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Overview of Black-Box Arc Models and Parameter Identification Techniques for Simulation of PV Systems

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ABSTRACT Solar energy is widely regarded as an environmentally friendly and sustainable source of power. It reduces greenhouse gas emissions and dependency on fossil fuels, contributing to a cleaner environment. It also provides cost savings and enhances energy security. However, technical challenges persist. Poor installation, inadequate maintenance, and aging can degrade photovoltaic (PV) systems, leading to failures or faults. These issues increase the risk of power losses, electrical shocks, and fires. Direct Current (DC) arcs, in particular, pose a significant fire hazard in PV systems due to their unpredictability and high potential for damage. However, accurately defining parameters for real-world DC arc faults is difficult. Developing computational models of electric arcs is essential for simulating, analyzing, and detecting these faults. In that sense, this work provides a comprehensive overview of the prominent black-box arc models documented in the scientific literature, along with various methods for parameter identification, to facilitate the investigation of arc-related incidents within PV systems.

KEYWORDS DC arcs, metaheuristics, parameters identification, solar energy.

I. INTRODUCTION

The urgency to combat climate change, with rising sea levels as a stark reminder, has propelled carbon peaking and carbon neutrality to the forefront of global development goals. Transitioning away from fossil fuels is crucial to curb carbon dioxide emissions. In this context, renewable energy sources offer a compelling solution [1].

The field of renewable energy, led by solar and wind power, has seen remarkable growth in recent years [2]. Solar photovoltaic (PV) systems are gaining significant attention as a renewable energy source for generating electricity. Unlike traditional sources, PV harnesses solar energy, a clean and abundant resource, to produce electricity without environmental pollution [1]. Their applications range from large-scale integration into grid systems to power individual homes, and even a new, innovative approach: agrivoltaics, which combines solar power generation with agricultural practices [3]. As the photovoltaic industry continues to expand, increasing focus is being placed on equipments for failures mitigation due to harsh environmental conditions and natural aging.

A photovoltaic system relies on a network of solar panels interconnected by long cables and plug connectors. However, these external components are exposed to environmental factors that can loosen connections or accelerate abrasion over time. This degradation can increase the risk of Direct Current (DC) series arc faults occurring at these connection points, potentially leading to fires [4], [5].

PV systems face a significant hurdle in maintaining reliable operation due to DC series arc faults. These occur when an electrical current preferentially flows through a plasma channel within the circuit, often caused by a break or looseness in a wire. Essentially, DC arcs form when air gases ionize due to the current's flow. The resulting arc discharge behaves like a high-resistance element in series with the circuit, leading to low fault currents that traditional protection methods might not detect [6], [7]. These faults often involve a significant energy release, including intense light and heat, posing a major fire hazard [8]. Additionally, the noise generated by the series arc fault can travel across the network, potentially causing false positives in separate current sensors [7], [9].

Detecting a DC series arc fault represents greater difficulty due to its minimal fluctuation in current and external effects, such as inverter noise [10], [11]. Therefore, the main challenge in detecting series arc faults is to distinguish between the arc fault and normal operating conditions. Arc Fault Circuit Interrupters (AFCIs) are essential for preventing fire hazards in PV systems by detecting and mitigating electrical arcs. AFCIs are increasingly being integrated into inverters for arc detection [12] and different detection methods are being developed [13]–[15].

DC arc faults pose a significant challenge due to their inherent complexity. These electrical anomalies exhibit a high degree of unpredictability and can manifest in diverse forms, presenting a substantial risk. This complexity stems from the inherent instability of electric arc dynamics, with properties influenced by factors such as arc length, electrode material, and the self-generated magnetic field of the arc current [16]. Consequently, defining precise physical constants for real-world DC arc faults within power systems proves particularly difficult. Considering this challenge, the development of arc fault models becomes a crucial tool. These models aim to represent the phenomenon, enabling simulation, analysis, and, most importantly, detection of DC arc faults.

