Improved Power Loss Estimation for Device- to System-Level Analysis

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Abstract

Power converters are found nearly everywhere electric power is used and are ubiquitous in renewable energy generation and electric vehicles. All power converters suffer from losses. Modern power converters have very high efficiency, often reaching peak efficiency $\geq 95\%$. However, the losses in these systems are still significant and must be considered for thermal and financial purposes. To enable maximum loss reduction, accurate estimation of the losses at the design stage is mandatory.

Gallium Nitride (GaN) power switches are an emerging technology due to their high efficiency operation and smaller size compared to traditional Silicon (Si) devices. To date, simplistic power loss models have been employed for loss predication and thermal management design with Gallium Nitride (GaN). However, these simplistic models do not provide accurate loss prediction, resulting in over-design of the thermal management systems. This work proposes a comprehensive method to predict losses in GaN devices using high-accuracy thermal measurement. The proposed model is validated experimentally and provides a four-fold increase in loss predication accuracy compared to traditional methods.

Having established accurate converter-level loss prediction, a higher level of abstraction is then considered. Existing system-level analysis focuses on distribution losses and oversimplifies converter losses by assuming fixed efficiency. In reality, converter losses are highly variable under different operating conditions. In this work, the Rapid Loss Estimation equation (RLEE) is proposed to provide computationally simple loss prediction under all operating conditions. The RLEE extracts detailed loss behavior from multi-domain simulation into a computationally simple parametric equation. Using the RLEE high accuracy and high speed loss estimation is obtained, as demonstrated in a DC microgrid with three different converters.

Ultimately, the tools developed in this work improve loss estimation in power converters from the component level up to the system level. The proposed techniques, while explained through specific examples, are widely applicable and can be readily implemented to other devices, topologies and systems. Improved loss estimation is valuable at all levels, from designing thermal management systems for individual devices in a converter to optimizing the financial outcomes of a complex grid with multiple power converters.
Lay Summary

Power converters are a fundamental technology for renewable energy generation and transportation electrification, among many other applications. However, these devices are subject to unwanted power losses. Reduction of losses, particularly in high power systems, can result in significant energy and cost savings. For this reason, it is critical to develop tools to better predict these losses and reduce them.

In this work, detailed models are developed to better predict the losses in power converters. First, the losses in the individual switches inside the converter are investigated. The developed models allow for accurate loss prediction of the next generation of power converters. Secondly, the losses in the whole converter are considered. The developed Rapid Loss Estimation Equation can be used for fast and accurate simulation of complex systems with high renewable energy integration. The proposed techniques are widely applicable, allowing for easy application by electrical engineers as they develop the energy systems of the future.
Preface

This work is based on research performed at the Electrical and Computer Engineering Department at the University of British Columbia by Matthieu Amyotte, under the supervision of Dr. Martin Ordonez.

A version of Chapter 2 was presented and published at the Institute of Electrical and Electronics Engineers (IEEE) Energy Conversion Conference & Congress (ECCE) 2018 [1]. Additional detail has been added here for completeness. Chapter 3 is based on work that has been submitted for publication, and is currently under review.

As the first author of the above-mentioned publications, the author of this thesis developed the theoretical concepts and procedures, designed the experiments and wrote the documents. Technical advice and guidance was provided by Dr. Martin Ordonez throughout the process. Furthermore, the work in Chapter 2 was supported by Ettore Scabeni Glitz and Maria Celeste Garcia Perez, who assisted in the development of the characterization procedure. They are acknowledged as secondary authors on the associated publication [1].
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Glossary

AC  alternating current

BES  battery energy storage

DC  direct current

DER  distributed energy resources

DOE  design of experiments

DPT  double pulse test

DUT  device-under-test

ECCE  Energy Conversion Conference & Congress

eHEMT  enhancement-mode high electron mobility transistor

EMI  electromagnetic interference

EV  electric vehicle

EVCS  electric vehicle charging station

FCCCD  face-centered central composite design

GaN  Gallium Nitride

HEMT  high electron mobility transistor

IEEE  Institute of Electrical and Electronics Engineers

IR  infrared
MOSFET  metal-oxide semiconductor field-effect transistor

MPP  maximum power point

MPPT  maximum power point tracking

NREL  National Renewable Energy Laboratory

PCB  printed circuit board

PFC  power factor corrector

PV  photovoltaic

RLEE  Rapid Loss Estimation equation

RTD  resistance temperature detector

Si  Silicon

SiC  Silicon Carbide

SOC  state of charge

SPICE  Simulation Program with Integrated Circuit Emphasis

WBG  wide-bandgap
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First and foremost, I want to graciously acknowledge the continued support of Dr. Martin Ordonez. Through his guidance, my technical knowledge and research abilities have expanded well beyond my expectations. Not only did he provide technical direction, but he emphasized a well-rounded graduate experience. His leadership provided a strong example for many of the extracurricular activities I pursued throughout my time at UBC, and will continue to guide my career in the years to come.

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Dedication

To Kristen,

For inspiring me in more ways than I can count.
Chapter 1

Introduction

1.1 Motivation

Renewable energy generation and transportation electrification are emerging fields that will play an essential role in addressing climate change. These technologies, in combination with myriad other solutions, will be needed to meet the targets outlined in the Paris Agreement, which formally came into effect in November 2016 [2]. Power converters are a critical component in all renewable energy generation and transportation electrification systems. Power converters transform electricity between alternating current (AC) and direct current (DC) and change voltage levels. A sample energy system with distributed renewable energy generation and various electrified loads is shown in Fig. 1.1. From the diversity of applications, it is clear that power converters will be omnipresent in the creation of a sustainable future.

In addition to new technology, efficiency improvements in existing systems are also needed [3]. High efficiency ($\geq 95\%$) is not uncommon in modern power converters [4, 5]. However, incremental improvements, particularly in high-power electronics, still yield significant energy and cost savings. For example, increasing the efficiency from 98% to 99% (only 1% change in efficiency) corresponds to a loss reduction of 50%. This could be the difference between an active (expensive and unreliable) cooling system or a passive cooling system. It also allows for significant size reduction, which is particularly valuable for space-constrained applications, like electric vehicles. Thus, to better understand converter efficiency, it is necessary to investigate the underlying challenge: power losses.

Power losses occur in the individual components of power converters, particularly in the power converter switches. Silicon (Si) switches are currently the standard for power converters, having been used for over 40 years [6]. However, Si devices are quickly approaching their physical limits, slowing the evolution of
Figure 1.1: Power converters will be omnipresent in a sustainable future from generating renewable energy to charging electric vehicles and powering zero-emission homes.

power converter technology. In order to achieve lower losses and the associated benefits, wide-bandgap (WBG) devices must be used. These WBG devices, namely Silicon Carbide (SiC) and Gallium Nitride (GaN), have substantially lower losses than Si devices [7]. WBG devices are also capable of operating at higher temperatures, which allows for simplified cooling systems that use less (or no) power [7]. However, GaN devices are still a new technology and their loss performance is not well understood [7]. There exists a need for high accuracy power loss estimation in GaN devices to enable the next generation of power converter design.

Shortcomings in power loss estimation extend into the design of energy systems, as well. As more power converters are added, system complexity grows rapidly. Existing simulation tools used for converter-level analysis are too computationally intensive for large systems. Traditional system-level simulation relies on oversimplifications, effectively eliminating any insight into the converter’s actual loss behavior. To effectively design the next generation of energy systems, loss models that are both accurate and computationally simple are required.

This work addresses the shortcomings of power loss estimation at all levels, from GaN switches to energy systems. First, an improved loss prediction model for GaN devices is developed through the use of thermal measurement to characterize device performance under different operating conditions. Using the developed high-accuracy device-level models, it is possible to analyze losses at the converter level. Then, the accurate
converter-level behavior is extracted for use in system-level simulation. The proposed Rapid Loss Estimation equation is a computationally-simple parametric equation for system-level loss prediction in all operating conditions. Ultimately, the improved loss prediction provided by this work enables the next generation of power converters and energy systems.

1.2 Literature Review

In order to place this work within a larger research context and to identify the contributions, it is important to first consider the existing work. In this section, a comprehensive literature review is provided.

Throughout this work, design of experiments (DOE) is used for statistical analysis. DOE is a powerful statistical technique used to intelligently design experiments with multiple variables. An introduction to this technique and a literature review of its use in different power electronic applications is presented in Section 1.2.1.

A literature review of the development and early implementation of GaN power switches is presented in Section 1.2.2. The many benefits that GaN devices provide compared to traditional Si devices is presented. Furthermore, through this early work, a number of challenges were identified. The particular challenge of interest, power loss prediction for GaN devices, is investigated in further detail. Existing solutions are presented and their shortcomings are highlighted.

Next, a review of existing techniques for power loss analysis of power switches is presented in Section 1.2.3. A number of traditional electrical and thermal loss measurement techniques are presented and their strengths and weaknesses are identified. Many of these techniques were implemented in early work to evaluate their utility for GaN devices. Ultimately, the disadvantages discussed here proved too significant to allow for accurate power loss characterization of GaN devices.

Finally, a literature review of converter loss prediction at the system-level is provided in Section 1.2.4. While existing system-level investigations of distribution losses have been performed regularly, it is common to oversimplify converter losses using the fixed efficiency approximation. Some recent work has shown that by including more detailed converter loss considerations for photovoltaic (PV) inverters, benefits can be seen in system optimization and reliability studies.

1.2.1 Design of Experiments

Design of Experiments is a statistical technique used for intelligently designing experiments with multiple variables. In particular, DOE serves two important purposes. First, it optimally selects specific operating con-
ditions to test. In this way, the number of experiments needed for a statistically valid model is minimized. Secondly, DOE applies statistical analysis to generate a parametric equation. This parametric equation accurately predicts the response under all operating conditions within the tested range [8]. In particular, it generates an equation of the form

\[
F(Y) = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} b_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} c_{ijk} x_i x_j x_k. \tag{1.1}
\]

Where \( Y \) is the response; \( F(Y) \) is a mathematical transform of the response (e.g. square root or natural logarithm); \( x_1 ... x_n \) are the experimental variables; \( a_0 \) is the overall average of the response; \( a_i \) are linear regression coefficients; \( b_{ij} \) are quadratic regression coefficients; and, \( c_{ijk} \) are cubic regression coefficients.

Design of Experiments can be used for design evaluation, model development and optimization problems. By running a small number of experiments, it is often possible to quickly identify which variables have a statistically significant impact on a response [8]. In [9–13], DOE is used extensively to understand, model and optimize different aspects of planar magnetics, such as trace and winding geometry.

Loss characterization using DOE was first proposed in [14], and has since been further investigated for Si metal-oxide semiconductor field-effect transistors (MOSFETS) [15–17]. In [15, 16], the losses in the Si MOSFETS of an LLC resonant converter are characterized using DOE techniques. Similarly, in [17], the losses in the semi-bridgeless power factor corrector (PFC) are investigated. This work expands on existing DOE loss characterization by developing models for emerging GaN devices [1]. In particular, this work uses DOE to capture the complex non-linear switch behavior into an easily implemented loss prediction model.

Energy resource modeling has also been performed using DOE. Direct methanol fuel cells are considered in [18] and wind turbine rotors are investigated in [19]. In these works, the focus is on the energy resource, rather than the power converter. In this work, the power converter is considered and a loss prediction method is developed using DOE to allow for computationally simple loss prediction in system-level simulation. In particular, DOE is used to extract detailed loss prediction behavior from complicated converter models into a computationally simple meta-model that can be effectively applied to system-level simulation.

### 1.2.2 Gallium Nitride Power Switches

Traditionally, power electronics have relied on Si-based switches; however, Si devices are nearing their theoretical limits. As an alternative, WBG devices have emerged, offering better switching performance, higher blocking voltage, and higher operating temperatures as outlined in Fig. 1.2a [7]. Based on manufacturing capabilities, Silicon Carbide has emerged as the dominant player for high-voltage and high-power applica-
Figure 1.2: a) Comparison of material properties of SiC and GaN compared to traditional Si. The connection to operating parameters, shown on the x-axis, highlights how WBG devices outperform Si in power electronic applications. b) Overview of the power electronics market to illustrate the operating niche that each material will occupy. GaN will be predominantly used in high-frequency low-to-medium power applications.

