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Uncertainty Quantification in Computational Electromagnetics: Techniques and Applications to Safety-Critical Systems

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Abstract
Computational electromagnetics (CEM) is now a vital tool for analyzing, designing, and certifying modern engineering systems. This holds particularly true in domains where safety and reliability closely correlate with electromagnetic performance. However, traditional electromagnetic simulations often overlook the uncertainties that come from material properties, geometric variations, excitation conditions, environmental factors, and numerical approximations. Ignoring these uncertainties can weaken the trustworthiness of simulation predictions in critical safety applications. This review offers a clear and current look at uncertainty quantification (UQ) methods in computational electromagnetics, focusing on their importance in safety-critical systems. It examines the sources and types of uncertainty in CEM, describes the key electromagnetic models and numerical solvers, and evaluates current UQ techniques. The paper discusses applications in biomedical electromagnetics, aerospace and transportation systems, electromagnetic compatibility, and power and high-voltage engineering to demonstrate how UQ enhances CEM's practical value. By combining methodical developments with insights from real-world applications, this paper serves as a valuable reference for researchers, engineers, and decision-makers aiming to improve uncertainty-aware electromagnetic modeling in safety-critical systems.

Keywords: Computational electromagnetics, uncertainty quantification, safety-critical systems, polynomial chaos, and electromagnetic compatibility.

1.0 Introduction

Uncertainty quantification (UQ) has become essential in computational electromagnetics (CEM), as electromagnetic simulations are increasingly used to guide design and certification decisions in safety-critical areas, such as aerospace, automotive, medical devices, and high-power radio-frequency systems (Zygiridis, 2017; Kimpton et al., 2017).

Computational Electromagnetics (CEM) is crucial in modern engineering analysis and design. It provides numerical approximations to Maxwell equations to suit complicated shapes, composite materials and realistic scenarios. Over the past few decades, numerical techniques such as the finite-difference time-domain (FDTD) method, the finite element (FEM) and integral-equation based methods have emerged as powerful tools and are heavily used in the design of antennas, microwave engineering, electromagnetic compatibility (EMC), in biomedical electromagnetism, in power systems and transportation infrastructure (Sumithra and Thiripurasundari, 2017). In these contexts, CEM simulations are routinely employed to predict electromagnetic field distributions, coupling mechanisms, interference levels, and exposure metrics under conditions that are difficult or impractical to assess experimentally.

Improvements in computing power and algorithm efficiency have allowed for large-scale, detailed electromagnetic simulations. These simulations reduce the need for expensive experimental prototypes.

Alongside these advancements, there has been a significant transition towards simulation-driven engineering and decision-making, especially in systems where electromagnetic performance is directly associated with safety. In aircraft, railway signaling, medical device certification, and power system protection, simulation results are becoming increasingly important for design qualification, compliance testing, and risk assessment. Regulatory and industry stakeholders now accept simulation-based evidence as part of certification processes if the models used can be shown to be dependable through verification, validation, and uncertainty assessment. Consequently, CEM has evolved from an exclusively predictive design instrument to an essential element of safety assurance frameworks.

Despite their widespread use, most CEM analyses are primarily deterministic. Model inputs like material properties, geometric dimensions, excitation parameters, and boundary conditions are usually specified using nominal or worst-case values. This method rarely reflects reality because it assumes complete knowledge of system parameters and operating conditions. In actual electromagnetic systems, variability comes from manufacturing tolerances, environmental changes, aging effects, and limited material characterization data.

In safety-critical applications, overlooking uncertainty can have profound consequences. Slight changes in dielectric properties, conductor placement, or source characteristics can lead to significant differences in resonant behavior, electromagnetic interference levels, or internal field distributions. As a result, deterministic simulations may underestimate risk or miss low-probability, high-consequence scenarios that are crucial for safety assessment. Research in verification, validation, and predictive science has consistently shown that deterministic predictions alone do not provide enough support for reliable decision-making when uncertainty is important and unavoidable.

These issues are especially clear in biomedical electromagnetics and EMC analysis, where safety margins are set in relation to regulatory thresholds. Deterministic CEM predictions that ignore variability in tissue properties, geometry, or exposure conditions may provide an incomplete or misleading picture of actual risk.

