Power Transformer Modelling for the Evaluation of a Reinforcement Learning-Based Inrush Current Minimization Strategy

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***Abstract* – Inrush currents in power transformers can affect the transformer lifetime and the reliability of electrical grids. Various inrush current minimization techniques have been proposed to mitigate these effects. To validate any minimization strategy, an accurate transformer model is required. This study focuses on developing a transformer model for inrush current minimization. The transformer is modelled through duality-based transformation, recognized for its accurate core representation. In addition, the laboratory environment and its constituent components are also modelled. The developed model is validated against real inrush current measurements. Finally, the model is employed to test a Reinforcement Learning (RL) based inrush current minimization strategy. The performance of the proposed method is validated by contrasting its outcomes with inrush current data obtained from traditional uncontrolled Circuit Breaker (CB) operations. The findings indicate that the proposed inrush current minimization approach reduces the peak inrush current by 77% compared to traditional uncontrolled CB switching.**

***Index Terms*—Circuit breaker, duality-based model, inrush current, reinforcement learning, power transformer**

I. Introduction

TRANSFORMERS are essential assets in ensuring the reliable and efficient operation of electrical grids. Monitoring their proper operation is critical, as malfunctions can lead to severe consequences. Energizing a transformer may lead to saturation of the iron core, a consequence of its ferromagnetic nature [1], resulting in high magnetizing currents known as inrush current. Inrush current is a transient current that flows into the transformer upon energization, often significantly higher than the nominal current. It can contribute to transformer degradation, reduce power quality, and potentially lead to grid instability events [2].

To mitigate these adverse effects, inrush current must be effectively reduced. In this context, controlled switching is among the most widely employed techniques for inrush current minimization, primarily due to its cost-effectiveness [3]. This method operates by precisely timing the opening and closing operations of the Circuit Breaker (CB) [4]. Traditionally, the closing time of the CB is estimated by comparing the expected transformer flux at connection with the remanent flux after disconnection. The remanent flux is usually calculated by integrating the terminal voltage during the disconnection of the transformer. However, some analyses have indicated that the remanent flux may diminish over extended disconnection periods [5].

Recent developments in intelligent control have opened new possibilities for enhancing traditional methods. In particular, a domain of machine learning known as Reinforcement Learning (RL), which focuses on sequential decision-making through interactions with dynamic environments, has demonstrate significant potential for tackling intricate control and optimization problems in power systems [6], [7]. Combining controlled switching with RL could provide an alternative to address and adjust the inrush current minimization strategy to the dynamic transformer operational environment [8].

Analyzing inrush current transients is key to developing inrush minimization techniques. This involves modelling the transformer, CB, and system cables. The modelling approach depends on the required accuracy and case specifics. Usually, duality-based transformer models are preferred due to their accurate core representation [9]. This transformation technique maps magnetic circuits onto equivalent electric circuits through the concept of duality. Furthermore, the amplitude of the inrush current is affected by the degree of magnetic saturation in the core during energization. Consequently, an accurate core model, typically presented by the Jiles Atherton (JA) model [10], is essential to properly simulate inrush current transients. The JA model uses five parameters to solve a partial differential equation (PDE), which are typically estimated with metaheuristic search algorithms. [11]. The parameter initialization in these algorithms significantly impacts their convergence. In this regard, initializing parameters with probability density functions have demonstrated enhanced accuracy and computational efficiency compared to random initialization approach [12], [13].

In this context, this paper presents a duality-based model of a 7.4 MVA 30/19.9 kV Dyn11 transformer [14] and proposes an RL-based switching strategy to reduce inrush current. Therefore, the main contributions are (*i*) the design and validation of a duality-based transformer model for inrush current analysis, and (*ii*) the development of an RL-based approach to minimize inrush current. The results demonstrate

This work was supported by the Spanish State Research Agency (grant No. CPP2021-008580) and the Department of Education of the Basque Government, Research Group Program (grant No. IT1634-22 and IT1504-22). In addition, Jose I. Aizpurua is funded by the Ramón y Cajal Fellowship, Spanish State Research Agency (grant number RYC2022-037300-I), co-funded by MCIU/AEI/10.13039/501100011033 and FSE+. Part of this work was undertaken by J. Ugarte Valdivielso at the University of Strathclyde, Scotland, UK, through an ERASMUS+ Student Mobility Award.