A challenge in DC arc modeling is the estimation of electric arc parameters. These parameters are fundamental for accurate prediction of how an arc interacts with its surrounding network or components, like PV inverters. [17], [18]. Correct parameter identification is critical for model performance, as it directly affects the model's ability to realistically capture arc behavior. Additionally, these arc parameters exhibit dynamic characteristics, varying across different test configurations (for example, short-circuit current and arc duration) and even over time due to aging phenomena [19].

In this scenario, there is a noticeable lack of studies that thoroughly analyze the development process of different black-box arc models. Typically, the models are presented with only a brief discussion of their characteristics [13], [19]. Furthermore, there are no comprehensive review papers specifically aimed at presenting the different parameter estimation methods. Therefore, this work aims to provide a comprehensive analysis of different DC arc models, highlighting their main features. Additionally, a concise overview of different parameter estimation methods will be presented. The remainder of this paper is organized as follows: Section II presents 7 different electric arc models. Section III examines different parameter estimation methods, which is followed by a conclusion in Section IV.

II. DC ARC MODELS

Historically, arc fault detection methods have primarily relied on empirical investigations through controlled laboratory experiments. The intrinsically chaotic and complex nature of arc behavior demands the incorporation of a comprehensive set of parameters for accurate modeling. These parameters encompass the conductor material properties, the inherent characteristics of the electrical system itself, and the prevailing operational state alongside the ambient environmental conditions [17]. At the same time, advancements in computational modeling techniques have emerged as a complementary approach. By incorporating established principles of arc physics into computer simulations, researchers can develop robust arc fault models [20]. These models offer a versatile and cost-effective methodology for analyzing practical power systems under diverse arc fault scenarios.

A comprehensive categorization of electric arc models can be established using three main categories: physics-based, data-driven V-I, and heuristic models [21]. Physics-based models leverage established principles of electromagnetism and thermodynamics to comprehensively describe arc phenomena through a set of governing equations. Conversely, data-driven V-I models utilize experimentally acquired V-I characteristics to provide a practical representation of arc behavior under specific conditions. Finally, heuristic models employ simplified mathematical techniques and approximations to capture the essential features of arcs, offering a computationally efficient approach. The selection of the optimal model hinges on the specific simulation objectives, the desired fidelity in replicating arc behavior, and computational resource constraints [13].

This work will address arc models based on physical principles, also known as black-box models, since most studies on parameter estimation use such models. A more complete study of all other types of arc models is the main theme of the paper presented in [22].

A. Physical principles-derived models

An electric arc, a continuous high-current discharge between two electrodes in a gas-filled space, generates temperatures sufficient to melt or vaporize most materials [23]. When the voltage is high enough, the air ionizes, leading to the formation of positively charged ions and free electrons. Models that describe the behavior of electric arcs simplify intricate physical processes, making them more accessible for analysis. These models use principles from fluid dynamics, thermodynamics, and Maxwell's equations, focusing on conservation of mass, momentum, and energy. Due to the computational intensity of solving these detailed equations, practical models incorporate necessary simplifications [24]. The following equations shows the physical effects associated with electric arcs.

Conservation of mass:

$$\underbrace{\frac{\delta\rho}{\delta t}}_{①} + \underbrace{\nabla.(\rho\mu)}_{②} \tag{1}$$

Conservation of momentum:

$$\underbrace{\rho\frac{\delta\mu}{\delta t}}_{③} = \underbrace{-\nabla p}_{④} - \underbrace{\rho(\mu.\nabla)\mu}_{⑤} \tag{2}$$