Uncertainty Quantification (UQ) has emerged as a methodical process to deal with deterministic modeling limits by explicitly defining, dispersing, and analyzing the uncertainty in computer simulations. Within the framework of CEM, UQ seeks to quantify the relationship between uncertainties related to input parameters, that is, due to physical variability, limited knowledge, and modeling assumptions, on a set of important electromagnetic quantities such as field strength, induced current, power density, and measures of interference (Kasdorf et al., 2024; Aylwin et al., 2023).

UQ techniques have progressively been used in electromagnetic issues over the past two decades because of the requirement to have dependable forecasts in the safety-critical systems. Other application areas of sampling-based techniques, stochastic spectral and surrogate modeling include electromagnetic scenarios. These approaches indicate that uncertainty-based simulation can expose sensitivity profiles and risk profiles that a deterministic analysis might fail to uncover (Gu et al., 2015). Significantly, UQ can also be used to transition to probabilistic predictions with confidence intervals and exceedance probabilities that play a crucial role during safety and compliance assessment.

UQ is necessary in contemporary verification and validation. It gauges the trust in model forecasts as opposed to pure accuracy. UQ, when used together with verification and validation activities, has been shown to promote transparent and justifiable simulation-based decision-making which is becoming essential in regulated and safety-critical electromagnetic applications (Nagaraj et al., 2020).

This narrative review examines the quantification of uncertainty in computational electromagnetics, with a focus on its application in systems critical to safety. The review compiles literature on the origins of uncertainty in electromagnetic modeling, frameworks for the representation and propagation of uncertainty, and principal uncertainty quantification methodologies pertinent to computational electromagnetic modeling. This review does not provide extensive mathematical derivation. Instead, it takes an integrative approach that focuses on methodological trends, practical problems, and new research directions.

2.0 Fundamentals of Computational Electromagnetics

2.1 Governing Equations and Physical Models

Owusu-Agyemang & Yowetu (2025) detail that maxwell's equations provide the basis for computational electromagnetics.

$$\nabla \times \boldsymbol{E} = -\frac{\partial \boldsymbol{B}}{\partial t} \qquad (1)$$

$$\nabla \times H = J + \frac{\partial D}{\partial t} \qquad (2)$$

$$\nabla \cdot D = \rho \qquad (3)$$

$$\nabla \cdot B = 0 \qquad (4)$$

These equations explain how electric and magnetic fields function and their impact on matter. Maxwell's equations in differential form contain Gauss's law for electricity and magnetism, Faraday's law of induction, and Ampère's law with Maxwell's correction. They work together to control how electromagnetic fields change over time and space. They are the basis for all electromagnetic modeling and simulation (Li et al., 2024).

Maxwell's equations are used alongside constitutive relations to show how materials react. Usually, these relations connect electric flux density **D** to electric field **E**, magnetic flux density **B** to magnetic field **H**, and current density **J** to **E** through conductivity, permeability, and permittivity.

$$D = \epsilon E \qquad (5)$$

$$B = \mu H \qquad (6)$$

$$J = \sigma E \qquad (7)$$

In real-world CEM applications, these characteristics can change according to the frequency, temperature, or field strength given as $\epsilon = \epsilon(\omega, T, E), \mu = \mu(\omega, T, H)$. They might also demonstrate anisotropy, dispersion, or nonlinearity. These kinds of problems are clear in heterogeneous or manufactured materials, like biological tissues, composites, and metamaterials.

The correctness of physical models is crucial in systems that are key to safety. Simplifying assumptions such as linear, isotropic, and homogeneous material behavior are often introduced to reduce computational cost but may limit predictive reliability when real-world variability is significant. But these assumptions could make predictions less dependable when there is a lot of variety in the real world. These choices about modeling have a direct impact on the quality of the simulation. When used with material qualities or boundary conditions that are not clear, they show how important it is to include uncertainty quantification to judge how confident we are in expected electromagnetic responses.

2.2 Common Numerical Methods in Computational Electromagnetics

A variety of numerical methods have been developed to solve Maxwell's equations under realistic conditions, each with distinct strengths, limitations, and domains of applicability.