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the accuracy of the proposed model and the effectiveness of the RL-based strategy in minimizing inrush current.

II. Methodology

The aim of the presented framework is to model a power transformer to assess and validate the proposed inrush current minimization technique. To do so, in addition to the transformer model, the laboratory setup and its components need to be modelled. In this context, the electrical grid and the cables located between the grid and the transformer are analysed. The modelling of the components and their simulation implementation are further explained in Section III.

The simulation model is validated by comparing its results with multiple inrush current measurements. The selected cases exhibit varying inrush current peak values and switching angles. As a result, the validation covers both inrush current peaks below and above 1 pu, which is the maximum acceptable value defined by the minimization strategy proposed by the authors. After validating the model, it is employed to design and implement the proposed inrush current minimization technique. The introduced method builds upon the selection of an optimal closing angle based on RL. RL trains an agent to make decisions based on its cumulative knowledge and past experiences. In this algorithm, the agent interacts with the environment (*i.e.*, the validated transformer and laboratory simulation models) by taking different actions, transitioning between states, and learning by receiving a reward according to the quality of the selected action. By repeating this process over each iteration, the agent, which is a Neural Network (NN) model, learns which actions are the best to minimize a cost function over time. Among existing RL variants, this study implements Deep-Q Learning (DQN) owing to its suitability for discrete state actions [6]. The agent-environment interaction, which is used for the learning process, is visualized in Fig. 1.

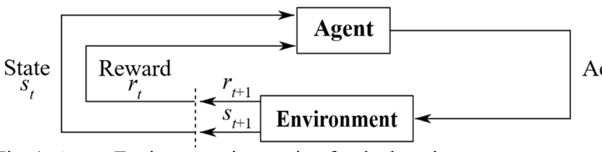

Fig. 1. Agent-Environment interaction for the learning process.

The remanent fluxes and opening angles of the CB are the states of the RL algorithm. In contrast, the closing angles of the CB are regarded as the actions performed by the agent. It is important to highlight that the switching angles are measured relative to the point where the phase-to-ground voltage of phase U crosses zero with a positive slope. The reward associated with each state–action pair is computed using the transformer model simulation. In this framework, the simulation is driven by the remanent fluxes defining the state and the closing angle representing the action. The simulation provides the corresponding inrush current peak value, and the reward is determined as follows:

$$r = \begin{cases} -I_{\max}, & I_{\max} > 1 \\ (1-I_{\max}), & I_{\max} \leq 1 \end{cases} \quad (1)$$

where r is the reward and $I_{\max}$ is the inrush current peak in per unit [pu] obtained from the transformer model. The [pu] base current is defined by the primary nominal current in TABLE III.

The development of the minimization strategy is divided into two parts: (*i*) the training of the RL-DQN algorithm and (*ii*) the validation of the proposed strategy. Training data, including opening angles and remanent fluxes, is generated by simulating CB openings across 360 degrees in one-degree steps. The training of the RL model relies on hyperparameters that control the learning rate and ensure proper convergence. To select the optimal hyperparameters, Bayesian optimization is employed using the Optuna library [15]. The chosen hyperparameters are displayed in TABLE I. Apart from that, the convergence criterion is set to 70,000 time steps, roughly half of the 129,600 unique possible combinations in the search space.