Conservation of energy:

$$\begin{aligned}\underbrace{\rho\frac{\delta h}{\delta t}}_{⑥} - \underbrace{\mu.\nabla(\rho h)}_{⑦} - \underbrace{\sigma E^2}_{⑧} &= \underbrace{-\nabla.(\rho\mu)}_{⑨} \\ &+ \underbrace{\nabla.(K.\nabla T)}_{⑩} + \underbrace{R(t,p)}_{⑪}\end{aligned} \tag{3}$$

where ρ is the gas density $[kg/m^3]$, t is time $[s]$, μ is the gas flow velocity $[m/s]$, p is the pressure $[kg/ms^2]$, h is the enthalpy of the gas $[J/kg]$, σ is the electric conductivity $[S/m]$, E is the electric field strength $[V/m]$, K is the thermal conductivity $[W/mK]$, T is the gas temperature $[K]$, and R is the radiation loss $[W/m^3]$. Furthermore, term ① change rate of density in unit volume, ② mass flow entering a unit volume, ③ acceleration at a point in space, ④ accelerating force by pressure distribution, ⑤ acceleration during the motion along flow lines, ⑥ change of energy in unit volume, ⑦ energy input by mass flow convection, ⑧ Joule heating, ⑨ work performed by flow, ⑩ thermal conduction loss, and ⑪ radiation loss.

Given the significant computational resources needed to solve the physical models outlined by the previous equations, black-box arc models have become a valuable tool for examining electric arcs in certain contexts. These black-box models are grounded in physical principles and originate from the energy balance principle, making them highly useful for simulating and computing circuits that involve arcs [25], [26]. They encompass the relationship between arc voltage, arc current, and energy, based on the solution to the general arc equation.

Arc conductance (g) is influenced by the power supplied to the plasma channel (P_{in}), the power lost from the plasma channel (P_{out}) due to cooling and radiation, and the duration of the arc (t):

$$g = F(P_{in}, P_{out}, t) = \frac{i}{u} = \frac{1}{R_e} \tag{4}$$

where i represents the arc current, u is the arc voltage, and R_e denotes the arc channel resistance. When P_{in} and P_{out} are not balanced, the arc conductance changes. The energy stored in the plasma channel, Q, can be expressed as:

$$Q = \int_0^t (P_{in} - P_{out})dt \tag{5}$$

Hence, the arc conductance is defined as follows:

$$g = F(Q) = F\left[\int_0^t (P_{in} - P_{out})dt\right] \tag{6}$$

The arc conductance's rate of change relative to the arc conductance is stated as:

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{g}\frac{dF(Q)}{dQ}\frac{dQ}{dt} \tag{7}$$

By deriving Equation (5) and substituting the outcome into Equation (7), the general arc equation can be written as:

$$\frac{d[ln(g)]}{dt} = \frac{F\,'(Q)}{FQ}(P_{in} - P_{out}) \tag{8}$$

Usually, certain considerations are taken into account to solve Equation (8). Based on these assumptions, various black-box models can be derived. Initially, it is assumed that the arc possesses a cylindrical shape (as illustrated in Fig. 1).

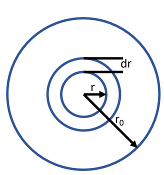

FIGURE 1. Cylindrical arc.

Assuming that energy loss happens only through radial heat conduction, the heat transfer along the circumference with radius r can be described as:

$$\varphi(r) = -2\pi r\kappa\frac{\delta T}{\delta r} \tag{9}$$

where φ(r) is the heat transfer per unit length $[W/m]$, T is the temperature as a function of time and the coordinate in radial direction $[K]$, and κ is the heat conductivity $[W/mK]$. The heat transfer through the infinitesimally thin layer dr at radius r + dr can be expressed as:

$$\varphi(r + dr) = \varphi(r) + \frac{\delta\varphi}{\delta r}dr \tag{10}$$

Consequently, the heat gain in the layer dr, per unit time and per unit length, can be expressed as:

$$\varphi(r) - \varphi(r + dr) = -\frac{\delta\varphi}{\delta r}dr = 2\pi\frac{\delta\left(r\kappa\frac{\delta T}{\delta r}\right)}{\delta r}dr \tag{11}$$

