

Review Article

A Survey on Adaptive Fault Tolerant and Control Strategy Techniques for Power Electronic Traction Transformer

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Received: 07 August 2025

Revised: 09 September 2025

Accepted: 09 October 2025

Published: 30 October 2025

Abstract - Among such disruptive technologies is the Power Electronic Traction Transformer (PETT) that not only challenges the traditional transformers but also offers many additional practical benefits, such as high efficiency, modularity, miniaturization, etc. These advantages position PETT as a transformative solution for modern electrical systems, enabling enhanced performance in various applications, including renewable energy integration and innovative grid implementations. As the demand for efficient power management continues to rise, the adoption of this technology is likely to accelerate, fostering innovations across the energy sector. However, fault tolerance and control, both important for reliability and operational stability, are fundamental challenges to the broad use of this technique. This survey covers the large body of adaptive fault-tolerant practices and control systems tailored to the PETT to address its special challenges. According to the paper, PETT is introduced and discussed with a focus on its architecture, internal working principles, and applications to a broad range of scenarios, including renewable energy integration, smart grids, and others. A DRILL-down of frequent fault classes in PETT is established, including thermal faults, open-circuit faults, and short-circuit faults. Furthermore, this taxonomy exposes the trust identifier faults and challenges concerning detection and resolution. The survey reports adaptive fault-tolerant methods (self-healing systems), out-of-the-box real-time Fault Detection and Isolation (FDI), recent state-of-the-art methods, and their adaptive reconfiguration. On the other hand, the paper surveys control methods based on voltage control, current control, and frequency control, and the new methods by way of model predictive control, neural network-based control, and adaptive sliding mode control. The survey combines these approaches to emphasize the complementarities between fault tolerance and control schemes and their combined effect on PETT reliability and performance. Recently, however, the potential applications of artificial intelligence and machine learning techniques on PETT domains are also described, indicating transformative capability to address issues related to fault management and control schemes. The article concludes with a summary of research limitations and recommendations on research investigations aimed at promoting the amenability and robustness of PETT. In general, this survey is helpful for researchers and industry players to innovate and design robust solutions that are sensitive to the technology of power electronic transformers.

Keywords - Power Electronic Traction Transformer (PETT), Adaptive Fault Tolerance, Control Strategies, Fault Detection and Isolation (FDI), Artificial Intelligence in Power Systems.

1. Introduction

As the sophisticated development of power systems transforms into a new era of modernization and an emphasis on renewable energy input grows, there is a dire need to introduce new technologies to ensure the capacity for better efficiency, flexibility, and resilience requirements. There is one such novel, the Power Electronic Traction Transformer (PETT); however, it has gained a lot of attention as the new power electronic devices can be integrated within the conventional transformer structures. PETT is a pivotal interface amongst today's systems, e.g., renewable power grid utility grids, electric vehicle charging systems, and smart

industrial automation. Integrating conventional transformer operation with power electronics, PETT provides enhanced control, miniaturization, and power efficiency and represents a paradigm change in power distribution and control doctrine [1]. Despite the power of classic transformers, they are light, bulky, and uncontrollable. Since they are in today's dynamic context of smart grids and renewable energy technologies, they are becoming obsolete [2]. To fill these gaps, PETT uses DC power electronic converters capable of providing voltage and frequency control, bidirectional transfer, and communication with distributed generation systems. Because of its modularity, it enables its use in a diverse range of



applications, and, as such, it is the most promising feature for next-generation power grids [3]. One feature of PETT is its (potential) feasibility in integrating renewable energy into the system [26]. Because of the intrinsic intermittency and finiteness in rates of change and responsiveness of wind and solar power, a switchable power distribution scheme is needed. PETT allows the required plasticity in such a manner as to guarantee that the system remains stable and uses the right amount of energy in a changing world. Moreover, due to the very small size and high operating frequency, it may be a cost-effective solution with the lowest installation cost; it can be a solution for the sake of a more urban and industrial society. Although very useful, the inherent difficulties of reliability and fault management exist for PETT. In PETT, mechanical failure, thermal loading, partial component degradation, and external perturbations can all play a role [4]. Such faults can have a damaging effect on the performance of the system, such as energy losses, unplanned shutdowns, and the need for more maintenance. Therefore, fault tolerance of PETT is an equally important issue in the successful deployment of PETT.

Addressing these challenges requires the implementation of robust monitoring systems and predictive maintenance strategies. By proactively identifying potential failures, operators can enhance the reliability of PETT and minimize operational disruptions. Fault tolerance measures the degree to which a system can maintain its correct function in the presence of failures. Due to the use of power electronic devices, in which power electronic components on the traditionally designed transformer components are more susceptible to failure, high reliability and fault-tolerant characteristics are critical aspects of the design of PETT [61-63]. Standard degradations of the PETT are short-circuit and open-circuit, thermal overload, and initiation failure [5].

However, if the liability of manipulation of the prompt is not utilized, errors can, at least in principle, travel through the system, leading to a chaining of collapses. To overcome these challenges, adaptive fault-tolerant schemes have also been proposed as a candidate solution. These techniques are based on the assumption that the innovation that will ultimately lead to the creation of in-situ monitoring and diagnostic tools in order to detect and isolate defects is such a function as to allow for time-efficient re-formatting. The use of algorithms from a family of Artificial Intelligence (AI) and Machine Learning (ML) helps these responsive strategies, which can predict failures and take remedial actions, achieve a level of system reliability in practice and reduce the downtime [6].

Specifically, effective policies that are not fault-tolerant are also important to obtain good performance of PETT. The ability to control voltage, current, and frequency is essential for functioning effectively under fluctuating loads and variations in supply current and voltage while maintaining high stability. Although control has been applied, this perhaps

oversimplifies the power system's needs due to the characteristics of power systems that include dynamic distributed power sources [7]. However, to meet the challenge of the breakdown of conventional control schemes, advanced control schemes based on Model Predictive Control (MPC) and neural networks have been proposed. There are both accurate and adaptive control algorithms for these schemes, and they allow PETT to respond to an exudative or acute change in the operating environment within a few seconds' reaction time. For instance, MPC uses mathematical models to predict the system's future behavior and to perform optimal control in real time, thus maximizing the energy that is used efficiently with low losses [8]. More specifically, neural network-based controllers can be learnt from information that has already been acquired (i.e., to generalize to a new situation) to make the PETT more robust to disturbance.

1.1. Objectives of the Survey

The main goal of the review is to comprehensively survey the adaptive fault-tolerant methods and PETT control strategies [60]. The survey is intentionally (explicitly) designed to reduce the gap between the knowledge base at this time and the level of application as much as practically possible through (a) a systematic review of the future prospects of the art and (b) next steps. Specifically, the survey addresses the following objectives:

To provide an overall description of PETT, including its architecture, principal components, and applications. Additionally, it aims to identify key challenges and limitations within current methodologies and propose innovative solutions that could enhance the efficacy of PETT systems.

- The aim of this study is to identify and classify the most common PETT defects and then to characterize the impact of their performance.
- Adaptive fault-tolerant methods are reviewed, with particular focus on their advantages and disadvantages and practical and engineering consequences.
- More specifically, with regard to the analysis of current state-of-the-art control strategies and their application to fault-tolerant solutions.
- To review recent progress and trends in the field and specify the applications of AI and machine learning methods.
- As part of a proposal for future research and development of adaptive fault tolerance and control of PETT.

Therefore, due to the achievement of these objectives, this survey aims to give important clues and data to researchers, engineers, and industry professionals to encourage innovation and to guide the development of powerful and efficient PETT systems. This article is organized around several subchapters in order to provide a consistent and encompassing perspective on the topic. A light introduction to the PETT, along with its architecture, function, and applications, is then given.

Section 4 describes the type of faults that are expected to be detected by PETT, the problem of detection in PETT, and the techniques for dealing with the problem i.e., Adaptive fault-tolerant methods are presented in Section 5, Taxonomy principles of operation classification and benchmarking.

Section 6 discusses advanced control approaches for PETT, with a particular focus on their contribution to the maintenance of stable and efficient performance. Integration of fault tolerance and control schemes is also discussed in this section, as well as the synoptic nature of the two components, i.e., the way in which they support and reinforce each other. Recent progress and developments in the field of (AI/ML) have been briefly discussed in Section 7, in which AI and ML techniques [19] are applied for fault detection and control optimization.

In Section 8, the related methods are compared, and their respective limitations and opportunities are presented. Last, Section 9 summarizes the results and presents some suggestions for further research. The same paper also contained a complete list of all sources consulted while retaining the academic character of the paper. Since the generation mix in power systems is changing and the distribution networks of the distributed/autonomous generation are pervasive, PETT is an enabler for power generation and power supply.

2. Overview of Power Electronic Traction Transformer (PETT)

2.1. Historical Development and Evolution of PETT

Power Electronic Traction Transformer (PETT) emerged out of the need for energy conversion systems that are not only practical and efficient but also intelligent, that is, capable of meeting the requirements of modern power systems. Conventionally, the power grid backbone for over one generation has been the stationary transformers, which are not ideal but cannot meet the demand in today's energy system [21].

The emergence of renewable generation technologies, distributed generation, and new grid structures at the end of the 20th century collectively emphasized these limitations, especially concerning standard transformers' size, mass, and static controllability. The presence of these challenges inspired the development of potential solutions that have the potential to give the required capacity from the growing complexity of contemporary power distribution. This childlike stage of PETT's development was, in actuality, well matched to the development of electronics and semiconductors, especially in the 1980s and the 1990s. The development of high-power switching devices (insulated-gate bipolar transistor (IGBT) and Gate Turn-Off Thyristor (GTO) is the initial step along the path of high-efficiency power conversion systems [22]. The first generation of PETT designs aimed at

combining power electronic converters with conventional transformers, thus controlling voltage and frequency with greater precision. But these initial efforts also incurred serious limitations in efficiency, and a grossly unacceptable high cost that prevented their scaling up in a successful manner.