TABLE I
SELECTED HYPERPARAMETERS FOR THE RL MODEL TRAINING

Parameter	Symbol	Value
Batch Size	-	256
Discount Factor	γ	0.99
Exploration Initial Epsilon	$\varepsilon_{\text{initial}}$	1
Exploration Final Epsilon	$\varepsilon_{\text{final}}$	8.67x10
Exploration Factor		0.49
Learning Rate	α	1.15x10
Replay Buffer Size		100,000

Finally, the proposed RL-DQN-based strategy is evaluated using opening angles and remanent fluxes from new scenarios. These new scenarios are based on traditional uncontrolled CB closing measurements. The trained NN predicts the optimal closing angle for each new scenario, which, together with the remanent fluxes, is fed into a simulation to calculate the inrush current peak. The measured and simulated inrush currents are then compared to validate the approach.

III. Component Modelling

The medium voltage laboratory where the tests are conducted is connected to a 30 kV power grid with a typical voltage of 31.5 kV. The resistance and inductance that determine the short-circuit power of the grid are 0.69 Ω and 7.9 mH, respectively. The single-line diagram of the test setup is shown in Fig. 2. The test object under study is a 7.4 MVA 30/19.9 kV Dyn11 medium voltage transformer.

There are two CBs depicted in the laboratory setup diagram. The main breaker remains closed during tests, while the second is used to energize the transformer. This switching action is remotely commanded from the laboratory control site. The current and the voltage at the transformer are measured at its primary. A *Dewesoft Sirius* data acquisition and analyser serves as the test measuring equipment [16].

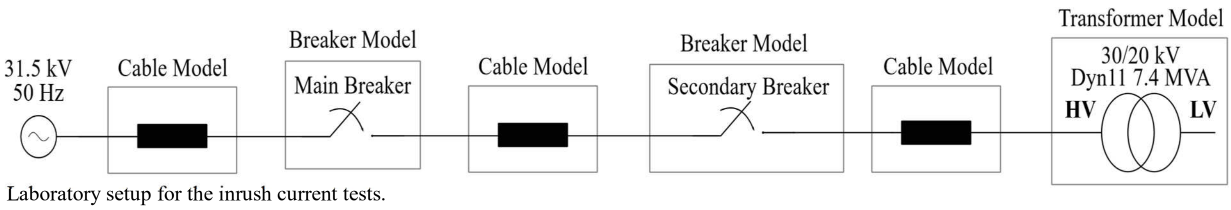

Fig. 2. Laboratory setup for the inrush current tests.

A. Cables

To replicate the test results, it is necessary to add the modelling of the laboratory cables to the simulation. The cable modelling is done following the pi model [17]. The cables are a HEPRZ AL Monopole 18/30kV and are divided into two parts. The first cable part is connected between the power grid and the laboratory and has a 240 mm^2 cross-section with a length of 245 meters. Therefore, the lumped parameters of this cable section are given as R_{240}, L_{240},and C_{240}. The second cable is divided into two sections: the first one is installed between the two CBs, and the second connects the secondary CB with the transformer. The cross-section of these cables is 150 mm^2, the sum of both parts results in 108 meters long, and the lumped parameters of this cable are named R_{150}, L_{150}, and C_{150}. The lumped pi model parameters for the two cables are presented in TABLE II.

TABLE II
PI MODEL PARAMETER VALUES TO MODEL THE CABLE SECTIONS

Parameter	Symbol	Value	Unit
240 mm^2 Cable Resistance	R_{240}	30.60	mΩ
240 mm^2 Cable Inductance	L_{240}	85.05	μH
240 mm^2 Cable Capacitance	C_{240}	73.74	nF
150 mm^2 Cable Resistance	R_{150}	22.25	mΩ
150 mm^2 Cable Inductance	L_{150}	40.57	μH
150 mm^2 Cable Capacitance	C_{150}	27.00	nF