However, the heat produced by the electric field within the layer dr is:

$$\varphi_{ef} = 2\pi r EJdr = 2\pi r\sigma E^2 dr \tag{12}$$

where E is the voltage gradient in the axial direction $[V/m]$, J is the current density $[A/m^2]$, and σ is the electrical conductivity $[S/m]$. The total heat accumulated in the layer dr can be represented as the sum of Equations (11) and (12):

$$Q = 2\pi\frac{\delta\left(r\kappa\frac{\delta T}{\delta r}\right)}{\delta r}dr + 2\pi r\sigma E^2 dr \tag{13}$$

The total heat accumulated in the arc per unit length can be determined by integrating the heat across the entire cross-section of the arc, from 0 to r_0, as showed by Equation 14:

$$Q = 2\pi\left(r\kappa\frac{\delta T}{\delta r}\right)_{ro} + E^2 g \tag{14}$$

Hence, the change in heat over time is given by:

$$\frac{\delta Q}{\delta t} = 2\pi r_0\kappa\left(\frac{\delta T}{\delta r}\right) + E^2 g \quad or \quad \frac{\delta Q}{\delta t} = -P + E^2 g \tag{15}$$

The equation presented above is a simplified form of the energy conservation equation and is known as the Elenbaas-Heller equation.

A significant advancement in understanding the interaction between arcs and circuits came with Cassie's paper on arc dynamics [27]. Cassie introduced a differential equation that provided a detailed view of arc behavior. The Cassie arc model is mainly used for high-current arcs, assuming that power dissipation is due to forced convection. This implies that the arc's cross-sectional area is proportional to the arc current. Additionally, the model assumes a constant plasma temperature and that heat transfer occurs through thermal convection, maintaining constant conductivity, power dissipation, and energy density [28]. In the model, a time constant was introduced, which is a measure of the energy storage capacity and the energy losses: $\tau = \frac{Q'}{P'}$. The Cassie arc model is represented by the following equation:

$$\frac{d(ln(g))}{dt} = \frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}\left(\frac{U^2}{U_0^2} - 1\right) \tag{16}$$

where g is the conductance of the arc in Siemens [S], τ is the arc time constant in seconds [s], U is the voltage across the arc in volts [V] and U_0 is the constant arc voltage in volts [V]. The Cassie model is well-suited for analyzing arc conductance in high-current scenarios where the plasma temperature exceeds 8000 K. In photovoltaic systems, this model is useful for detecting DC series arc faults at the array level, where currents are generally higher.

Later, O. Mayr extended the model to address the time interval around zero current [29]. The Mayr model suggests that power dissipation through thermal conduction remains constant, making it suitable for low-current arcs. It is based on energy balance with several assumptions: the arc maintains a constant cylindrical cross-section, the conductance is an exponential function of the arc's internal energy and the heat transfer from the arc to its surroundings is constant, occurring solely through thermal conduction. The Mayr model in its classical form is given by:

$$\frac{d(ln(g))}{dt} = \frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}\left(\frac{U^2 g}{P} - 1\right) = \frac{1}{\tau}\left(\frac{ui}{P} - 1\right) \tag{17}$$

where g is the conductance of the arc [S], τ is the arc time constant [s], u is the voltage across the arc in volts [V], i is the arc current [A] and P is the the cooling power constant [W]. The term "arc cooling power" is frequently used in the literature to describe the effect of thermal energy removal from the conductive arc column [30]. In PV systems, the Mayr arc model is useful for detecting DC series arc faults at levels below the string, where currents are generally lower.

