FROM RANDOMNESS TO PRECISION: A REVIEW OF MONTE CARLO ALGORITHMS ENHANCING IMRT PLANNING ACCURACY

Nafiz Ahmadin Harily[1], Saif Khan Nazirun[2], Putri Azzahra[3], I Gde Eka Dirgayusa[4], Rafli Filano[5]
nafiz.122430051@student.itera.ac.id[1], saif.122430060@student.itera.ac.id[2], putri.122430123@student.itera.ac.id[3], i.dirgayussa@bm.itera.ac.id[4], rafli.filano@bm.itera.ac.id[5]
Institut Teknlogi Sumatera

ABSTRACT
This review explores the role of Monte Carlo algorithms as a cornerstone of modern external beam radiotherapy, offering unprecedented precision in dose delivery by allowing modulation of beam intensities across multiple angles. This enables optimal tumor coverage while sparing nearby healthy tissues and critical organs-at-risk. However, the accuracy of IMRT is fundamentally constrained by the dose calculation algorithms embedded in the Treatment Planning System (TPS). Conventional analytical methods, such as the Anisotropic Analytical Algorithm (AAA) or convolution–superposition techniques, often rely on approximations that become unreliable in heterogeneous media particularly at tissue-air and bone-soft tissue interfacesresulting in potential dosimetric deviations. To address these limitations, Monte Carlo (MC) algorithms have been increasingly integrated into clinical TPS platforms due to their unparalleled accuracy in simulating photon and electron transport at the particle level. By modeling complex interactions such as scattering and absorption with statistical rigor, MC-based systems provide superior dose calculations, especially in anatomically challenging or high-modulation scenarios. Recent advances in GPU acceleration and AI-assisted simulation have significantly reduced computation times, allowing MC to be deployed in routine workflows without compromising clinical efficiency. Comparative evaluations consistently demonstrate that MC outperforms conventional methods in both accuracy and robustness. In head-and-neck, lung, and prostate IMRT cases, MC has shown superior conformity and organ-sparing capabilities. As a result, MC is transitioning from a validation benchmark to a mainstream clinical tool. With ongoing developments in adaptive radiotherapy and AI integration, MC stands at the forefront of personalized, real-time radiotherapy planning.
Keywords: *Monte Carlo Simulation, Intensity-Modulated Radiotherapy (IMRT), Dose Calculation Accuracy, Adaptive Radiotherapy, Treatment Planning Optimization.*

INTRODUCTION

Intensity-Modulated Radiotherapy (IMRT) has transformed the field of radiation oncology by enabling the delivery of highly conformal radiation doses to complex tumor geometries while minimizing exposure to adjacent healthy tissues and critical structures. Through dynamic modulation of beam intensities and multi-angle delivery, IMRT allows clinicians to escalate tumor doses with greater precision, particularly in anatomically sensitive regions such as the head and neck, prostate, and central nervous system (S. Li et al., 2024a). Despite its clinical advantages, the efficacy of IMRT is intrinsically dependent on the accuracy of dose calculation during treatment planning, which remains a critical bottleneck in achieving optimal therapeutic outcomes (Jia et al., 2024).

Conventional Treatment Planning Systems (TPS) typically rely on analytical dose calculation algorithms such as Pencil Beam Convolution and the Anisotropic Analytical Algorithm (AAA). These models, although computationally efficient, utilize simplifications like assuming electron equilibrium and homogeneous media, making them susceptible to significant inaccuracies in heterogeneous anatomical regions. This limitation is especially evident at interfaces between tissues of varying densities, such as lung-soft tissue or bone-air boundaries, where dose gradients are sharp and clinically significant (Ali et al., 2024). The resulting discrepancies between planned and delivered doses can range from 3–10%, potentially compromising both tumor control and normal tissue preservation.