The first commercially-available GaN devices were normally-on GaN high electron mobility transistors (HEMTs) [7]. While these devices exhibited the expected performance benefits over Si, their applicability was limited. To create the normally-off devices needed for power electronics, two main solutions have emerged. Firstly, cascode structures are created by adding a normally-off low-voltage Si transistor in series with the normally-on GaN HEMT [7, 20]. This cascode structure provides normally-off behavior, but reintroduces some of the restrictions that arise with Si devices, such as limited temperature performance. The alternative structure is the enhancement-mode high electron mobility transistor (eHEMT), which modifies the original HEMT structure to allow for normally-off behavior [21]. In this way, the benefits of GaN are maintained.

GaN eHEMTs are now commercially available from a number of manufacturers [5, 21]. When compared to similarly rated Si MOSFETS, GaN eHEMTs provide better performance through two main improvements: faster switching and no reverse recovery [21]. The improved switching speed has been leveraged to develop high efficiency power converters at high frequency, such as the 97.8% efficient 1MHz boost in [22] and the
97.5% efficient 500kHz LLC in [23], among many others [24, 25]. The lack of reverse recovery, however, has proven even more interesting by enabling the totem-pole PFC topology, which was not previously possible with Si MOSFETS [4, 26]. Significant effort has been invested in this topology, as it exhibits performance and cost benefits compared to other PFC topologies [26–29].

Despite the many advancements occurring with GaN, there are still challenges that must be addressed. Firstly, reliability of this new technology is a work-in-progress [5, 7]. In order to better understand the reliability, the loss performance and thermal management must be considered [5]. Reliability is also compromised by the sensitivity to parasitic elements. Because GaN devices can be so small, external elements, such as circuit board traces and driver selection, now play a larger role in the performance of the switch [30, 31]. This is problematic as adding measurement devices, such as oscilloscope probes, can change the switches’ performance. Furthermore, electrical measurement is susceptible to electromagnetic interference (EMI) which increases with switching frequency [32]. Instead, thermal measurement can be used to avoid the need for electrical measurement in power loss measurement [31, 32].

1.2.3 Power Loss Analysis in Power Switches

Analysis of power losses in semiconductor devices is a critical part of power converter design. By comparing the losses in different devices, it is possible to select the best device for a particular application [33]. Furthermore, the converter efficiency can be determined in order to compare different topologies [15, 34, 35]. Loss analysis is also valuable in thermal management design, which is particularly necessary for GaN devices because of their small thermal mass [1, 35]. To this end, significant efforts have been made to develop loss models from experimental techniques using electrical and thermal measurement.

Fundamentally, power losses, \( P_{\text{loss}} \), occur anytime there is both a drain current, \( I_d \), and a drain-to-source voltage, \( V_{ds} \), present in the device, as described by

\[
P_{\text{loss}} = I_d V_{ds}
\]  

In GaN devices, this occurs in two instances: conduction losses (when the switch is turned on) and switching losses (when the switch is changing from on-to-off or vice-versa). These two loss mechanisms are illustrated in their simplest form in Fig. 1.3a. Conduction losses are relatively easy to measure, as they occur in a steady-state condition. Switching losses, on the other hand, are very difficult to measure as they occur very quickly. Therefore, most research efforts focus on the characterization of switching losses.

Loss characterization using electrical measurement attempts to capture more accurate current and voltage
Figure 1.3: a) Simplified $V_{ds}$ and $I_d$ waveforms and the resultant $P_{loss}$ during turn-on, conduction and turn-off instances. The real waveforms are significantly more complicated than those depicted here. b) At its simplest level, thermal loss measurement determines power losses from the difference in temperature at two points. Commonly, a calorimeter, shown here, is used to isolate the thermal behavior of the DUT.

... waveforms, compared to the simplified version used in Fig. 1.3a. The approach described in [36] considers the effect of the MOSFETs parasitic capacitance on the speed and timing of the rise/fall of the $I_d$ and $V_{ds}$ waveforms. This is a common approach in industry, as all the necessary information is available on the datasheet. This approach was further improved by [37, 38] by considering the parasitics in the circuit which cause ringing at the MOSFET gate. For the most accurate understanding of the $I_d$ and $V_{ds}$ waveforms, the double pulse test can be used, as in [39, 40].

All of these electrically-based techniques provide valuable insight into the switching behavior of the device; however, they have one significant limitation. At high frequencies, as are typically seen in modern power converters, the accuracy of electrical measurement quickly degrades [35, 41]. Electrical measurement is particularly problematic for GaN devices where the addition of probes can alter the circuit performance by introducing unwanted parasitics [30]. Device manufacturers provide best practices [40] for electrical measurement, but even the models developed by manufacturers are not necessarily accurate [1].

An alternative to electrical techniques is to use thermal measurements, which are generally considered more accurate [41]. The fundamental principle of thermal measurement is to determine the heat (losses) produced by the device by measuring the temperature at two different points. As illustrated in Fig. 1.3b, this is commonly done using a calorimeter, where the DUT is thermally isolated from the environment and a cooling fluid is heated by the losses [41]. Alternatively, the temperature change of the DUT can be used for the loss calculation. Thermal measurement has been applied at the device level in [42, 43], but is more generally...
applied to converter level study because of the challenges associated with isolating the DUT\cite{35,41,43}. In addition to the difficulty of isolating the individual device, thermal measurement can also be very slow as the system must reach thermal equilibrium before a measurement can be taken\cite{41}.

1.2.4 System-Level Power Loss Prediction

As described above, power loss analysis is critical in the design of power converters. The importance extends to system-level studies as converters are increasingly installed into distributed energy resources (DER) systems. In\cite{44,45}, a solar PV plant is optimized and advanced modeling of the inverters is considered. Both conclude that consideration of the detailed inverter behavior is necessary for accurate results. In particular,\cite{44} is able to increase the financial benefit by 1%, reduce payback period by 6.95% and increase harvested energy by 9.3%. Furthermore,\cite{5,46} uses advanced loss modeling to study life-cycle reliability. These works recognize that converters operate under a wide range of operating conditions throughout their life-cycle, and that consideration of the losses under these diverse conditions is critical.

The primary challenge with loss prediction at a system-level is computation speed which is directly related to computational complexity. In order to study large time scales, such as years, simulations must be very fast. However, power electronic simulation tools, such as Plexim’s PLECS and Powersim’s PSIM, are very computationally complex as they study the individual switching transitions in a converter\cite{47,48}. With a frequency of 100kHz, there would be more than three trillion switching transitions when simulating one year. Even simulating a few seconds to reach thermal equilibrium can take significant time.

Traditionally, computationally simple models have been used by assuming the fixed-efficiency method. In this approach, a fixed value is used to calculate the losses using

\[
P_{\text{loss}} = P_{\text{in}} \left(1 - \eta_{\text{fixed}}\right),
\]

This approach is used by\cite{49-52} for a variety of DER and microgrid optimization problems.\cite{52} considers the efficiency of different converters in the system, but still uses a fixed efficiency for each.

The European efficiency, $\eta_{\text{euro}}$, can also be considered\cite{53,54}. This is a weighted efficiency which accounts for the efficiency change as $P_{\text{in}}$ changes, as defined by

\[
\eta_{\text{euro}} = 0.03\eta_{5\%} + 0.06\eta_{10\%} + 0.13\eta_{20\%} + 0.1\eta_{30\%} + 0.48\eta_{50\%} + 0.2\eta_{100\%}
\]

where $\eta_{x\%}$ is the efficiency $x\%$ of the rated load. Still, this approach uses a fixed value in the system-
level simulation that does not consider how the losses dynamically change as the operating conditions vary throughout the year.

Then, there exists a gap where existing system-level loss prediction is computationally simple, but overly simplified; and, converter-level simulation is accurate but too computationally complex. This work addresses this gap by developing accurate computationally simple loss prediction by extracting converter-level detail using DOE.

### 1.3 Contribution of the Work

Through the above literature review, a number of shortcomings are evident in power loss analysis for power conversion. The work proposes solutions to improve loss analysis from the device level to the system level, as outlined below.

- The first contribution of this work is the development of a characterization procedure for GaN eHEMTs. This procedure uses thermal measurement to accurately determine the losses of the GaN device under a variety of different operating conditions. By using different circuit configurations, conduction and switching losses can be characterized independently.

- Using the loss characterization, a loss model for the GaN eHEMT is created. By applying DOE, a minimum number of test conditions can be used to model the loss behavior under all operating conditions. The proposed model can easily be implemented in PLECS for accurate loss prediction in any power converter topology. The model is validated through experiment with a boost converter and the results are compared to other common loss-prediction practices. The loss prediction error is improved from 50% using current best practices to 12% with the developed model.

- Moving to a higher level of abstraction, loss prediction at the system level is also considered. The Rapid Loss Estimation equation (RLEE) is developed to allow for accurate converter loss prediction under the diverse operating conditions seen in system-level simulation. The RLEE uses DOE to extract detailed converter behavior into a computationally-simple parametric equation.

- Finally, the RLEE is applied to the analysis of a DER DC microgrid. For this study, the RLEE is developed for three different converter topologies to highlight its versatility and ease of use. The microgrid is simulated for one year to compare the performance of the RLEE and the traditional fixed-efficiency method. It is found that the RLEE has very fast simulation speed and provides improved accuracy in loss prediction.
Ultimately, the greatest contribution of this work is the procedures developed. While demonstrated for particular devices and converters in this work, these methods can be applied to any power electronic device, converter topology and/or energy system.

1.4 Thesis Outline

This work is outlined in the remainder of this document as follows.

- In Chapter 2, the device characterization procedure and its application for loss prediction in a boost converter is presented. First, the loss mechanisms of GaN devices are introduced. Then, the thermal characterization procedure is explained, including the circuits used to isolate the individual loss mechanisms. Design of experiments is introduced and applied to the development of a loss prediction model for the GaN eHEMT. Finally, the loss model is applied in a boost converter, where its performance is validated.

- In Chapter 3, the Rapid Loss Estimation equation is presented. First, the procedure to develop the RLEE is presented. This procedure is applied to three different converters that are commonly used for DER. Through these examples, the ability of the RLEE to consider different operating conditions is highlighted. The three converters are included in the design of a DC microgrid, which is simulated for one year. The simulation validates the computational simplicity of the RLEE, while demonstrating the pitfalls of the traditional fixed-efficiency method of loss prediction at system level.

- In Chapter 4, the experimental and simulation results are summarized and conclusions are drawn on the impact of the presented work. Finally, future work is presented to apply the developed techniques in the continued advancement of power conversion.
Chapter 2

Power Loss Characterization of Gallium Nitride Power Switches

GaN power switches provide multiple benefits over traditional Si MOSFETS, such as lower losses, higher switching frequencies and increased power density. To date, multiple converter topologies have been demonstrated using GaN transistors; however, GaN devices are still a developing technology. Their small physical size and low thermal capacitance are particularly challenging to deal with. Significant emphasis must be placed on thermal management of the heat generated by the losses in the device. To this end, accurate power loss prediction is needed to properly design the thermal management system and reach the full benefits of GaN technology.

In order to characterize the loss behavior of GaN eHEMTS, it is necessary to consider the two loss mechanisms in the device, as first presented in Fig. 1.3 in 1.2.3. For eHEMTS, there are only two main loss mechanisms: conduction losses and switching losses. Unlike Si MOSFETS, there is no anti-parallel diode, and so there are no reverse recovery losses to consider. The individual loss mechanisms and the techniques used to isolate them from each other are described in the subsequent sections. For each of the two loss mechanisms, it is necessary to be able to test the loss performance under a variety of realistic operating conditions.

