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Monte Carlo Modeling of Elekta VERSA HD for Out-of-Field Dose Characterization

Maxime Jacquet^{1,2}, Thomas Baudier^{1,2}, Eric Deutsch^{3,4}, Charlotte Robert^{3,4}, and David Sarrut^{1,2}

¹ CREATIS, CNRS, Univ of Lyon, France

² Centre Léon Berard, 28 rue Laennec, 69373 Lyon

³ UMR 1030 ImmunoRadAI, Université Paris-Saclay, Institut Gustave Roussy, Inserm, Villejuif, France

⁴Department of Radiation Oncology, Gustave Roussy, Villejuif, France

Abstract

Modern radiotherapy has significantly improved cancer patient survival rates, yet challenges remain in optimizing both tumor response and quality of life. Out-of-field doses play a role potentially impacting patient overall survival, but are not well-estimated by the conventional treatment planning systems. We propose here the development of a full Monte Carlo simulation model of the Elekta VERSA HD accelerator to assess the out-of-field deposited doses. We introduce an original Compton splitting method aiming to compensate for simulation low convergence in the out-of-field region. Results emphasize that achieving a 5% statistical precision on the far out-of-field deposited dose requires 200 days of simulations on a single thread. The proposed variance reduction technique led to a 1.4 efficiency gain. This model will be used to generate out-of-field dose maps on a large database of patients that will be used to train a deep learning model for quick dose calculation [1].

1 Introduction

Photon therapy modalities, such as Intensity-Modulated Radiation Therapy (IMRT) or Volumetric Modulated Arc Therapy (VMAT), use multiple beams with distinct configurations, enabling a highly conformal dose deposition within the targeted tumor volume. This involves an expansion of the irradiated volume compared to traditional 3D-Conformal Radiation Therapy (3D-CRT) [2]. However, the Out-Of-Field (OOF) deposited dose, often considered to be less than 5% of the prescribed dose, is notably lower than that within the irradiation field, but still is around 100 mGy at 15 cm far from the 5% isodose curve [3].

These very low doses can contribute to the development of radiation-induced malignancies or lymphopenia (lymphocyte deficiency), both of which reduce overall patient survival post-radiotherapy [4]. To quantify these effects and strive for the inclusion of lymphoid organs as potential organs at risk in Treatment Planning Systems (TPS), a key consideration is the precise estimation of the OOF deposited dose within the patient. However, conventional TPS are designed for in-field dose calculations and exhibit significant discrepancies when compared to experimental measurements, reaching up to 100% in the "near" OOF region [5, 6]. Consequently, several research initiatives focused on improving dose estimation in the OOF regions, employing analytical calculations, as reviewed in [7], or Monte Carlo (MC) simulations [8]. While the former method is relatively fast (taking several

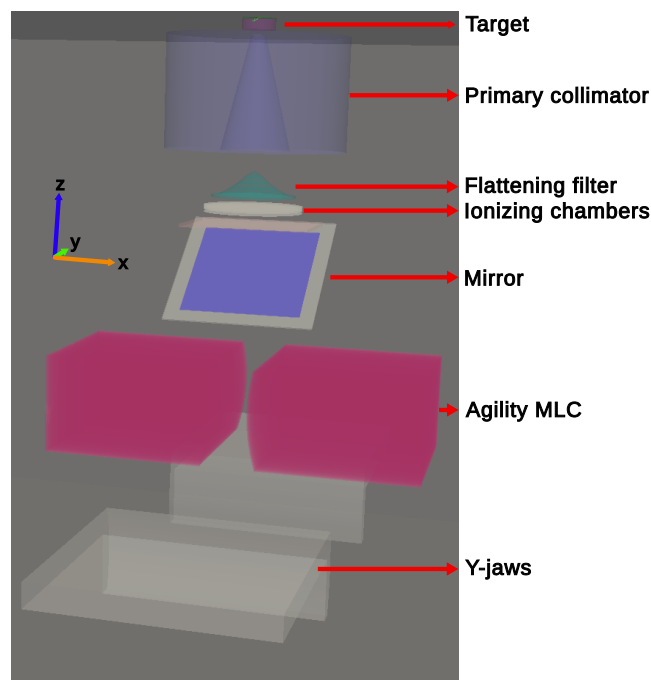


Figure 1: Simulation view of the different parts of the LINAC head. The jaws representation is here simplified. A phase space is inserted between the mirror and the MLC and acts as a particle source.

minutes), its precision can be outperformed by MC simulations. However, the latter approach is time-consuming, and the statistical precision to achieve is often defined from in-field simulations.

In the following, we present the statistical errors associated with the OOF deposited dose for the Elekta Versa HD, as a function of the simulation running time and introduce a Variance Reduction Method (VRM) named Compton Splitting to speed up the simulation.

