Iranian Journal of Medical Physics

ijmp.mums.ac.ir

Assessment of Different Training Methods in an Artificial Neural Network to Calculate 2D Dose Distribution in Radiotherapy

Mahdi Saeedi-Moghadam[1, 3], Kamal Hadad[3], Banafsheh Zeinali-Rafsanjani[1,2*], Reza Jalli[1]

1. Medical Imaging Research Center, Shiraz University Of Medical Sciences, Shiraz, Iran
2. Nuclear Medicine and Molecular Imaging Research Center, Shiraz University of Medical Sciences, Shiraz, Iran
3. Nuclear Engineering Department, School of Mechanical Engineering, Shiraz University, Shiraz, Iran

ARTICLE INFO

Article type:
Original Article

Article history:
Received: Apr 08, 2019
Accepted: Sep 04, 2019

Keywords:
Simulation Training
Radiation Dosage
Radiotherapy Planning
Computer-Assisted

ABSTRACT

Introduction: Treatment planning is the most important part of treatment. One of the important entries into treatment planning systems is the beam dose distribution data which maybe typically measured or calculated in a long time. This study aimed at shortening the time of dose calculations using artificial neural network (ANN) and finding the best method of training the ANN using Monte Carlo-N-particle (MCNP5) modeling.
Material and Methods: Back-propagation learning algorithm was applied to design the neural network. The ANN was trained by MCNP5 calculations, and different kinds of methods were tested to determine the best method for training. In order to evaluate the accuracy of the ANN, the beam profiles and percentage depth dose (PDD) in the field size of 15×15 cm^2 were anticipated by ANN using various training methods. Eventually, the results were compared with those obtained from the MCNP5 code.
Results: There were good agreements between the results of comparing MCNP5 calculations with experimental measurements. Among the different training methods, Trainbfg had the least error for calculation of PDD and beam profile.
Conclusion: The best training method was found to be Trainbfg, and the results revealed the sufficient accuracy of the modeled ANN.

► *Please cite this article as:*
Saeedi-Moghadam M, Hadad K, Zeinali-Rafsanjani B, Jalli R. Assessment of Different Training Methods in an Artificial Neural Network to Calculate 2D Dose Distribution in Radiotherapy. Iran J Med Phys 2020; 17: 114-119. 10.22038/ijmp.2019.39429.1522.

Introduction

An artificial neural network (ANN) is a MATLAB calculating model that contains a group of interconnected neurons. As it is obvious from the name, this network has been inspired by the animal's central nervous system. The function of this network is similar to that of the brain. Some entries should be inserted to the network which using the activation function transfer to the other neurons and calculate the result. The main components of a neural network are entries, weights, adding function, activation function, and output [1, 2]. This model is used to solve a wide variety of problems in different fields, such as engineering, mathematics, medicine, business, economics, aviation, and robotic [3-8].

There are different kinds of neural network models, including feed-forward networks, feedback networks, network layers, and perceptrons. Just like a brain that learns from experience, neural network requires sufficient representative examples which enable it to generalize to new cases. Therefore, in the first step, the network should be trained by sufficient information. This network can solve the problems in a pretty short time; accordingly, it is mostly used in time-consuming computations [9].

In this study, ANN was utilized to help the dose calculations in radiotherapy treatment planning. Nowadays, treatment planning is the most important part of the treatment. Many kinds of treatment planning systems have been developed to plan the treatment in the best manner to deliver the prescribed dose to the target and spare the organ at risk. One of the important entries to these systems besides the machine and patient data is the beam dose distribution data, such as central axis percentage depth dose and off-axis ratios [10]. These data can be experimentally measured by a phantom and a dosimetric device, such as a diode or can be calculated by a calculation code, including Monte Carlo codes.

These methods are quite precise; however, they are very time consuming as well. For instance, the Monte Carlo N-Particle Transport (MCNP) code may require hours to calculate the dose distribution precisely in a simple homogeneous phantom which is completely irrational in clinical use. An alternative method is using artificial neural network to shorten the dose calculation time.