In this work, experimental characterization of the switch using thermal measurement allows for the creation of a high accuracy power loss model. First, the conduction losses are evaluated through a simple experimental procedure. During this procedure, the thermal behavior of the system is also characterized. Using this thermal characterization, the switching losses can then be evaluated experimentally. Using the experimental results from select operating conditions, a power loss model for the GaN switch can be created.
Figure 2.1: When the eHEMT is turned on, a parasitic resistance between drain and source exists, $R_{ds,on}$. When current $I_d$ flows through $R_{ds,on}$, conduction losses, $P_{cond}$, occur.

to predict the losses under any operating conditions. The developed model is applied to the simulation of the losses in a boost converter. Experimental validation is performed on the simulated converter to demonstrate the performance benefit of the proposed model over traditional loss estimation techniques.

### 2.1 Conduction Losses

The first loss mechanism, and the simplest to characterize, is conduction loss. Conduction losses, $P_{cond}$, are caused by the resistive behavior of the device between the drain and source, $R_{ds,on}$, when the eHEMT is turned on, as shown in Fig. 2.1.

When the device is on and current, $i_d$, flows, the conduction losses, $P_{cond}$, are given by

$$P_{cond}(t) = v_{ds}(t) \cdot i_d(t)$$  \hspace{1cm} (2.1)$$

where $v_{ds}$ is the voltage between drain and source. Assuming that variations of the current and voltage are negligible in the conduction interval, the average values can be assumed, $V_{ds}$ and $I_d$ for voltage and current, respectively. Then, $R_{ds,on}$ is defined such that

$$P_{cond} = V_{ds}I_d = R_{ds,on}I_d^2$$  \hspace{1cm} (2.2)$$

and so

$$R_{ds,on} = \frac{V_{ds}}{I_d}.$$  \hspace{1cm} (2.3)$$
2.1.1 Datasheet Model

\( R_{ds, on} \) is provided by the manufacturer on the datasheet, however, the provided model lacks detail. Often, the dependence of \( R_{ds, on} \) on the junction temperature, \( T_j \) is provided, but only for a specific value of \( I_d \). For GaN Systems’ GS66508B, considered throughout this work, a relatively detailed model is provided. As is common, the dependence of \( R_{ds, on} \) on \( T_j \) is given, normalized to the value at \( T_j = 25^\circ C \). In addition, the dependence of \( R_{ds, on} \) on \( I_d \) is given for \( T_j = 25^\circ C \) and \( T_j = 150^\circ C \). Then, the datasheet value of \( R_{ds, on} \) for a given operating point can be obtained by assuming a linear interpolation between the \( T_j = 25^\circ C \) and \( T_j = 150^\circ C \) curves for a given value of \( I_d \).

2.1.2 Characterization with Design of Experiments

Given (2.2), it is easy to determine the conduction losses if \( I_d \) and \( V_{ds} \) can be measured. The circuit used for testing conduction losses is given in Fig. 2.2 A DC current supply is used to generate \( I_d \) and the DUT is turned on by a constant \( V_{gs} = 6V \). Two highly accurate (error \( \leq 0.01\% \) of the reading) digital multimeters \[55\] are used to measure \( I_d \) and \( V_{ds} \). The multimeter is used to measure \( I_d \) as the precision of the current supply is limited. As these are DC measurements, there are none of the challenges for electrical measurement mentioned in 1.2.3.

The \( T_j \), however, cannot be measured as the junction is concealed by the device’s case. Instead, the case temperature, \( T_c \), is used as a proxy because it can easily be measured. \( T_j \) can readily be found from \( T_c \) using

\[
T_j = T_c + P_{\text{loss}} R_{\theta,jc}
\]  

(2.4)

Where \( R_{\theta,jc} \) is the thermal resistance between the junction and case given on the device datasheet. \( T_c \) is controlled by placing the DUT in a thermal chamber. A thermocouple is mounted to the case with thermally-conductive epoxy and the temperature value is directly fed to the thermal chamber controller. Additional

![Figure 2.2: \( I_d \) is applied by a DC source and \( I_d \) and \( V_{ds} \) are measured with high accuracy.](image)

As described in 1.2.1, design of experiments can be used to intelligently select specific test conditions. From these specific test conditions, the behavior under all operating conditions can be expressed as a parametric equation. For the conduction losses a face-centered central composite design (FCCCD) was selected for the DOE analysis. In this design approach, the boundary conditions of the operating area are considered, as well as multiple replicates of the center point. Each independent variable, \( x_i \), can be considered to have a normalized range of \(-1 \leq x_i \leq 1\). Then, the test conditions can be represented graphically in Fig. 2.3. For the FCCCD with two variables, 13 test points are needed including 5 replicates at the center point. These replicates are used to quantify the random error that is present in any experimental measurement.

For the conduction loss characterization, the operational limits were selected based on the 1.85kW boost converter in 2.4 which was designed using the GS66508B GaN devices. \( I_d \) is limited to 1 A \( \leq I_d \leq 6 \) A, and \( T_c \) is limited to 25°C \( \leq T_c \leq 110°C\). The test points and characterization results are given in Table 2.1.

From the measured \( I_d \) and \( V_{ds} \), \( R_{ds, on} \) and \( P_{cond} \) can be calculated using (2.3) & (2.2). As \( R_{ds, on} \) is typically given on the datasheet, it is the focus of the DOE analysis. Using DOE software to analyze the FCCCD runs, a parametric equation for \( R_{ds, on} \) was found. Given in (2.5), the equation can be used to predict \( R_{ds, on} \) (and subsequently \( P_{cond} \)) for any combination of \( I_d \) and \( T_c \) within the tested limits.

\[
R_{ds, on} = 46.1 + 0.3 T_c - 2.3 I_d + 0.02 I_d T_c + 2.9 \times 10^{-3} T_c^2 + 0.4 I_d^2 \text{ [mΩ]}
\] (2.5)
Table 2.1: Test Points for Conduction Loss Characterization of a GaN enhancement-mode high electron mobility transistor

<table>
<thead>
<tr>
<th>Normalized Values</th>
<th>Operating Conditions</th>
<th>Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_d$ [norm.]</td>
<td>$T_c$ [norm.]</td>
<td>$I_d$ [A]</td>
</tr>
<tr>
<td>0 -1</td>
<td>3.5 30</td>
<td>51.8</td>
</tr>
<tr>
<td>0 0</td>
<td>3.5 70</td>
<td>73.7</td>
</tr>
<tr>
<td>1 -1</td>
<td>6 30</td>
<td>54.7</td>
</tr>
<tr>
<td>1 0</td>
<td>6 70</td>
<td>79.4</td>
</tr>
<tr>
<td>1 1</td>
<td>6 110</td>
<td>114.9</td>
</tr>
<tr>
<td>0 0</td>
<td>3.5 70</td>
<td>75.2</td>
</tr>
<tr>
<td>0 0</td>
<td>3.5 70</td>
<td>72.9</td>
</tr>
<tr>
<td>0 0</td>
<td>3.5 70</td>
<td>72.0</td>
</tr>
<tr>
<td>0 1</td>
<td>3.5 110</td>
<td>105.5</td>
</tr>
<tr>
<td>-1 -1</td>
<td>1 30</td>
<td>50.1</td>
</tr>
<tr>
<td>-1 0</td>
<td>1 70</td>
<td>73.4</td>
</tr>
<tr>
<td>-1 1</td>
<td>1 110</td>
<td>101.8</td>
</tr>
<tr>
<td>0 0</td>
<td>3.5 70</td>
<td>73.6</td>
</tr>
</tbody>
</table>

Figure 2.4 shows the DOE characterization of $R_{ds, on}$ graphically and compares the result to the datasheet model (as described in 2.1.1). There is a significant portion of the operating region that is not accurately described by the datasheet model from 2.1.1. This is because the linear interpolation required by the datasheet model fails to capture the complexity of $R_{ds, on}$, which is non-linear. By performing the experimental characterization presented here and applying DOE a much more accurate model of $R_{ds, on}$ is obtained. Then it is possible to accurately predict $P_{cond}$ using the improved $R_{ds, on}$ model and (2.2).

Figure 2.4: Response surface for the actual $R_{ds, on}$ showing considerable error when compared to the datasheet model, particularly under heavy load (high $I_d$) where losses are highest.
2.2 Loss Determination with Thermal Measurement

In order to avoid the pitfalls of electrical measurement, thermal measurement can be used. The underlying principal of thermal measurement is that the losses in the device are converted into heat. The losses can be expressed as an electrical circuit, shown in Fig. 2.5a, where \( P_{\text{loss}} \) is analogous to current; the temperature of a specific point (x), \( T_x \), is synonymous to voltage; and, the thermal resistance between two points (x and y), \( R_{\theta xy} \), is synonymous to electrical resistance. Shown in Fig. 2.5b, the two points of interest in this work are the eHEMT case, c, and another point, b, on the board near the eHEMT. Then, if \( R_{\theta cb}, T_c \) and \( T_b \) are known, \( P_{\text{loss}} \) can be found in

\[
P_{\text{loss}} = \frac{\Delta T_{cb}}{R_{\theta cb}} = \frac{T_c - T_b}{R_{\theta cb}}.
\]

To determine the value of \( R_{\theta cb} \) for the selected points, a calibration is performed in the first part of the methodology. By performing this calibration, the choice of c and b are flexible. This was verified by testing a variety of points at different locations on the device and board. The measured losses for each combination of points was found to be within experimental error. This calibration stage, which is done in parallel with the conduction loss calibration in 2.1.2, is detailed in 2.2.2.

2.2.1 Test Setup

A number of temperature measurement devices were considered for thermal measurement. Electrical-based temperature sensors are a common choice. Thermocouples are cheap and readily available, but have limited accuracy. resistance temperature detectors (RTDS) are still relatively low cost but provide improved accuracy. However, it was found that when placed in close proximity to a device switching at high frequency, these electrical-based sensors were susceptible to EMI. While the EMI did not compromise the controller of the
Figure 2.6: a) The flexible power platform for GaN eHEMT. b) The PCB is mounted vertically and installed in the thermal chamber to provide temperature regulation. c) is the IR transparent window to allow the thermal camera, mounted to the thermal chamber, to view the DUT. d) The power supply, electronic load, and digital multimeters.

thermal chamber, the more sensitive thermometers being used for temperature measurement of $T_c$ and $T_b$ were rendered ineffective. To mitigate EMI effects, a thermal camera was used. While expensive, the thermal camera is immune to EMI and is non-invasive (i.e. it does not need to be in contact with the DUT).

Given the above considerations, the test setup in Fig. 2.6 was built. The test circuits given in Fig. 2.2 and Fig. 2.12a for both conduction losses and switching losses, respectively, were implemented using the GaN flexible power platform in Fig. 2.6a. The printed circuit board (PCB) was mounted vertically and positioned in the thermal chamber, as shown in Fig. 2.6b. Using the thermal chamber it was possible to control the $T_c$ of the DUT. The thermal camera was mounted to look into the chamber through an infrared (IR) transparent window, as shown in Fig. 2.6c, giving the view shown in Fig. 2.5b. Finally, the digital multimeters, power supply and load were connected outside the chamber, as shown in Fig. 2.6d.
Figure 2.7: a) The three steps of the calibration procedure. b) By measuring $\Delta T_{cb}$ and $P_{loss}$ under DC conditions, $R_{\theta cb}$ is found from the slope of the line. As shown by the excellent fit, $R_{\theta cb}$ is constant under diverse operating conditions.

### 2.2.2 Thermal Resistance Calibration

The characterization procedure can be divided into two steps: thermal resistance calibration and power loss measurement. Thermal resistance calibration, outlined in Fig. 2.7a can be done in parallel with the conduction loss characterization in[2.1.2]

During the conduction loss characterization, $P_{cond}$ was measured, which is the power loss under a specific operating condition (step 1 in Fig. 2.7). $P_{loss}$ is known with very high accuracy because of the digital multimeters used to measure $I_d$ and $V_{ds}$. The two temperature points $T_c$ and $T_b$ were also measured (step 2 in Fig. 2.7). The temperature difference between these two points can then be calculated, $\Delta T_{cb} = T_c - T_b$.