Building on the foundational concepts of the Mayr and Cassie arc models, the Habedank model inventively divides the arc into two interconnected segments, allowing for a more detailed representation of varying current intensities [31]. Essentially, the Habedank model combines the Cassie and Mayr conductance's in series, leveraging the strengths of both models. At high currents, only the Cassie equation influences the voltage drop, while as zero current approaches, the Mayr equation starts to play a role, and the Cassie equation diminishes. This makes the Habedank model effective for both high-current and low-current phases of the arc. The model is described by the following equations:

$$\begin{cases} \frac{1}{g_c}\left(\frac{dg_c}{dt}\right) = \frac{1}{\tau_c}\left(\frac{u_c^2}{U_0^2} - 1\right) \\ \frac{1}{g_m}\left(\frac{dg_m}{dt}\right) = \frac{1}{\tau_m}\left(\frac{u_m i}{P} - 1\right) \\ \frac{1}{g} = \frac{1}{g_c} + \frac{1}{g_m} \end{cases} \tag{18}$$

where g is the total arc conductance [S], g_c and g_m are conductance described by the Cassie and Mayr arc models respectively [S], u_c is the voltage across the Cassie arc model [V], u_m is the voltage across the Mayr arc model [V], i is the arc current [A], τ_c is the Cassie arc time constant [s], U_0 is the Cassie steady-state arc voltage [V], and τ_m is the Mayr arc time constant [s]. Regarding PV systems, the current output of a solar array is influenced by the solar irradiance and the array's configuration. This implies that the Habedank arc model is more appropriate for simulating DC fault arcs of varying currents than the Cassie and Mayr arc models.

The KEMA model consists of three arcs in series, each of which is a modified Mayr model subject to numerical fitting [32].

$$\begin{cases} \frac{1}{g_1}\left(\frac{dg_1}{dt}\right) = \frac{1}{\Pi_1\tau_1} g_1^{\lambda_1} {u_1}^2 - \frac{1}{\tau_1} g_1 \\ \frac{1}{g_2}\left(\frac{dg_2}{dt}\right) = \frac{1}{\Pi_2\tau_2} g_2^{\lambda_2} {u_2}^2 - \frac{1}{\tau_2} g_2 \\ \frac{1}{g_3}\left(\frac{dg_3}{dt}\right) = \frac{1}{\Pi_3\tau_3} g_3^{\lambda_3} {u_3}^2 - \frac{1}{\tau_3} g_3 \\ \frac{1}{g} = \frac{1}{g_1} + \frac{1}{g_2} + + \frac{1}{g_3} \end{cases} \tag{19}$$

The KEMA model describes the total arc conductance g and individual arc conductances g_i (for $i = 1, 2, 3$), with τ_i as the time constant, u_i as the voltage, and Π_i as the cooling constant. The Cassie-Mayr control parameter λ_i defines the model type: Cassie ($\lambda_i = 1$) or Mayr ($\lambda_i = 2$). Key parameters include $\lambda_1 = 1.4$, $\lambda_2 = 1.9$, $\lambda_3 = 2$, with empirical relationships for time constants and cooling constants. The KEMA model's versatility, incorporating both Cassie and Mayr characteristics, allows for detecting DC arcs in PV systems across different current levels.

Building on the Mayr model, Schwarz integrates the effect of arc conductance on arc parameters [33]. While the Mayr model assumes that time and cooling power are constant, this is only accurate for a specific, limited time interval. Schwarz demonstrated that these values vary, so his model includes the impact of arc conductance on cooling power and the time constant:

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau g^{\alpha}}\left(\frac{ui}{P g^{\beta}} - 1\right) \tag{20}$$

In Schwarz's arc model, P denotes cooling power [W], τ stands for arc time constant [s], α influences the conductance-dependent variation of τ, and β affects the conductance-dependent variation of P. In Schwarz's arc model, the parameters τ, α, P, and β are the adjustable arc parameters. By using a conductance-dependent function to depict the changes in dissipated power and arc time, Schwarz's model offers broader applicability compared to the Cassie and Mayr models. In photovoltaic systems, this model proves useful for detecting DC series arcs across both high and low current scenarios.

The Schavemaker arc model combines elements of the Mayr and Cassie arc models, incorporating time constant and cooling power as functions of power input [34]. This model, represented by Equation 21, requires estimating several parameters to predict arc behavior accurately, including time constant, cooling power, cooling constant, and reference

TABLE 1. Summary of arc models.