2 Materials and Methods

The MC simulation work is performed using GATE [9], an open-source software based on the GEANT4 toolkit [10], to model a LINAC head based on available information about Elekta Versa HD (Figure 1). The physics list used for the MC simulations was *G4EmStandardPhysics option3*.

The LINAC head simulation is divided into two parts. The

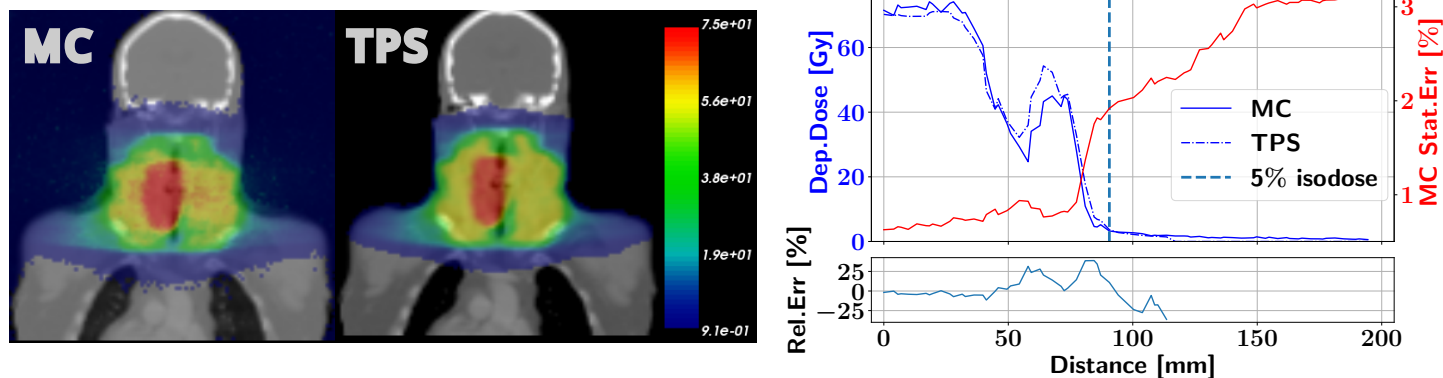


Figure 2: Left: Comparison, between the MC simulation (left) and Monaco TPS (right), of deposited doses, on a coronal plan, generated according to a DICOM RT plan. The dose is normalised at 70 Gy corresponding to the deposited dose at the LINAC isocenter position. The colormap scale is in Gray. Right: Comparison between the TPS and the MC simulation of deposited dose 1D profiles along a path starting from the isocenter to the minimum deposited dose value within the patient. The start of the OOF region (5% isodose) is depicted for visualisation purposes.

first part encompasses all patient-independent devices, including the electron target, primary collimator, flattening filter, ionizing chambers, and mirror. Particles exiting this part are stored in a phase space file and subsequently used as a particle source for the second simulation part. This part involves target-specific components, the Agility™ Multi-Leaf Collimator (MLC) and Y-jaws. The simulated LINAC head irradiates either a water tank or a voxelized CT-scan, on which a *dose actor* is attached. It enables to store of both the deposited dose and corresponding statistical uncertainties in $4 \times 4 \times 4 \text{ mm}^3$ dose scoring voxels. The simulated accelerator parameters were fine-tuned to reproduce the dose deposition experimentally measured, i.e. percentage depth-dose curves and dose profiles in X and Y-axis. The simulated dose well reproduces experimental data, and ongoing work involves refining simulation parameters.

The statistical assessment was conducted in a two-step process. The first step investigated, for MLC apertures from 2 to 11 cm in both axis, the impact of the three main mechanisms generating the OOF dose: (1) low-energy scattered photons within the target (patient-scattered photons, or PS photons), (2) scattered photons at the MLC/Y-jaws tips, or in the flattening filter (head-scattered photons or HS photons), and (3) photons crossing the MLC/Y-jaws (head leakage photons, or HL photons). The second step assessed deposited dose and its uncertainty as a function of the OOF distance, starting from the 5% isodose curve. The required simulation time was defined as the simulation duration, on a single thread (Intel® Core™ i9-13950HX), to achieve mean statistical uncertainties of 5% on a given dose scoring voxel. We also devised a method that reads any DICOM RT Plan to replicate a whole volumetric irradiation (e.g. few arcs, several hundreds of control points). It allows us to compute an entirely MC-based patient absorbed dose distribution, which is compared afterwards to the one obtained from Monaco TPS. Photons responsible for the OOF dose deposition (mainly HS and HL photons) are relatively rare compared to photons go-