In 2004, Blake used ANN to calculate the dose distribution of a Varian 2100c radiotherapy machine. The experimentally measured percentage depth dose

*Corresponding Author: Tel:+98 712270238; Fax: +98 7132289113; E-mail: b.zeinali.r@gmail.com

(PDD) of 6 and 10 MeV x-ray was used to train the network [11]. In 2005, Monte Carlo calculated data of a cobalt machine was utilized by Mathieu et al. to train the network [12]. In the same line, Vasseur et al. (2008) planned a network for inhomogeneous water phantom and TA6V4. In their study, the cobalt source and an inhomogeneous phantom were modeled in DOSXYZ nrc code, and the results of this simulation were used to train the network [13]. Furthermore, Kalantzis et al. (2011) employed the ANN to reconstruct the dose map in intensity-modulated radiotherapy (IMRT). In their study, the ANN was trained with fluence and dose maps of IMRT, which was obtained by the electronic portal imaging device [14]. In the same year, Hadad et al. used the MCNP dose calculation information on Varian 2100c radiotherapy machine for training the network [15]. This network was utilized to fasten the dose calculation of a homogeneous phantom.

To the best of our knowledge, there has been no study utilizing the MCNP5 code to model an inhomogeneous phantom to train the ANN to calculate the 2D dose distributions of 6 Mev x-rays. Therefore, this study aimed at assessing the most suitable method for training the ANN using MCNP5 code to calculate the 2D dose distribution of 6 MeV x-rays in an inhomogeneous phantom.

Materials and Methods

A simulated linear accelerator (Linac-Varian 2100c) was used to calculate the information which should be applied to train the neural network model. The Linac was simulated regarding all details, such as primary and secondary collimators, target, exit window, and flattening filter [15, 16]. Figure 1 demonstrates the MCNP5 scheme of the Linac head.

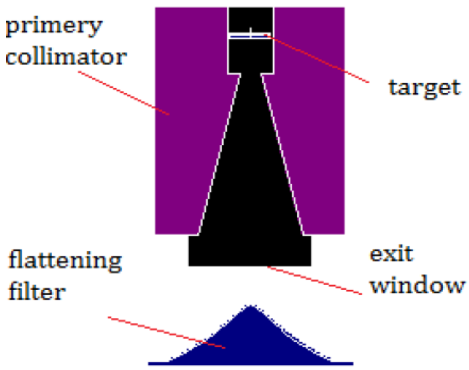

Figure 1. A plot of the simulated Linac head

The accuracy of the Monte Carlo model was verified by comparing the results of PDD calculations with those of the experimental measurements of the 6 MeV Linac in a homogeneous phantom. The experimental measurements of PDD were done using gafchromic film and a homogeneous phantom [15].

In this study, an inhomogeneous phantom was modeled using MCNP5. The MCNP codes are wildly used for radiation protection purposes or simulating the medical situation to evaluate the radiation dose [17-25]. The phantom is a 30×30×30 cm3 water phantom and a cork layer with the dimension of 30×30×1 cm^3 in the depth of 5 to 6 cm of water (Figure 2).

Figure 2. A cross-section of the modeled inhomogeneous phantom

To verify the model in an inhomogeneous phantom, the experimental measurements of PDD was performed in an inhomogeneous phantom with the same features of a simulated phantom (Figure 2). Subsequently, the results of the calculations and measurements were compared with each other. The PDD measurements and calculations were performed in 2 field sizes of 10×10 and 18×18 cm^2.

Calculations

After the verification of the model, ANN was trained by the model calculations. The PDD and beam profiles of the model were measured in the depth of 5.5 cm in the middle of the cork inhomogeneity in 7 field sizes (8×8 to 20×20 cm^2 with the steps of 2 cm). The output results of MCNP5, PDD, and beam profile calculations in the mentioned field sizes were used to train the network. Moreover, Multilayer Perceptron Network with a backpropagation learning algorithm was employed to design the neural network. The entries on the network were dimension, dose distribution, field size, and density. Field sizes of 12×12 and 18×18 cm^2 were used as test patterns and the field size of 15×15 cm^2 was utilized to assess the accuracy of ANN function. Figure 3 illustrates both MCNP and ANN steps.