B. Circuit Breaker

The main factors that need to be considered for modelling the behavior of the CBs are the characteristic times of the opening and closing operations. As the objective of this study is to monitor the closing instant of the CBs, the focus is on the closing mechanism of the contacts. The closing time can be affected by the dielectric material inside the CB. The dielectric properties of the material can affect the time of the pre-arc, which relies on the Rate of Decrease of Dielectric Strength (RDDS) [18]. This parameter is usually expressed in kV/ms and affects the moment when the current starts circulating between the contacts. As the distance between the contacts of the CB starts decreasing, the voltage-blocking capability of the CB begins decreasing. At a certain point, the voltage across the contacts may exceed the dielectric strength of the medium, resulting in an electrical breakdown and the start of a pre-arc. Ideally, if the RDDS remains higher than the maximum derivative of the voltage across the contacts, no pre-arc would occur. This is a critical consideration when designing inrush current minimization strategies, as the RDDS can influence the desired closing angle. Hence, it directly affects the inrush current amplitude as a mismatch in the desired and real closing angles can cause the saturation of the core.

After the laboratory tests are conducted, it is observed that no pre-arc occurs when vacuum CBs are closed. This can be seen in the two examples shown in Fig. 3, where V_U presents the phase-to-ground primary side voltage of phase U, and 52 A is a trigger signal that indicates the moment when the contacts of the CB close. The voltages in Fig. 3a and Fig. 3b appear only after the contacts come together; therefore, it is concluded that there is no pre-arc. Accordingly, in this study, the RDDS is considered negligible for the vacuum CB model. Although the CBs in Fig. 3 are not vacuum CBs, for the sake of simplicity, the CB model for this study is considered ideal, thereby neglecting the pre-arc phenomena.

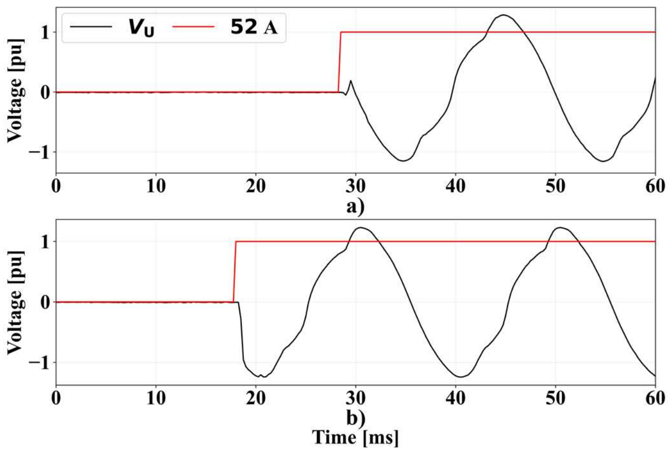

Fig. 3. Transformer primary side voltage and 52 A signal with no pre-arc.

C. Power Transformer

The chosen transformer modelling methodology is an equivalent circuit derived by duality transformation [19], shown in Fig. 4. This modelling approach is selected due to the frequent presence in the literature (e.g. [9], [20]), accurate transformation without precision loss from a magnetic-to-electric circuit, and accuracy of the core modelling.

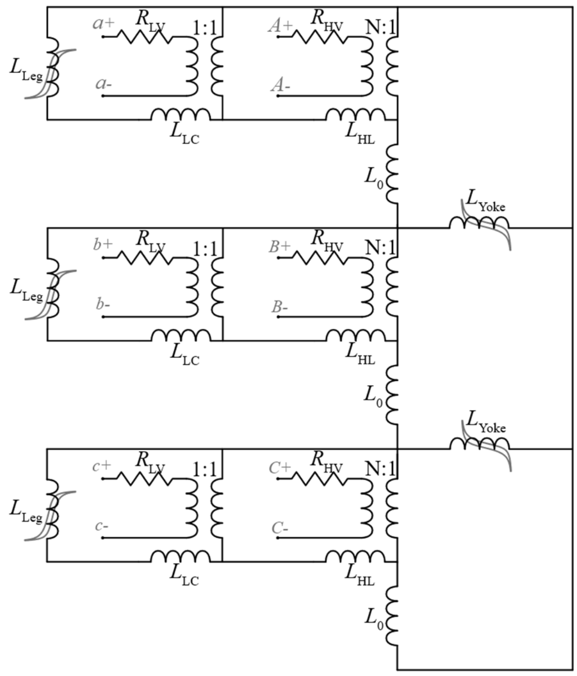

Fig. 4. Three-phase transformer model based on duality transformation [9].