The Finite-Difference Time-Domain (FDTD) method uses finite-difference approximations to discretize Maxwell's curl equations in both space and time.

$$E^{n+1} = E^n + \frac{\Delta t}{\epsilon} \nabla \times H^{n+1/2} \quad (8)$$

Because it uses explicit time-stepping and is easy to set up, it is especially useful for broadband and transient analyses, like studies of electromagnetic pulse propagation and human exposure (Chakaeothat et al., 2021). However, FDTD often requires fine spatial discretization to accurately represent complex geometries and material interfaces, resulting in increased computational cost. **The Finite Element Method (FEM)** puts Maxwell's equations in a variational framework and breaks the computational domain into unstructured meshes.

$$\int_\Omega (\nabla \times E) \cdot (\nabla \times W)\, d\Omega - k^2 \int_\Omega E \cdot W\, d\Omega = 0 \quad (9)$$

FEM is a great tool for modeling high-frequency devices and analyzing electromagnetic compatibility (Medeiros & Rubia, 2025). It works well with complicated shapes, materials that are not uniform, and problems with boundary values. There are time-domain FEM formulations, but they usually take more computing power than frequency-domain ones.

The Method of Moments (MoM) is a way to change Maxwell's equations into surface or volume integral equations. This relationship is expressed through the matrix equation $[\boldsymbol{Z}][\boldsymbol{I}] = [\boldsymbol{V}]$, where $[\mathbf{Z}]$ is a dense impedance matrix representing the electromagnetic interactions between basis functions, $[\mathbf{I}]$ is the vector of unknown current coefficients, and $[\mathbf{V}]$ is the known excitation vector (Chew & Tong, 2022). These equations are then broken down into smaller pieces using basis functions. MoM works for problems that happen in open areas, like antenna radiation and scattering, because it automatically meets radiation conditions at infinity. But the resulting dense system matrices make it hard to scale up for problems that are electrically large or accept a lot of space.

The Transmission Line Matrix (TLM) method models electromagnetic field propagation using equivalent transmission-line networks and advances the solution in time through local scattering processes at discrete nodes. At each node, incident voltage pulses are transformed into reflected pulses according to a scattering relation of the form $\mathbf{V}^r = \mathbf{S}\mathbf{V}^i$, where $\mathbf{S}$ represents the node scattering matrix. This scattering-based formulation provides a clear physical interpretation of wave interaction and is mathematically analogous to S-parameter representations used in network theory and port-based formulations in FEM and MoM. While TLM is primarily a time-domain method, its reliance on local scattering matrices highlights a conceptual connection to frequency-domain network and integral-equation approaches, complementing the differential-equation-based formulations employed by FDTD and FEM. Discretization, truncation, and solver tolerances are all ways that these methods add numerical approximations. These numerical approximations represent an additional source of uncertainty that may interact with physical, material, and parametric variability, underscoring the necessity for uncertainty-aware modeling frameworks in safety-critical analyses.

2.3 Role of CEM in Safety-Critical Applications

Computational electromagnetics has become essential in designing, certifying and assuring regulatory compliance with safety-critical systems. Electromagnetic simulations are applied to many industries to improve performance, as well as to prove that they are safe and compatible. They can be things like assessing electromagnetic interference (EMI) of aerospace and railway systems, insulation management in high-voltage power devices, and exposure evaluation in wearable and biomedical devices.

There is a transition in the industry's practices towards this higher dependence on simulation. With properly verified and validated models, regulatory bodies and standards organizations are starting to approve simulations-based evidence to compliance and certification procedures. In biomedical electromagnetism, e.g. numerical analysis is applied in estimating specific absorption rate (SAR) and electric field exposure. This assists in addressing international safety requirements. Likewise, in rectangular aerospace and transportation systems, CEM evaluates the risk of EMC and assists safety cases required by certification authorities.

Predictive credibility is essential with the increased involvement of CEM in regulatory processes. Unknown uncertainty may result in safety risks when the results of simulation are used to make certification or operating limits. Thus, the safety-critical applications that CEM provides do not merely include getting the numbers right. It also involves understanding the level of uncertainty, assessing risk, and measuring confidence. This broader view lays the groundwork for incorporating uncertainty quantification techniques into electromagnetic modeling workflows, as discussed in later sections.

3.0 Classification of Uncertainty

Uncertainty in CEM is usually divided into two types: aleatory and epistemic uncertainty. Aleatory uncertainty refers to inherent variability in physical systems and operating environments. This includes factors like manufacturing variability, environmental changes, and biological differences. This type of uncertainty cannot be reduced and is modeled using random variables or random fields (Smith, 2024; Yi et al., 2020).