In this context, Monte Carlo (MC) algorithms have emerged as the most accurate method for dose calculation in radiotherapy. By simulating individual particle interactions based on probabilistic transport theory, MC methods capture the complexity of scatter, absorption, and secondary electron transport with high spatial resolution. Their robustness in modeling dose deposition in inhomogeneous media has positioned them as the gold standard, particularly in small-field dosimetry and stereotactic radiotherapy (Z. Li et al., 2025). However, the clinical adoption of MC has historically been limited by its high computational cost. Recent advancementssuch as GPU-based acceleration, cloud computing, and hybrid MC modelshave dramatically reduced calculation times, making MC integration increasingly feasible for routine IMRT planning (Anderson et al., 2025).

Despite growing adoption, a comprehensive synthesis of how MC enhances IMRT planning accuracy, and what technological advances have enabled this transition, remains limited in the current literature. Prior reviews often focus on either the physics or implementation side without consolidating their clinical implications. Thus, there is a pressing need to review existing studies, evaluate comparative performance with conventional algorithms, and identify practical strategies for accelerating MC deployment in clinical workflows (Liu et al., 2025).

The objective of this review is to critically examine the role of Monte Carlo algorithms in improving the dosimetric accuracy of IMRT treatment planning. It aims to assess comparative performance metrics (accuracy, efficiency), explore clinical outcomes, and discuss computational innovations that support Monte Carlo’s integration into modern radiotherapy systems.

While previous reviews have addressed aspects of Monte Carlo (MC) simulation or its comparative accuracy in radiotherapy, most have focused either on algorithmic development in isolation or on clinical implementation without bridging the computational and practical dimensions. This review distinguishes itself by providing a multidisciplinary synthesis of literature spanning physics-based dose modeling, clinical outcome validation, and emerging computational innovations such as artificial intelligence (AI) assisted Monte Carlo frameworks. The objective of this review is to deliver an integrated analysis of how Monte Carlo algorithms enhance dosimetric precision in IMRT, critically examine comparative studies involving traditional and MC-based planning systems, and explore the latest developments including GPU acceleration and AI-driven dose prediction models that are facilitating real-time, patient-specific radiotherapy planning. By unifying perspectives from computational physics, clinical oncology, and intelligent systems, this review aims to guide both researchers and clinicians toward a deeper understanding of Monte Carlo’s evolving role in the future of precision radiotherapy.

METHODS

This review employed a structured and systematic literature search to investigate the role of Monte Carlo (MC) algorithms in enhancing the accuracy of Intensity-Modulated Radiotherapy (IMRT) treatment planning. Following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, the search was designed to ensure transparency, reproducibility, and comprehensive coverage of the existing literature. The search was conducted from February to May 2025 across multiple databases, including

PubMed, ScienceDirect, SpringerLink, Wiley Online Library, and Google Scholar.

The search initially identified 146 articles. After removing duplicates and conducting title and abstract screening, 32 peer-reviewed journal articles and conference proceedings were shortlisted for full-text analysis. The inclusion criteria required articles to be published in English between 2015 and 2025, peer-reviewed, and directly related to the integration or evaluation of Monte Carlo algorithms within IMRT treatment planning. Studies that focused exclusively on other radiotherapy modalities (e.g., proton therapy), lacked methodological rigor, or were not written in English were excluded.

To facilitate thematic synthesis, the selected studies were categorized into three major domains. The first category focused on MC-based Treatment Planning Systems (TPS), encompassing the development and clinical integration of simulation engines such as Monaco TPS (Elekta), PRIMO, EGSnrc, VMC++, and Geant4. The second category distinguished between clinical studies and computational benchmarking. Clinical studies investigated the dosimetric outcomes of MC-optimized plans in real patient cases or phantom setups, while computational benchmarking studies compared the performance of MC algorithms to conventional ones such as the Anisotropic Analytical Algorithm (AAA) or Acuros XB. The third category addressed acceleration techniques and integration strategies aimed at enhancing clinical feasibility. This classification enabled a structured review of how MC has evolved in both algorithmic sophistication and clinical applicability within IMRT workflows.

