TCP (50.7% to 50.5% and 50.2%). No relevant change was observed when including range errors in the robust evaluation of the patient with the worst clinically acceptable coverage (< 0.1 GyRBE).

Conclusion

Reducing the robust optimization setting from 3%/5mm to 3%/2mm reduces OAR dose and can be safely implemented in our clinical practice for HNC IMPT treatment using a 5-point mask, a robotic couch and daily CBCT.

Figure 1: Average dose volume histogram of 25 robust evaluations of a single patient for a plan optimized with a 5mm, 3mm and 2mm robustness shift.

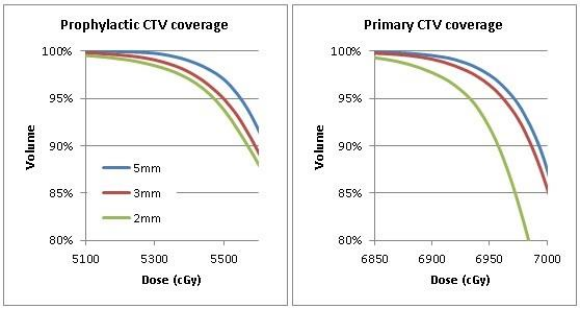


Table 1: Dose differences of 25 robust evaluations between a plan optimized with a 5mm robustness margin versus 3mm and 2mm. *: p < 0.05 in Wilcoxon signed rank test.

	5mm	3mm	Δ	2mm	Δ
Organ at risk dose (Mean, Gy_{RBE})					
Parotid ipsi	21.1	19.6	1.5*	18.5	2.6*
Parotid contra	10.2	9.0	1.2*	8.3	1.9*
Submand ipsi	40.8	40.2	0.5*	39.2	1.5*
Submand contra	25.4	24.5	0.9*	23.5	1.9*
Inferior PCM	19.1	17.7	1.4*	16.7	2.4*
Superior PCM	34.3	33.1	1.2*	31.9	2.4*
Cricopharyngeus M.	14.6	12.8	1.8*	11.8	2.8*
Supraglottic Larynx	23.6	21.7	1.9*	20.3	3.3*
Oral cavity	20.5	19.2	1.3*	18.4	2.1*
Target coverage					
D99 CTV7000 (Mean, Gy_{RBE})	69.0	68.7	0.3*	68.4	0.6*
D99 CTV5425 (Mean, Gy_{RBE})	54.7	54.0	0.7*	53.5	1.2*
D98 > 95% CTV7000 (%)	100.0	100.0	0	100.0	0
D98 > 95% CTV5425 (%)	100.0	100.0	0	100.0	0
TCP* (Mean, %)	50.7	50.5	0.2	50.2	0.5*

Proffered Papers: PH 2: Applications of dose modelling and calculation

OC-0087 A new method for modelling the tongue-and-groove in treatment planning systems

V. Hernandez[1], J.A. Vera-Sánchez[1], L. Vieillevigne[2], C. Khamphan[3], J. Saez[4]

[1]Hospital Universitari Sant Joan de Reus, Medical Physics, Reus, Spain; [2]Institut Claudius Regaud - Institut Universitaire du Cancer de Toulouse & Centre de Recherche et de Cancerologie de Toulouse, Medical Physics, Toulouse, France; [3]Institut Sainte Catherine, Medical Physics, Avignon, France; [4]Hospital Clinic de Barcelona, Radiation Oncology, Barcelona, Spain

Purpose or Objective

Accurate modeling of the MLC by TPSs is known to be a crucial aspect in IMRT dose calculations, the most important characteristics being MLC transmission, the leaf tip end and the tongue-and-groove (TG). However, TPSs typically model the TG by extending the projections of the leaf sides by a certain constant width and it has been found that this model may produce discrepancies of as much as 7-10% in the calculated average doses [1]. The purpose of this study is to introduce and validate a new method for modeling the TG that uses a non constant TG width.

Material and Methods

We provide the theoretical background with analytical expressions and a detailed methodology to determine the optimal shape of the TG width from measurements of the aSG (asynchronous sweeping gap) tests with a Farmer ion chamber [1]. For a difference between adjacent leaves equal to *s*, the total area of the TG profile to be subtracted from the fluence map, A(s), can be obtained from measurements. The TG width w(s) can then be determined as the first derivative of A(s) and fitted to a function with two parameters a1 and a2. Parameter a1 represents the TG width for large *s* values and a2 introduces a reduction in the TG width near the leaf tip end to account for the increased transmission through the tongue due to the rounded leaf design.