ing in the field. Since they are mostly generated by photons undergoing Compton processes within the MLC/jaws before interacting within the patient, we decided to split Compton events occurring in the MLC/jaws regions. This splitting, coupled with Russian roulette for scattered photons with backward direction angles relative to the patient, is confined to the first two Compton processes of the particle (either primary or split). Each split particle is then conventionally tracked, with an associated weight bias. The simulation acceleration was assessed by computing the efficiency, denoted as ε , where $\varepsilon = \frac{1}{\sigma^2 t}$. σ^2 represents the total deposited dose variance, and t corresponds to the simulation running time. This efficiency was calculated from a box-shaped phase-space placed in the far OOF area. This efficiency is subsequently compared to the one obtained with a reference simulation without any applied bias.

3 Results

Figure 2 (left) illustrates the deposited dose within the patient according to the MC simulation (left) and the TPS (right). The MC simulation effectively reproduces a VMAT session, despite observable discrepancies in the deposited dose between the two images. A quantitative comparison is presented in Figure 2 (right), highlighting the deposited dose along a path starting from the isocenter to the coordinates of the minimum deposited dose, within the patient. Along this path, the difference in the in-field dose deposition is less than 5% near the isocenter but can reach up to 35% in the dose gradient. It has to be noted that here, below 1 Gy, the TPS no longer calculates the deposited dose.

The phase space emits $\sim 10^{11}$ γ , with ~ 50000 particles per second simulated, requiring 23 days of simulation on a single thread. The resulting OOF deposited dose uncertainties, 10 cm beyond the 5% dose limit, remain low, around 3%.

Figure 3 provides a summary of the required simulation running time to achieve a 5% statistical uncertainty in $4 \times 4 \times 4$

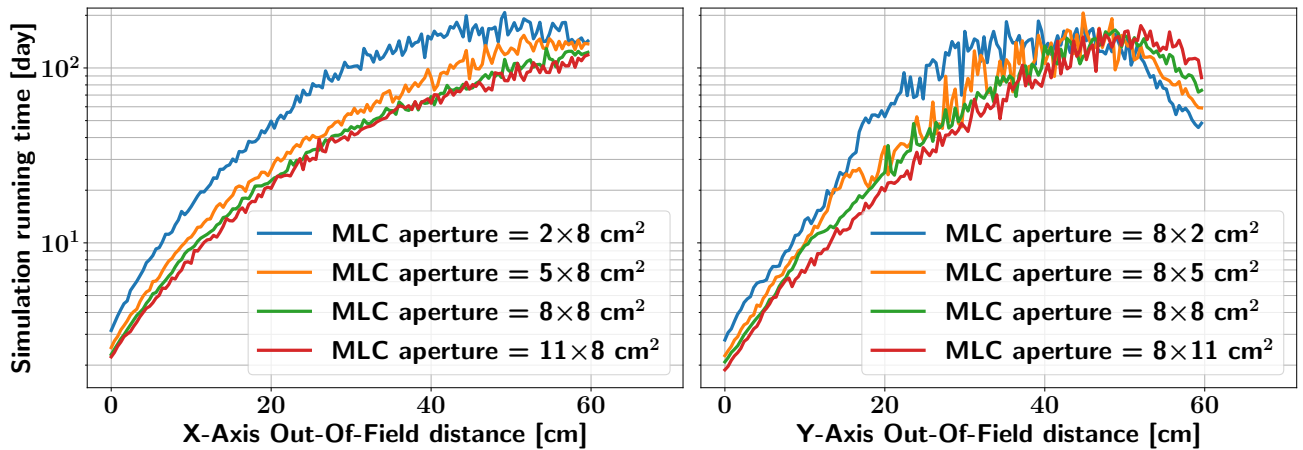


Figure 3: Required simulation running time to achieve 5% of statistical uncertainties within the OOF region, as a function of the MLC aperture and OOF distance from the 5% isodose curve, along the X-axis (left) and the Y-axis (right).

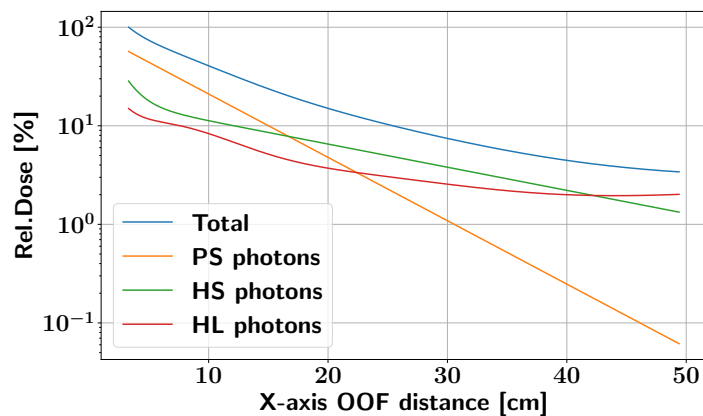


Figure 4: Individual component contributions to the OOF deposited dose plotted against the X-axis OOF distance for a MLC aperture of $8 \times 8 \text{ cm}^2$. Each process is fitted based on its distinct behavior and the fit is presented solely to illustrate the trends within each process. The patient-scattered (PS) contribution is represented in orange, the head-scattered (HS) contribution in green, and the head-leakage (HL) contribution in red.