On the other hand, epistemic uncertainty comes from gaps in knowledge, limited data, or modeling assumptions. Mentions can include inadequate characterization of material properties, simplified geometric models, and assumptions about boundary conditions or excitation models. Unlike aleatory uncertainty, Hüllermeier et al. (2021) posit that epistemic uncertainty can be reduced through improved measurements, enhanced modeling accuracy, or increased experimental validation. Recent research on safety-critical simulation underscores the necessity of differentiating between these two categories of uncertainty. They have distinct roles in risk assessment and model credibility. Aleatory uncertainty helps inform probabilistic safety margins, while epistemic uncertainty affects confidence in simulation-based decisions. It must be addressed directly in verification, validation, and uncertainty quantification processes. Uncertainty in computational electromagnetics arises from multiple sources spanning physical parameters, geometry, environmental conditions, and numerical modeling choices

3.1 Material Property Uncertainty

Uncertainty in material properties significantly contributes to variability in electromagnetic simulations. Key parameters, such as relative permittivity, permeability, and electrical conductivity, are often derived from experimental measurements that exhibit variability due to differences in sample properties, measurement errors, and environmental factors.

In engineered dielectric and magnetic materials, small variations in these properties can lead to major changes in resonant frequencies, impedance matching, and field localization. This is especially true at microwave and millimeter-wave frequencies. Recent CEM studies indicate that overlooking material uncertainty can lead to overly optimistic predictions of electromagnetic performance, particularly in tightly coupled or resonant systems (Li et al., 2021; Gu et al., 2022).

Material uncertainty is especially critical in biological tissues. Electromagnetic properties can differ from person to person and across anatomical regions, hydration levels, and physiological conditions. Recent numerical dosimetry studies indicate that both inter- and intra-subject differences in tissue dielectric properties can result in significant variations in predicted specific absorption rate (SAR) and internal electric field distributions (Yi et al., 2023; Turgut & Engiz, 2023a). These results have important implications for meeting international exposure guidelines and demonstrate the necessity of probabilistic exposure assessment in biomedical electromagnetics.

Moreover, many materials show frequency- and temperature-dependent behavior. This adds more uncertainty when operating conditions are variable or not fully characterized. High-power and high-frequency applications are particularly sensitive to these issues, reinforcing the need to include such dependencies in uncertainty-aware CEM models.

3.2 Geometric and Structural Uncertainty

Geometric uncertainty arises from differences between ideal computational models and the actual physical electromagnetic systems. Manufacturing tolerances, surface roughness, and size variability cause unavoidable deviations that can affect electromagnetic behavior, especially in high-frequency or resonant structures.

Recent research in antenna and microwave system design shows that small geometric changes can lead to significant alterations in radiation patterns, coupling behavior, and impedance characteristics (Yi et al., 2023). In safety-critical systems like aerospace wiring, railway signaling equipment, and high-voltage insulation structures, geometric uncertainty can influence levels of electromagnetic interference and the risk of failure.

Structural uncertainty also includes errors in alignment and assembly, which are common in complex multi-component systems. Misalignment of conductors, shielding elements, or connectors can create unintended coupling paths and localized field strengthening. Deterministic CEM models that assume perfect alignment may not consider the worst-case scenarios for electromagnetic exposure or interference unless geometric uncertainty is included in the analysis.

3.3 Boundary Conditions and Excitation Uncertainty

Boundary conditions and excitation models add more sources of uncertainty in electromagnetic simulations. Typically, boundary conditions are simplified, for instance, assuming perfectly conducting enclosures, ideal absorbing boundaries, or simplified radiation conditions. While these assumptions help with computational efficiency, they may not accurately reflect real-world electromagnetic environments. Variability in the environment, such as temperature, humidity, and proximity to surrounding structures or electronic systems, complicates boundary modeling further. Recent research shows that environmental uncertainty can significantly alter electromagnetic coupling and propagation characteristics, especially in open or semi-enclosed systems (Bosi et al., 2021).

Excitation uncertainty arises from a lack of knowledge about the source's characteristics, including amplitude, phase, polarization, waveform shape, or spatial distribution. In studies of electromagnetic compatibility and interference, uncertainty in source modeling can dominate overall prediction uncertainty, especially when multiple sources interact. In safety-critical situations, inaccurate excitation modeling can lead to overly conservative or insufficiently protective design decisions.

3.4 Numerical and Model-Form Uncertainty

The numerical uncertainty is due to the discretization and solution of the Maxwell equations. This consists of spatial and temporal discretization errors, numerical dispersion errors, computational domain truncation errors, and solver convergence errors. Despite such practices as mesh refinement and convergence studies, the latest studies indicate that residual numerical uncertainty may still be large in large-scale or highly dynamic simulations (Li et al., 2020; Yi et al., 2021).