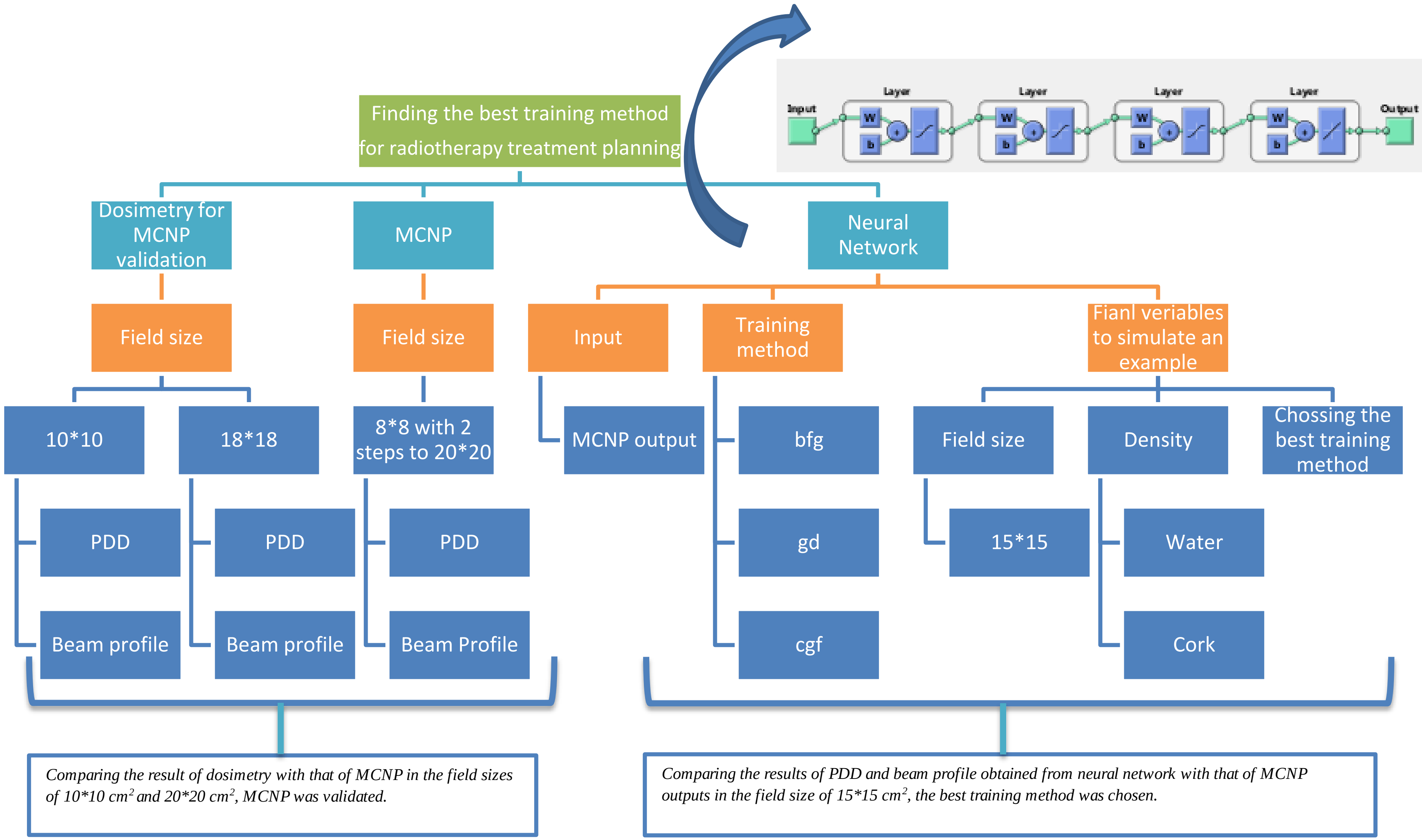

Figure 3. Different steps in this study including the experimental measurement of PDD and beam profile in two field sizes, MCNP calculation of PDD and beam profile, validation of Monte Carlo simulation, application of MCNP output as ANN inputs, Neural network training, and finally finding the best training method

After training the network and with regard to the train and network output, the number of layers and neurons increased properly to decrease the error to a rational level. Finally, the best design was obtained with 4 layers, including 3 hidden layers and 1 output layer with neuron numbers of 35, 15, 8, and 1, respectively.
Due to the nonlinearity problem, hyperbolic tangent function (tanh) was used as an activation function of latent layers; in addition, because of the unlimited output, a pure linear function (purlim) was employed as the activation function of the output layer.