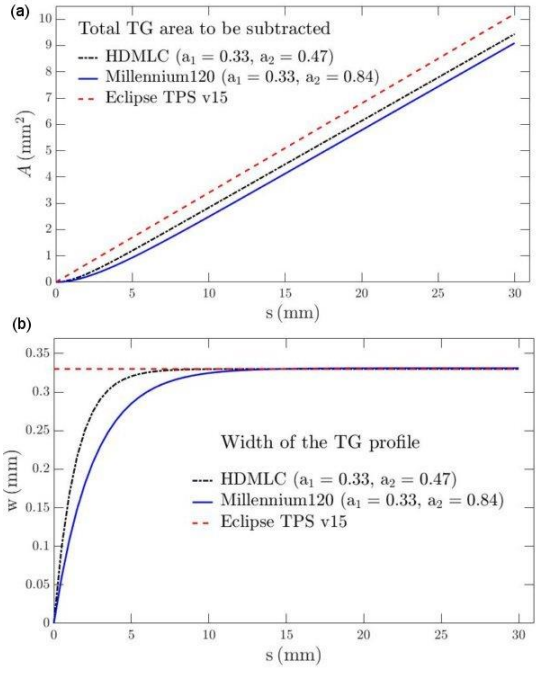
An MLC model similar to the one used by the Eclipse TPS was implemented in MATLAB. Calculated dose maps were obtained by convolution with a dose kernel [2] and were compared to Eclipse v15 calculations and to measurements from six Varian linacs from 4 different institutions: 3 linacs (2100CD, iX, TrueBeam) with the Millennium120 MLC and 3 (Trilogy and 2 TrueBeamSTx) with the HDMLC.

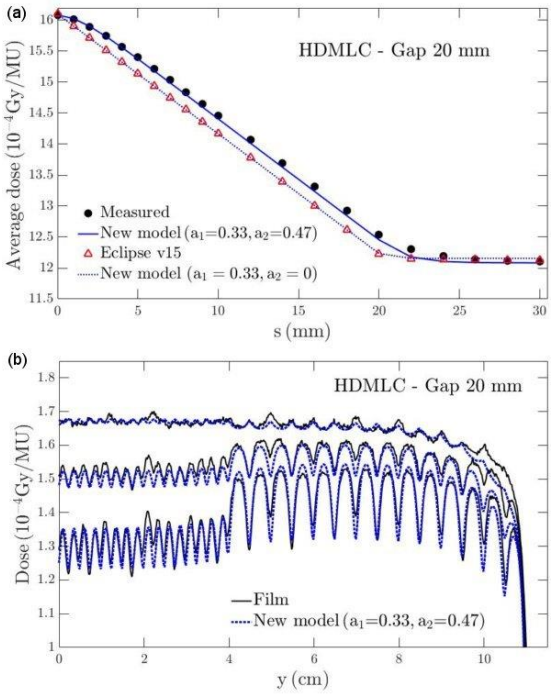
Results

Parameters a1 and a2 were determined from the aSG tests. Parameter a1 was 0.33 mm for both MLC models, in agreement with the value used by Eclipse. Parameter a2 was 0.84 mm^2 and 0.47 mm^2 for the Millennium120 and the HDMLC, respectively (Fig 1).

Eclipse produced large discrepancies with respect to measurements, with differences in average doses as high as 4% and 6.5% for the Millennium120 and the HDMLC, respectively, and these calculations were accurately reproduced with the new model for a2=0. On the other hand, with the experimentally determined parameters a1 and a2, the new model produced calculations in close agreement with measurements, with all differences in average doses <1% (Fig 2a).

The new model was also in good agreement with radiochromic film results, recreating the fine spatial details associated to TG effects (Fig 2b). We also found that the parameters a1, a2 depend solely on the MLC design and are independent of the specific MLC device.