Next, $\Delta T_{cb}$ vs $P_{loss}$ is plotted, as shown in Fig. 2.7b. The data points are fitted with a linear regression, the slope of which is $R_{\theta cb}$, as can be found from rearranging (2.6) as

$$R_{\theta cb} = \frac{\Delta T_{cb}}{P_{loss}} \quad (2.7)$$

25 data points (13 from the $P_{cond}$ characterization and 12 additional $R_{\theta cb}$ validation points), are plotted in Fig. 2.7b. It can be seen that there is good agreement with the $R_{\theta cb}$ calibration line for all points, with an $R^2$ value of 0.9978.
Apply calibrated \( R_{\theta cb} \)

\[ P_{\text{loss}} = \frac{T_c - T_b}{R_{\theta cb}} \]

**Figure 2.8:** a) The three steps of the measurement procedure. b) By measuring only \( T_c \) and \( T_b \), \( \Delta T_{cb} \) and the calibrated \( R_{\theta cb} \) can be used to find \( P_{\text{loss}} \) without any electrical measurement.

### 2.2.3 Power Loss Measurement

Once \( R_{\theta cb} \) has been calibrated, it is possible to analyze the losses under any operating condition with no electrical measurement. Again, a simple three step procedure is used, as outlined in Fig. 2.8a.

In this measurement stage, only the temperature at the two specified points, \( T_c \) and \( T_b \) are measured (step 1). The same two points must be used in order for the \( R_{\theta cb} \) calibration to remain valid. Using this measurement, and the calibrated \( R_{\theta cb} \) (step 2), \( P_{\text{loss}} \) can be calculated with (2.6) (step 3). This is shown graphically in Fig. 2.8b.

### 2.3 Switching Losses

Using the developed thermal measurement technique, it is possible to measure the losses under any operating condition. However, in order to generate a loss model, it is desirable to isolate the switching losses. In this way, the two loss mechanisms (conduction and switching) can be modeled independently.

The more complicated of the two loss mechanisms, switching losses occur when the switch transitions from the on to off or vice versa. The theoretical switching waveforms and resulting losses are shown in Fig. 2.9. When the switch is off, no current can flow so \( I_d \) is zero, and \( V_{ds} \) is high. When the switch is on, current can flow so \( I_d \) is high and \( V_{ds} \) is low (but non-zero because of \( R_{ds, on} \) described in 2.1).

Consider the turn-on transition with ideal waveforms shown in Fig. 2.9a. First, \( I_d \) begins to increase to
its final value during the current rise time $t_r$. Once $t_r$ is complete, $V_{ds}$ begins to fall during the voltage fall time $t_f v$. Once $V_{ds}$ reaches its final value, the switch is said to be turned on and the transition is complete. During this switching transition, the instantaneous power loss, $p_{sw}$, is given by

$$p_{sw}(t) = i_d(t)v_{ds}(t)$$

(2.8)

where $i_d(t)$ and $v_{ds}(t)$ are the time varying values of $I_d$ and $V_{ds}$, respectively.

From the instantaneous power, the energy of the turn-on transition, $E_{sw, on}$ can be found in

$$E_{sw, on} = \int_{t_0}^{t_0 + t_r + t_f v} p_{sw}(t)dt$$

(2.9)

If the ideal waveforms of Fig. 2.9a are considered, $E_{sw, on}$ is given by

$$E_{sw, on} = \frac{1}{2} I_d V_{ds} (t_r + t_f v)$$

(2.10)

For a given switching frequency, $f_{sw}$, the average turn on losses, $P_{sw, on}$, can be found from

$$P_{sw, on} = E_{sw, on} f_{sw}$$

(2.11)

The turn-off transition behaves symmetrically, as shown in Fig. 2.9b. In this case, $V_{ds}$ increases first

![Diagram](image)

**Figure 2.9:** Shown with simplified waveforms, in a) turn on losses occur as the eHEMT begins conducting ($I_d$ increases) before $V_{ds}$ decreases. Similarly, in b), turn off losses occur as $V_{ds}$ increases before $I_d$ decreases.
during the voltage rise time $t_{rv}$ and then $I_d$ falls to zero during the current fall time $t_{fi}$. When the current reaches zero, the switch is off. During the turn-off transition, the instantaneous losses are again given by (2.8), while the switching energy, $E_{sw,off}$ and average power losses, $P_{sw,off}$ are given in (2.12) and (2.13), respectively.

$$E_{sw,off} = \int_{t_0}^{t_0 + t_{rv} + t_{fi}} p_{sw}(t) dt \quad (2.12)$$

$$P_{sw,off} = E_{sw,off} f_{sw} \quad (2.13)$$

If the ideal waveforms of Fig. 2.9a are considered, $E_{sw,on}$ is given by

$$E_{sw,off} = \frac{1}{2} I_d V_{ds} (t_{rv} + t_{fi}) \quad (2.14)$$

The total switching energy, $E_{sw}$, and total switching losses, $P_{sw}$, are the sum of the turn-on and turn-off losses, as given in (2.15) and (2.16).

$$E_{sw} = E_{sw,on} + E_{sw,off} \quad (2.15)$$

$$P_{sw} = P_{sw,on} + P_{sw,off} \quad (2.16)$$

Generally, the values of $t_{ri}$, $t_{fv}$, $t_{rv}$, and $t_{fi}$ are given by the device manufacturer on the datasheet. Then, it would appear, that switching loss estimation is quite easy. However, the real $I_d$ and $V_{ds}$ waveforms vary significantly from the theoretical values, as shown in Fig. 2.10a. The overshoot and subsequent ringing of the waveforms during the transition occur because of parasitic inductance and capacitance present in the circuit. During this ringing period, there are additional ringing losses given by (2.17) and (2.18) and shown in Fig. 2.10b.

$$E_{ring} = \int_{ringing\ time} i_d(t) v_{ds}(t) dt \quad (2.17)$$

$$P_{ring} = E_{ring} f_{sw} \quad (2.18)$$

### 2.3.1 Double Pulse Test

The electrical loss measurement techniques in 1.2.3 attempt to capture this ringing. The dominant technique for electrical measurement of switching losses is the double pulse test (DPT). In the DPT, the switching waveforms of a single switching cycle (turn on and turn off) are studied under specific operating conditions. In this way, there is no self-heating of the DUT and $T_c$ can be controlled very easily.
Figure 2.10: a) Oscilloscope capture of the ringing in $I_d$ and $V_{ds}$ during the turn-on transition of a GaN eHEMT. b) Illustration of $P_{ring}$, the losses which occur because of this ringing. This loss mechanism is generally ignored in simple switching loss calculations.

To generate the switching transition, the circuit in Fig. 2.11a is used. First, the DUT, $S_1$ is turned on and the inductor current, $i_L$ charges linearly based on the DC voltage, $V_{ds-set}$. Once $i_L$ reaches the desired test current, $I_{d-set}$, $S_1$ is turned off. This provides the $I_d$ and $V_{ds}$ waveforms for the turn-off transition. After turn-off, $i_L$ remains constant as it freewheeling through the diode. By turning $S_1$ on, the waveforms for the turn-on transition can be captured. The waveforms of $i_L$, $I_d$, and $V_{ds}$ are illustrated in Fig. 2.11b.

Using the DPT results $i_d(t)$ and $v_{ds}(t)$, $E_{sw,on}$, $E_{sw,off}$, and $E_{ring}$ can be found using (2.9), (2.12), and

Figure 2.11: a) Circuit schematic used for the double pulse test. b) Illustration of the waveforms produced by the DPT. However, these waveforms are very hard to capture accurately with electrical measurement.
respectively. Then, $P_{sw, on}$ and $P_{sw, off}$ can be found from (2.11) and (2.13). $P_{sw}$ is given by (2.16).

Finally, $P_{ring}$ can be found using (2.18).

The DPT can be applied either in simulation or experiment. Manufacturers often provide Simulation Program with Integrated Circuit Emphasis (SPICE) models for their devices, which allow for circuit simulation of the DPT procedure. While these models provide high accuracy of the switch behavior, they neglect the parasitic elements that arise from surrounding circuitry when the switch is installed on a PCB. As a result, SPICE simulation of the DPT often has poor results.

2.3.2 Switching Cycle Losses using Thermal Measurement

This work avoids high-frequency electrical measurement of the switching transition; instead relying on non-invasive thermal measurement as described in 2.2. In this approach, the individual $P_{sw, on}$, $P_{sw, off}$ and $P_{ring}$ cannot be isolated, so the combined switching cycle losses is proposed $P_{sw-cycle}$, as given in

$$P_{sw-cycle} = P_{sw, on} + P_{sw, off} + P_{ring}$$

In most converter applications, for every turn-on, there is a corresponding turn-off under very similar operating conditions. In this case, combining the losses into $P_{sw-cycle}$ does not compromise loss prediction. Therefore, the inability to isolate $P_{sw, on}$, $P_{sw, off}$, and $P_{ring}$ is deemed an acceptable trade-off for the elimination of low accuracy electrical measurement.

To measure $P_{sw-cycle}$ independently from $P_{cond}$, the boost converter in Fig. 2.12a is used. The DUT is the boost switch, $S_1$, and the duty cycle, $D$, is very low. The low duty cycle is set in such a way as to immediately turn the switch off as soon as it is fully turned on, as shown in the oscilloscope capture of Fig. 2.12b. In this way, the switch experiences no $P_{cond}$, thus isolating $P_{sw-cycle}$.

The boost converter is supplied by a DC voltage source, $V_{in}$, and an electronic load is applied to the output. $V_{ds}$ is equal to the boost converter’s output voltage, calculated using (2.20) and controlled via the DC source.

$$V_{ds} = V_{out} = \frac{V_{in}}{1 - D}$$

If $D$ is very small, (2.20) simplifies to

$$V_{ds} = V_{out} \approx V_{in}$$

$I_d$ is the boost converter’s input current $I_{in}$. By over-sizing the inductor, ripple is minimized, so $I_{in}$ is can be approximated as constant. Then, $I_d$ can be controlled by changing the electronic load resistance, $R_{load}$.
Figure 2.12: a) A boost converter is used to test $P_{\text{sw-cycle}}$ under different operating conditions. $V_{\text{in}}$ and $R_{\text{load}}$ are controlled and thermal measurement is used for the losses from $S_1$. b) Oscilloscope capture of $I_d$, $V_{ds}$, and $P_{\text{sw-cycle}}$ in the boost converter during $P_{\text{sw-cycle}}$ testing. As soon as the switch is fully on, it is immediately turned off so that $P_{\text{cond}}$ is negligible. It can also be seen that electrical measurement of $P_{\text{loss}}$ is inaccurate.

According to

$$I_d = I_{\text{in}} = \frac{V_{\text{out}}^2}{R_{\text{load}}V_{\text{in}}} \quad (2.22)$$

With control over $I_d$, $V_{ds}$ and $T_c$ (using the thermal chamber) it is possible to determine the $P_{\text{sw-cycle}}$ under any operating conditions.

2.3.3 Characterization with Design of Experiments

Similar to the $R_{\text{ds,on}}$ model used for conduction losses, DOE is employed in the development of a model for $E_{\text{sw-cycle}} = \frac{P_{\text{sw-cycle}}}{f_{\text{sw}}}$ in the GaN eHEMT. A FCCCD was selected for the three variables of interest: $I_d$, $V_{ds}$ and $T_c$, which required 17 test points, including 5 center points. Again, the operational limits were selected based on the 1.85kW boost converter in [2.4] $I_d$ is limited to $1 \text{A} \leq I_d \leq 6 \text{A}$, $V_{ds}$ is limited to $250 \text{V} \leq V_{ds} \leq 450 \text{V}$, and $T_c$ is limited to $30^\circ \text{C} \leq T_c \leq 110^\circ \text{C}$. The switching frequency was $f_{\text{sw}} = 100 \text{kHz}$.