mm^3 voxels. The required time is plotted against the out-of-field (OOF) distance along the X-axis (left plot) and the Y-axis (right plot). The results are presented for the different MLC apertures simulated (from 2 to 11 cm). As expected, the simulation running time depends on the OOF distance (Figure 3).

In the near OOF region (approximately 0 - 15 cm), the dominant contribution comes from patient-scattered photons and the simulation duration peaks at a maximum of around 10 days (Figure 4). In the middle OOF region (approximately 15-40 cm), PS photons are primarily absorbed within the patient, and the dose is deposited through head-scattered photons and head-leakage photons. The deposited dose decreases and leads to an augmentation of the simulation running time to a maximum of 100 days. In the far OOF region (> 40 cm), the deposited dose increases because of photons passing beyond the collimation system. Since they are not interacting

in the collimation system, they enhance the photon statistics, potentially reducing the simulation running time.

Splitting factor	q_D	$\frac{\epsilon}{\epsilon_{\text{ref}}}$
5	0.97 ± 0.08	1.33 ± 0.04
10	0.98 ± 0.07	1.39 ± 0.04
20	0.98 ± 0.06	1.44 ± 0.04
100	0.95 ± 0.11	1.43 ± 0.06

Table 1: Efficiency gain of the Compton splitting method for far OOF deposited dose. q_D is the quality in terms of deposited dose. $q_D = 1$ means that the deposited dose estimator is unbiased. ϵ_{ref} is the efficiency of the reference simulation.

Table 1 presents an unbiased deposited dose estimator (q_D close to one), with a modest simulation efficiency improvement, reaching up to 44%, in comparison to the reference simulation. The efficiency plateaus around a splitting factor of 10.

For higher values, all photons entering the collimation system consistently pass through it, ensuring no waste in tracking primary photons stopped by the collimators. As a result, all simulated events have the potential to attain the OOF region, contributing to the deposited dose. While a further increase in the splitting factor augment the number of split tracks passing through the collimation system, it concurrently extends the time spent in the collimation system per event. Hence, increasing the splitting factor does not enhance simulation efficiency further.

4 Discussion

We presented a model to evaluate the simulation running time required to achieve a specific statistical uncertainty (5%) in the OOF region. The trend of the curves aligns with the current state-of-the-art [11, 12].

The dose distribution generated by the MC simulation, which

replicates the radiotherapy session, exhibits differences when compared to the dose map calculated by the TPS, and suggesting a potential need for further refinement in the MC model. However, even though a simulation is fine-tuned according experimental data, previous research highlighted that large discrepancies peaking to 30% may remain with respect to the TPS [13].

In the far OOF regions, the required simulation running time peaks at 200 days for a single thread. This time can be significantly reduced, by employing multi-job simulations (about one day on our cluster). Despite this acceleration, training a deep-learning algorithm still demands the computation of around hundred images. Creating such a patient dataset, even with the support of a cluster, remains a time-consuming process taking several months. This highlights the need to strive for efficiency improvements in Monte Carlo simulation performance.

This statistical assessment will also provide a reference for calculation efficiency in OOF regions. This efficiency will serve as a ground truth for estimating potential gains in efficiency through the application of variance reduction methods [14]. A preliminary evaluation indicates that, even if allowing a 1.4 efficiency gain, Compton splitting alone may not be dedicated or sufficiently effective to enhance simulation efficiency. Alternative pseudo-deterministic VRMs, as SeTLE [15], or deep learning-based techniques to denoise low-statistic Monte Carlo dose distribution maps [16] could improve further simulations efficiency.

5 Conclusion

This study introduces a MC simulation model for the Elekta Versa HD LINAC using GATE. The model is used to generate a dose map according to a DICOM RT-plan, and is then employed to estimate simulation running times in the OOF region for various collimation system apertures. It was shown that achieving a precise simulation with a 5% statistical uncertainty demands around 200 days of simulation on a single thread. The proposed Compton splitting method allowed to 1.4 efficiency gain. These data can serve as a benchmark to improve MC simulation efficiency or for dataset creation to train deep-learning algorithms tailored to LINAC applications.

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