Conclusion
A new method was presented that greatly improves the TG modeling. This method can be easily implemented in commercial TPSs and has the potential to further increase their accuracy, especially for MLCs with rounded leaf ends.
This method is currently in patent pending status.
[1] Phys Med Biol 62;2017:6688–6707
[2] Med Phys 9(37);2010:4634-4642

OC-0088 A pilot study on the sensitivity of common beam modeling parameters in Eclipse
M. Glenn[1], D. Followill[1], R. Howell[1], J. Pollard-Larkin[1], S. Zhou[2], S. Kry[1]
[1]The University of Texas MD Anderson Cancer Center, Radiation Physics, Houston, USA ; [2]The University of Texas MD Anderson Cancer Center, Biostatistics, Houston, USA

Purpose or Objective
Recently, the accuracy of beam modeling parameter configuration has come into question, as IROC Houston has determined that considerable treatment planning system errors exist among institutions that fail its phantom credentialing test. The aim of this study was to determine the calculated dosimetric effects caused by the variations of several common beam modeling parameters in the Eclipse treatment planning system, based on realistic parameter values used by the radiotherapy community at large (as collected across the United States from over 500 institutions).
Material and Methods
In this pilot study, a clinical 6 MV beam model for a Varian Clinac 2100iX was adapted in Eclipse (AAA 13.5.35) to match reference data collected from the IROC Houston site visit program, thus modeling an "average" performance linear accelerator. 23 output measurements, including PDD values, off-axis factors, and 12 square test fields ranging from 2x2 to 30x30 using both primary collimator- and multileaf collimator (MLC)-defined fields, were assessed in order to characterize the goodness of fit with respect to the reference output data. Once the model was verified, ten clinically acceptable head and neck phantom IMRT plans utilizing both dynamic MLC and VMAT techniques were recalculated following modification of the dosimetric leaf gap (DLG), MLC transmission factor, and effective target spot size parameters. Parameter values chosen represented the 2.5th, 25th, 50th, 75th, and 97.5th percentiles of IROC survey responses in order to encompass the realistic extent of modeling variance in the radiotherapy community. Values examined for variations were the minimum dose, maximum dose, and mean dose to TLD structures, primary target volumes, and the organ at risk in the head and neck phantom.
Results
The "average" performance 6 MV beam model represented the IROC reference data very well, having an average error of only 0.28%. Of the parameters tested herein, the dose calculations using the AAA algorithm were most sensitive to changes in the DLG, which ranged in value from 0.048 cm to 0.235 cm and produced changes from -6% to +3% of the calculated dose to identified structures. MLC transmission and effective target spot size contributed less significant changes, yielding up to ±1% difference based on the most extreme values tested.
Conclusion
Based on these initial findings, careful consideration should be made when commissioning clinical beam models, especially with respect to the measurement of the DLG. In this work the use of parameter values that are clinical but are still far from what is agreeable by the radiotherapy community are shown to potentially contribute to clinically significant changes in dose calculations.

OC-0089 Mitigating inherent noise in Monte-Carlo dose distributions using UNet
U. Javaid[1], J. Lee[1], K. Souris[1], S. Huang[2], J. Madrigal[1]
[1]UCLouvain, IREC/MIRO, Brussels, Belgium ; [2]Memorial Sloan Kettering Cancer Center, Physics, New York, USA

Purpose or Objective
Monte-Carlo (MC) algorithms offer accurate modeling of dose calculation by simulating the transport and interactions of many particles through the patient geometry. However, given their random nature, the resulting dose distributions from MC algorithms are affected by statistical uncertainty (*noise*), which renders it difficult to make accurate clinical decisions. This issue can be addressed to some extent using a huge number of simulated particles but it is computationally expensive. Therefore, there is a trade-off between the computation time and the noise level in MC dose distributions. Previous work on denoising the MC dose distributions is based on smoothening the distributions. In this work, we address the mitigation of noise inherent to MC dose distributions using UNet – an encoder-decoder styled fully convolutional neural network, which allows fast and fully automated denoising of whole-volume dose distributions.
Material and Methods
We propose UNet that has three down-sampling layers for denoising whole-volume MC dose distributions. Mean-squared error (MSE) is used as loss function to train the model. MSE measures the pixel intensity difference between the denoised and reference image by summing all the squared differences. Lower the value of MSE, the similar the two images under observation therefore, we use it to evaluate the optimal weights for our model in its training phase. We train our model on proton therapy MC dose distributions of different tumor sites (*brain, head & neck, liver, lungs, prostate*) acquired from **31** patients. In training phase, we use three different noise realizations per patient to better model the noise inherent to MC dose distributions. We train the network in 3D manner with input MC dose distributions simulated using **1e^{6}** particles while keeping **1e^{9}** particles as reference.
Results
After training, our model successfully denoises new MC dose distributions. In the example test case (Figure 1), we