Table 1. Different types of algorithms for training the ANN

MATLAB command	Description
Bfg	BFGS Quasi-Newton backpropagation
Cgf	Conjugate gradient backpropagation with Fletcher-Reeves restarts
Gd	Gradient-descent backpropagation

The suitable training rate was selected considering the convergence and speed of the network training.

Different kinds of methods were tested in order to find the best and optimized method for training the model (Table 1).

Results

Figure 4 illustrates the results of the PDD experimental measurements and calculations for verifying the MCNP code in an inhomogeneous phantom in two field sizes of 10×10 and 18×18 cm^2 and SSD of 100 cm.

Different types of training methods (Table 1) were used in order to find the best method to train the network. The results of PDD from different training methods in an inhomogeneous phantom and field size of 15×15 cm^2 are illustrated below (Fig 5-7).
Table 2 summarizes the results of the percentage difference between ANN and MCNP5 outputs.

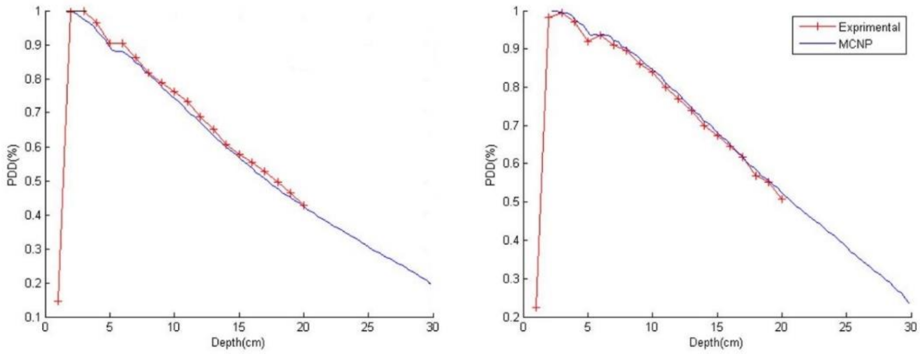

Figure 4.PDD of 6 MeV x-rays, A) Field size of 10×10 cm^2, B) Field size of 18×18 cm^2, SSD of 100 cm in an inhomogeneous phantom

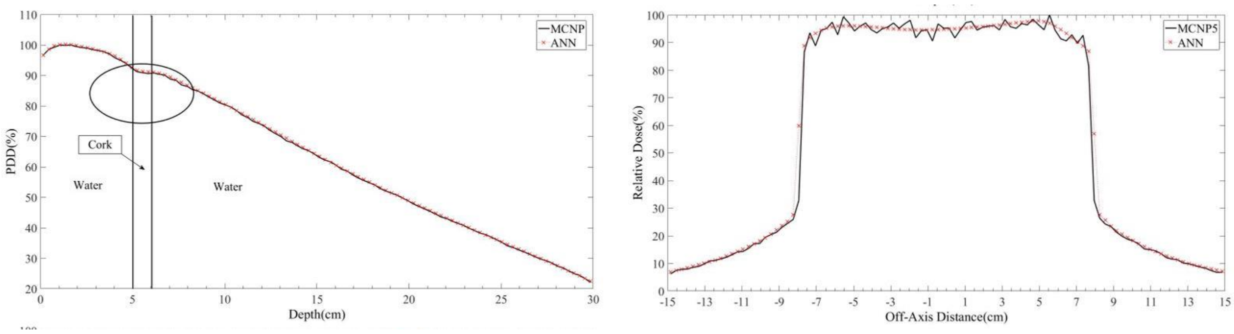

Figure 5. ANN with bfg training algorithm and MCNP5 results of 6 MeV x-rays PDD and beam profile, the field size of 15×15 cm^2 and SSD of 100 cm