In the early 2000s, the region took a giant leap in disseminating high-performance power electronic elements, particularly devices based on Silicon Carbide (SiC) and Gallium Nitride (GaN). These technologies allowed a considerable performance, efficiency, and reliability increase of PETT [23], which effectively opens the possibility for the design of actual electronic transformers. Compared to earlier generations, these modern architectures may also be able to comprehensively substitute the classical transformers for a broad class of tasks [56].

After years, PETT's paradigm has finally reached the state-of-the-art level in terms of module-based architectures, energy consumption, and the depth of implementation on grid-tie aspects. Until that point in time, the ability of PETT is one of the key technologies allowing the realization of smart grids, renewable energy, and electric mobility systems. This advancement not only optimizes energy efficiency but also enhances the reliability of these systems. Consequently, the integration of such technologies paves the way for a more sustainable and innovative future in energy management. Because of its ability to adapt to the volatile demand of contemporary power grids, PETT is now regarded as a paradigm shift technology with the potential of transforming the future of power grid engineering.

2.2. Key Components and Working Principles of PETT

Power Electronic Transformers (PETT) are, by definition, not identical to standard transformers, not only in their build but also in how they operate. PETT is based around a set of panel components, namely, high-frequency transformers, power electronic converters, advanced control actuators, and, by their application, it is shown that one can operate in a way that extends far beyond basic voltage transfer. The additional functionalities are implemented as power factor correction, harmonic filtering, and bidirectional energy transfer control.

The heart of the PETT is a high-frequency transformer that runs at tens of orders of magnitude higher frequencies than standard transformers. By using the high-fidelity design, the transformer is miniaturized greatly, and the transformer's energy consumption is made more efficient. These transformers are mounted in conjunction with power converters, i.e., power source rectifiers, inverters, and DC-DC converters, the latter applying to more than one stage of the energy conversion process. Nevertheless, for instance, the proposed AC input is almost always a rectified DC power transformed into an AC power and inverted to the final AC output. The PETT controller is the key module in a PETT, which is in charge of RT feedback acquisition and the precise

dialogue of operation parameters. These kinds of devices are designed on the top-level high-fidelity voltage, current, and frequency control algorithms and ensure stable and efficient performance under a broad range of operating conditions.

Therefore, the fault detection and isolation function is also integrated into the PETT control system, making the system more reliable. By augmenting this excellent building block, PETT introduces a novel capacity for structure as well as a novel capacity for the flexibility of a classical transformer. Therefore, it is very relevant to the current power system challenges, which have different but still pressing needs for efficiency, flexibility, and reliability than in the past.

2.3. Applications of PETT in Power Systems

Because of the power of its powerful features and its general adaptability, Power Electronic Traction Transformer (PETT) has been considered one of the primary actors in a large number of power system applications. Most likely, PETT will find its way into a smart grid, where it will play an important role in making the grid more stable as well as enabling the operation of bidirectional energy flow. Adaptive and dynamic characteristics must be provided in smart grids to meet variable energy demands and the generation of power systems in the 21st century. For those purposes, PETT controls the voltage and the frequency, and thereby allows the adiabatic mixing of embedded energy applications (e.g., solar cells, generators) [2]. In renewable power systems, PETT is defined to address the issues of variability and intermittency. As illustrated, it can recover from power failures by incrementally adjusting the output parameters in a way that always ensures a stable and steady power grid connection.

Furthermore, PETT allows the direct interconnection between renewable energy converters and energy storage devices, thus increasing the energy efficiency and the resilience of energy storage units as a whole. Electric mobility is one of the other key areas for which PETT has served as the driving force of this high momentum. Vehicle-to-electric (V2E) charging points are required to be extremely flexible and efficient for dealing with the variable load that emerges from EV (electric vehicle) users, as well as knowing how to cope with supply from multiple energy sources. In view of all the above factors, the small size and the bidirectional energy transfer ability of PETT endow it with great adaptability for integration in EV charging systems.

On the other hand, PETT is also scalable to V2G schemes in which vehicles act as distributed energy storage systems during periods of surplus demand and, as such, contribute to grid stability. Industrial applications also benefit greatly from PETT's capabilities. Systems (Actuators and power-demanding operations) characterizing high-power actuators and high-power-demanding work tasks are in need of high-precision power control so as to ensure robust and efficient movement of the lightweight sensitive devices. PETT's power

quality control and harmonic distortion reduction performance are suitable for satisfying the above requirement. Besides, its modularity and reconfigurability allow it to be applied to various industrial scenarios, from small operations to large-scale production lines. Based on fulfilling a broad spectrum of applications, PETT has served as a disruptive technology, along with the increasing demands associated with modern power systems and energy communities.

2.4. Advantages and Limitations of PETT

Power Electronic Traction Transformer (PETT) provides multiple benefits over conventional transformers and serves as the technological foundation of contemporary power systems. One of the most significant benefits is its small footprint and easy interface. PETT is programmable at higher frequencies and enables the operation of magnetic elements in a miniaturized size, thus making it a simple installation and transport system. Miniaturization is one such need, with high demand for urban applications in which standard transformers are not feasible. Beyond its physical advantages, PETT provides enhanced functionality. Unlike traditional transformers, however, PETT can support even more complex tasks, e.g., power factor correction, harmonic removal, and dynamic voltage regulation. For instance, these characteristics are considered since they are related to power quality and energy efficiency of power distribution networks optimization.

Moreover, PETT looks at energy transfer direction during reverse (ie, energy transfer in the opposite direction), and this relation fits naturally by associating it with energy generation and storage devices based on renewable energy. PETT's adaptability is another defining feature. Due to its modular architecture, its use may be tailored to the needs of an application, and it seems to have the potential for many applications. Incorporated in high-performance control systems, PETT provides stable operation even in the face of uncertainty (i.e., online measurement and control of control variables). Despite these benefits, PETT is not without its challenges. Undoubtedly, the biggest issue is the high initial cost, which may restrict its applications, especially those in the developing world. Manufacturing cost and installation cost are much more expensive than conventional transformers due to the integration of a new power electronic device and a complex control system.

Additionally, the design complexity and the implementation of PETT are, on their own, a limitation. There is a dependency on a high level of control algorithms and power electronic components for which some specialized knowledge is necessary to maintain and diagnose them. Electrical power components are susceptible to failure due, for example, to (thermal) stress effects and electromagnetic (EM) disturbance effects that can destroy the global reliability of the whole system. Second, high power level efficiency is also an issue. Although the power consumption of PETT is highly

conservative for low/medium power, it can be scaled to the high power regime without any restriction of longer losses or lower reliability. This limitation points particularly to the need to further develop and learn how the PETT performs in the high-power regime. Conclusions: Power system technology, through unique power, flexibility, and opportunity for modern application, makes a claim as an innovative contribution to the field. Its application in smart grids, renewable energy systems, electric mobility, and industrial systems alike underlies its potential transformative impact in energy systems. However, what needs to be addressed in the process to solve the cost, complexity, and reliability problem is essential for its completion. After the release from these constraints, PETT now holds great promise to provide a dominant contribution towards an environmentally conscious, efficient, and robust energy for the future. This advancement could lead to unprecedented efficiencies and sustainability in energy consumption. As research continues to evolve, the integration of PETT into existing infrastructures may pave the way for a greener, more resilient energy landscape.

3. Faults in Power Electronic Traction Transformer (PETT) Types and Challenges

There are three types of faults: abrupt, incipient, and intermittent. Each category poses its own set of challenges, including detection, diagnosis, and eradication, and the need for high-performance fault-tolerant algorithms that can effectively deal with these challenges in an accessible way, as depicted in Figure 1.

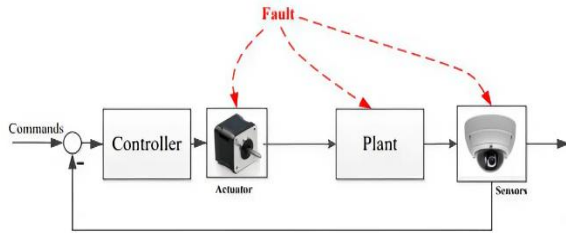


Fig. 1 Potential faults in a control system

3.1. Abrupt Faults in PETT

Transient failures are characteristics of the transient initiation, which, as a consequence, are transient, high interferences within the Power Electronic Traction Transformer (PETT) operation. These faults are typically caused by stress factors, such as short circuits, open circuit faults, or component failure due to extreme thermal or high voltage stress environments. For example, for supplying control power to a power electronic converter, a sudden short circuit of the power electronic converter causes the system DC current to skyrocket (potentially damaging the converter and its associated components and the converter component itself). Furthermore, a fault condition of an open circuit can lead to the interruption of the supply power, which is, consequently, the loss of the supply power and the inability of

the transformer to do its "job list". The most severe attack caused by an erupting fault is its fast spreading of the erupting fault. Hence, the erupting fault has a great probability of causing a system crash (i.e., cascade failure) after the erupting fault. Real-time fault detection and fault division both need effective control to reduce the magnitude of the damage [9] and, in order to avoid as much as possible, interrupt less. State-of-the-art protection systems have been designed to resolve these limitations by implementing fault-tolerant controller schemes with permanent, real-time, sensor-driven monitoring.