In simplifying assumptions taken in developing a model Model-form uncertainty is associated with simplified models that simplify the model, e.g., reduced-dimensional models or linearized material behaviour, or through omission of multiphysics interactions. Although these assumptions are useful in controlling the cost of computation, they may introduce a mismatch between the computational model and the physical system that are not necessarily easy to measure. In safety critical electromagnetic systems, the effects of numerical and model-form uncertainties may be combined with uncertainty in physical parameters to augment the overall variability of predictions. Recent work highlights that these causes of uncertainty must be mitigated in frameworks of integrated uncertainty quantification and verification to have high assurance in decision-making based on simulations (Riedmaier et al., 2022; Roy and Oberkampf, 2011).

Furthermore, the inability to accurately describe and spread this uncertainty sources may compromise regulatory compliance, risk assessment, and confidence in certification through simulations in safety-critical electromagnetic systems.

Table 1. Summary of uncertainty sources in computational electromagnetics, their classification, impacted quantities of interest (QoIs), and typical modeling approaches.

Uncertainty Source	**Type**	**Impacted Application / Quantity of Interest (QoI)**	**Typical Modeling Method**
Material properties	Aleatory & Epistemic	SAR assessment, resonant frequency, antenna bandwidth	Parametric random variables (e.g., Gaussian, lognormal), spatially correlated random fields
Manufacturing tolerances	Aleatory (Epistemic in early design phases)	Radar cross-section (RCS), coupling levels, impedance matching	Parametric random variables, interval bounds
Anatomical variability	Aleatory	Biomedical dosimetry, specific absorption rate (SAR)	Voxel-based spatial random fields, stochastic anatomical phantoms
Geometric alignment	Aleatory & Epistemic	Electromagnetic interference (EMI), shielding effectiveness	Geometric perturbation analysis, parametric random variables
Boundary conditions	Primarily Epistemic	Wave propagation in open or semi-enclosed regions	Interval analysis, probability boxes (P-boxes)
Excitation sources	Aleatory & Epistemic	Electromagnetic compatibility (EMC), interference risk	Stochastic waveforms, multi-parameter random variable models
Discretization error	Epistemic	Numerical convergence, total field accuracy	A posteriori error estimator, mesh sensitivity analysis

Uncertainty Source	Type	Impacted Application / Quantity of Interest (QoI)	Typical Modeling Method
Model simplification	Epistemic	Multiphysics coupling accuracy, linearized material response	Model-form error frameworks, multi-fidelity modeling

4.0 Uncertainty Quantification Frameworks in Computational Electromagnetics

Computational electromagnetics requires a clear framework of quantifying uncertainty. This framework must allow a systematic description of uncertainty, propagation of uncertainty via electromagnetic models and a statistical analysis of the results of simulations. UQ frameworks contrast with deterministic modeling in that they attempt to describe the full set of system behaviors and the levels of confidence. It is a method to make concrete and well-informed decisions during safety-related circumstances (Smith 2024).

Uncertainty Propagation in the Safety-Critical CEM.

After identifying the sources of uncertainty and mathematically modeling them, the second issue with a safety-critical workflow is propagation. This is by taking the input distributions and running them through the CEM solver to identify the statistical properties of the output such as the risk of a medical device going beyond SAR safety limits or the risk of an aircraft part failing because of electromagnetic interference (EMI). In the existing studies, the most common way of uncertainty propagation is split into sampling-based, spectral, and surrogate-modeling techniques.

4.1 Sampling-Based Methods: The Monte Carlo Gold Standard

The Monte Carlo (MC) method remains the most straightforward and reliable approach for uncertainty quantification (UQ) in electromagnetics. Its key advantage is its non-intrusive nature: the CEM solver, whether FDTD or FEM, can be treated as a black box, requiring no modification. By running simulations multiple times with randomly sampled inputs, one can estimate output statistics, including mean, variance, probability density functions, and exceedance probabilities, all critical for safety assessment.

The primary limitation of Monte Carlo is its slow convergence, typically proportional to $1/\sqrt{N}$, where Nis the number of simulations. For high-fidelity CEM models, where a single simulation can take hours, thousands of iterations are often computationally prohibitive. Recent developments aim to overcome this through Multi-Level Monte Carlo (MLMC) and Quasi-Monte Carlo (QMC) techniques. MLMC is increasingly used in safety-critical applications; it leverages telescoping sum decomposition, performing inexpensive coarse-mesh simulations to capture most of the variance, supplemented by a few fine-mesh simulations to ensure accuracy (Zygiridis, 2017). QMC methods improve convergence by using low-discrepancy sequences, especially effective when the input-output relationship is smooth.