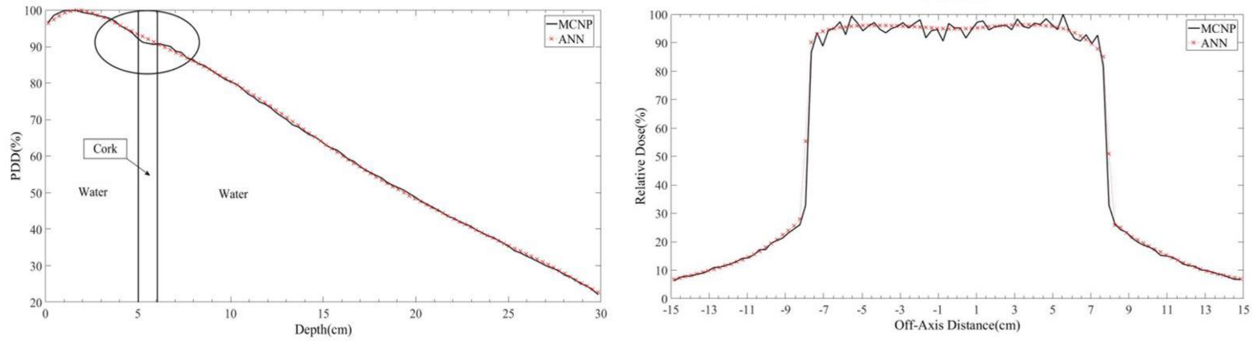

Figure 6. ANN with cgf training algorithm and MCNP5 results of 6 MeV x-rays PDD and beam profile, the field size of 15×15 cm^2 and SSD of 100 cm

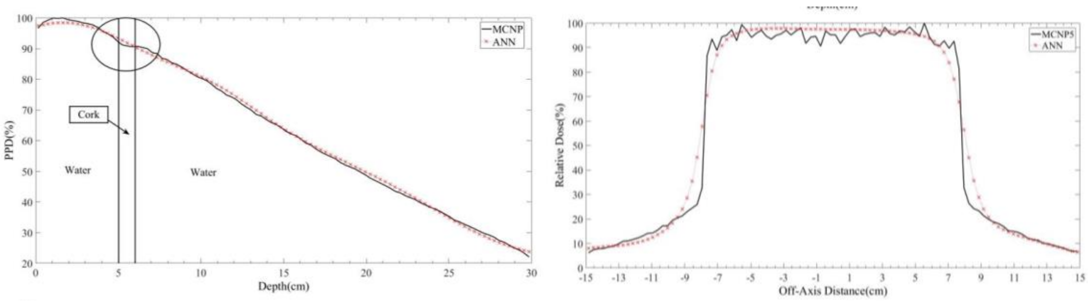

Figure 7. ANN with gd training algorithm and MCNP5 results of 6 MeV x-rays PDD and beam profile, the field size of 15×15 cm^2 and SSD of 100 cm

Table 2. Results of the percentage difference between ANN and MCNP5 for PDD and beam profile in the field size of 15×15 cm^2

Training algorithm	Error of inhomogeneous region for PDD (%)	Error of homogeneous for PDD(%)	Error of beam profile (%)(summit)	Error of beam profile (%)(tail)
bfg	0.86	0.6	4.50	1.10
cgf	1.58	1.58	5.14	1.15
gd	4.96	2.37	8.89	2.15

Discussion

The previous studies have shown that ANN could successfully estimate the radiation dose in unknown points [26]. This ability can be very helpful in radiotherapy treatment planning where it is important to know the radiation dose distribution in different filed sizes.

Although a good knowledge of therapy beam dose distribution in all field sizes can help in efficient treatment planning, it requires special devices to measure the dose which can be very time-consuming. Modeling is one of the methods which do not need any devices to evaluate the dose distribution; however, accurate modeling is very time consuming and is not suitable for daily clinical use.

Recently, ANN has been shown to be very fast and accurate to replicate the results of complicated modeling. Therefore, the most accurate methodology was used to model and calculate dosimetry parameters (i.e., MCNP5 Monte Carlo Coder). Subsequently, ANN was employed to create a tool for fast and accurate dose evaluation. Moreover, our method was implemented to calculate the 2D dose distribution of 6 MeV x-rays in an inhomogeneous phantom.