Continuous acquisition of the pulse shape of the current and voltage pulse is obtained, and the occurrence of any deviation of the waveform from a set of predefined thresholds triggers a protective response. For example, such tasks could consist of (but are not limited to) sweeping out destroyed sections, restoring power, or even backing it up. Mathematical modeling of spuriously failing systems has important applied utility in (1) characterizing and predicting the dynamics of spuriously failing states of systems and (2) capturing failures in communication with spuriously failing systems, such as in BCI systems. Likewise to the conventional case, in this class of models, the response of the system to an impulsive input is assumed and incorporated to design fast and accurate fault mitigation laws:

$$i(t) = i_{\text{nominal}} + \Delta i(t) \quad (1)$$

Where $i(t)$ is the instantaneous current, i_{nominal} is the nominal current, and $\Delta i(t)$ represents the fault-induced deviation. For a short-circuit fault, $\Delta i(t)$, it exhibits a rapid and significant increase, requiring immediate intervention by circuit breakers or fault-tolerant mechanisms.

3.2. Incipient Faults in PETT

Development errors are very sneaky, silent problems that, although in theory do not influence the efficiency of operation of Power Electronic Traction Transformer (PETT), can ruin the whole system efficiency—it is the case in the event the development error is not resolved because it does not lend itself to fast changes of functioning. These defects are a normal consequence of the degradation of defective zones, thermal analysis, and small manufacturing imperfections. Typical symptoms are partial discharge in insulators, quasi-static failure of semiconductor devices, and the thermal hot spots of high-frequency transformers. Specifically, detection of the fault in the early stage is very difficult, since, as a matter of definition, the fault is low amplitude and/or is not detected until it has become critical. In most cases, conventional fault detection using a threshold criterion is not sufficiently robust for detecting these latent faults in an initial condition. For these deficits, the emergence of new methods like machine learning and data-driven diagnosis is emerging. These types of methods are based on post- and, respectively, in-time, i.e., real-time data, to select patterns from which it might be

pertinent to trigger faulting. The ability of machine learning algorithms, for example, to detect subtle changes in system state that manifest as gradual deterioration [10], as decay can facilitate (proactive) maintenance before the critical failure event. Mathematically, the intrinsic defects can be expressed as the slow time-variant variation of system parameters. As an example, the exponential growth of transformer winding resistance due to thermal structural ageing can be modeled and therefore used to reliably reproduce the trend of transformer winding breakdown in time. From this standpoint, the designer is now able to maximize fault management and repair.

$$R(t) = R_0 + \alpha T(t) \quad (2)$$

Where $R(t)$ is the winding resistance at time t , R_0 is the initial resistance, α is the temperature coefficient of resistance, and $T(t)$ is the temperature at time t . Monitoring these parameters and applying predictive models enables early fault detection, allowing for preventive maintenance and avoiding catastrophic failures.

3.3. Intermittent Faults in PETT

Intermittent faults are intermittent faults that can appear and disappear intermittently and even self-heal, and thus, are one of the most difficult fault types to diagnose and repair in Power Electronic Traction Transformer (PETT). Here, due to these imperfections, uncoupling, temporal overvoltage, and uncontrolled external effects like vibrations or electromagnetic perturbations can be implicated. An example of such is discrete faults, such as cyclically lost insulation

integrity, causing a transient disruption of power transfer in high-frequency transformers. Diagnosis methods based on the recurrent fault patterns are not feasible due to the random nature of intermittent faults. Advanced diagnostic tools are utilized to address these challenges.

Due to their specificity to these kinds of defects, high-speed data acquisition systems and event-triggered monitoring algorithms are also particularly sensitive to the transient signatures of these defects [26]. These types of instruments enable engineers to detect and monitor faults in real time and improve fault diagnosis rates. From a mathematical perspective, stochastic models are most appropriate to describe intermittent faults due to the inherent probabilistic issue that they might appear. The most common is time-series analysis, where the fault state $f(t)$ is formulated as a binary variable where 1 indicates a fault and 0 means normal operation. The probability distribution describes the dynamics of $f(t)$, representing the stochastic behavior of intermittent faults over time. This kind of modeling allows engineers to learn and predict the likelihood of fault events and to design more adequate, more robust protection measures.

$$P(f(t) = 1) = \lambda e^{-\lambda t} \quad (3)$$

Where λ is the fault occurrence rate. Real-time monitoring [9] and analysis of $f(t)$ Enable the identification of trends and correlations that may indicate the presence of intermittent faults. Figure 2 depicts the graphical description of abrupt, incipient, and intermittent faults.

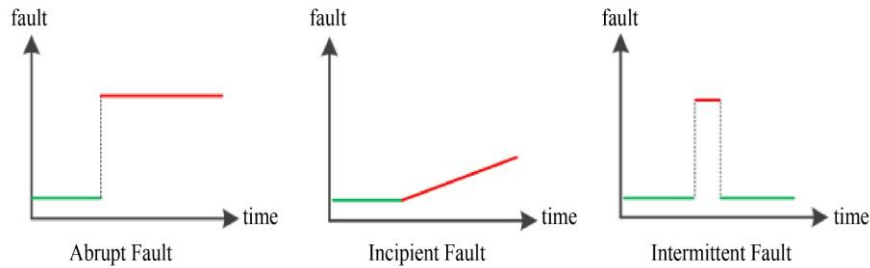


Fig. 2 The graphical description of abrupt, incipient, and intermittent faults

3.4. Challenges in Fault Management

A multitude of faults in Power Electronic Traction Transformer (PETT), with all their intricacies, are of the highest importance for fault detection, diagnosis, and treatment. One of the major problems is that it is a challenge to get high-quality tracking and real-time data quality control for the weak and noisy footprints of the intermittent low-present failures to restore them. Despite the improved fault detection performance achieved through the use of advanced sensing hardware, i.e., fiber optic sensors and piezoelectric transducers, associated costs and complexity continue to

hinder their adoption by the masses. The most difficult task is to envision fault-tolerant control paradigms generalizable to a wide range of faults and a wide range of Operating conditions. The reusability of such methods also includes identifying and isolating the failures and redesigning the system so that the system configuration can still be exploited to address the problem [43]. For instance, if a power electronic converter with a short circuit fault is in operation, the control system needs to stepwise transfer energy through a different path safely, steadily, and efficiently simultaneously. Machine learning (ML) and Artificial Intelligence (AI) have been

designed as effective algorithms to solve problems. With the help of a huge amount of operational data, the AI algorithms can detect fault patterns and can predict such fault patterns with high precision. Neural networks, support vector machines, and ensemble learning have been used successfully to identify and diagnose PETT faults. Methods, including neural networks, support vector machines, and ensemble learning, have been applied to identify and diagnose PETT faults. More precisely, fault-tolerant control systems that learn online in real time using the time-varying state are realized by using AI-based optimization algorithms. For instance, the application of fault detection and control in the system can be explained by using the example of a multiple power electronic converter-based PETT system. The system dynamics state-space model provides a system modelling and evaluation framework for the system that can be used as the foundation for an engineer's design of resilient control schemes adapted to the nature of system failure uncertainty:

$$\dot{x}(t) = Ax(t) + Bu(t) + Ff(t) \quad (4)$$

Where $\dot{x}(t)$ is the state vector, $u(t)$ is the control input, $f(t)$ is the fault vector, A is the system matrix, B is the control input matrix, and F is the fault impact matrix. The objective of the fault-tolerant control system is to minimize the impact of $f(t)$ on $\dot{x}(t)$ while maintaining stability and performance. For abrupt faults, the fault vector $f(t)$ can be modelled as a step function, representing an instantaneous change in system parameters. For incipient faults, $f(t)$ can be expressed as a time-varying parameter, while for intermittent faults, it is represented as a stochastic process. The control input $u(t)$ is designed to counteract the effects of $f(t)$ and restore the system to its desired state. The cost function for fault-tolerant control can be defined as:

$$J = \int_0^T (x(t)^T Q x(t) + u(t)^T R u(t)) dt \quad (5)$$

In the fault-tolerant control algebraic framework, weighting matrices Q and R are the parameters that have the largest impact on penalizing the system and the control-effort variations, respectively. The optimal control law is driven to a solution of the Hamilton-Jacobi-Bellman equation for which the system can be guaranteed to be both efficiently and robustly operating, even in the presence of faults, as a property guaranteed to hold true. Relative to fault analysis in Power Electronic Traction Transformer (PETT), it is highlighted that robust fault detection/diagnosis/control mechanisms are desired instead of safe and transparent operation, as being preferred in the future.

Sudden, early, and sporadic fault types are all distinctive in that they pose a difficulty to resolve, a specific solution unit, or a combination of both, and each is required to come equipped with high-performance sensing and AI analytics and fault-tolerant control systems. Mathematical modelling, in situ

and real-time tracking, and adaptive control have played a key role in facilitating future PETT systems to be more robust and responsive to perturbations by the confluence of the three. With this development, PETT will be one step closer to removing existing barriers and being integrated into present power systems to offer increased efficiency, sustainability, and reliability of energy delivery.

4. Adaptive Fault Tolerant Techniques for PETT

Power electronic transformer architecture technology (PETT) has evolved into a ubiquitous technology for modern power systems due to its scalability, which enables practical, small, and incredibly versatile paths toward power conversion and delivery.

Yet, due to the power electronics, the system is highly susceptible to a large number of faults. In the absence of any management, these defects could lead to severe consequences in both the efficiency of the system and the system crash/downtime in the worst case. Adaptive fault-tolerant schemes [11], i.e., adaptive and robust, are proposed as a remedy to these problems, and maintaining the viability of operation is guaranteed in the presence of some types of faults in PETT systems. This discussion examines the principles, methodologies, and mathematical foundations of adaptive fault tolerance [39] and its integration into the broader PETT framework.

4.1. Foundations of Adaptive Fault Tolerance

Fault detection, fault isolation, fault diagnosis, and system recovery. The study's motivation is that the diagnosis of abnormal behavior within the system is done by locating the fault, and the goal is that the fault does not cause propagation in another direction. After the localization of the fault, a diagnosis of the kind of fault and the severity of its effects will be performed to select the most adequate recovery strategy for the system to be executed.