Arc model	Current level	Dynamic	Complexity	Accuracy	Detection of PV series arc fault
Cassie [27]	High	Yes	Low	Low	Possible, at array level
Mayr [29]	Low	Yes	Low	Low	Possible, at below string level
Habedank [31]	Low/High	Yes	Medium	Medium	Possible
KEMA [32]	Low/High	Yes	High	Medium	Possible
Schwarz [33]	Low/High	Yes	Medium	Medium	Possible
Schavemaker [34]	Low/High	Yes	Medium	Medium	Possible
Time-variant Schwarz based model [36]	Low/High	Yes	High	High	Possible
Enhanced Cassie-Mayr based model [37]	Low/High	Yes	High	High	Possible

voltage constant [35]. These parameter values vary with operational conditions, making it crucial to determine them for the specific working conditions to accurately capture voltage and current waveforms.

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}\left(\frac{ui}{max(U_{arc}|i|, P_0 + P_1 ui)} - 1\right) \quad (21)$$

In this model, P_0 is the cooling constant [W], P_1 determines how the cooling power is influenced by the input power, and U_{arc} represents the constant arc voltage in the high-current region. For high currents, the model aligns with the Cassie model, while near zero current, it simplifies to the Mayr model. After the current reaches zero, P_0 is set to zero, indicating the arc has extinguished. These properties make the model suitable for detecting DC arcs in PV systems across various conditions.

Two new models derived from the Schwarz model have been developed to enhance the accuracy of detecting DC series arcs in PV systems [36]. These models integrate time-varying characteristics inherent to electric arcs. The original Schwarz model uses four fixed parameters. The first new model includes two constant model orders and two time-varying coefficients, while the second new model treats all four parameters as time-varying. When compared to the traditional Schwarz model and other models like Cassie and Mayr, these modified models proved more effective for modeling DC series arc faults in PV systems, with the fully time-varying model being the most precise.

To incorporate the time-varying characteristics of DC series arc faults in PV systems, three new arc models were developed by combining features of the Cassie and Mayr models [37]. The original Cassie and Mayr equations have two constant parameters each. The first new model modifies the Cassie-Mayr equation to include three parameters: one constant and two time-series coefficients. The second model extends this to five parameters, with two constants and three time-series coefficients. The third model is fully time-variant, with all coefficients as time series. These new models were tested and found to be more accurate, according to the authors, than the original Mayr and Cassie-Mayr models. [37]. In Table I, a comparison between models are presented.

III. PARAMETER IDENTIFICATION

Parameter estimation, inverse modeling, or system identification addresses an optimization problem to find the optimal model parameters within an acceptable range by maximizing or minimizing an objective, cost, or fitness function [38]. Parameter estimation involves determining the optimal values of certain parameters in a numerical model through data assimilation or other similar techniques.

Estimating model parameters is challenging across various fields. Identifying parameters as an optimization problem can be particularly difficult, especially in complex situations with many input parameters of interest or a lack of knowledge about their range. Thus, there are numerous algorithms available to solve optimization problems [39]–[41]. The effort needed and the quality of the solution depend on various factors, such as the quantity and limits of the input parameters of interest, the model's complexity, and the quality of the initial parameter values. Since it is impractical to evaluate all possible combinations of input parameter values, sometimes only a local optimum is found instead of the global one [42].

Arc parameters are crucial for the performance of arc models, making their determination the most challenging aspect [43]. In arc models, the parameters differ with each test based on conditions like short-circuit current and arcing time, as well as the aging process such as nozzle degradation and contact erosion. Accurate parameter identification is essential for the arc model to correctly describe arc characteristics [19], [44].