Using DOE software to analyze the $P_{\text{sw-cycle}}$ characterization results, a parametric equation for $E_{\text{sw-cycle}}$ was found. Given in (2.23), the equation can be used to predict $E_{\text{sw-cycle}}$ (and subsequently $P_{\text{sw-cycle}}$) for any combination of $I_d$, $V_{ds}$, and $T_c$ within the tested limits. Figure 2.13 shows (2.23) graphically.

$$E_{\text{sw-cycle}} = -252.2 + 6.1T_c + 1.7V_{ds} + 20.1I_d - 4.4 \times 10^{-2}T_cV_{ds} - 0.3T_cI_d$$

$$+ 1.4 \times 10^{-2}T_c^2 - 2.6 \times 10^{-3}V_{ds}^2 + 6.6 \times 10^{-5}T_cV_{ds}^2 \quad (2.23)$$
Figure 2.13: Response surfaces for the proposed model and the datasheet model under typical operating conditions: a) $V_{ds} = 350$ V, and b) $I_d = 3.5$ A. The proposed model shows a higher-order response to the relevant variables and predicts much larger losses than the datasheet.

For comparison, $E_{sw}$ calculated by the datasheet is also shown. Two differences stand out. First, the DOE model provides a higher-order response. That is, the DOE model shows second- and third-order behavior and interactions, while the datasheet model is linear. Also, it is clear that the datasheet significantly underestimates the switching losses. By not including $E_{ring}$, the datasheet cannot accurately account for the effects of parasitics in the circuit.

2.4 Loss Prediction for GaN Devices

For the purposes of validating the proposed thermal characterization method, a 1.85 kW boost converter is designed using the GS66508B GaN eHEMT. The boost converter is chosen as it is a fundamental power electronics topology and is often used in advanced converters, such as PFCS and solar inverters. The relevant specifications for the test boost converter are provided in Table 2.2 and the schematic is given in 2.14.

2.4.1 Simulation

Multi-domain power electronics software can be used to predict the losses in different circuit topologies. These software tools simulate the individual switching transitions within the circuit and evaluate the losses at each transition. Then, the losses in the GaN eHEMT are calculated as the total of conduction losses and switching losses.

For the boost converter, three different approaches are considered:
Table 2.2: Boost Converter Design Specifications

<table>
<thead>
<tr>
<th>Specification</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switch</td>
<td>GS66508B</td>
</tr>
<tr>
<td>Rated Power, $P_r$</td>
<td>1.85 kW</td>
</tr>
<tr>
<td>Output Voltage, $V_{out}$</td>
<td>250 - 450 V</td>
</tr>
<tr>
<td>†Input Voltage, $V_{in}$</td>
<td>90 - 325 V</td>
</tr>
<tr>
<td>Input Current, $I_{in}$</td>
<td>1 - 6 A</td>
</tr>
<tr>
<td>Switch Temperature, $T_c$</td>
<td>30 - 110 °C</td>
</tr>
</tbody>
</table>

† $V_{in} < V_{out}$ for all operating conditions

Figure 2.14: A boost converter is used for validating the proposed model. $P_{loss}$ of $S_1$ is measured under different operating conditions and compared to the different loss prediction techniques.

1. The datasheet model uses the datasheet information for both the conduction and switching loss models.

2. The double-pulse-test model also uses the datasheet information for conduction losses. For switching losses, the DPT was performed using the SPICE model and DPT circuit provided by GaN Systems. A number of DPT tests were performed and a lookup table was created. For test conditions that were not considered, the linear interpolation is used within the lookup table.

3. The proposed DOE model uses the $R_{ds.on}$ characterization from 2.1.2 for conduction losses. For switching losses, the $E_{sw-cycle}$ characterization from 2.3.3 is used.

Using each of these models, the predicted power losses under different operating conditions can be obtained. Furthermore, the conduction and switching losses can be estimated individually. This provides additional insight into the nature of $P_{loss}$ for different operating conditions.
Power Losses [W]

\[ P_{\text{out}} : 150 \text{ W} \]

\[ P_{\text{out}} : 500 \text{ W} \]

\[ P_{\text{out}} : 1.5 \text{ kW} \]

\[ P_{\text{out}} : 1.85 \text{ kW} \]

\[ V_{\text{in}} : 90 \text{ V} \]

\[ V_{\text{in}} : 170 \text{ V} \]

\[ V_{\text{in}} : 295 \text{ V} \]

\[ V_{\text{in}} : 325 \text{ V} \]

Figure 2.15: Comparison of experimental results with loss prediction from the datasheet model, SPICE double-pulse-test model and the proposed model. The dark color shows the low conduction losses, while the lighter color shows the much greater switching losses. The datasheet model is the least accurate, while the SPICE model is only marginally better. The proposed model is much more accurate under all operating conditions.

### 2.4.2 Experimental Validation

The designed boost converter is implemented in hardware to allow for experimental validation of the proposed method. Different operating conditions are applied and \( P_{\text{loss}} \) is measured using the thermal measurement technique described in 2.2. In the selected operating conditions, both conduction and switching losses are present; however, the two losses cannot be separated in experiment. A sample of the operating conditions with \( V_{\text{out}} = 350 \text{ V} \) is given in Fig. 2.15, while the average error in \( P_{\text{loss}} \) prediction is given in Table 2.3.

<table>
<thead>
<tr>
<th>Method</th>
<th>Average Error [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Datasheet</td>
<td>65</td>
</tr>
<tr>
<td>Double-Pulse Test</td>
<td>50</td>
</tr>
<tr>
<td>Proposed</td>
<td>12</td>
</tr>
</tbody>
</table>

Table 2.3: Average Loss Prediction Error

From the experimental results, the proposed method had an average error for only 12%, while the datasheet model’s average error was 65% and the double-pulse-test model’s was 50%. It is clear that the existing methods (both datasheet and DPT) are inadequate for accurate loss prediction. Furthermore, from
the loss breakdown in Fig. 2.15, it can be seen that switching losses comprise the majority of the losses for the selected switch. This further highlights the detrimental impact of neglecting ringing losses caused by parasitic circuit elements. The proposed model, by considering the parasitic effects in the characterization process, is able to provide significantly improved loss prediction.

2.5 Summary

In this chapter, an improved loss prediction model for GaN eHEMTs was developed. The proposed model uses accurate thermal loss measurement to characterize the eHEMT under specific operating conditions. First, $P_{\text{cond}}$ is characterized using very accurate DC measurement. During this step, $R_{\text{thcb}}$ is also calibrated. Using the $R_{\text{thcab}}$ calibration, $E_{\text{sw-cycle}}$ is characterized. DOE is used for both characterizations to develop two parametric equations: one for conduction losses and one for switching cycle losses. Finally, the losses under any operating condition can be predicted using multi-domain power electronic simulation software.

The developed method was compared to a number of traditional loss prediction techniques. The datasheet model is very fast to apply since the data is readily available; however, it lacks accuracy with an average error of 65% in the tested boost converter. While more accurate than the datasheet model (average error of 50%), the DPT model uses electrical measurement which is unreliable for high switching frequencies. Existing calorimetric methods require complicated test setups and are difficult to build, without providing device-level detail. The proposed method uses thermal measurement to provide accurate (average error of 12%) measurements at high frequency. Meanwhile, DOE is used to minimize the number of tests needed for characterization, allowing for relatively fast model creation.

The increased accuracy provided by the proposed model is an invaluable tool in estimating efficiency and planning effective thermal management systems. Through improved thermal management, maximized power density will be achieved as GaN devices become increasingly viable for commercial development in the power electronics industry.
Chapter 3

The Rapid Loss Estimation Equation

Growth in distributed energy resources (DER) has led to increasingly complex systems with more power converters. As highlighted in Fig. 3.1, many converters are present in a DER microgrid and each converter will experience a diverse range of operating conditions throughout its lifetime. Given the expanded role of power converters, it is necessary to consider converter performance in system-level analysis. In particular, the power losses in the converter should be considered for accurate financial and reliability evaluation.

Converter-level simulation typically employs multi-domain power electronic simulations, as seen in

Figure 3.1: An example DC microgrid with PV generation, BES and EVCS. There is a large number of power converters, each of which experiences a wide variety of operating conditions (one week shown).
Chapter 2. While accurate, these simulations are very computationally complex, requiring long simulation times to analyze even a few seconds of converter performance. Conversely, existing system-level simulation of DER uses the fixed-efficiency method which is overly simplified. This work addresses this gap by providing accurate and computationally simple converter loss prediction: Rapid Loss Estimation equation (RLEE).

To develop the RLEE, the relevant operating conditions must be determined. Then, detailed converter behavior is extracted from multi-domain simulation. Using DOE, the loss performance of the converter under any operating condition can then be predicted. The detailed model development procedure, as well as its application to three converter topologies is detailed in this chapter. Finally, the proposed RLEE is used in system-level simulation of a DER DC microgrid designed for Vancouver, Canada. The results are compared to existing loss prediction techniques.

### 3.1 Loss Model Development Procedure

In order to accurately predict the losses in each converter of a complex system, a computationally-simple loss model is needed. It is necessary to distill the detailed converter behavior, which involves trillions of switching actions per year, into a simple parametric equation: the Rapid Loss Estimation equation (RLEE). This concept is highlighted in Fig. 3.2a and the resulting benefit in system-level simulation is illustrated in Fig. 3.2b. The RLEE is represented as a loss surface to demonstrate the variability of losses at different operating conditions. The high-level development process of the RLEE is given in Fig. 3.3.

The first step in the development of the RLEE is the identification of the system-level variables. In general, converter-level simulation relies on electrical variables: voltage, current and power. However, from a system-level perspective, these are often not the variables of interest. For example, when working with batteries, the state of charge (SOC) is often more relevant than the battery voltage. These system-level variables are valuable in defining the operating conditions of the associated converters.

In order to generate a set of DOE test conditions, the operational limits of the system-level variables must be determined. DOE software is used to select specific test conditions within these operational limits. The provided list of test conditions is optimized to provide the best possible model with the minimum number of points. Once the relevant test conditions are established, the system-level variables can be translated into voltage, current and power for use at the converter-level.

In addition to identifying the system-level variables, it is also necessary to select a specific converter topology for the given application. For a selected topology, the translated converter-level variables can be used to design the converter for the defined system-level operational limits. In this way, the converter
design is focused on the realistic operating conditions, rather than constraints on converter-level variables which may have no system-level meaning. The designed converter is then implemented in multi-domain simulation software to allow for accurate loss modeling.

With the variables established (at both system and converter level) and the converter simulation built, the DOE test conditions can be simulated. This simulation, using multi-domain software, provides highly accurate power loss prediction for the given operating condition. While accurate, this simulation is much too slow to simulate all possible operating conditions, which justifies the selection of specific conditions using DOE.

Finally, the high-accuracy simulation results from the select test conditions can be processed using DOE software to generate a parametric equation of the general form given in (1.1). This is the Rapid Loss Estimation equation (RLEE). The RLEE describes the effect of each system-level variable on the converter losses. This equation is valid within the entire operating region defined in the initial system-level variable identification. The RLEE is computationally simple, but extracts detailed converter behavior for accurate loss prediction in system-level simulation. In the subsequent sections, the RLEE is demonstrated for three unique converter topologies.

![Diagram of Detailed Converter Simulation in PLECS](image)

**Figure 3.2:** a) The proposed method transforms computationally-complex multi-domain simulations into the computationally-simple RLEE. b) The RLEE considers both real operating conditions and detailed converter behavior for accurate system-level loss prediction.
Figure 3.3: The RLEE creation procedure can be summarized in four stages. 1 Identification and analysis of the system-level variables. 2 Selection and implementation of the converter in multi-domain simulation software. 3 Simulation of DOE test conditions. 4 Analysis of DOE results to generate the RLEE.
3.2 Converter Topologies

Each application within a DC microgrid requires a unique converter topology, tailored to the particular demands and operating conditions of that application. While there are infinite choices for each converter, three common topologies are considered here as illustrative examples.

3.2.1 Boost Converter for PV Generation

PV generation is highly variable throughout the year. The output of the PV panels is dependent on the irradiance and the panel temperature. However, the RLEE is derived for the boost converter, and therefore should be independent from the selection of PV panel. Then, the irradiance and panel temperature must first be converted into variables that affect the boost converter: PV panel voltage, $V_{pv}$, and power, $P_{pv}$.