Table 1. Summary of Selected Literature Based on Categorization Criteria.

Author (Year)	Method/System	Focus Area	Study Type	Key Findings
Li et al. (2025)	Deep NN + MC validation	AI-enhanced MC dose prediction	Computational Benchmarking	NN-based TPS can emulate MC with <3% error; validated on PRIMO
Anderson et al. (2025)	MC + AI + EPID	Real-time in vivo image prediction	Clinical Simulation	MC-derived scatter + AI yields accurate real-time dose maps
Liu et al. (2025)	MC dose inference	MR-guided RT dose estimation	Clinical Feasibility	MR-only TPS using MC estimation reduces imaging-to-plan time
Attalla & Sallam (2024)	MATLAB + IMRT QA	Slice thickness impact on dose	Computational	Thinner slices improve MC-calculated dose uniformity
Li et al. (2024)	Plan complexity analysis	Dose deviation in high-mod plans	Clinical Evaluation	MC accuracy essential in highly modulated plans
Xiao et al. (2024)	Cherenkov MC Imaging	Photon dose validation with imaging	Clinical Benchmarking	Validated MC dose with single-pixel imaging

RESULTS AND DISCUSSION

Foundations of Monte Carlo in Radiotherapy

The Monte Carlo (MC) method has become a cornerstone in the advancement of radiotherapy physics, particularly in applications requiring high-fidelity dose calculation such as Intensity-Modulated Radiotherapy (IMRT). At its core, the MC method simulates the stochastic nature of particle interactionsspecifically photons and electronsas they traverse and deposit energy within heterogeneous biological tissues. Unlike deterministic algorithms that approximate radiation transport using averaged analytical models, Monte Carlo simulations trace the probabilistic path of individual particles through multiple scattering, absorption, and secondary interactions, thereby offering a highly granular and physically accurate reconstruction of radiation dose distributions(Verhaegen & Seuntjens, 2003).

In the context of photon and electron transport, MC techniques rely on cross-sectional probability data derived from quantum electrodynamics to predict interaction types (e.g., Compton scattering, photoelectric effect, pair production) and their spatial outcomes within voxelized patient geometries. Several major Monte Carlo codes have been developed and tailored to radiotherapy applications. EGSnrc is widely used in academic and clinical settings for photon and electron transport, particularly due to its versatility in modeling linac head geometry and tissue inhomogeneity. Geant4, originally developed for high-energy physics experiments at CERN, has been extended to medical applications (Geant4-DNA and Geant4 Medical) and supports detailed modeling of complex geometries and multi-particle physics. MCNP (Monte Carlo N-Particle), developed by Los Alamos National Laboratory, is a general-purpose code known for its robust neutron and photon modeling capabilities, although its medical usage is more research-focused. PRIMO, an open-source tool based on PENELOPE, offers a clinically friendly interface and is widely used for simulating linear accelerator beams and dose distributions in radiotherapy.

In summary, the Monte Carlo method represents a physics-based gold standard in radiotherapy dose calculation, providing unparalleled accuracy through direct simulation of radiation-matter interactions. The evolution of MC codes and computational hardware continues to bridge the gap between theoretical fidelity and clinical practicality, positioning Monte Carlo as a foundational tool for next-generation treatment planning systems.