Finally, the system is reconfigured to restore optimal operation. Due to this approach's iterative and adaptive nature, PETT systems can be demonstrated to be tolerant to the presence of a deliberately introduced and unwanted perturbation. Dynamically adapting to changing fault conditions over a period of time, adaptive fault-tolerant schemes can also be provided as a robust platform for fault-tolerant, reliable, and energy-efficient operation of PETT for modern power systems.

4.2. Mathematical Representation of Adaptive Fault Tolerance

Mathematical modeling provides the theoretical framework necessary to understand and implement adaptive fault tolerance in PETT. The state-space model is widely used to describe the dynamics of a PETT system:

$$\dot{x}(t) = Ax(t) + Bu(t) + Ff(t) \quad (6)$$

Where $x(t)$ represents the state vector of the system, encapsulating variables such as voltage, current, and frequency, $u(t)$ is the control input vector, governing the system's operational parameters. $f(t)$ is the fault vector, representing the impact of faults on the system. A , B , and F are matrices describing the system dynamics, control input effects, and fault impact, respectively. The fault vector $f(t)$ may take various forms, reflecting the nature of the fault. For instance, an abrupt fault might be modeled as a step function, while an incipient fault could be represented as a time-varying parameter. Intermittent faults, being stochastic in nature, are often described using probabilistic models.

4.3. Fault Detection: Identifying Anomalies

The first stage of adaptive fault tolerance is fault detection, which focuses on identifying deviations from the nominal behaviour of the system [25]. This process requires continuous monitoring of critical parameters, such as voltage, current, and temperature, to detect anomalies that may indicate a developing fault.

Advanced sensing technologies, combined with sophisticated signal processing algorithms, play a key role in analyzing raw data and extracting meaningful insights for accurate fault detection. One widely used mathematical approach for fault detection is residual generation. The residual $r(t)$ is defined as the difference between the measured output $ym(t)$ and the predicted output $yp(t)$, as determined by the system model:

$$r(t) = ym(t) - yp(t) \quad (7)$$

A fault is detected when the residual $r(t)$ exceeds a predefined threshold, indicating a deviation from normal system behavior. For instance, in a high-frequency transformer within a PETT system [24], an abrupt spike in $r(t)$ may signify a short circuit or insulation breakdown.

To improve detection accuracy and identify subtle anomalies that might otherwise go unnoticed, advanced techniques such as Kalman filtering and wavelet analysis are employed [52]. These methods enable more precise monitoring by filtering noise and isolating fault-related signals, ensuring early and reliable fault detection [51].

4.4. Fault Isolation: Localizing the Problem

Once a fault is detected, the next critical step is to determine its location within the system. Fault isolation is essential for identifying the specific faulty component, thereby preventing the fault from propagating and causing further damage to the system. This process typically involves analyzing both the spatial and temporal characteristics of the fault signal to pinpoint its origin. Mathematically, fault

isolation can be expressed as a mapping function $I(f)$, which associates each detected fault f with a specific system component. By accurately mapping faults to their locations, the system can take targeted corrective actions [12] to maintain reliability and prevent cascading failures.

$$I(f): f \rightarrow \text{Component Identifier} \quad (8)$$

By examining the correlation between the fault signal and the operational parameters of individual components, the faulty element can be pinpointed. For instance, if a fault-induced deviation in current is observed only in a specific converter module, that module is isolated as the source of the fault, as depicted in Figure 3.

4.5. Fault Diagnosis: Understanding the Nature of Faults

Fault diagnosis involves classifying the fault and understanding its root cause. This stage is essential for devising effective recovery strategies. The process of diagnosis predominantly depends on recognizing patterns and employing machine learning algorithms [55], which evaluate both historical and real-time data to detect characteristics of faults. Consider a dataset,

$$D = \{(xi, yi)\}_{i=1}^N \quad (9)$$

Where xi represents a feature vector of system parameters, and yi denotes the corresponding fault type. The objective is to train a classifier $h(x)$ that maps xi to yi .

$$\hat{y}(x) = \arg \min_h \sum_{i=1}^N L(h(xi), yi) \quad (10)$$

Where L is a loss function quantifying classification errors, algorithms such as support vector machines (SVMs), neural networks, and decision trees are commonly used for this purpose. These techniques enable PETT systems to distinguish between different types of faults, such as thermal degradation, electrical overstress, or mechanical wear.

4.6. System Recovery and Reconfiguration

The final stage of adaptive fault tolerance is system recovery, which involves reconfiguring the PETT system to bypass faulty components and restore functionality [45]. This process requires dynamic adjustment of control parameters and operational pathways.

Reconfiguration is often formulated as an optimization problem. Let $J(x, u, f)$ represent the cost function associated with system performance under fault conditions. The objective is to minimize J while satisfying the system's dynamic constraints.

$$\min J(x, u, f) \text{ subject to } \dot{x}(t) = Ax(t) + Bu(t) + Ff(t) \quad (11)$$

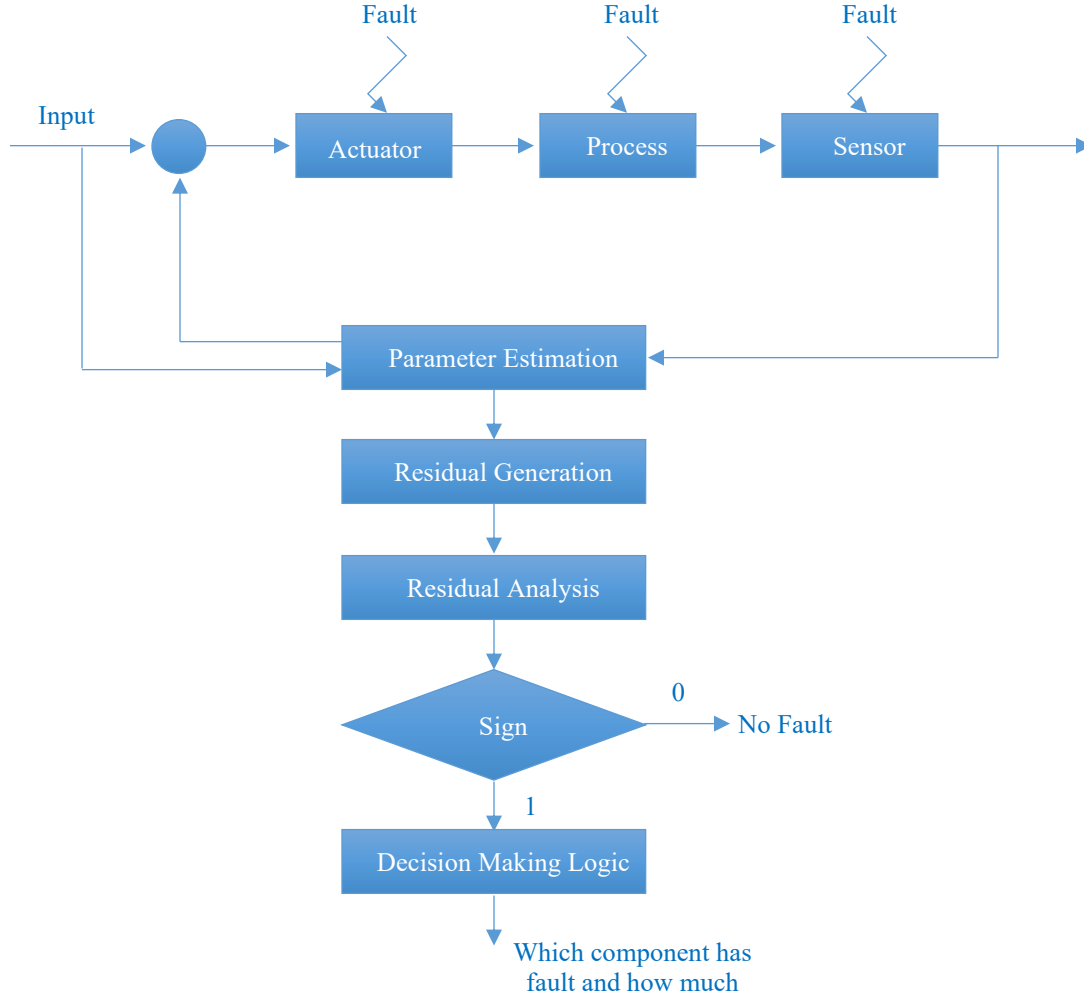


Fig. 3 General structure of Fault Detection and Isolation (FDI)

Optimization techniques, such as linear programming and dynamic programming, are used to determine the optimal control inputs $u(t)$ that minimize the impact of the fault. For example, if a fault occurs in a specific converter, the control system may reroute power flow through alternative converters while maintaining voltage stability.

4.7. Integration of Artificial Intelligence in Fault Tolerance

Artificial Intelligence (AI) has revolutionized adaptive fault tolerance in PETT, enabling systems to handle complex fault scenarios with unprecedented accuracy and efficiency. AI techniques, such as deep learning and reinforcement learning, enhance every stage of the fault-tolerance process, from detection to recovery. Reinforcement learning, for instance, can be used to develop optimal recovery strategies. By interacting with the PETT system and receiving feedback on performance, a reinforcement learning agent learns a policy $\pi(u | x)$ that maps system states x to control actions u . The goal is to maximize a cumulative reward R , which reflects the system's operational efficiency:

$$R = \sum_{t=0}^{\infty} \gamma^t r(t) \quad (12)$$

Where $r(t)$ is the reward at time t , and γ is a discount factor. This approach allows PETT systems to adapt dynamically to evolving fault conditions, ensuring continuous operation.