4.2 Stochastic Spectral Methods: Polynomial Chaos Expansion

To improve efficiency over Monte Carlo, Polynomial Chaos Expansion (PCE) has emerged as a key method in the CEM community. PCE represents the stochastic output as a series of orthogonal polynomials of the input random variables (e.g., Hermite polynomials for Gaussian inputs, Legendre polynomials for uniform inputs). For smooth input-output mappings, PCE can achieve exponential convergence, allowing highly accurate results with far fewer simulations than MC in moderate-dimensional systems.

PCE has found high usage in frequency-domain analysis, antenna design and biomedical dosimetry, such as in determining the effect of manufacturing tolerances and resonance or the effect of tissue permittivity variations on SAR allocation among populations (Turgut and Engiz, 2023b). Nonetheless, PCE has the dimensionality curse, i.e. the cost of computation grows exponentially with the count of uncertain inputs. In order to counter this, researchers utilize sparse-grid collocation, basis-adaptive expansions, and dimension reduction methodology. The most common method in safety-critical CEM is non-intrusive PCE that considers the solver as a black box. The recent studies combine physical constraints with PCE and maintain governing equations with fewer model evaluations, guaranteeing uncertainty estimates that are physically consistent (Sharma et al., 2024).

4.3 Surrogate Modeling and Machine Learning.

Another recent trend in UQ is the application of Machine Learning (ML) surrogates. Having a system too complex to be studied with spectral methods, and too expensive to be studied with Monte Carlo, researchers develop a meta-model that is trained on a small number of expensive high-fidelity simulations. Such common methods as Gaussian Process Regression (Kriging) and Deep Neural Networks (DNNs) are popular. Surrogate models like Gaussian process regression (Kriging) not only make UQ tasks faster, but also have intrinsic prediction uncertainty estimates, which are used to perform safety certification (Shi et al., 2025). Well-trained surrogates can anticipate electromagnetic reactions within milliseconds, which permits real-time what-if scenarios vital to safety-important systems. As an example, real-time uncertainty bounds of MRI-induced heating of metallic implants in patients have been given by the help of ML surrogates (Notaros et al., 2025).

The structure of the training dataset is of essential concern: Latin hypercube sampling, low-discrepancy sequences or adaptive sampling are all strategies that provide accuracy of surrogates. Gaussian Process models also give intrinsic uncertainty estimates, which are useful in the certification of safety.

More recently, Physics-Informed Neural Networks (PINNs), incorporate Maxwell equations directly as a part of the ML architecture. This encourages physical consistency and minimizes unphysical predictions, and eliminates predictions that contravene fundamental electromagnetic laws (Zhang and Alemazkoor, 2024). Speed, accuracy, and physical fidelity of surrogates are therefore a potent three-way combination, which helps in probabilistic safety assessment of real time application.

4.4 Sensitivity Analysis

Sensitivity analysis is important in quantification of uncertainty because it helps to identify the most influential uncertain parameters that have an impact on electromagnetic responses (Ceballes et al., 2021). Local and global sensitivity analysis is used in computational electromagnetism. Global sensitivity metrics, such as variance-based measures, are becoming common to rank uncertain parameters to inform model improvement, experimental design and effort in uncertainty reduction (Liu et al., 2024a). Sensitivity analysis can be used in safety-critical systems to identify the uncertainties to be more controlled or better characterized to increase predictive confidence (Liu et al., 2024b).

The recent literature has indicated the importance of combining sensitivity analysis into larger uncertainty quantification models in order to aid the clear and justifiable decision making, particularly where simulation results are part of regulatory compliance or risk evaluation.