Various methods for parameter identification have been developed using black-box models, as documented in the literature for determining the parameters of electric arc models. Often, these parameters are identified through testing circuit breakers [45], [46]. Amsinck's method [47] is specifically designed for determining electric arc parameters in scenarios where a circuit breaker test results in a current interruption followed by a reignition. Amsinck posits that the cooling power $P(g)$ and the time constant $\tau(g)$ are the same at points with identical conductance.

Ruppe's [48] method hinges on the idea that, if $P(g)$ and $\tau(g)$ are functions of conductance, they should behave similarly for different arcs under comparable conditions. Therefore, multiple tests of the same device under identical conditions are required. Finally, Rijanto's method [49] is based on the principle that the parameter functions can be derived from singular points on the dynamic arc traces.

However, such methods depend on a series of tests on circuit breakers and the application of regression techniques to find the parameters. With the increase in computational power, some authors have begun treating the problem of finding electric arc parameters as an optimization problem, using both classical optimization techniques and metaheuristic algorithms, thus avoiding the need for repetitive testing [19].

System identification theory provides an alternative approach for identifying parameters in electric arc models. This technique involves creating a mathematical model to represent a dynamic system by measuring the input and output signals of the system. In [50] was proposed a method for estimating parameters in the Modified Cassie-Mayr arc model using nonlinear least squares with the Gauss-Newton algorithm. This method eliminates the need for numerical differentiation, which is a common requirement in many parameter extraction methods. The study used the squared norm of the cost function, resulting in a least squares optimization problem.

The authors in [51] adapted Medina's approach to determine the parameters of black-box arc models, applying the fundamental Cassie and Mayr models. The research aimed to evaluate these models' effectiveness in simulating electromagnetic transients in DC systems, showing that black-box arc models can accurately describe the interaction between the arc and the electrical circuit, thus serving as a valuable simulation tool.

Another application of system identification theory in arc modeling was proposed in [52], in which a linearization is performed around an operating point and then an optimization of the model parameters is carried out using the Kalman Filter and the Maximum Likelihood method, further demonstrating the versatility of system identification theory in arc modeling.

In a study presented in [19], the authors introduce a new black-box arc model, validated through short-line fault interruption tests on high-voltage circuit breakers. The arc parameters of each model are optimized over a time interval to minimize the difference between measured and simulated arc voltages. Applied to a simplified circuit, the models' accuracy in interruption prediction and waveform fitting was quantitatively assessed. Named the "TP KEMA" model, it simplifies the conventional KEMA model, reducing the number of parameters from six to two. The extraction of arc parameters is formulated as an optimization process minimizing voltage differences while satisfying the discretized equation of arc conductance. Comparisons with five other models during short-circuit tests indicate that the TP KEMA model provides the best overall performance with fewer parameters.

In [43], the authors used the TP KEMA model and applied the metaheuristics Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to optimize parameters by minimizing arc conductance error from random initial values. The total square error of arc conductance serves as the objective function to evaluate performance. Both GA and PSO aim to minimize this function, and their optimization results showed to be very similar.

In the paper [53] is proposed a method using a library of black-box arc models and heuristic optimization algorithms aims to accurately determine arc parameters from experimental or simulated waveforms of arc voltage and current. Using MATLAB Simulink, the waveforms are derived by solving the differential equation of the arc model. The optimization goal is to minimize the accumulated relative error between the observed and calculated arc conductance over a specified time interval. Heuristic algorithms like GA, PSO, and Simulated Annealing (SA) are used to estimate the model parameters, with comparisons of their performance. The authors recommend the GA algorithm for parameter estimation due to its global search capability, solution stability, efficiency, and detailed control options.

In the study [54], the task is to study black-box models and evaluate various arc models compared to the KEMA model for circuit breakers, aiming to find optimal parameters for breaking ability. Six main arc models (Cassie, Habedank, Mayr, Modified Mayr, Schavemaker, and Schwarz) are analyzed, using GA to minimize the differences between the conductances of KEMA and the test models. The optimization goal is to enhance the parameters of these models. In each step, an arc model replaces the test model box, and the GA minimizes the difference in conductance, selecting the best parameters. The results show improved parameters for the six arc models.

