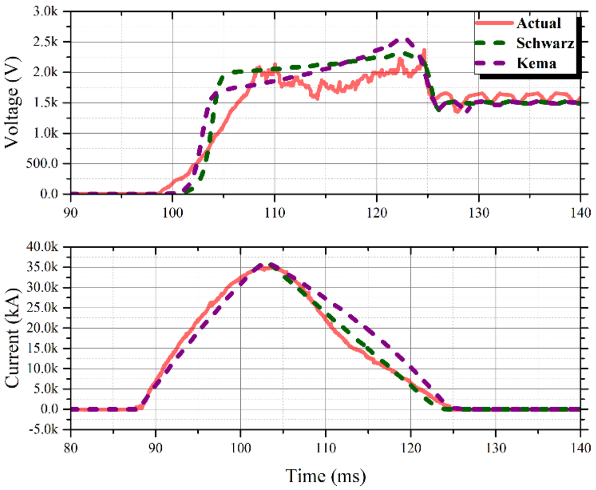

FIGURE 8. The results of parametric sweep methods. Graph of results for initial values selected based on the parametric sweep method. Schwarz arc model (τ = 0.4 ms, P=7.35 MW, α = 0.12, β = 0.8), Kema model (τ_1 = 0.6 ms, P_1 = 11 MW, P_2 = 1.5 MW).

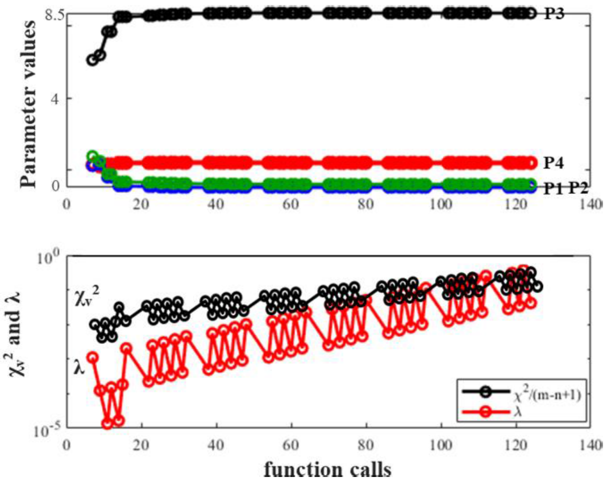

FIGURE 9. Convergence plot of X_V^2 (Residuals^2) and λ (LM parameter) for Schwarz arc model.

IV. SIMULATION RESULTS

A. PARAMETRIC SWEEP METHOD

1) SCHWARZ ARC MODEL

As mentioned earlier, the Schwarz arc model comprises four free parameters: τ, P, α, and β. By adjusting these parameters, the breaker arc can be described. Initially, the breaker arc characterization was carried out using the parametric sweep method to select the initial parameter values for the optimization simulation. The DC arc characterization for each parameter of the Schwarz arc model was performed based on the existing reference [26]. Furthermore, the arc characterization of the LV DC CLCB designed in this paper was conducted based on relevant references.

In the case of the DC CLCB, unlike general ACBs, it possesses the characteristic of rapidly interrupting the fault current by detecting and breaking it off autonomously in case of an accident, utilizing internal relays. Consequently, the interrupting waveform of the DC CLCB differs from that of a typical LV ACB. Therefore, several iteration simulations were conducted based on fundamental prerequisites to determine each free parameter. Through a comparison with actual arc current and voltage waveforms, initial parameter values were derived, resulting in the waveform depicted in Fig. 8. The initial parameter values were selected as τ = 0.4 ms, P = 7.35 MW, α = 0.12, and β = 0.8.

2) KEMA ARC MODEL

For the Kema arc model, the same DC CLCB interrupting voltage and current waveforms were utilized to derive the parameter values. Regarding the parameter values, τ_1, P_1, and P_2 were selected by fixing the values of k_1, k_2, and k_3. However, since there is no available information on the values of the k_1, k_2, and k_3 constants for the breaker, the values of k_1 = 0.25, k_2 = 0.8, and k_3 = 0.3333 were randomly selected, as mentioned earlier. The Kema model consists of three bins and is primarily based on the analysis of AC breakers, which posed difficulties in describing the voltage wave form of DC CLCBs. As previously mentioned, DC CLCBs can be rapidly interrupted, causing the breaker to trip and the arc voltage to rise quickly. However, in order to represent this voltage waveform using the Kema arc model, the P value in the first phase must be selected as large, resulting in a significant increase in arc voltage until interrupting occurs. Hence, it becomes challenging to accurately describe the DC CLCB voltage curve where the arc voltage remains relatively constant from the beginning. We selected the initial parameters valeu based on the arc current waveform: τ_1 = 0.6 ms, P_1 = 11 MW, P_2 = 1.5 MW.