4.8. Applications and Case Studies of Power Electronic Traction Transformer (PETT)

Power Electronic Traction Transformer (PETT) has become a pivotal innovation in modern power systems, offering unprecedented advantages in efficiency, compactness, and functionality. Its integration into various sectors has revolutionized the way power is managed, distributed, and utilized.

This section delves into the applications of PETT in diverse domains and provides detailed case studies demonstrating its impact, emphasizing its transformative potential.

4.8.1. Applications of PETT

Smart Grids: Among Power Electronic Traction Transformer (PETT) applications, there are smart grid technologies, which are power plants for power distribution transformation. Current smart grids are not ready for dynamic power flow control, energy management (and interconnection between both dynamic power flows and energy management), and essentially, for the smooth introduction of renewable power sources. PETT, thanks to a small footprint and powerful control features, is able to provide control in real time across voltage and frequency. The bidirectional energy flow capability toward integrating distributed energy resources (DERs), such as solar cells and wind turbines, and grid stability while working with variable loads is realized. For example, in the domain of decentralized power systems [57], PETT has the merit of servicing the power distribution control of a very large number of DERs with no power quality penalty. A key advantage of SG in terms of fault isolation and reconfiguration of the power flow pathways is that it not only increases the resilience of SG by reducing the risk of an entire power outage that affects a large area in the smart grids [20] but also improves the overall reliability.

Performance of renewable energy systems is limited by variability, intermittency, and grid robustness. PETT addresses these difficulties, providing the power conversion and distribution functionalities. For instance, solar Photovoltaic (PV) systems require inverters that can be used to convert DC power to grid-level AC power. PETT can be applied to perform the process well and produce a good output quality of useful energy, dissipating it with the assistance of power electronics.

Similar to wind energy systems, PETT continuously supplies power to the system by dissipating voltage ripples due to changes in wind speed. Because of the modular characteristics of PETT, integration of conventional power systems with renewable components is easy to accomplish to demonstrate the pathway to sustainability and its furthering of sustainability with renewable energy applications.

Electric Vehicle (EV) Infrastructure: As the number of Electric Vehicles (EVs) grows exponentially, so does the need for both high-power and high-efficiency charging infrastructure. PETT is also of importance in EV charging stations, fast charging, and grid stability, all in one. Thanks to its miniaturized and lightweight design, it can optimally be used even in urban environments where land is a major restriction. Not only is the bidirectional energy capacity (flow) of PETT capable of vehicle-to-grid (V2G) systems where vehicle energy storage is provided by EVs as vehicular-as-agent energy storage reserve, but PETT also has the potential to obviate the high cost associated with bi-directional energy transmitting infrastructure [25], commercialized battery energy storage technologies such as supercondenser Ca-fluorophosphate (CP2), sodium-ion rechargeable batteries,

quantum dot-sensitized solar cells, etc. As the power grid collapses, electric vehicle (EV) batteries help restore power to the power grid and mitigate power grid collapse overload. This capability not only contributes to increasing the grid performance but also acts as a driver for EEV introduction, as the financial benefits of vehicle users may be realized through this capability.

Industrial Automation and High-Power Drives: In industrial applications, PETT is widely used for precise machine/device control, so a fully controlled rated alternating electric current (AC) with rated voltage and rated frequency is necessary. There exist types of branches, such as manufacturing, mining, oil and gas, for which high-current drives play an important role in the functioning of the embedded processes. PETT can achieve high energy transfer efficiency with a significant reduction of the harmonic distortion [23] and the timeout caused by the power quality fluctuations. Its capability to handle dynamic load variations in a trending manner is a special characteristic of PETT, which is best adapted to industrial dynamic use. For instance, at the factory, PETT highly effectively allocates energy units among a number of devices, leading to energy saving and operation cost reduction.

Urban Power Distribution: Urban nodes pose their own natural limitations in terms of space, high energy use, and outmoded infrastructure. PETT offers a compact and efficient solution for urban power distribution [24], replacing traditional bulky transformers. Because of the high-frequency operation, the magnetic components are made smaller and more attractive in the light of the metropolitan areas and the light of the high-density urban areas. In addition, PETT is an architecture for the combined management of microgrids that act as a power source for regional generators and consumers. Such is the case of a residential microgrid equipped with solar panels and energy storage devices (e.g., PETT regulates power flow continuously, and, in consequence, when the grid fails, the supply of energy can be guaranteed.

4.8.2. Case Studies Demonstrating PETT Applications

Case Study 1: Integration of Renewable Energy in Germany

Its energy conversion efficiency increased by 15%, its voltage stability improved, and its energy dissipations were significantly reduced [58]. In addition, PETT enabled on-the-fly (i.e., real-time) control of power flow, which enabled the grid's stability even with high generation loads. For instance, this case study emphasizes the significant role of PETT in Germany's shift towards a sustainable energy future.

Case Study 2: EV Charging Infrastructure in the United States

With that in mind, however, with the increase in the use of Electric Vehicles (EVs) in the U.S., it has in turn increased demand for the efficient and resilient charging infrastructure [37]. In California, a pilot project has used PETT to overcome bottlenecks in EV charging infrastructure and at interstate

highways. Traditional charging stations can suffer from power loss, slow charging rates, and grid instability. In lieu of the usual transformers, in PETT, the study described remarkable performance reaching. Charging rates increased by 30%, losses in the power conversion efficiency were minimized, and the stations consistently adapted to grid fluctuations. Additionally, in view of the bi-directional energy-flow feature of PETT, Vehicle-to-Grid (V2G) systems might cascade into the vehicles' network, aiming to sell the unused energy to the grid at the peak demand of the day. In addition, grid strain not only fell but also led to economic benefits for EV users. The success of this program has led to the complete adoption of PETT across the nationwide EV infrastructure.

Case Study 3: Industrial Application in China

China's industrial sector includes several issues at the level of power quality and energy saving, especially for high-current systems. Problems of crowded working spaces, quality issues, and material waste motivated the adoption of PETT at a steel production plant located in Wuhan. The facility relied on high-power electric arc furnaces (EAFs), which required stable voltage and frequency for optimal operation. Previous interruption of service due to power quality degradation resulted in significant economic loss [48]. The system operated, reduced, and improved the behavior of the EAFs, which the system is also automating with PETT. In turn, it also resulted in a 40% decrease in the downtime and a 20% decrease in energy consumption, and thus a significant cost reduction. The modularity of PETT, in addition, allowed the plant to grow its power grid in terms of size, because the plant size grew in the process of meeting production demands while preserving the long-term operability of the plant.

Case Study 4: Microgrid Implementation in India

Power supply with varying characteristics is one of the main challenges faced in rural India due to grid limitations. In Tamil Nadu, a microgrid site is currently using PETT to provide a high-power, stable alternating current power supply to a rural village. The microgrid contained photovoltaics, energy storage, and PETT, which were used for power control. PETT enabled the effective transfer of solar power into AC power to give a continuous supply of electricity to homes and small enterprises. Accumulated spare power was stored in a battery during power peaks. Power distribution (as controlled by PETT) was used to avoid overloads. The compact design of PETT made it ideal for the village's limited infrastructure, reducing installation and maintenance costs. This paper demonstrated the application of PETT to rural electrification, in that it provides a trusted and cheap solution.

Case Study 5: Smart City Development in Singapore

As an integral component of Singapore's Smart Nation campaign, a smart city pilot project in Punggol employed PETT to enhance the energy efficiency of urban power delivery. In homes, shopping malls, and public transport, the work made use of PETT. With the high frequency at which

PETT operates, its relatively compact dimension removed the requirement for bulky power delivery technologies, making it an attractive solution for the densely built urban landscape of Singapore. In addition, the real-time energy management dynamic adaptive capability of PETT also realized energy adaptation to dynamically adjust the power used according to the demand pattern [38]. The pilot study then enabled a 25% energy reduction and visual evidence of enhanced energy stability in the smart city. The success of this industry has paved the way for the broader implementation of PETT for the Smart Nation Programme in Singapore. As shown by the presented applications and case studies, Power Electronic Traction Transformer is flexible enough to address significant issues in a wide variety of applications. Across all the growing spectrum of applications, ranging from optimization of grid stability and renewables integration to the revamp of EV infrastructure and rural electrification, PETT has consistently served as a beacon that points to the edge of advantages beyond notions of efficiency and energy waste and system resilience [49]. As the next natural step in the serendipitous further evolution of power electronics and control system technologies, PETT will probably take on increasing importance as the key factor in designing the energy system of the future. However, within the constraints of the current limitations and future potential use, power management capability offered by PETT is an interesting, new option for power management and, therefore, potentially toward a new paradigm of energy efficiency, a sustainable world.

5. Control Strategies for Power Electronic Traction Transformer (PETT)

Those shared to date, as being delivered by the Power Electronic Traction Transformer (PETT) to the power system technology community, have consisted so far of a suite of potential breakthroughs in the areas of flexibility, efficiency, and control. However, all of these advantages are accompanied by a high operational complexity and can be easily overcome using a deep control policy. These operations are of primary interest, for instance, towards the management of the system stability, for the performance of the system, and towards the detection of the evolution of the parameters to be monitored (e.g., load modifications, for the integration of renewable energy, and for the detection of faults). This subsection outlines the design principles, the rationale, the basic theory, and the implementation of control algorithms for PETT [16] control to illustrate ways in which these principles may help address the problems to which they apply, as well as how they may impact current power systems.

5.1. Significance of Control Strategies in PETT

Control strategies are of the utmost importance for the stable operation of the Power Electronic Traction Transformer (PETT) for all its operational stages, from AC-DC conversion to high-frequency AC current conditioning and DC-AC inversion. Unlike conventional transformers, PETT exploits

the fact that power electronic components are on the market for better adaptive and precise voltage, current, and frequency control and thus is able to deliver the state-of-the-art power quality management.