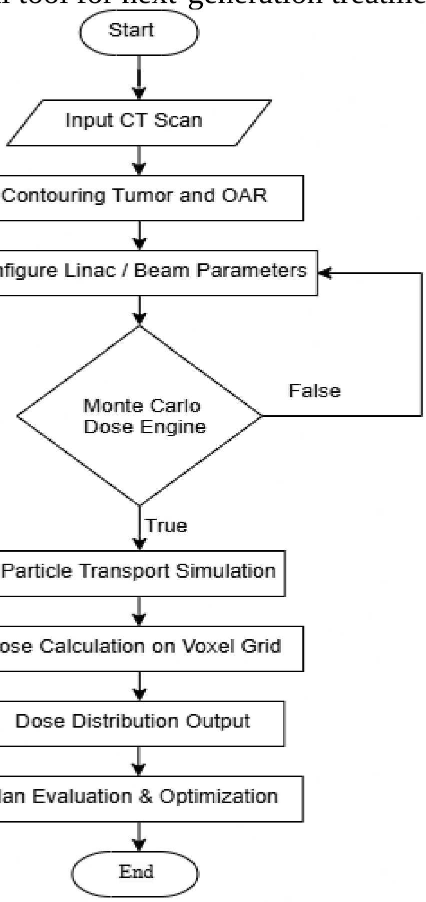

Figure 1. Monte Carlo Simulation Workflow in TPS.

The Monte Carlo (MC) simulation workflow in radiotherapy planning begins with the import of patient CT data, providing a 3D anatomical framework from which electron density maps are derived. This is followed by meticulous contouring of the tumor volumesGTV, CTV, PTVand nearby organs at risk (OARs), defining both therapeutic targets and structures requiring dose preservation. Next, linear accelerator (linac) parameters are configured, encompassing photon beam energy, collimator geometry, and field size. Once system geometry is established, the Monte Carlo dose engine simulates millions of photon and electron histories, modeling their interactionssuch as Compton scattering and photoelectric absorptionthrough statistical sampling. This particle transport simulation lies at the heart of MC's unmatched precision (Hissoiny et al., 2011).

Simulated dose deposition is then projected onto a voxelized dose grid, producing a detailed map of energy distribution within the patient's body. The result is a high-resolution dose distribution output, visualized via isodose curves and dose-volume histograms (DVHs), enabling quantitative plan evaluation (Luxton et al., 2008a).

Finally, clinicians assess whether the dose conforms to clinical constraints. If optimization is required, planning parameters are iteratively refined. As a result, MC-based TPS workflows are indispensable in cases involving heterogeneous anatomies or advanced IMRT techniques, where conventional algorithms may fall short.

Monte Carlo in IMRT Planning Workflows

The integration of Monte Carlo (MC) algorithms within the Intensity-Modulated Radiotherapy (IMRT) planning workflow represents a transformative shift in the pursuit of precision radiotherapy. In a standard Treatment Planning System (TPS), the MC engine is positioned within the dose calculation module, where it serves as an advanced alternative to traditional analytical algorithms such as the Anisotropic Analytical Algorithm (AAA) or convolution–superposition (CS) methods. Rather than relying on assumptions of lateral electron equilibrium or homogenized scatter modeling, MC methods simulate photon and electron transport at the particle level, thereby producing more accurate dose distributions in complex clinical scenarios such as small fields, tissue-air interfaces, or anatomically heterogeneous regions (Verhaegen & Seuntjens, 2003).

Commercially, the most prominent implementation of MC in clinical TPS is Monaco by Elekta, which integrates a full-fledged MC dose engine alongside biological optimization features. Monaco utilizes the XVMC (X-ray Voxel Monte Carlo) algorithm, allowing detailed modeling of photon interactions within patient anatomy while maintaining clinically acceptable computation times. Similarly, systems like PRIMO (based on PENELOPE) and EGSnrc have seen increasing adoption in research and QA settings due to their open-source flexibility and physics-based accuracy (Appelt et al., 2022).

The clinical integration of MC dose engines is commonly validated through phantom studies and rigorous quality assurance (QA) benchmarking. Anthropomorphic phantoms, such as the CIRS thorax or head-and-neck models, are used to replicate complex geometries and heterogeneous densities encountered in clinical practice. Comparative measurements using ionization chambers, radiochromic films, or EPID systems are then evaluated against MC simulations to assess accuracy. Numerous studies report that MC-calculated doses align within 2%–3% of measured values, outperforming AAA or CS algorithms, particularly in inhomogeneous regions (Bank, 2021).