5.0 Applications to Safety-Critical Systems

Uncertainty quantification in computational electromagnetics is crucial in safety-critical systems where regulatory limits, reliability goals, and human life are impacted by electromagnetic (EM) phenomena. In fields like biomedical, aerospace, power engineering, and defense, variations in shapes, materials, operating conditions, and environmental factors must be accurately modeled to ensure that safety margins are robust. In these contexts, UQ helps in risk-informed design, certification, and real-time decision-making by connecting EM field predictions to safety indicators, such as exposure levels, failure probabilities, and reliability metrics (Wang et al., 2023, Narayan et al., 2023)

5.1 Biomedical Electromagnetics

Human exposure assessment

Biomedical electromagnetism numerical dosimetry is used to assess (quantify) human exposure to electromagnetic fields by computing internal field distributions and absorbed energy (e.g., specific absorption rate, SAR) using numerical simulations. External electromagnetic sources excite voxel-based or CAD-based anatomical phantoms, and dosimetric quantities such as SAR or induced electric fields are computed, accounting for associated uncertainties. These uncertainties stem from anatomical variability, tissue electromagnetic properties, subject positioning, and source operating conditions. As a result, worst-case exposure levels may deviate significantly from deterministic predictions (Narayan et al., 2023; Wang et al., 2023).

Recent research has incorporated stochastic collocation, polynomial chaos expansion (PCE) and Monte Carlo simulation on full-wave solvers to quantify variability in exposure measures of different human bodies and postures and frequencies. As an example, adaptive sparse PCE and global sensitivity analysis have been applied to monitor uncertainties in exposure cases and tissue characteristics to identify induced field peaks in organs and offer probabilistic information about the safety margin as compared to ICNIRP or IEEE limits (Wang et al., 2023; Narayan et al., 2023).

Implantable and wearable medical devices

In implantable devices such as metallic stents, neurostimulators, and pacemaker leads, the geometry, location and anatomy of patients have been identified to cause uncertainty in Radio Frequency (RF) heating and induced currents, important to Magnetic Resonance Imaging (MRI) safety and compliance. RF safety analyses reveal that there can be substantial alterations of local SAR and temperature rise around the metallic implant due to uncertainty of an anatomical measure. This observation justifies the application of probabilistic safety factors as opposed to single-scenario margins.

New UQ research is also into this contact between medical implants and external sources of EM, e.g., electric vehicle wireless power transfer (WPT) systems. The range of induced fields within and around the implant is measured by stochastic modeling of alignment, coil currents, and patient pose. The same approach is implemented to wearable technologies and body-centric communications, where fitness, movement, and conditions of contact uncertainties are measured to compare the worst-case exposure and device functionality (Guo et al., 2025; Shah and Yoo, 2019).

5.2 Aerospace and Avionics Systems

Electromagnetic interference (EMI)

Aerospace and avionics systems have dense, diverse electronic components that are particularly sensitive to electromagnetic interference, especially under uncertain operating conditions. Variability in cable routing, source spectra, shielding effectiveness, and external fields can significantly impact interference at sensitive locations, making deterministic EMC simulations inadequate for thorough certification (Yuan et al., 2015).

Simulation-based EMI assessment methods are increasingly combining full-wave or transmission-line models with Monte Carlo sampling of physical parameters to evaluate the likelihood of EM disturbances exceeding immunity thresholds. By linking stress-strength models and probabilistic failure concepts with EM solvers, these methods provide reliability indicators for aviation electronics under uncertain EM conditions, supporting risk-based design and certification (Yuan et al., 2015)

Electromagnetic compatibility (EMC)

Aviation electromagnetic compatibility is regulated to high standards with limits on emissions and susceptibility being set by MIL-STD-461. Nonetheless, compliance should also be maintained regardless of uncertainties in factors to do with installation, setup and aging. UQ-based EMC testing considers uncertain inputs, such as layout tolerances, grounding layout, cable terminations, and component variation, as random inputs. This method measures the probability of system-level emission or vulnerabilities going above necessary levels.

Probabilistic EMC models can be used particularly at exceedingly early design and integration stages. This is when the margin of configurations is large, and deterministic margins can be unreasonably cautious or safe. UQ determines effective mitigation measures by quantitatively determining the sensitivity of EMC indicators to critical design considerations. These measures, which include shielding, filtering, and rerouting, assist in reducing risk at an efficient level.

5.3 Power Systems and High-Voltage Engineering

Insulation reliability

In high voltage equipment like transformers, cables, bushings also gas insulated switchgear, insulation behavior under the influence of electromagnetic stress is vital to the reliability and safety of the system. Dielectric characteristics of solid, liquid, and gaseous insulations are subject to manufacturing tolerance, aging, environmental factors and transitory overvoltage, which causes confusion in the prediction of breakdown strength and partial discharge.