TABLE III.
MAIN CHARACTERISTICS OF THE POWER TRANSFORMER

Parameter	Symbol	Value	Unit
Apparent Power	S	7.4	MVA
Primary Voltage	V_p	30	kV
Secondary Voltage	V_s	20	kV
Primary Current	I_s	142.4	A
Frequency	f	50	Hz
Primary Turns	N	824	-
Primary Winding Resistance	R_{HV}	1.28	Ω
Secondary Winding Resistance	R_{LV}	0.26	Ω
Secondary to Core Leakage Inductance	L_{LC}	55.58	mH
Primary to Secondary Leakage Inductance	L_{HL}	81.12	mH
Zero-Sequence Inductance	L_0	25.37	μH

The resistance and inductances in Fig. 4 are presented in TABLE III, along with the main transformer parameters. These parameters are obtained from the transformer datasheet. Delta (D) and star (Y) configurations, phase difference, and stray capacitance circuit are linked from outside to the terminals A+/-, a+/-, B+/-, b+/-, C+/- and c+/-.

D. Core Modelling

The transformer core in the model is represented using nonlinear inductances L_{leg} and L_{yoke}, allowing accurate modelling of the electromagnetic behavior of each limb and preserving the core topology. Hysteresis is modelled using the JA approach, which characterizes the *BH* curve through five parameters [12]. By adjusting these parameters, the JA model solves a PDE to compute *H* from *B*. Fig. 5 presents the *BH* curve of the M120-27S core material used in the transformer.

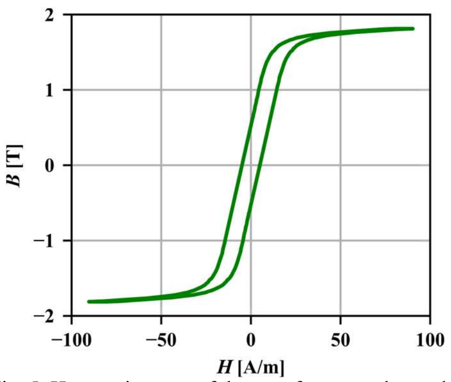

Fig. 5. Hysteresis curve of the transformer under study.

In the inrush current simulation, each leg and yoke shown in Fig. 4 are modelled by a linear resistance R_{fe}, representing the eddy current losses, and a nonlinear controllable current source, which captures the hysteresis behavior of the iron core. The magnetizing current of each leg and yoke is obtained by measuring the voltage across each limb, as shown in Fig. 6. The saturation model represents the steps to follow for determining the magnetizing current injected by the source at each time step.

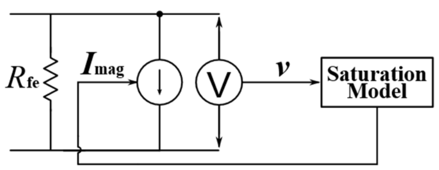

Fig. 6. Representation of each leg and yoke core model in Fig. 4 [21].

The voltage measurement is integrated to obtain the magnetic flux in each time step, as follows [1]:

$$\Phi = \frac{1}{N}\int v(t)\,\mathrm{d}t \tag{2}$$

where Φ is the magnetic flux in webers [Wb], N is the number of turns of the winding and $v(t)$ is the voltage across the limb in volts [V]. The magnetic flux and the flux density are related by the area of the core as follows:

$$B = \frac{\Phi}{A} \tag{3}$$

where B is the magnetic flux density in teslas [T] and A is the area of the limb in square meters [m^2]. The field strength value is derived from the JA model. Following Ampère's law, the field strength and the magnetizing current can be related by the core length and number of turns:

$$I_{\text{mag}} = \frac{Hl}{N} \tag{4}$$

where I_{mag} is the magnetizing current in amperes [A], H is the field strength in ampere per meter [A/m], and l is the length of the limb in meters [m]. This magnetizing current is injected into each limb in Fig. 4. A block diagram of the saturation model used to calculate the magnetizing current from the voltage in each limb is shown in Fig. 7.