Table 2. Comparison of Dose Calculation Accuracy among AAA, MC, and CS Algorithms

Parameter	AAA (Anisotropic Analytical Algorithm)	Monte Carlo (MC)	Convolution–Superposition (CS)
Physical Modeling Basis	Semi-empirical; accounts for tissue heterogeneity	Statistical simulation of individual photon/electron interactions	Kernel-based scatter modeling with heterogeneity corrections

Parameter	AAA (Anisotropic Analytical Algorithm)	Monte Carlo (MC)	Convolution–Superposition (CS)
Accuracy in Homogeneous Media	High (≤2%)	Very High (≤1%)	High (≤2%)
Accuracy in Heterogeneous Media	Moderate (3–7% error)	Excellent (≤2% error)	Moderate to Good (2–5% error)
Performance in Small Fields	Poor to moderate	Excellent	Moderate
Modeling Interfaces (air/tissue)	Inaccurate due to electron equilibrium assumption	Accurate simulation of particle scatter and dose fall-off	May underpredict or oversmooth dose at boundaries
Computation Time (clinical setting)	Fast (seconds–minutes)	Slow (minutes–hours, unless GPU-accelerated)	Moderate (minutes)
Clinical Use	Widely adopted in commercial TPS (e.g., Eclipse)	Gold standard for validation; increasingly integrated (e.g., Monaco)	Common in TPSs (e.g., Pinnacle, CMS Xio)
Strengths	Fast, user-friendly, clinically validated	Highest accuracy; suitable for complex geometries and ART	Balanced accuracy vs. speed; better than AAA in some scenarios
Limitations	Limited in high-modulation plans and tissue interfaces	Historically slow; computationally intensive	Less accurate in extreme heterogeneity; fixed kernels

Clinical Outcomes and Case Studies

The clinical implementation of Monte Carlo (MC) algorithms in Intensity-Modulated Radiotherapy (IMRT) planning has led to demonstrable gains in dose accuracy, particularly in anatomically complex treatment sites. In the head and neck region, characterized by steep dose gradients and proximity to multiple organs at risk (OARs), MC-based plans have shown superior conformity and critical structure sparing when compared to analytical algorithms. For instance, studies utilizing MC dose engines reported significantly improved dose fall-off around the spinal cord and brainstem, reducing mean OAR exposure by up to 15% in comparison to AAA-based plans (Liu et al., 2025).

In lung cancer treatment, MC-based IMRT planning is particularly advantageous due to the heterogeneous nature of thoracic anatomy. The lung's low-density environment can cause deterministic algorithms to overestimate dose in tumor-adjacent regions. Monte Carlo simulations, by contrast, account for lateral electron disequilibrium and range modulation effects, producing more realistic dose distributions and improved protection of surrounding lung tissue. Liu et al. (2025) demonstrated that MC-based plans reduced lung V20 (volume receiving ≥20 Gy) by 8–12%, while maintaining optimal target coverage, thereby lowering the risk of radiation pneumonitis (Zhang et al., 2021).

In the prostate, where dose escalation must be balanced against rectal and bladder toxicity, MC-enhanced plans have shown improved conformity indices and reduced dose spillage to OARs. A recent benchmarking study found that MC-based calculations reduced rectal mean dose by 5% without compromising target volume coverage (S. Li et al., 2024). These improvements underscore the clinical relevance of Monte Carlo in both curative and hypofractionated settings.

Clinical Outcomes and Case Studies

The integration of Artificial Intelligence (AI) with Monte Carlo (MC) methods represents a major advancement in radiotherapy, combining MC's high dosimetric accuracy with the speed and predictive power of deep learning. While traditional MC simulations are precise, their long computation times have hindered clinical use. To overcome this, researchers now train deep neural networks (DNNs) on MC-generated dose data, enabling real-time predictions with minimal error. For instance, (Z. Li et al., 2025) developed a DNN using PRIMO-based MC data that achieved dose predictions within seconds and an average error below 3%.