The latest grading techniques are the integration of high-frequency EM field simulations with statistical analysis of the insulation damage to produce probabilistic indices of the remaining life and risk of failure. UQ facilitates monitoring of material property uncertainties, defect distributions and operating conditions using field and degradation models that assist condition-based maintenance and risk-based management of critical distribution transformers and other high-voltage parts.

Fault and breakdown analysis.

High-voltage systems fault and breakdown analysis is a rare occurrence of severe events such as flashovers, insulation punctures, and ignitions. These events can only be explained probabilistically. EM diagnostics techniques are also increasingly being used together with probabilistic fault identification techniques and predictive maintenance systems to approximate the possibility of failure under uncertainties in measurement data and model assumptions.

Addition of UQ to EM transient analysis of switching surge, lightning strike and ferroresonance allows the operators to determine the distribution of overvoltage and associated breakdown probabilities, rather than just the worst-case scenario. This results in the enhanced specification of insulation coordination margins, and the reinforcement of the most critical parts in the network is given priority (Afzali et al., 2024).

5.4 Other Safety-Critical Domains

Automotive electronics

Modern vehicles feature complex electronic systems for driving, control, sensing, and communication. EMI and EMC issues can threaten safety, especially in advanced driver-assistance and autonomous systems. Manufacturing variability, cable routing tolerances, component aging, and unpredictable external EM environments lead to significant changes in EM coupling paths. This variability makes UQ a useful tool for evaluating EMC design strength (Afzali et al., 2024)

Stochastic EM simulations and data-driven models are being used to assess the likelihood of failing to meet automotive EMC standards and to improve designs for shielding, filtering, and grounding. In electrified and connected vehicles, similar methods evaluate uncertainties in human exposure near high-power electronics and WPT systems, linking EM field predictions to probabilistic safety metrics for passengers and bystanders (Afzali et al., 2024)

Defense and radar systems

In defense and radar systems, mission success and safety depend on reliable performance in uncertain and often hostile EM environments, including jamming, high-intensity fields, and complex signal paths. EM models of antennas, radomes failure chances, and platforms must consider uncertainties in material properties, structural tolerances, threat scenarios, and environmental factors to assess detection performance and system reliability (Yowetu & Owusu-Agyemang, 2025).

UQ in this realm is connected to robust design and survivability analysis. Stochastic EM simulations aid in evaluating detection of chances, false alarm rates, and system degradation under unpredictable EM stress. Emerging frameworks couple EM-system UQ to examine how EM disturbances affect safety-critical command, control, and communication links, informing both hardening strategies and operational tactics.

Across these safety-critical fields, uncertainty quantification in computational electromagnetics encounters a common set of challenges that reach beyond individual domains. High-fidelity electromagnetic models can be costly to compute, while the uncertainties involved are often high-dimensional, varied, and only partially understood. This limits how practical brute-force uncertainty quantification can be. Many safety assessments depend on rare or extreme electromagnetic events, such as localized exposure spikes, insulation breakdowns, or exceeding electromagnetic interference limits. These events are not effectively captured by standard analyses based on averages or variances. Therefore, converting probabilistic electromagnetic predictions into formats that match regulatory and certification standards remains an ongoing challenge. This issue encourages a closer integration of computational electromagnetics, uncertainty quantification methods, and experimental validation.

6.0 Conclusion

Computational electromagnetics has become a valuable tool in design, analysis, and certification of safety-critical systems. The dependability of these systems and their safety to human beings is crucially important. But, as this review has indicated, deterministic electromagnetic simulations do not usually reflect the variability and limited knowledge of real-world systems. The quantification of uncertainty offers an effective means to solve these difficulties because it explicitly models and propagates uncertainty using electromagnetic models. This review has provided the principal sources of ambiguity in computational electromagnetism. These are material properties, geometry, boundary conditions, excitation models and numerical approximations. It has also talked of significant uncertainty quantifying techniques such as Monte Carlo techniques, stochastic spectral techniques, surrogate modeling, and sensitivity analysis. The use in areas like biomedical, aerospace, power, automotive and defense demonstrates that uncertainty accounting models give more useful and reliable predictions compared to those made by single values. Despite important progress, the issues still exist. These are in dealing with high dimensional uncertainties, measuring infrequent events, managing the costs of computation, and interacting with regulatory regimes. More intimate relationship between uncertainty quantification, experimental validation and standards-driven modeling practices will be required to overcome these challenges. Further developments in this field are essential in assisting plausible, simulation-based decision-making in safety critical electromagnetic systems.

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