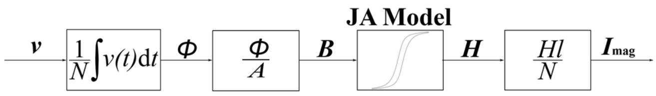

Fig. 7. Inrush current calculation in the simulation using the JA model.

The values of the lengths and areas of the legs and yokes of the transformer under study are given in TABLE IV.

TABLE IV
DIMENSIONS OF THE LEGS AND YOKES OF THE TRANSFORMER IN FIG. 4

Parameter	Symbol	Value	Unit
Leg Length	L_{leg}	1.93	m
Leg Area	A_{leg}	0.06	m^2
Yoke Length	L_{yoke}	1.65	m
Yoke Area	A_{yoke}	0.05	m^2

IV. NUMERICAL RESULTS

The numerical results are divided into two sections. First, the transformer model is validated. Then, this validated model is used to test and confirm the effectiveness of the RL-based strategy for minimizing inrush current.

A. Transformer Validation

The transformer model in Section III. C. is validated by comparing simulation results with inrush current measurements under various uncontrolled CB closing scenarios. These scenarios cover inrush currents ranging from 0.19 pu to 2.04 pu. To replicate the measurements, the simulation is divided into two stages: opening and closing. The opening stage determines the remanent fluxes, which, together with the corresponding measured closing angles, are used as inputs for the closing stage. The resulting inrush current peak values are then compared with the inrush current measurements in Fig. 8.

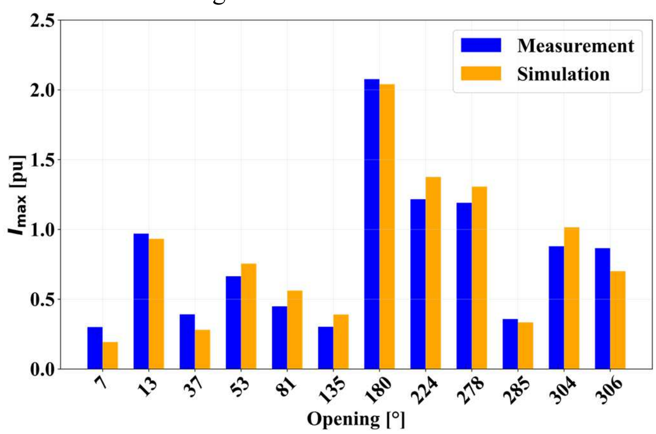

Fig. 8. Comparison of measured and simulated inrush current peak values.

A more detailed representation of the results shown in Fig. 8 is given in TABLE V. These results show that (*i*) the measured and simulated inrush currents differ by less than 0.17 pu and (*ii*) the mean difference is 0.10 pu. Considering these results, the transformer model is deemed acceptable and capable of replicating inrush current transients.

TABLE V
NUMERICAL RESULTS CORRESPONDING TO FIG. 8

Opening [°]	Classical Closing [pu]	Simulation [pu]	Absolute Difference [pu]
7	0.30	0.19	0.11
13	0.97	0.93	0.04
37	0.39	0.28	0.11
53	0.66	0.76	0.10
81	0.45	0.56	0.11
135	0.30	0.39	0.09
180	2.08	2.04	0.04
224	1.22	1.38	0.16
278	1.19	1.31	0.12
285	0.36	0.33	0.03
304	0.88	1.02	0.14
306	0.87	0.70	0.17

B. Reinforcement Learning Validation

The training evolution of the RL-DQN algorithm is illustrated by the mean episode reward and its 95% Confidence Interval (CI) in Fig. 9. Each episode refers to 100 steps, and the reward is calculated from 10 randomly selected steps per episode. The training process shows that the mean episode reward increases with each iteration. Moreover, the results show a steady increase in the mean episode reward over time. Initially, the 95% CI indicates high variance, which gradually decreases as training progresses, reaching its lowest point upon completion of the maximum training steps.