B. ARC MODEL PARAMETER OPTIMIZATION

1) CONVERGENCE PLOT OF THE PARAMETERS AND X_V^2 (RESIDUALS^2), $\wedge$ (LM DAMPING FACTOR)

The parameter values selected for each model through the parametric sweep method are P_{init} values, and parameter optimization was performed by fitting the models with the actual voltage and current waveforms of the CLCB. Fig. 9 and Fig. 11 display the convergence plots of χ_v^2 and λ for the Schwarz and Kema arc models. The convergence plot illustrates the complete simulation trace of χ_v^2 and λ. Throughout the simulation, we observe that, for the Schwarz arc model, the value of χ_v^2 does not converge to 1 but rather converges to 89.6 %. Additionally, for the Kema arc model, we can observe that the χ_v^2 value is lower than that of the Schwarz arc model 85.4 % of the time. Moreover, λ starts with a high value at the beginning of the simulation and gradually converges to 1, indicating that the solution was initially found using GDM and later optimized using GNM. Furthermore, by examining the convergence plot for each parameter, we can see that the initial parameter values selected by the parametric sweep method are relatively accurate for the Schwarz model. However, in the case of the Kema model, we note a somewhat significant increase in the P_2 cooling power value.

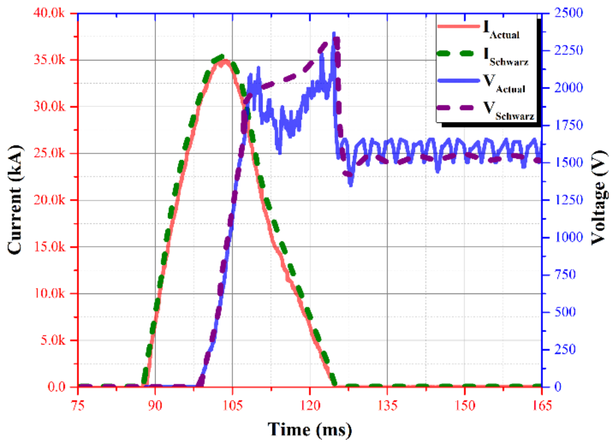

FIGURE 10. Optimization results of Schwarz arc model.

TABLE 3. Schwarz and Kema arc model fitted parameters.

Model	τ, τ_I [ms]	P, P_I [MW]	P_2 [MW]	α / β
Schwarz	0.3874	8.5684	-	0.0943/ 0.8548
Kema	0.5487	8.7869	7.8437	-

2) COMPARISON WITH OPTIMIZATION CURVE AND ACTUAL CURVE

The parameter optimization results of the Schwarz arc model compared to the actual interrupting data are presented in Fig. 10 and Fig. 12. Both the Schwarz model and the Kema model exhibit a very high confidence interval with an R^2 factor of 99 % for the fault current. However, when it comes to voltage, the Schwarz model fits 89.6 % of the confidence interval, while the Kema model fits 85.4 %, indicating a slightly lower level of fitting accuracy. The Kema model has been extensively studied to provide high accuracy for the more common ACB. However, describing the voltage in breakers with extremely rapid voltage rise and size, such as CLCB, poses a challenge.

V. DISCUSSIONS

A. ARC MODEL PARAMETER OPTIMIZATION

In this paper, we optimized the parameters of the existing Schwarz and Kema black-box arc models for describing the LV DC CLCB arc characteristics and identified the following features:

1) Regardless of whether it is AC or DC, the arc characteristics can be expressed using the main parameters of the black-box arc model: arc time constant and cooling power. The voltage and current of an electric arc can be described by the black-box arc model, which is controlled by the change in arc conductivity, regardless of the presence of a current zero point.
2) A shorter arc time constant results in faster arc extinguishing and a steeper upward slope of the arc voltage. A higher cooling power leads to faster arc extinguishing, which also affects the magnitude of the arc voltage.

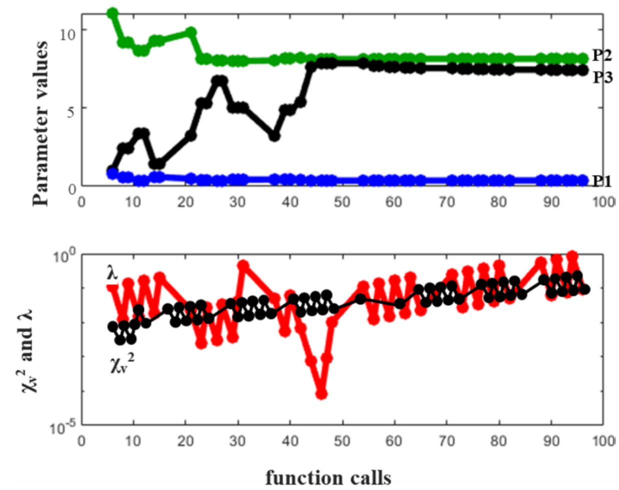

FIGURE 11. Convergence plot of X_V^2 (Residuals^2) and λ (LM parameter) for Kema arc model.