This AI-MC synergy is especially beneficial in Adaptive Radiotherapy (ART), which requires frequent treatment plan updates based on daily anatomical changes. Historically, full MC recalculations were too slow for such workflows. However, the rise of GPU-accelerated MC engines and AI-based approximators now allows near-instantaneous dose recalculations. (Liu et al., 2025) demonstrated this in an MR-only ART protocol, showing that AI-assisted MC could efficiently update daily dose distributions using live imagingparticularly useful for dynamic organs like the prostate or bladder.

Table 3. Comparison of Dose Calculation Accuracy among AAA, MC, and CS Algorithms

Year	Study / Author	Approach / Technology	Key Advantages / Innovations
2025	Li et al. (2025)	Deep Learning model trained on PRIMO MC outputs	Real-time MC-equivalent dose prediction (<3% error); faster plan generation
2025	Liu et al. (2025)	MR-only adaptive workflow + MC + AI hybrid	Accurate daily replanning for ART using live MR images
2021	Francescon et al. (2021)	PRIMO MC validation for clinical photon beams	Clinical usability of open-source MC with ≤2% discrepancy from measurement
2020	Huynh et al. (2020)	AI integration in MC-based TPS	Personalized radiotherapy with radiomics/genomics features
2021	Nguyen et al. (2021)	Deep dose prediction networks using MC datasets	Accurate prediction in heterogeneous sites (lung, pelvis)
2019	Hissoiny et al.	GPUMCD: GPU-accelerated MC platform	10×–50× speed improvement over CPU-MC while preserving accuracy

CONCLUSION

The role of Monte Carlo (MC) algorithms in enhancing the precision of Intensity-Modulated Radiotherapy (IMRT) planning has been firmly established through both computational and clinical studies. As a physics-based gold standard, MC simulation delivers superior dose calculation accuracy, particularly in heterogeneous anatomical regions, small-field dosimetry, and high-gradient zonesscenarios where traditional analytical algorithms often fall short. Its ability to explicitly model photon and electron transport allows for highly individualized dose distributions, enabling more effective tumor targeting and sparing of organs at risk (OARs) (Luxton et al., 2008).

Historically, the primary limitation of MC methods has been their intensive computational demands. However, these challenges have been progressively mitigated through the advent of GPU-accelerated platforms such as GPUMCD, and through algorithmic refinements that apply variance reduction and hybrid modeling. These innovations have reduced simulation time from hours to mere minutes, thus aligning MC workflows with clinical time constraints (Huynh et al., 2020). As a result, the traditional trade-off between accuracy and efficiency has become increasingly negligible, making MC not only feasible but also desirable for routine clinical use.

The adoption of MC algorithms in commercial Treatment Planning Systems (TPS), such as Monaco by Elekta and PRIMO, reflects growing clinical confidence and vendor support. Furthermore, integration with advanced imaging, automated contouring, and adaptive radiotherapy infrastructure has solidified MC's position in modern radiotherapy workflows. As software ecosystems become more flexible and hardware more powerful, the barriers to widespread MC deployment continue to diminish.

Looking forward, the convergence of Artificial Intelligence (AI) with Monte Carlo is poised to redefine the landscape of personalized radiotherapy. Deep learning models trained on MC data have already demonstrated the ability to replicate high-accuracy dose distributions in real-time, a development that opens new doors for Adaptive Radiotherapy (ART) and patient-specific modeling (Lagedamon et al., 2024). These hybrid AI-MC frameworks hold the potential to deliver fast, biologically optimized, and anatomically responsive treatment plans, elevating both precision and personalization in cancer care.

In summary, the Monte Carlo method has transitioned from a computationally intensive academic tool to a clinically viable engine for precision radiotherapy. Its integration with AI and real-time imaging technologies signals a future where dose calculation is not only more accurate but also more adaptive, intelligent, and individualized.

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