In [55], the authors present a method to determine the coefficients of the dynamic Cassie-Mayr electric arc model using simplex annealing and genetic optimization algorithms. This approach minimizes the error between the Transient Recovery Overvoltage (TRV) of an ideal switch breaker model and the arc-based model. TRV values are calculated for specific chopping currents in a test circuit simulation. Results show that simplex annealing outperforms the genetic algorithm in accuracy, measured by Mean Absolute Percentage Error (MAPE), regardless of optimization settings or iterations, with the variable range selection being crucial for accuracy.

The authors in [56] propose an estimation method for arc parameters based on the Mayr arc model, addressing both sinusoidal and non-sinusoidal current waveforms. Heuristic optimization methods, such as GA and PSO, are used to

TABLE 2. Summary of optimization algorithms to define model parameters.

Reference	Objective or Fitness Function	Arc model	Number of Unknown Parameters	Algorithm
[19]	$e = \sum_{t=t_1}^{t_2} [u_m(t) - u_s(t)]^2 = \sum_{t=t_1}^{t_2} \left[u_m(t) - \frac{i_m(t)}{g_s(t)}\right]^2$	TP KEMA	2	Not Mentioned
[39]	$e = \sum_{i=1}^{n} [g_m(t) - g_s(t)]^2 = \sum_{t=t_1}^{t_2} \left[\frac{i_m}{u_m} - g_c\right]^2$	TP KEMA	2	GA and PSO
[53]	$f = \sum_{t=t_1}^{t_2} \frac{\lvert g_{opti}(t) - g(t)\rvert}{g(t)} x100$	Cassie, Mayr, KEMA Habedank and Schwarz	2 - 6	GA, SA and PSO
[54]	$f = \lvert g_{kema}(t) - g_{TestModel}\rvert^2$	Cassie, Mayr, HabedanK KEMA, Schwarz and Schavemaker	2 - 6	GA
[55]	$f = \lvert TRV_{ideal} - TRV_{CM}\rvert$	Cassie – Mayr	2	GA and SA
[56]	$LSE = \sum_{t=1}^{n} \lvert u_{test}(t) - u_{arc}(t)\rvert^2$	Mayr and Schwarz	2 - 4	GA and PSO
[57]	$error = \frac{\sum_{t=t_1}^{t_2} \sqrt{(g_{opti}(t) - g(t))^2}}{N}$	Cassie, Mayr, KEMA Habedank and Schwarz	2 - 6	GA

evaluate the arc model parameters. The approach minimizes the Least-Square Error (LSE), defined as the sum of squared differences between measured and predicted arc voltages. The optimization goal is to determine the arc parameters by minimizing the LSE. Finally, according to the authors, the GA method is the most recommended due to its global search capacity.

In [57], a method for estimating black-box arc parameters using a genetic algorithm is presented. This approach models a DC short-circuit in a railway system protected by a High-Speed Circuit Breaker (HSCB). Experimental data from a DC HSCB in a railway system validated the method. The estimation of arc model parameters was based on Zhang's work [53], with modifications such as defining the fitness function involving arc conductance. According to the authors, simulated results presented strong agreement with experimental data. Table 2 presents a summary of works that use optimization algorithms to define model parameters.

IV. CONCLUSION

Modeling DC arcs is a complex challenge, however it is crucial for understanding arc faults in PV systems. These faults pose significant risks, including severe damage and fire, endangering both the system and human life. This paper focus on one of the main modeling alternatives, which is made from simplifications of physical principles, creating models known as black-box.

One of the main challenges in modeling DC arc faults is determining the model parameters. These parameters are indispensable for producing accurate predictions of how an arc behaves within its operational context, including its interactions with nearby equipment and infrastructure. Therefore, this work also presented an overview of the main works related to parameter estimation for electric arc models.

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PLAGIARISM POLICY

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