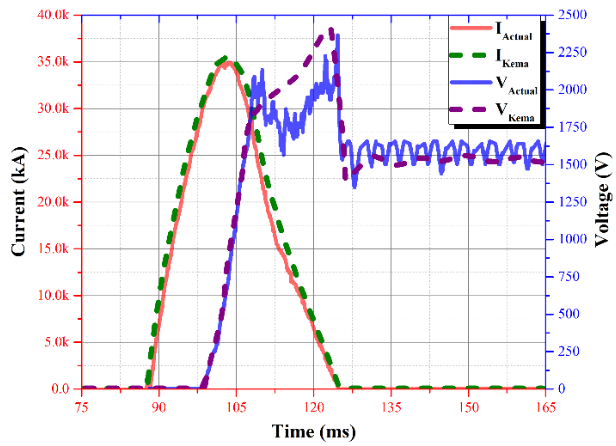

FIGURE 12. Optimization results of Kema arc model.

3) For LV DCCBs, the fault current waveform is nearly similar regardless of the model used, and accurate fitting can be achieved by selecting the appropriate arc time constant and cooling power from the existing Schwarz and Kema black-box arc models.
4) However, when it comes to voltage, even with the same interrupted fault current, different patterns are observed depending on the topology of the mechanical LV DCCB. It is challenging to achieve a perfect voltage waveform using only the existing black-box arc model. For instance, in the case of the CLCB applied in this paper, the arc voltage differs from the typical breaker waveform (where the arc voltage generally rises until it is extinguished). Therefore, it is not easy to achieve a perfect fit using optimization tools alone.
5) In the case of LV DCCBs, the trace of the arc voltage generated when the contacts open is highly significant. Even the slightest difference can lead to breaker failure. Therefore, an additional method is required to accurately describe the arc voltage of CLCBs.

6) In this paper, parameter optimization was performed and validated on the results of a single experiment of DC CLCB. Uncertainty verification was performed through residuals and goodness-of-fit judgments and visual evaluation, thus credible results were obtained. However, to ensure better reliability of optimized parameters it is considered that the general validity should be verified by performing repeated simulations with various data of the same experiment, calculating the standard error value to estimate the variability of the parameter estimation, and calculating the confidence interval.

B. COMPARISON ANALYSIS

A study was conducted to evaluate the applicability of the parametric sweep method and LMA (Levenberg-Marquardt Algorithm) for describing the DC CLCB arc characteristics using the two most popular black-box models. Both methods yielded excellent results in terms of describing the current characteristic curve. However, when it comes to describing the voltage characteristic curve, the Schwarz model performs slightly better than the KEMA model.

In LV DCCBs with reverse voltage interrupting, the voltage curve plays a crucial role in breaker design. The detailed characteristics of each step of the voltage curve can determine the success or failure of the interrupting operation. In the existing KEMA model, the λ values, which determine the characteristics of the arc model for each phase, are specified as 1.4, 1.9, and 2, respectively. This setup gives significant influence on phase 1 of the model in the large current range, while the influence of phase 3 is relatively smaller. As a result, the KEMA model can be an effective choice for AC systems with a natural current zero point, accurately describing a typical LV DCCB with a gradually increasing arc voltage. However, it can be observed that the fitting reliability is somewhat reduced for models with a large initial increase in arc voltage, such as CLCBs.

C. PRACTICAL SCENARIOS

It is believed that black box arc model simulations performed based on actual test can be examined for various practical applications based on their reliability. We proposed that it can be divided into two main areas, one is the characteristics of arc time constant (τ) and cooling power (P) parameter applied to the arc model, which can make a contribution to the improvement of actual CB performance, and the other is the transient simulation aspect, which can effectively verify the applicability of the designed CB to an arbitrary power system. In this regard, we have proposed two practical scenarios, which can be considered as future projects.

1) The simulation studies using the black-box arc model can predict the results of tests that have not been conducted or understand the behavior of relevant parameter values of the arc model to design actual CBs. For instance, combining actual tests with black-box arc model simulations can reduce the opportunity cost of physical verification tests, and analyzing the graph of failed interruption test results can reveal the cause of failure based on the influence of parameters τ and P, subsequently applied to actual CB design.
2) The designed CBs applicability can be verified under various power systems conditions. Utilizing the reliable black-box arc model, we can judge the applicability verification for arbitrary systems to which the designed CB may be applied based on the simulation results.

VI. CONCLUSION

In this paper, we conducted simulations to assess the applicability of the black-box arc model, primarily used for AC breakers and arc description, to DC arcs. We specifically focused on arc modeling of CLCBs, which have the capability of rapid interrupting among DCCBs. The widely used Schwarz and Kema arc models were employed for the black-box arc model, and the parameters of each model were optimized using the Levenberg-Marquardt Algorithm (LMA). The simulation results demonstrated excellent fitting of the arc current; however, for the arc voltage, the R^2 factor was below 90%. It appears that in the case of DCCBs, where the current zero point is an inherent characteristic of the breaker, the arc voltage waveform is influenced in detail by factors related to the breaker's design. Therefore, to enhance the reliability of DC circuit breaker design, improvements that can incorporate these intricate factors of the circuit breaker itself are necessary. Future research should focus on modeling techniques that accurately reflect these improvements.

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