In this work, solar irradiance data is obtained from the National Renewable Energy Laboratory (NREL) National Solar Radiation Database Data Viewer [56]. This resource provides the direct normal irradiance, $DNI$; global horizontal irradiance, $GHI$; zenith angle, $\theta_Z$; ground albedo, $\rho$; and, air temperature, $T_{air}$. The panels are tilted at an angle equal to the latitude of their installation $\theta_{tilt} = L = 49^\circ$ for Vancouver. Then, it is necessary to calculate the plane-of-array irradiance, $POA$, to know the actual irradiance perpendicular to the panels throughout the year. $POA$ is given by

$$POA = POA_{direct} + POA_{reflected} + POA_{diffuse}$$

(3.1)

where $POA_{direct}$ is the direct irradiance found in (3.2); $POA_{reflected}$ is the irradiance reflected off the ground in (3.5); and, $POA_{diffuse}$ is the diffuse irradiance from the atmosphere in (3.6).

$$POA_{direct} = DNI \cos(AOI)$$

(3.2)

Where $AOI$ is the angle of incidence of direct irradiance on the panel in

$$\cos(AOI) = \cos(\theta_Z)\cos(\theta_{tilt}) + \sin(\theta_Z)\sin(\theta_{tilt})\cos(\theta_{hour})$$

(3.3)

Where $\theta_{hour}$ is the hour angle, given in (3.4), which describes how the sun moves from east to west through the day.

$$\theta_{hour} = 15^\circ(12 - hr)$$

(3.4)

Where hr is the hour of the current time of day.
Figure 3.4: a) $P_{pv}$ throughout the year in Vancouver with the weekly average power overlaid. b) Zoomed view of seasonal power generation of the $pv$ array on representative days. It can be seen that PV generation changes significantly throughout the year.

$$POA_{reflected} = GHI\rho \frac{1 - \cos(\theta_{tilt})}{2} \quad (3.5)$$

$$POA_{diffuse} = DHI \frac{1 + \cos(\theta_{tilt})}{2} \quad (3.6)$$

Where $DHI$ is the direct horizontal irradiance found in

$$DHI = GHI - DNI\cos(\theta_Z) \quad (3.7)$$

Using the NREL data and above equations, the $POA$ and $T_{amb}$ are known in half-hour increments throughout the year. Then, $V_{pv}$ and $P_{pv}$ must be found for the year. The BP365 65 Watt panel is selected as a demonstrative panel in this work and is installed in an array with 15 panels in series per string and 6 strings in parallel. For the given panel, the maximum power point (MPP) of the panel for each $POA$ and $T_{amb}$ operating condition can be found using a manufacturer provided lookup table. The annual $P_{pv}$ profile in vancouver is given in Fig. 3.4a, and three representative days of different seasons are shown in Fig. 3.4b. In this work, it is assumed that the boost converter always works at the MPP. This is an acceptable assumption as modern maximum power point tracking (MPPT) systems are very good [57, 58]. Furthermore, if the converter is not at the MPP it is expected to be very close, so the difference in power losses will not be significant.

For the selected array, a 4 kW boost converter was selected as the DC-DC converter for PV generation. The boost converter is a well-established technology for DC-DC systems and often makes up the input stage of PV inverters for AC-DC conversion as well. In the boost converter, the input voltage is the PV MPP voltage, $V_{in} = V_{pv}$, and the input power will be the PV MPP power, $P_{in} = P_{pv}$. The output voltage will be fixed by the
With the variables identified, the operational limits must also be considered, as highlighted in Fig. 3.5. Firstly, $V_{in}$ must be constrained to ensure balanced utilization of the low-side and high-side switches in the boost converter. If the input is too low or too high, one switch carries the majority of the current and will be prone to failure. In this case, the lower limit is set to 80 V, which corresponds to an 80% duty cycle from (2.20). Similarly, the upper limit is set to 320 V, which corresponds to a 20% duty cycle. So $80 \, V \leq V_{in} \leq 320 \, V$ and outside of these limits the converter cannot operate.

The power is also limited. While the maximum rated power of the converter is 4 kW, this is only valid for input voltages above 200 V. At $V_{in} = 200 \, V$ and $P_{pv} = 4 \, kW$, the input current is 20 A. This is the current limit for the converter which is enforced to prevent overheating of the selected switches. Then, if the input voltage is below 200 V, the maximum power will be limited by the maximum current. If at any point $P_{pv}$ exceeds the rated input power, the solar generation is reduced to the rated power by adjusting the voltage away from the MPP. As mentioned earlier, it is assumed that the shift in $V_{pv}$ from this adjustment is small and has a negligible effect on the loss behavior of the converter. Then, the operating limits of the converter can be expressed as a single piece-wise function given in (3.8). Fig. 3.5 shows the various operating conditions that are experienced by the boost converter in the three sample days of Fig. 3.4b in comparison to the operational limits. It can be seen that during peak production (sunny summer at midday), the array power exceeds the
power rating of the converter and must be curtailed.

\[
P_{in} \leq \begin{cases} 
0 & V_{in} \leq 80V \\
20A \cdot V_{in} & 80V \leq V_{in} \leq 200V \\
4kW & 200V \leq V_{in} \leq 320V \\
0 & V_{in} \geq 320V 
\end{cases} \tag{3.8}
\]

Based on the expected operating conditions and operational limits, a DOE was developed for the three independent variables mentioned above: \(V_{pv}, P_{pv}, \) and \(T_{amb}\). \(T_{amb}\) is considered for \(-25^\circ C \leq T_{amb} \leq 50^\circ C\) to account for operation in most climates. Since the operational area is constrained by (3.8), the FCCCD used in Chapter 2 is not ideal. In this case, the DOE software was used to create an optimal design that would allow for a cubic regression. This optimal design, shown in Fig. 3.6, ensures that no PV operating conditions are tested that would violate the input limits of the boost converter. 27 unique operating conditions were identified for this design. Note that no duplicated center points are needed because the response is the result of simulation and is not subject to random experimental error. Where there are duplicate points in the power-voltage plane of Fig. 3.6, these correspond to different temperature conditions. These conditions were simulated in multi-domain software to accurately capture the boost converter’s loss behavior.

Using the simulation results, the DOE software performed statistical analysis to develop the parametric

![Figure 3.6](image.png)

**Figure 3.6:** Optimized test points are generated by DOE software to generate the best result in the constrained operating area of the boost converter. Where points are close together in the power-voltage plane, different temperatures were considered.
Figure 3.7: The RLEE shown graphically for the PV boost converter. The traditional fixed-efficiency method is shown for comparison. The RLEE is able to capture complex loss behavior that is lost in the fixed-efficiency method.

\[ P_{\text{loss}} = 70 - 1.8V_{pv} + 0.15P_{pv} - 1.1 \times 10^{-3}V_{pv}P_{pv} + 1.1 \times 10^{-2}V_{pv}^2 + 3.3 \times 10^{-6}P_{pv}^2 \]
\[ + 2.1 \times 10^{-6}V_{pv}^2P_{pv} - 4.1 \times 10^{-8}V_{pv}P_{pv}^2 - 1.9 \times 10^{-5}V_{pv}^3 + 1.8 \times 10^{-9}P_{pv}^3 \text{ [W]} \] (3.9)

The RLEE result can be compared to the traditional fixed-efficiency method introduced in 1.2.4. If the efficiency is fixed, the losses can be found using (1.3). As the boost converter is being used for PV generation, the European efficiency, \( \eta_{\text{euro}} \), will be used, as defined in (1.4). \( \eta_{\text{euro}} \) neglects the variability of losses with \( V_{pv} \), so the center point is used, \( V_{pv} = 200 \text{ V} \). For the boost converter, this gives a fixed efficiency of \( \eta_{\text{boost-euro}} = 97.7\% \). The fixed-efficiency loss surface is also plotted in Fig. 3.7 for comparison with the RLEE. It can easily be seen that the fixed-efficiency method fails to capture the complexity of the converter’s losses under different operating conditions. In particular, the losses are highly dependent on \( V_{pv} \), especially at high power.

In order evaluate the two methods, 40 additional evenly-distributed operating conditions were simulated, giving a total for 67 evaluation points. A comparison of the multi-domain simulation (actual) values and the predicted values is given in Fig. 3.8 and is summarized in Table 3.1. In this figure, the distance from the ideal case represents the error in the prediction technique. It is immediately clear that the RLEE provides
**Figure 3.8:** Predicted vs actual plot of the boost converter losses. The proposed RLEE equation shows much less deviation from the ideal (black line) than the traditional fixed-efficiency method.

**Table 3.1:** Comparison of Loss Prediction Techniques for the Boost Converter

<table>
<thead>
<tr>
<th>Technique</th>
<th>Average Error [W]</th>
<th>Maximum Error [W]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional Fixed-Efficiency</td>
<td>±17</td>
<td>88</td>
</tr>
<tr>
<td>Proposed RLEE</td>
<td>±4</td>
<td>14</td>
</tr>
</tbody>
</table>

much better loss prediction than the fixed-efficiency method. In particular, the fixed-efficiency method with the $\eta_{\text{fixed}}$ is prone to either over or under predict the losses. When a year’s worth of operation is considered in 3.3, it will be shown that the over and under prediction are not balanced and do not cancel out to give an accurate prediction. The fixed-efficiency method had an average error of $\pm 17$ W and a maximum error of 88 W. By contrast, the RLEE is much more accurate with an average error of only $\pm 4$ W and a maximum error of 14 W.

Through this validation, it is verified that the proposed RLEE provides improved accuracy over the traditional fixed-efficiency method. The parametric equation obtained by the DOE and the operational limits are computationally simple and can easily be implemented in system-level simulation, as demonstrated later in 3.3. The result is a computationally-simple method for accurate loss prediction of the boost converter for PV generation.
Figure 3.9: a) Charging current and single cell voltage as a function of state of charge. The charge current is expressed as a percentage of the battery’s maximum rated charge current. b) The trajectory in the power-voltage plane of a $C_{\text{rated}} = 15$ A, 100-cell EV battery as it charges from $\text{SoC} = 10\%$ to $\text{SoC} = 90\%$. The converter’s operating conditions vary constantly as the battery charges.

3.2.2 LLC Converter for EV Chargers

In modern electric vehicles (EVS), the primary battery technology is lithium-ion. Lithium-ion batteries have a well defined ideal charge profile that defines the current and voltage as the battery charges. This profile is shown for a single cell battery in Figure 3.9a. It can be seen that the battery voltage, $V_{\text{bat}}$, and the battery current, $I_{\text{bat}}$, are both a function of the battery’s state of charge, $\text{SoC}$. $I_{\text{bat}}$ is expressed as a percentage of the battery’s maximum rated current, $C_{\text{rated}}$.

For the EV battery charger, the converter-level variables would be the output voltage, $V_{\text{out}} = V_{\text{bat}}$, and the output power, $P_{\text{out}} = V_{\text{out}}I_{\text{out}} = V_{\text{bat}}I_{\text{bat}}$. However, the system-level variables that correspond to $V_{\text{bat}}$ and $I_{\text{bat}}$ are $\text{SoC}$ and $C_{\text{rated}}$. Figure 3.9b shows how the converter-level variables change in response to $\text{SoC}$. If $C_{\text{rated}}$ is lower, a similar trend is observed but at a lower $P_{\text{out}}$. The converter input voltage is fixed by the DC bus and the input power follows the output power.

The LLC resonant converter is a popular battery charger topology because of its high efficiency [59, 60]. In this system, a 6.6 kW LLC converter is used in the EVCS. Based on the converter- and system-level variables above, the operational limits for the EV charger are given in Table 3.2. $\text{SoC}$ is limited from 10% to 90% as operation outside this range is detrimental to battery longevity and be avoided. In this particular charger, the rated power (6.6 kW) exceeds the maximum loading condition (6.0 kW), so no additional constraints are needed on the converter-level variables. The diverse operating conditions that will be encountered as different EVS plug in to charge is explored further in 3.3.1. As in 3.2.1, an ambient temperature range for most climates is also considered.