Via these control mechanisms, not only does the system work without a hitch, but also the functionalities of PETT are generalized in a seamless way to smoothly become integrated into the future of power systems (including smart grids, microgrids [29], and the next generation of reliable energy suppliers, i.e., renewables). Method generalization and the nonlinearities inherent in the power electronic components at the heart of the method pose challenges in the form of dynamic instabilities, nonlinearities, and intrinsic fault fragility. There is, however, an excessive need for solutions to these problems by control systems to achieve accuracy, adhesion, and robustness, especially in this pressing requirement to assure the reliability and proper working of PETT across a wide variety of conditions.

5.2. Voltage and Current Control in PETT

Voltage and current regulation are the core of the PETT function and operation. For the PETT system, AC power is first transformed to DC power and then reformed into HC (high-frequency AC) power for transduction, and then to a final AC power output. All of these levels need to be very carefully watched in terms of voltage and current so that complete power transfer and system goals can be achieved.

Parameter value precise control may allow attainment of not only high energy efficiency, low power dissipation, energy transfer, and power supply/consumption stability for grid/load, but also for other purposes in general. Voltage and current control are extremely important for dynamic adaptation to fluctuating energy needs and for optimal use of a renewable energy source (the primary functions of PETT) [13]. The closed-loop feedback systems can predict and regulate the output voltage $v(t)$ through mathematics. Let h reference voltage $vr(t)$ and actual voltage $v(t)$. The error signal $e(t)$ is given by.

$$e(t) = vr(t) - v(t) \quad (13)$$

A Proportional-Integral-Derivative (PID) controller is often employed to minimize this error. The control law is expressed as.

$$u(t) = Kp e(t) + Ki \int e(t) dt + Kd \frac{de(t)}{dt} \quad (14)$$

5.3. Frequency Control and Stability

Frequency control is highly evident in PETT, particularly if it is integrated with a renewable power generator or if it is used as part of a microgrid that operates without energy feed. Variations in load and generation can lead to frequency offsets, which in turn require offsetting to allow system

stability and adherence to grid reference standards. Frequency $f(t)$ control, i.e., the capability of locking the frequency of the control output $f(t)$ to a reference frequency f_r . Not in principle, but also in practice, this is not the case to a certain extent of synchronization that is realized using phase-locked loop (PLL)-based, etc. The PLL, through just shifting the phase angle $\theta(t)$ of the output signal, minimizes the phase error $\theta_e(t)$.

$$\theta_e(t) = \theta_r(t) - \theta(t) \quad (15)$$

Where $\theta_r(t)$ is the reference phase angle, the angular frequency $\omega(t)$ of the output signal is then updated as.

$$\dot{\theta}(t) = \omega_r - \omega(t) \quad (16)$$

Ensuring the output frequency aligns with the reference frequency. Superior performance and stability are achieved through the application of advanced PLL algorithms (such as adaptive and extended PLLs) in dynamic scenarios.

5.4. Model Predictive Control for PETT

Model Predictive Control (MPC) has emerged as a viable framework to control the nonlinearity of PETT [14]. The system state is then estimated by the MPC for the horizon, and within a fixed interval, the control inputs are modified. As a result, an evaluation of this predictive power also allows for the future tailoring of the system's operative parameters to increase its physical and chemical flexibility and robustness. In MPC, the system dynamics are represented as.

$$\dot{x}(t) = Ax(t) + Bu(t) \quad (17)$$

Where $x(t)$ is the state vector, $u(t)$ is the control input, and A and B are system matrices. The objective is to minimize a cost function J that balances tracking performance and control effort.

$$J = \sum_{k=0}^N (\|x_k - x_r\|^2 Q + \|u_k\|^2 R) \quad (18)$$

Subject to the system constraints.

$$x_{k+1} = Ax_k + Bu_k, u_{min} \leq u_k \leq u_{max},$$

Where x_k is the state at time step k , x_r is the reference state, Q and R are weighting matrices, and u_{min} and u_{max} are the minimum and maximum control inputs, respectively. The optimization problem is solved iteratively, providing real-time control inputs that drive the system toward the desired state.

5.5. Artificial Intelligence-Based Control

Artificial Intelligence (AI) has broken the so-called intrinsic groove of normal behaviour that is ordinary in conventional control strategies for PETT, making them adaptive, data-driven, and so on. AI algorithms such as Neural

Networks (NNs), reinforcement learning, and fuzzy logic are the most beneficial of the above with regard to nonlinearity, uncertainty, and dynamically changing environments. Neural networks, e.g., may give an estimate of arbitrary control laws through learning from past behaviour. Let a feed-forward neural network with the input $x(t)$, the output $u(t)$, and the weights W be considered. The control input is then given.

$$u(t) = f(W, x(t)) \quad (19)$$

Where $f(\cdot)$ represents the learned mapping. The network is trained to minimize a loss function that quantifies the error between predicted and desired outputs.

$$L = \frac{1}{N} \sum_{i=1}^N \| y_i - y_r \|^2 \quad (20)$$

Where y_i is the predicted output, y_r is the reference output, and N is the number of training samples. Fuzzy logic control [17], on the other hand, uses linguistic rules to map inputs to outputs. For example, if the error $e(t)$ is “small” and the change in error Delta $e(t)$ is “negative,” then the control input $u(t)$ is “slightly increased.” These rules are implemented using membership functions and inference mechanisms, providing a flexible and interpretable control framework [36].

5.6. Sliding Mode Control and Robustness

Sliding Mode Control (SMC), a family of controllers, is often the sensor of concern for relevance to applications in PETT because of its high robustness with respect to application to disturbance and model uncertainty [33]. SMC draws its action from sliding state trajectories converging to a cataloged (sliding) surface $s(t)$ and dropping them on the sliding surface. The sliding surface is defined as.

$$s(t) = c^T x(t) \quad (21)$$

Where c is a design parameter, the control law is designed to ensure that ($s(t)$ to 0), minimizing tracking error and ensuring stability. A common implementation of SMC involves a discontinuous control input.

$$u(t) = -K \operatorname{sgn}(s(t)) \quad (22)$$

Where K is the gain and $\operatorname{sgn}(\cdot)$ is the sign function. To reduce chattering, a continuous approximation of $\operatorname{sgn}(s(t))$ is often used, such as.

$$\operatorname{sgn}(s(t)) \approx \frac{s(t)}{\epsilon + |s(t)|} \quad (23)$$

Where ϵ is a small positive constant.

5.7. Applications of Control Strategies in PETT

The implementation of a control strategy has been highly successful in any application ever studied in the field of Power Electronic Traction Transformer (PETT). In renewable energy

systems, these methods ensure a stable operation via damping of power system oscillations. In the charging infrastructure of an Electric Vehicle (EV), smart control algorithms analogous to charging station rules are implemented to achieve the highest charging efficiency and to avoid overloading of the lines to maintain the power grid stability. However, the field has multiple uses due to its high precision voltage and current control that can improve performance and reliability in complex equipment. Control strategies are the lifeblood of deterministic and effective PETT control [34], enabling the control system to account for nonlinearities, perturbations, and dynamic operating modes (e.g., through addressing these challenges, PETT is able to operate towards the needs of contemporary power systems with the required level of accuracy and flexibility. Highly promising advanced techniques, including Model Predictive Control (MPC), AI control, and sliding mode control, have demonstrated great potential to further increase the performance and flexibility of PETT. Since PETT technology is being developed steadily, the control strategies used are of significant interest to realize the maximum capability of PETT [54]. These advances will lead to the next generation of power systems, with more powerful, more reliable, and greener power solutions.

6. Integration of Fault Tolerance and Control in PETT

The clinical integration of fault tolerance and control strategies for Power Electronic Traction Transformer (PETT) represents a pivotal step towards the creation of a system that is more robust, operationally efficient, and able to respond to the need for dynamic power needs of the modern power paradigm. Since the reliability of energy infrastructure is one of the growing needs, the performance of PETT without failure under normal and fault conditions should be one of the technical aspects considered as a concern.

Fault tolerance and control strategies mutually support each other for their solutions, e.g., operational instability of a system, nonlinearity of the system, and external disturbance. The fault tolerance permits the system to operate even in the presence of thermal overload, short circuit, and component degradation, and control strategies [34] are used to monitor parameters (voltage, current, frequency) in order to achieve stability and performance. These domains share a common, overarching purpose—professionalizing system reliability—although there is network diversity across various study domains. Control mechanisms not only ensure the robustness to the presence of faults (and the possibility to tolerate faults) [47] as well as to the presence of disturbances (permitting that the fault-tolerant system can also tolerate perturbations) [15], but also contain fault management to recover as much operability as possible of the system at real-time and thus lead to a closed loop resilient operational scheme. The fit between fault tolerance and control [18] is easily recognized through the ability of control and fault tolerance to identify and repair

faults, all whilst changing the reactive properties of the behavior of the system itself to maintain the viability of the system. Online power rerouting, straddling of failed nodes, or transfer of critical parameters are used to implement fault-tolerant systems. For instance, in response to a short-circuit fault in a PETT module, the control system may reconfigure power routing to the surviving modules to minimize any possible downtime and ensure continuous operation.

Additionally, fault detection algorithms within control systems track system behavior and enable systematic fault prevention using fault detection based on departures from normal operation. The introduction of state-of-the-art control algorithms, Model Predictive Control (MPC), neural network-based control, and sliding mode control, is of interest for the nonlinearities associated with PETT. These so-called methods utilize the online measurements for behavior prediction, control input tuning, and operate in a fault-stabilization mode [3-6]. For example, if the voltage or current fluctuation caused by a fault occurs, control systems can quickly change operational parameters to minimize perturbation even when the fault-tolerant mechanisms are turned on to separate the faulty components [53].