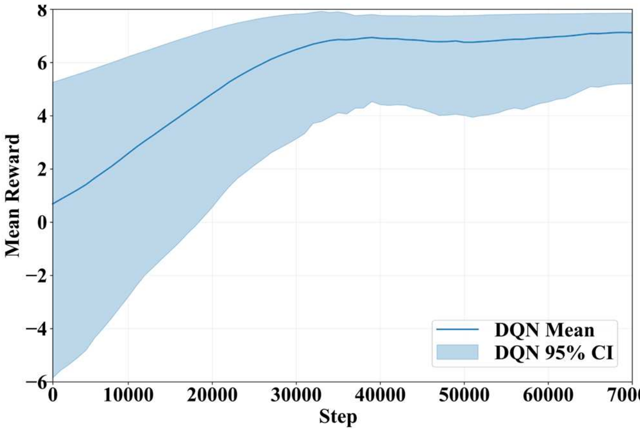

Fig. 9. Average episode reward and 95% CI for RL-DQN training.

Subsequently, the trained RL model is evaluated on new scenarios. For each case, the trained NN predicts the optimal closing angle, and this value is then used in simulations to compute the resulting inrush current peaks. These results are compared to classical uncontrolled CB closing measurements, with results shown in Fig. 10 and detailed in TABLE VI. Note that differences in inrush current peaks arise from variations in closing angles across cases, as the measurements are uncontrolled, whereas the RL predictions are based on the trained model. For the RL-DQN results, the reported values represent the mean peak inrush current obtained from evaluating 10 learning trials.

The results show that with classical uncontrolled switching, inrush current exceeds 1 pu 33.33% of the time. In contrast, the RL-DQN algorithm keeps the average maximum inrush current below 0.28 pu. The mean inrush current peak for the measured cases is 0.87 pu, while for the RL-DQN method, the mean of the average inrush current is 0.20 pu. These results represent a 77% reduction of the average inrush current peak when applying the proposed strategy, demonstrating its effectiveness.

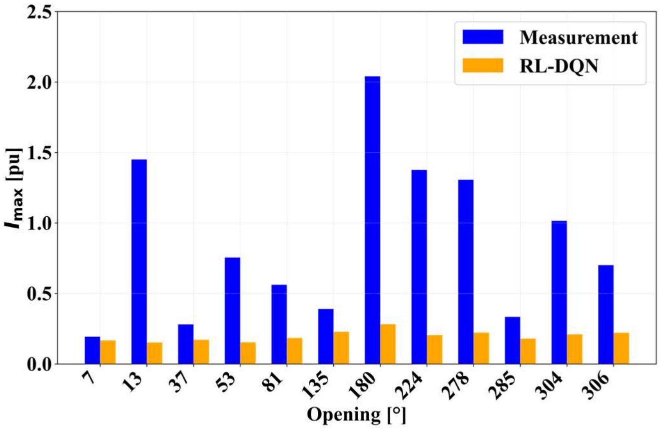

Fig. 10. Comparison of measured and RL-DQN inrush current peaks.