Using the system-level variables, $\text{SoC}$, $C_{\text{rated}}$, and $T_{\text{amb}}$, an optimized DOE was generated with 30 test
points. Each test point was evaluated in multi-domain simulation and the results were analyzed to create the RLEE given in (3.10). Unlike the PV boost converter, temperature has a significant effect on the loss behavior. Figure 3.10 plots the RLEE across different temperatures to illustrate the effect.

\[
P_{\text{loss-LLC}} = 108 + 0.43\text{SoC} + 2.6C_{\text{rated}} + 0.20T_{\text{amb}} \\
+ 9.8 \times 10^{-2}\text{SoC} \cdot C_{\text{rated}} + 2.6 \times 10^{-2}\text{SoC} \cdot T_{\text{amb}} + 6.2 \times 10^{-2}C_{\text{rated}} \cdot T_{\text{amb}} - 1.0 \times 10^{-3}\text{SoC}^2 \\
- 4.5 \times 10^{-4}\text{SoC} \cdot C_{\text{rated}} \cdot T_{\text{amb}} - 1.3 \times 10^{-3}\text{SoC}^2 \cdot C_{\text{rated}} - 2.2 \times 10^{-4}\text{SoC}^2 \cdot T_{\text{amb}} \quad [W] \quad (3.10)
\]

Similar to the boost converter, 40 additional points across the design space were used for validating the

Table 3.2: Operating Range of a 6.6 kW LLC EV Battery Charger

<table>
<thead>
<tr>
<th>Variable</th>
<th>Lower Limit</th>
<th>Upper Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>SoC [%]</td>
<td>10</td>
<td>90</td>
</tr>
<tr>
<td>C\text{rated} [A]</td>
<td>5</td>
<td>15</td>
</tr>
<tr>
<td>T\text{amb} [^\circ]C</td>
<td>-25</td>
<td>50</td>
</tr>
<tr>
<td>\text{\dagger}V_{\text{out}} [V]</td>
<td>374</td>
<td>416</td>
</tr>
<tr>
<td>\text{\dagger\dagger}P_{\text{out}} [W]</td>
<td>495</td>
<td>6023</td>
</tr>
</tbody>
</table>

\text{\dagger} V_{\text{out}} is a result of SoC and is not a separate variable in the DoE.
\text{\dagger\dagger} P_{\text{out}} is a result of SoC and C\text{rated} and is not a separate variable in the DoE.
The predicted versus actual plot is given in Fig. 3.11 and the error results are summarized in Table 3.3. In the case of EV chargers, there is no euro-efficiency equivalent for a weighted average. Instead, the efficiency from a single operating point can be considered. There are two values that are commonly used: the peak efficiency, $\eta_{\text{peak}}$ (i.e. the highest efficiency the converter has under any operating condition), and the full-load efficiency, $\eta_{\text{full-load}}$ (i.e. the efficiency when the converter is operating at its rated power). For the 6.6 kW LLC used here, $\eta_{\text{peak}} = 98.4\%$ and $\eta_{\text{full-load}} = 97.5\%$, based on the efficiency at room temperature (25°C). These two fixed-efficiency values are also considered in Fig. 3.11 and Table 3.3. Both of the fixed-efficiency selections exhibit very poor prediction accuracy compared to the RLEE. Only a few select points have accurate loss predictions, which are the conditions at which the fixed efficiency is defined. Otherwise, the fixed efficiency drastically under-predicts the losses. This is due to two major shortcomings of the fixed-efficiency approach. First, the converter efficiency drops significantly under light-loading conditions which are completely ignored by the fixed-efficiency approach. Secondly, the effect of temperature on the loss behavior is completely ignored. By comparison, the RLEE extracts accurate loss behavior from the multi-domain simulation including under light load conditions and at various ambient temperatures.

From these results, it is clear that the operating conditions have a significant impact on the loss performance of the LLC resonant converter when used as an EV charger. The RLEE effectively captures the variability of losses in a computationally-simple parametric equation.
Table 3.3: Comparison of Loss Prediction Techniques for the LLC Converter

<table>
<thead>
<tr>
<th>Technique</th>
<th>Average Error [W]</th>
<th>Maximum Error [W]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed $\eta_{\text{peak}}$</td>
<td>±92</td>
<td>173</td>
</tr>
<tr>
<td>Fixed $\eta_{\text{full-load}}$</td>
<td>±89</td>
<td>172</td>
</tr>
<tr>
<td>Proposed RLEE</td>
<td>±2</td>
<td>9</td>
</tr>
</tbody>
</table>

3.2.3 Bidirectional DC-DC Converter for Battery Energy Storage

For battery energy storage systems, many battery options are available since the high energy density of lithium-ion is less critical. Still, lithium-ion is a common choice because of their widespread availability and popularity. Then, the same dependency of $V_{\text{bat}}$ on $\text{SoC}$ seen in Fig. 3.9 can be expected for the BES converter output voltage $V_{\text{BES}} = V_{\text{bat}}$. The input voltage will again be fixed by the DC bus. In this case, however, the power, $P_{\text{BES}}$, will be dictated by the difference between the PV generation power, $P_{\text{PV}}$, and the EVCS load power, $P_{\text{EVCS}}$, as described in

$$P_{\text{BES}} = P_{\text{PV}} - P_{\text{EVCS}}$$ (3.11)

In this case, the converter must be bidirectional: able to charge the BES when $P_{\text{PV}} > P_{\text{EVCS}}$ and able to discharge when $P_{\text{PV}} < P_{\text{EVCS}}$. A 12 kW bidirectional DC-DC converter works well for this application; operating in buck mode to charge the batteries and boost mode to supply the DC bus. This power rating allows for the converter to supply to EV chargers at the EVCS without PV support.

The relevant variables will then be $\text{SoC}$, $P_{\text{BES}}$, $T_{\text{amb}}$ and direction of power flow, with the limits outlined in Table 3.4. Again, $10\% \leq \text{SoC} \leq 90\%$ to ensure the longevity of the batteries. With this charge limit, the battery voltage will not change significantly, so the system is designed for full power at all battery voltages; i.e. there is no power de-rating for low voltage as was seen in the PV boost converter. This also highlights a crucial benefit of considering system-level variables in the DOE. For a 65-cell battery, $V_{\text{bat}}$ will only change from 240 V to 270 V as it charges from 10 to 90%. If converter-level variables were considered without this insight, the DOE would likely consider converter voltages in the range of $80 \text{ V} \leq V_{\text{BES}} \leq 320 \text{ V}$ (similar to the PV boost); but, most of these voltages would never be seen in the BES application. Instead, by focusing only on actual operating conditions for the system-level variables, a more accurate model can be generated using the same number of test points.

A DOE with 30 test points was performed with different $P_{\text{loss}}$ responses for charging and discharging.
Table 3.4: Operational Limits of the 12 kW Bidirectional DC-DC Converter

<table>
<thead>
<tr>
<th>Variable</th>
<th>Lower Limit</th>
<th>Upper Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>SoC [%]</td>
<td>10</td>
<td>90</td>
</tr>
<tr>
<td>$P_{BES}$ [kW]</td>
<td>1.2*</td>
<td>12</td>
</tr>
<tr>
<td>$T_{amb}$ [°C]</td>
<td>-25</td>
<td>50</td>
</tr>
<tr>
<td>†Direction</td>
<td>Charging</td>
<td>Discharging</td>
</tr>
<tr>
<td>‡$V_{BES}$ [V]</td>
<td>240</td>
<td>270</td>
</tr>
</tbody>
</table>

* $P_{BES}$ is not tested below 1.2 kW as losses below this point are not statistically significant. For operation below 1.2 kW, the 1.2 kW loss value is assumed as a worst-case assumption.
† The direction (charge vs discharge) was found to have a negligible impact on the loss behavior.
‡ $V_{BES}$ is a result of SoC and is not a separate variable in the DOE.

operation. It was found that the direction had an insignificant effect on the loss performance, and thus could be neglected moving forward. This is a reasonable result, as the buck and boost modes are symmetrical, so the magnitude of the currents and voltages on the switches will be the same in both charge and discharge modes. The RLEE for the bidirectional DC-DC converter for the BES system is

$$
P_{loss-BES} = 18 + 0.28SoC - 1.2 \times 10^{-2}P_{storage} - 0.44T_{amb} - 7.2 \times 10^{-5}SoC \cdot P_{storage} + 1.5 \times 10^{-4}P_{storage} \cdot T_{amb} - 3.1 \times 10^{-3}SoC^2 + 4.4 \times 10^{-6}P_{storage}^2 - 9.1 \times 10^{-3}T_{amb}^2 + 9.7SoC^2 \cdot P_{storage} - 1.0 \times 10^{-8}SoC \cdot P_{storage}^2 - 1.2 \times 10^{-8}P_{storage}^2 \cdot T_{amb} + 2.6 \times 10^{-4}T_{amb}^3 \ [W] \quad (3.12)
$$

Figure 3.12: The RLEE shown graphically for the DC-DC bidirectional converter for the BES shows significant variation in losses under different operating conditions.
Much like the converters above, the RLEE was validated using 40 additional test points and compared to the fixed-efficiency method. Again both $\eta_{\text{peak}} = 99.4\%$ and $\eta_{\text{full-load}} = 96.4\%$ were considered for the fixed-efficiency method. The results are presented in the predicted-versus-actual graph in Fig. 3.13 and summarized in Table 3.5. From the predicted-versus-actual graph, it can be seen that both the fixed-efficiency methods are very inaccurate. The peak efficiency generally results in a significant under-prediction of the losses, while the full-load efficiency generally results in a significant over-prediction of the losses. In comparison, the RLEE consistently provides accurate loss estimation under all operating conditions.

For all three converters considered investigated here, the RLEE provides more accurate loss prediction across all of the diverse operating conditions. The parametric equation is computationally simple, but captures the detailed converter behavior of the multi-domain simulation. Thus, the RLEE is well positioned for use in simulation of large systems, as shown in the following section.

**Figure 3.13:** Predicted vs actual plot of the DC-DC bidirectional converter losses. The proposed RLEE equation shows much less deviation from the ideal (black line) than the traditional fixed-efficiency method.

**Table 3.5:** Comparison of Loss Prediction Techniques for the DC-DC Bidirectional Converter

<table>
<thead>
<tr>
<th>Technique</th>
<th>Average Error $\eta_{\text{peak}}$ [W]</th>
<th>Maximum Error $\eta_{\text{full-load}}$ [W]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed $\eta_{\text{peak}}$</td>
<td>±92</td>
<td>211</td>
</tr>
<tr>
<td>Fixed $\eta_{\text{full-load}}$</td>
<td>±85</td>
<td>149</td>
</tr>
<tr>
<td>Proposed RLEE</td>
<td>±4</td>
<td>14</td>
</tr>
</tbody>
</table>
Figure 3.14: The DC microgrid used for evaluation of the RLEE with PV generation, BES and EVCS. 6 PV arrays provide power for the EVCS with two EV chargers. Two BES converters allow for fast energy storage when PV generation is high.

3.3 System-Level Loss Prediction

To demonstrate the performance of the RLEE, a multi-converter energy system is analyzed over one year. The DC microgrid for this simulation is shown in Fig. 3.14. This system uses multiples of the three converters investigated in 3.2: 6 parallel PV arrays, a BES with two parallel strings and an EVCS with two charge ports, each of which sees a different charge profile.

For PV generation, the BP365 65 W panel is used with 15 panels in series and 6 parallel strings per array. 6 arrays, each with a corresponding PV boost converter, provide adequate energy generation for the microgrid. The BES system is designed with 2 DC-DC converters to capture all the generated energy form the 6 PV boost converters at full power. Each converter is connected to 2.5 MWh of storage capacity provided by 65-cell strings (to match the voltage range considered in 3.2.3). This configuration allows for no energy shortage throughout the year. Note that this configuration has not been optimized; it was selected simply to meet the basic requirements and highlight the functionality of the RLEE.