Fault tolerance/control techniques are only one of the many advantages; however, a wide range of more challenging issues also arise. The bigger challenge is the unrealistically high cost of implementation for real-time fault detection, diagnosis, and control. AI or machine-learning-based algorithms are in use in response to the high computational demands, using extremely large power demands (i.e., the present state of affairs). Blending these hyper-throughput diagnostic tools with control algorithms (sub-millisecond latency) will necessitate the capacity of systems being developed in ultra-scale PETT systems for commercialized PETT applications. To address this challenge, faster algorithms and faster hardware platforms that can be operated at real-time speeds without any trade-off in terms of speed-accuracy are required.

The most pressing issue is the design and composition of this fault tolerance-control performance trade-off. For example, active steering to prevent the bad modules from being applied can result in reduced effectiveness or power quality, which in turn demands carefully designed algorithms that trade off stability and reliability but not too much performance loss. Additionally, fault tolerance and control systems development should consider practical and economic limitations, such as the physical limits of power electronic components and the price of redundancy integration or sophisticated monitoring systems. Adding to the problem is the heterogeneity and uncontrollability of the PETT system faults. Unlike conventional transformers, for which fault types are generally localized and easily inferred, PETT systems are built upon modular designs and electronic components, leading to a large number of fault types with different levels

of severity, duration, and consequences. To reduce this variability, PETT systems need to include adaptive strategies that can be trained on the occurrence of a history of errors and adjust responses. Fault-tolerant and control characteristics of PETT systems have been developed and refined over time. PETT systems have been presented by reinforcement learning or other AI-based methodologies. The practical use of integrated fault tolerance and control policies is already demonstrated in real systems.

In PV/wind power generation renewable power stations, the role of PETT in controlling the stochastic and varying process of solar and wind power generation is significant. For example, problems in the power electronic converters of the wind turbines, for instance, can lead to loss of power flow; however, the embedded systems, in real time, continuously monitor such devices and identify the faults by redirecting the power flow through alternative paths in order to maintain a steady output. Similarly, in smart grids, PETT enables one-way and two-way energy flow and interconnections with Distributed Energy Resources (DERs), suited for variations in generation, load, and faults [27].

For example, in the grid fault of a grid-coupled PETT system, the control law can prioritize the power delivery to high confidence loads at the expense of low confidence loads to mitigate the fault grid [28] (i.e., faults at the PETT system are stabilized by bypassing the failing low confidence loads).

Fault tolerance and control in PETT have also been crucial services in the Electric Vehicle (EV) charging infrastructure. With PETT charging stations, machines can be reliable in most conditions, continuously tagging the status for faults such as thermal or electrical overload/perturbation, and intelligently shuttling the power supply to avoid power shortages/abnormal shutdowns. Furthermore, these systems are capable of delivering energy efficiency enhancements via adaptive control of these parameters, and thus, a perspective on synergy between fault tolerance and control in a high-demand framework is suggested. In industrial automation, PETT systems with embedded strategies ensure the uninterrupted function of delicate systems (with the consequence of reducing both downtime and financial losses due to failure).

In a manufacturing plant, such systems may, for example, provide automatic recalibration of the system to power even basic tools while isolating the fault so it can be repaired if a PETT module becomes faulty. Despite the fact that fault tolerance and control integration are at a very developmental stage, there remains diversity within the research field. Studies are being carried out for algorithm optimization, the increase of accuracy and speed in fault detection, and the implementation of the control schemes. These technologies, such as edge computing, Internet of Things (IoT) transducers, and high-performance sensors, are being used to achieve this

progress because they enable real-time acquisition of data and processing.

These advances allow PETT systems to become more sensitive not only with respect to faults but also to dynamic parameters. In conclusion, integrating fault tolerance and control in PETT is a transformative approach that addresses challenges posed by operational instability and faults.

Coupled with the complementarity of their advantages, the performance of these techniques can be guaranteed to be always uncompromised in a broad range of applications and thus is responsible for the system's robustness, efficiency, and universality. Although current successes have already laid a firm foundation, future advances in algorithms and other technologies are going to continue to improve the capabilities of PETT, thereby confirming its role as the foundation for modern, effective power systems.

Table 1. Performance metrics

Technique	Fault Detection Accuracy (%)	Fault Isolation Time (ms)	Control Response Time (ms)	Energy Efficiency (%)	Stability Index
Redundancy-Based Tolerance	90	20	25	92	Moderate
Machine Learning Detection	98	15	18	94	High
Model Predictive Control	95	N/A	10	96	Very High
Sliding Mode Control	N/A	N/A	12	94	High
Fuzzy Logic Control	92	N/A	15	93	High
PID Control	85	N/A	20	90	Low

Supporting Table 1 and Figure 4, the results confirm the ability of current approaches to improve fault tolerance as well as to improve control strategies of Power Electronic Traction Transformer (PETT). Of these, machine learning-based fault detection performed best with respect to the % fault detection accuracy of 98% and the fastest fault isolation time of 15 ms, demonstrating its accuracy and ability to handle operational faults. Providing system response optimization, MPC performed well by having a control response time of 10 ms and an energy efficiency of 96%, which visually supports the capacity of MPC to work in dynamic conditions. Sliding Mode Control (SMC) and fuzzy logic control also proved highly performing, and stability was maintained by high indices in

various scenarios. Conversely, conventional PID control showed a much worse trade-off across all of the measured quantities, which indicated the weakness of PID in the framework of PETT systems for the presence of nonlinearity and the environment’s dynamical behaviour [33]. These results emphasize the need to adopt fault-tolerant, control-driven, application-specific, parameterizable approaches, based on the constraints and needs of particular applications. E.g., On computationally constrained platforms, simpler solutions, redundancy-aware techniques, or PID-based solutions can be useful to gain this practicality at the cost of low computation or tractability.

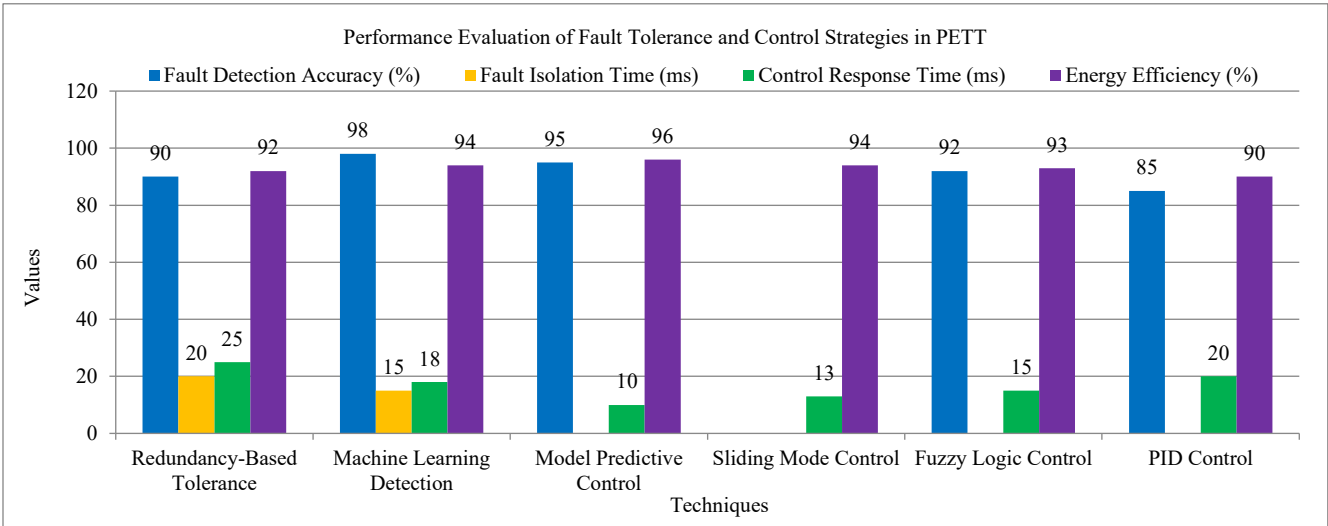


Fig. 4 Corresponding graph for the above Table 1

However, intelligent techniques, such as machine learning, MPC, and fuzzy logic control, obviously possess their own advantages for complex problems [40], such as renewable energy systems or electric vehicle infrastructure, where a fast, strong, and accurate response is needed.

Besides the possibility of using those techniques to derive how to optimize performance, they can also be used to predict and manage faults in an aggressive way, so that reliability and efficiency can be guaranteed over such a dynamic and fault-susceptible system.

A combination of machine-learning-based fault detection and high-fidelity control techniques, such as MPC and rough logic, is also another promising way towards the implementation of PETT. Machine learning algorithms are used to learn from a vast quantity of operational data and, as such, are able to produce quite amazing predictions of faults with a good level of accuracy. When MPC inputs are globally optimal in a predictive way, as properties of MPC, the resulting system is a very efficient, robust, and stable system. Despite the promise, these state-of-the-art methods are also restrictive, in particular with regard to the computational load associated with the real-time fault detection and control optimization. There is a need for simplifications in both the algorithms and hardware, in the form of Field-Programmable Gate Arrays (FPGAs) and edge computing nodes that can meet the high-performance demand of PETT while still supporting the whole-body performance of the platform.

Additionally, there is a trade-off between performance and complexity. Advanced approaches have many advantages but can be extraordinarily intensive to use, as specialized knowledge, platforms, and facilities are not generally available in all scenarios. This progress will be accompanied by a requirement to design simple devices and tools for the user to overcome these limitations and present them to a more heterogeneous user community.