TABLE VI
NUMERICAL INRUSH CURRENT PEAK RESULTS PRESENTED IN FIG. 10

Opening [°]	Classical Closing [pu]	DQN [pu]
7	0.19	0.17
3	1.45	0.15
37	0.28	0.17
53	0.76	0.15
81	0.56	0.18
135	0.39	0.23
180	2.04	0.28
224	1.38	0.20
278	1.31	0.22
285	0.33	0.18
304	1.02	0.21
306	0.70	0.22
Mean	0.87	0.20

V. CONCLUSIONS

This work presents an integrated framework combining a detailed model of a 7.4 MVA real-scale power transformer, able to capture inrush current transients, with a Reinforcement Learning (RL) approach aimed at mitigating inrush currents. A real-scale 7.4 MVA power transformer is modelled by a duality-based transformation, with core magnetics characterized by the Jiles-Atherton (JA) method. The model validation is performed by comparing measured and simulated inrush current amplitudes under various uncontrolled Circuit Breaker (CB) closing scenarios. The results indicate a maximum difference of 0.17 pu and a mean difference of 0.10 pu between the measurement and simulation results, which is considered an acceptable tolerance.

Additionally, the transformer model is used to evaluate an inrush current minimization strategy based on Reinforcement Learning (RL). A Deep-Q Network (DQN) algorithm is trained to select the optimal CB closing time. Its performance is evaluated using new opening scenarios of the classical uncontrolled CB closings. The inrush current peak results of these closing measurements are compared against the results obtained with RL-DQN. The RL-based approach reduces the average inrush current peak by 77% and keeps the mean peak below 1 pu. These results indicate that the proposed approach effectively reduces the inrush current peak to within acceptable limits.

The proposed framework has primarily focused on opening angles and remanent fluxes to develop the inrush current minimization strategy, assuming an ideal CB based on laboratory tests that showed no significant pre-arcing effects. However, in practical applications, CB timing and dielectric properties can significantly impact switching performance, with factors such as dielectric ageing and mechanical wear causing variability over time. Additionally, the analysis has been limited to short disconnection periods of a few hours, without addressing remanent flux evolution over longer times. Therefore, examining the variation of remanent flux as a function of the transformer disconnection time remains an open area for further study. To manage these dynamic operating conditions with optimal control actions, RL could be further exploited due to its capacity to learn and adapt within complex, time-varying environments. All these aspects could be experimentally evaluated by implementing them in an external controller that acts over the closing coils of the CB.

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VII. Biographies

Jone Ugarte Valdivielso received her B.Sc. degree in Energy Engineering from Mondragon University (MU) in 2019 and her M.Sc. in Electrical Power Systems and High Voltage from Aalborg University (AAU) in 2021. Since 2020, she has been with the Electronics and Computer Science Department at MU. In 2023, she began pursuing her PhD focused on inrush current minimization in power transformers. Her research interests include medium- and high-voltage technologies within electrical power systems.

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Asier Torres earned his B.Sc. degree in Energy Engineering from Mondragon University (MU) in 2020 and his M.Sc. in Energy and Power Electronics from MU in 2022. Since 2022, he has been with the Electronics and Computer Science Department at MU, where he works as an engineer in the Medium Voltage Laboratory. His research interests include energy and power electronics.

Brian G. Stewart is a Professor of High Voltage Engineering at the University of Strathclyde, Glasgow, UK. He holds B.Sc. and Ph.D. degrees from the University of Glasgow, UK. His research interests include electrical condition monitoring, dielectric insulation diagnostics, and high voltage asset management. He is a Chartered Engineer, a Member of the IET, and a Past President of the IEEE Dielectrics and Electrical Insulation Society.

Jose I. Aizpurua is a Ramon & Cajal Research Fellow at the University of the Basque Country (UPV/EHU), Faculty of Computer Science, Department of Computer Science & Artificial Intelligence and an Ikerbasque Research Fellow. He received his Eng., M.Sc., and Ph.D. degrees from Mondragon University (MU) in 2010, 2012, and 2015, respectively. He was a Visiting Researcher at the University of Hull, Dependable Intelligent Systems Group in 2014 (Hull, UK), Research Associate at the University of Strathclyde, Institute for Energy & Environment during 02/2015-12/2018 (Glasgow, UK), and Lecturer & Researcher at MU, Department of Electronics and Computer Science during 02/2019-09/2024. Dr Aizpurua's research interests include the development of intelligent solutions for the power and energy sector.