3.3.1 EVCS Load Profile

One of the challenges of simulating public EVCS is that the load profile is poorly defined and highly random. SoC, $C_{rated}$ and time spent charging can very significantly as different cars plug in. For this investigation, statistical data was obtained for a 2-stall public charging station in Vancouver from [61]. Shown in Table 3.6, the data was used to create a random, normally-distributed EV charge profile. Using the half-hour time step, cars would randomly arrive with varying likelihood based on the time of day. If a charger was available, the car would park and being charging. Each car that charged would have a random SoC, $C_{rated}$ and charge duration. It was assumed that all cars have a 100-cell battery for consistency with the DOE performed in
Table 3.6: Statistical Data for a 2-Stall Public Charging Station in Vancouver, Canada

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual Vehicles</td>
<td>4072</td>
<td>N/A</td>
</tr>
<tr>
<td>Time of Day</td>
<td>13:45</td>
<td>4hr</td>
</tr>
<tr>
<td>Duration [hr]</td>
<td>1.46</td>
<td>1</td>
</tr>
<tr>
<td>†SoC at plug-in [%]</td>
<td>50</td>
<td>13</td>
</tr>
<tr>
<td>†C_{rated} [A]</td>
<td>10</td>
<td>2</td>
</tr>
</tbody>
</table>

† SoC and C_{rated} mean and standard deviation were selected for consistency with the LLC parameters considered earlier and were not provided with the EVCS data.

Figure 3.15: Distribution of the many different operating conditions seen by the EV charger in one year, based on a normally-distributed random profile.

However, this could be an additional variable in future work. As the car remained charging, SoC would increase and the remaining charge time would decrease. If the car was fully charged before the time completed, the charger would turn off, but the port remained full. An example of one week of charging data is given in Fig. 3.16. This charging approach resulted in the operating condition distribution shown in Fig. 3.15. From this sample profile, it is very clear that the EV chargers in the EVCS experience a wide variety of operating conditions.
Figure 3.16: One week of EVCS data generated using a normally-distributed random profile. As different vehicles plug in to charge, the operating conditions vary significantly.

3.3.2 System Simulation

With the operating conditions established through the PV and EVCS profiles above, one year of system operation was simulated in half-hour time steps. As the primary goal of the simulation is to evaluate the RLEE, a relatively simple simulation is used, as outlined in Fig. 3.17. For each time step, the generation of the PV arrays is calculated first. The PV panel data is established as described in 3.2.1. The PV data provides the energy generated during that time step using (3.13), as well as the system-level operating conditions used to calculate the losses in the boost converter.

\[ E_{PV} = N_{array}P_{pv}t_{step} \]  

(3.13)

where \( N_{array} \) is the number of solar arrays in the system and \( t_{step} \) is the length of the simulation time step (0.5 hr in this case).

Next, the EVCS load is calculated for the two EV chargers based on the profile described in 3.3.1. From the EV profile, the energy demand of the EVCS, \( E_{EV} \) is calculated for each charger. SoC and \( C_{rated} \) are also given by the profile and used to calculate the losses in the two LLC EV chargers.

Finally, the BES status can be evaluated for the time step. The energy balance, that is if there is net generation or net consumption is calculated using

\[ E_{BES} = E_{PV} - E_{EV} \]  

(3.14)
Figure 3.17: Process flow for simulating the DC microgrid for evaluation of the RLEE. The PV generation and EV consumption are calculated and the BES provides energy accordingly. The converter losses are evaluated at each time step to consider the diverse operating conditions seen throughout the year.

If $E_{BES} > 0$, then there is net generation. In this case, if the batteries are not fully charged, the generated energy is added. If the batteries are fully charged, this energy is assumed to be wasted. If $E_{BES} < 0$, then there is net consumption. In this case, the batteries are discharged to power the load. In both the generation and consumption cases, the SoC of the batteries is updated and the losses in the BES DC-DC converter are calculated. Figure 3.18 shows the performance of the BES system throughout the year. It can be seen that the battery is sized in such a way that the load can always be met. Furthermore, it can be seen that the BES is routinely charging and discharging throughout the year with a large variety of operating conditions. This process is repeated for each time step for one year of system operation.

Figure 3.18: a) The annual SoC of the complete BES throughout the year. b) The annual $P_{BES}$ of one DC-DC bidirectional converter in the BES system. The operating conditions vary significantly throughout the year, particularly when the SoC drops due to low generation in winter.
3.3.3 Loss Prediction Evaluation

There are two key considerations for evaluation of loss prediction techniques: speed (i.e. computational simplicity) and accuracy. The RLEE excels in both of these categories, as demonstrated in the subsequent analysis.

Computational simplicity is needed in order to ensure rapid simulation at the system-level when multiple converters are present. While there are many factors that affect simulation speed, the simplified simulation presented in 3.3.2 was used to evaluate both the proposed RLEE and the fixed-efficiency method. The simulation was run repeatedly 1000 times, with only the equation used for loss prediction changing for the two cases. The results are given in Table 3.7. From this result, it is clear that the RLEE is not significantly more complex than the fixed-efficiency method; however, as demonstrated in 3.2 the RLEE is significantly more accurate. If multi-domain simulation were used, the expected simulation time would be approximately 120 days. This is assuming one-second of converter operation (to reach thermal steady-state) is simulated at each half-hour time step. If a continuous simulation was desired, the required time would be much larger. Clearly the RLEE provides very fast simulation, while multi-domain simulation is unusable for system-level loss prediction.

The second consideration in evaluating the proposed RLEE is the accuracy of the loss prediction. Based on the validation in 3.2, the error of the RLEE is shown to be significantly less than the error of the fixed-efficiency approach. This is also highlighted in the predicted-versus-actual graphs (Fig. 3.8, 3.11 & 3.13). The extreme error in loss prediction of the fixed-efficiency methods extends to system-level simulation where it compounds throughout the year. The total annual losses predicted by each method are given in Fig. 3.19, where the compounding error can be seen from the error bars. The percent error of the different fixed-efficiency methods relative to the RLEE prediction is given in Table 3.8. The large discrepancy both in terms

| Table 3.7: Simulation Time for One-Year Simulation of the DC Microgrid |
|---------------------------|--------|----------------|
| Method                    | Mean [s] | Standard Deviation [s] |
| Fixed-efficiency          | 0.14    | 0.01            |
| †Multi-domain             | 120 days | N/A             |
| Proposed RLEE             | 0.15    | 0.01            |

† The multi-domain simulation time is estimated based on the simulation time for a one-second simulation at each half-hour time step. Due to the length, simulation for a full year is impossible.
Figure 3.19: Comparison of predicted annual losses via the proposed RLEE and the traditional fixed-efficiency method. Significant discrepancy between the two methods is observed, regardless of the fixed-efficiency value used. The LLC EV charger and the BES DC-DC have particularly high error.

Regardless of which efficiency is considered, the annual loss result deviates significantly from that predicted by the RLEE. When \( \eta_{\text{peak}} \) is assumed, the fixed-efficiency method grossly underestimates the losses in the system. This is not surprising, as the converter cannot be expected to operate at it’s peak efficiency under all operating conditions. Still, this value is often quoted on manufacturer datasheets and marketing materials. While providing a different result, \( \eta_{\text{full-load}} \) does not necessarily provide a better result. The converters often operate under light- or partial-loading conditions where the efficiency varies significantly.

Table 3.8: Percent Error for One-Year Simulation of the DC Microgrid

<table>
<thead>
<tr>
<th>Fixed Efficiency</th>
<th>Percent Error [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PV Boost</td>
</tr>
<tr>
<td>( \eta_{\text{euro}} )</td>
<td>35</td>
</tr>
<tr>
<td>( \eta_{\text{peak}} )</td>
<td>-30</td>
</tr>
<tr>
<td>( \eta_{\text{full-load}} )</td>
<td>76</td>
</tr>
</tbody>
</table>

† All fixed efficiency approaches have significant error when compared to the RLEE. Both over (positive percent error) and under (negative) prediction can be detrimental to system design.
from that at full-load. In the case of the boost converter, even $\eta_{\text{euro}}$ does not provide a better result as it is no more accurate than $\eta_{\text{peak}}$ in this case.

It is clear that the fixed-efficiency method is severely lacking in accuracy and so cannot be relied upon for system-level loss prediction. Similarly, multi-domain simulation is unusable because of the incredibly long simulation times. The proposed RLEE is an ideal solution. The computationally simple parametric equation allows for high-speed system-level simulation while providing accurate loss prediction. In doing so, accurate system design is made possible.

### 3.4 Summary

In this chapter, the Rapid Loss Estimation equation was presented. The RLEE is a computationally-simple loss prediction tool for system-level analysis. It extracts detailed converter behavior to accurately predict losses under all operating conditions. The benefits compared to the traditional fixed-efficiency method and multi-domain simulation are highlighted in Fig. [3.20]. While the traditional fixed-efficiency method is inaccurate, the proposed RLEE is very accurate. While multi-domain simulation is slow, the proposed RLEE is very fast. The exceptional performance was demonstrated in a sample DC microgrid where the RLEE was applied to three different converter topologies. Ultimately, the RLEE allows for fast system-level simulation with accurate converter-level detail.

**Figure 3.20:** Traditional fixed-efficiency simulation is inaccurate, while the proposed RLEE is accurate. Similarly, the RLEE is very fast, while multi-domain simulation is too slow for system-level simulation.
Chapter 4

Conclusion

4.1 Summary

In this work, techniques for improved power loss prediction in power converters are developed. At the device level, GaN eHEMTs are characterized in detail to provide accurate power loss prediction in converter-level simulation. The two loss mechanisms, conduction and switching, are studied independently to allow for loss prediction under any operating condition. Conduction loss characterization provides improved modeling compared to the manufacturer datasheet and also provides the thermal resistance calibration necessary for accurate thermal measurement. The switching losses are characterized to include the ringing that occurs as a result of parasitic elements in the circuit. By including the effects of the parastics, significantly improved loss prediction is obtained. The developed characterization is applied through DOE to build an accurate model of losses under any operating conditions. Finally, the developed model is validated through experiment and is demonstrated to provide significantly more accurate loss prediction in converter-level simulation.

At the converter level, the Rapid Loss Estimation equation is developed to provide fast and accurate power loss prediction in system-level simulation. The RLEE is developed by identifying the relevant system-level variables that define the operating conditions of the different converters in a system. Then, DOE is applied to select key operating conditions, which are simulated in multi-domain software to extract the detailed loss behavior. Ultimately, the RLEE is created as a parametric equation which accurately reflects the converter’s loss behavior under any operating condition. The RLEE is developed for three different converters in a DC microgrid to highlight the procedure. System-level simulation of the microgrid demonstrates the high accuracy and computational simplicity that the RLEE provides.

In conclusion, the power loss prediction techniques developed in this work allow for improved estimation
of power losses at different levels of power converter simulation. The proposed techniques actively account for the large variety of operating conditions seen by power converters in any application. At the converter level, improved loss prediction ensures effective thermal management design and optimal topology selection. At the system-level, rapid and accurate loss prediction enables optimization of cost, energy collection and reliability. Ultimately, the proposed tools will allow power electronics and power systems engineers further advance the adoption of new technology and renewable energy systems.

The contribution to the scientific community is proven through the presentation and publication of one conference paper at the Institute of Electrical and Electronics Engineers (IEEE) Energy Conversion Conference & Congress (ECCE) [1]. It is further supported by the submission of a journal publication to IEEE Transactions on Industrial Electronics, which is currently under peer review.

4.2 Future Work

In this work, the methodology for developing accurate power loss prediction is developed. Though specific examples are considered in this work, the proposed methodologies are completely generic. They can readily be applied to any area of power electronics where loss prediction is of value.

The thermal characterization of GaN eHEMTS provides accurate loss models for an emerging class of devices. The developed models could readily be applied to the development of new converter topologies using GaN devices. Furthermore, as new devices come to the market, the developed process can be used to develop highly accurate loss models for these new devices. Similarly, the same methodology can be used for devices made with other materials such as Si and SiC.

The RLEE is also a process that can readily be applied to different applications. The selection of converter topologies used in this work is arbitrary. Once the RLEE has been applied for a given set of converters, the accurate loss prediction it provides is invaluable. The high number of converters in DER systems requires the computational speed and accuracy provided by the RLEE. Thus, the RLEE enables the advancement of optimization in these systems. In particular, there remains significant work in the field of optimizing systems with PV generation, BES systems and EVCS systems.
Bibliography


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