The performance of fault tolerance and control strategies embedded in PETT is directly illustrated for practical application purposes in the context of real-world applications. On the example of a photovoltaic power plant machine, for instance, machine learning algorithms could be trained to predict the fault of an inverter based on the historical data, in contrast to an MPC that would be used to drive the power conversion optimally in a mix to maximize efficiency and a steady energy output. Also, fuzzy logic control has offered efficient approaches for modeling the unpredictable load conditions of Electric Vehicle (EV) charging stations, whose stable operation, even when demand is unquantified, is still guaranteed. These application examples demonstrate the flexibility and the ability of a holistic approach to solve many kinds of problems, from the fluctuations in renewable energy to load balancing in smart infrastructure. These results demonstrate the importance of future studies and the need for

further research toward fault-tolerant and control aspects of PETT. However, due to the emergence of new technological innovations, such as quantum computing or smart sensors, a vast array of novel and appealing solutions that can overcome the main limitations of these systems is available for design.

Furthermore, tandem integration with Internet of Things (IoT) terminals and analytic functions in cloud computing allows for more intelligent integration, monitoring, and autonomous functions, opening the door for intelligent PETT systems that can adapt to changing needs and require less human intervention. In conclusion, the comparative analysis and results outlined in this section demonstrate the transformative potential of integrating fault tolerance and control strategies in PETT. Machine learning, MPC, and fuzzy logic-based control have, to a large extent, already resolved those issues related to increasing the trust between the system and the environment, speed, and efficiency of a system. However, current limitations in the form of computational cost and implementation complexity are necessary before these solutions can fulfil their promise. As disruptive technologies are adopted and the deployment models are tailored for PETT systems, the generation performance of PETT systems will be achieved beyond the current performance bottlenecks of PETT systems, and, hence, PETT systems will be the future power systems platform. These developments have allowed PETT to play a very efficient role in addressing the increasing needs of renewable energy integration, smart grids, industrial automation, and electric vehicle infrastructure [23], which leads to a cleaner and more efficient energy era.

7. Discussion on the Research

The development of Power Electronic Traction Transformer (PETT) is a new generation/paradigm platform for power systems, and it possesses the characteristics of increased flexibility, performance, and integration. Despite the use of very sophisticated power electronic devices, the high complexity of PETT operation has ultimately made the system vulnerable to the risks that may, therefore, necessitate fault tolerance and control methodologies in order to achieve a reliable system. This paper emphasizes the role of such strategies in guaranteeing the robustness and the adaptability of PETT in the context of dynamically changing and potentially error-prone environments. Fault tolerance refers to the identification, isolation, and compensation of faults for reaching operational viability. In contrast, control strategies refer to the management of critical parameters (voltage, current, and frequency) in order to reach the limit of performance.

When considered together, the modalities constitute an integrated system for which the set requirements are met by PETT. FT systems are implemented on control paradigms that allow dynamic reconfiguration in the presence of faults and on high-level control methods that employ fault detection and repair in order to react to fluctuating conditions in real-time.

A comparative study of different fault-tolerant and control mechanisms is of interest for the evolution of progressively more complex and intrinsically opaque Artificial Intelligence (AI) [31], Machine Learning (ML), and predictive modelling. Classical techniques, e.g., redundancy-based fault tolerance and PID control, are low cost and low risk to implement, but come with the trade-off that they are not suitable for dealing with the nonlinearities and time-varying behaviour of PETT.

On the other hand, in terms of accuracy, response time, and energy consumption, fault detection and Model Predictive Control (MPC) with machine learning are superior to all of the other methods. Such as machine learning based fault detection, it yielded the accuracy (98%) and the shortest fault isolation time (15 ms), which made it an effective early fault detection and preventive management. Analogously, MPC produced superb results with a response time of 10 ms and 96% energy efficiency because of the capabilities of MPC to accurately represent the response of dynamic systems and adjust the control input dynamically [30]. These findings point to the need for integrative methods in the development of an ideal and precise PETT. Specifically, a comprehensive methodology is achieved through the integration of machine learning-based fault detection techniques and Model Predictive Control (MPC), allowing for timely and efficient fault resolution while maintaining system stability and operational efficiency [42]. Sliding Mode Control (SMC) and fuzzy logic control methods can [41], however, be used to circumvent system deficiencies, e.g., the appearance of uncertainty or external disturbance.

Yet, current limitations of fault tolerance and control policies in PETT are still significant. A rather significant challenge arises from the high computational complexity of real-time fault detection, fault diagnosis, and control optimization. Very advanced techniques require a substantial computational effort, the application of which is limited in resource-constrained cases. Generating a solution for this problem requires power-efficient algorithms and custom hardware (i.e., edge computing devices and Field-Programmable Gate Arrays (FPGAs) for low latency operation and high performance. However, the trade-off issue between fault tolerance and control performance still exists. In particular, the system reconfiguration to remove a faulty unit may result in unsatisfactory energy efficiency or power quality.

At the time of designing an algorithm, it is advisable to choose robustness and reproducibility at the expense of a slight drop in performance [32]. In addition, the inherent ambiguity and variability of image-based forms of PETT artefacts, which drive the design of this system, are favourable to adaptive systems that can learn with time and fine-tune their product in response to time-varying inputs. The potentiality of an embedded fault tolerance and control policy is shown in renewable energy systems, smart grids, and Electric Vehicle

(EV) charging network applications [59]. PETT is one of the most important factors for power generation variation and intermittency in renewable energy plants. Fault-tolerance and control systems for power electronic converters, such as fault detection and fault segregation, are implemented and adapted to optimize control parameters for stable control and energy effectiveness [35].

However, as the energy management and support are provided by the DERs in PETT, they are extremely effective. In faults, these systems can dynamically shift load priorities to maintain grid stability. The fault-tolerance and the control policies are developed to maximize the performance and to guarantee an uninterrupted operation even with load variation and extrinsic disturbances. These systems track the progression of charging and may identify anomalies and correct the power delivery to avoid them. Fuzzy logic control and SMC-based methods enhance the practicability and robustness; therefore, the charging process has been smooth and sustained. Such advancements in control systems not only improve efficiency but also contribute to a more resilient energy infrastructure. As these technologies evolve, integrating real-time data analytics will further optimize performance, ensuring that power distribution remains reliable even in the face of unexpected challenges.

7.1. Future of PETT Systems

Findings of this study also suggest the need for future work to address current limitations and enable the future promise of PETT. In particular, owing to the emergence of quantum computing, Internet of Things (IoT) devices, and high-end sensors, it could completely transform the future of fault-tolerant sensing and control. These technological advances allow for more complete monitoring, faster data processing, and intelligent decision making, and enable PETT systems to function autonomously and reliably in more challenging situations. Indeed, by integrating the winning applications, PETT is on the verge of breakthrough performance, and with the impact of those performances, it becomes intelligent, adaptive, and reconfigurable energy systems [44]. In conclusion, fault tolerance and control allow the best tradeoff between the reliability and efficiency of Power Electronic Traction Transformer. The application of advanced techniques, like fault detection based on machine learning driven MPC, fuzzy logic control, and SMC, has shown them to improve the PETT's adaptability [46], stability, and energy consumption. Nonetheless, due to a lack of computational complexity and performance tradeoff, these future research and development projects are a considerable challenge. After overcoming these described barriers and the implementation of new technology, PETT systems may further develop to be effective, adaptive, and robust tools for handling dynamic, increasingly interconnected energy system dynamics. These developments will place PETT at the heart of smart and next-generation power grids.

8. Conclusion

Power Electronic Traction Transformer (PETT) is a new generation platform for power systems that offers increased flexibility, performance, and integration. However, its high complexity makes it vulnerable to risks, necessitating fault tolerance and control methodologies to ensure reliability. Fault tolerance involves identifying, isolating, and compensating for faults for operational viability, while control strategies manage critical parameters to reach performance limits. These strategies are crucial in dynamically changing environments. FT systems are implemented on control paradigms that allow dynamic reconfiguration in the presence of faults and on high-level control methods that employ fault detection and repair to react to fluctuating conditions in real-time. Traditional techniques, such as redundancy-based fault tolerance and PID control, are low cost and low risk but not suitable for dealing with PETT's nonlinearities and time-varying behavior. Fault detection and Model Predictive Control (MPC) with machine learning are superior in terms of accuracy, response time, and energy consumption. Combining fault detection based on ML-based methods and MPC can provide instantaneous and effective fault removal while maintaining system stability and operational effectiveness. However, current limitations of fault tolerance and control policies in PETT remain significant, particularly due to the high computational complexity of real-time fault detection, fault diagnosis, and control optimization. Advanced techniques require power-efficient algorithms and custom hardware for low-latency operation and high performance. The potential of embedded fault tolerance and control policy

in renewable energy systems, smart grids, and EV charging network applications is evident. Future work should address these limitations and enable PETT to function autonomously and reliably in more challenging situations.

This will necessitate continued research into innovative algorithms and hardware solutions that can adapt to dynamic environments. By enhancing the robustness of these systems, we can ensure greater efficiency and resilience in the face of unforeseen challenges. The exploration of embedded fault tolerance in renewable energy systems reveals significant limitations in current control policies and their ability to ensure reliability. Addressing these challenges is imperative for the development of autonomous, dependable Power Electronic and Transmission Technologies (PETT). Future research must focus on innovating algorithms and hardware solutions that enhance the robustness of these systems, ultimately leading to improved efficiency and resilience. By overcoming the existing shortcomings, we can pave the way for more sustainable energy solutions that not only meet current demands but also adapt seamlessly to future challenges. This holistic approach will be crucial in realizing the full potential of renewable energy systems in our transition towards a greener future.

Acknowledgement

The authors acknowledge the support from Sir M Visvesvaraya Institute of Technology, Bengaluru, and BMS Institute of Technology and Management, India, for the facilities provided to carry out the research.

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