It should be noted that some of the previous studies used homogenous phantom which might not be attributed to the inhomogeneous regions [11]. Some of the other studies that employed inhomogeneous phantoms could not provide a good agreement between the output of ANN and experimental or calculation results in deep regions of the phantom [13]. This study introduced a training method that helped to provide good results of dose distribution even in a deep area of phantom showing better accuracy in dose calculation.

According to Figure 3, a good agreement is seen between the results of MCNP5 and those of the experimental measurements. The maximum error for the field sizes of 10×10 cm^2 and 18×18 cm^2 were 2.8% and 1.8%, respectively. According to the International Atomic Energy Agency and American Association of Physicists in Medicine, the acceptable error in the central axis of an inhomogeneous phantom between measurements and calculations should be less than 3% and 5%, respectively [26- 28]. Since the errors between measurements and calculations were less than 3% in all points, the accuracy of the model was verified in this study. A notch was observed in both curves at 5 cm where the cork inhomogeneity existed. This is due to the changes in the density of the phantom material in the inhomogeneity interface region.

According to figures 4-6 and table 2, it is clear that the Trainbfg training method has the least error of 0.6% and 0.86% in the homogeneous and inhomogeneous region, respectively. Accordingly, it can be regarded as the most suitable method for PDD calculations. After Trainbfg, Traincgf training method with the percentage error of almost 1.58% in inhomogeneous and homogeneous region can be performed well in the second place. However, Traingd was the worst method to train the ANN with a percentage error of 4.96%.

Table 2 shows the percentage differences in the summit and tail for Trainbfg training method which were 4.50 and 1.10, respectively. As can be seen in figures 4-6 and table 2, this training method also obtains the least error for beam profile calculations and it is the most suitable method for training ANN. The second suitable training method is Traincgf with the percentage errors of 5.14, 1.15% in summit and tail, respectively. However, the worst training method was Traingd with the percentage errors of 8.89 and 2.15% in the summit and tail respectively.

Conclusion

This study revealed that Trainbfg was the best training method with the percentage error of 0.6% in PDD calculations and percentage errors of 4.5 and 1.1% in summit and tail regions in beam profile calculations. Therefore, this training technique can accurately calculate the PDD and beam profile. The calculated dose distribution in the field size of 15×15 cm^2 using ANN model was accurate enough; accordingly, it is reliable for 2D dose calculations in order to decrease the calculation time in clinical applications.

Acknowledgment

The present study was sponsored by a research grant (number 98-01-48-19465) from the Medical Imaging Research Center, Shiraz University of Medical Sciences, Shiraz, Iran.

References

1. Zurada JM. Introduction to Artificial Neural Systems. New edition ed: Jaico Publishing House; 2012.
2. Kriesel D. A brief introduction to neural networks 2005. Available from: http://www.dkriesel.com/en/science/neural_networks.
3. Nakamura E. Inflation forecasting using a neural network. economics letters. 2005;86:373-8.
4. Mano M, Capi G, Tanaka N, Kawahara S. An artificial neural network based robot controller that
5. Fernandez FG, Santos ISL, Martinez JL, Izquierdo SI, Redondo FL. Use of Artificial Neural Networks to Predict The Business Success or Failure of Start-Up Firms. Artificial neural networks-architecture and applications. 2013:245-56.
6. Bondarets A, Kreerenko O. Using of Artificial Neural Networks (ANN) for Aircraft Motion Parameters Identification. In: Palmer-Brown D, Draganova C, Pimenidis E, Mouratidis H, editors. Engineering Applications of Neural Networks. Communications in Computer and Information Science. Springer Berlin Heidelberg. 2009;43:246-56.
7. Nasr MS, Moustafa MAE, Seif HAE, El Kobrosy G. Application of Artificial Neural Network (ANN) for the prediction of EL-AGAMY wastewater treatment plant performance-EGYPT. Alexandria Engineering Journal. 2012;51(1):37-43.
8. Himmelblau D. Applications of artificial neural networks in chemical engineering. Korean J Chem Eng. 2000;17(4):373-92.
9. Haykin S. Neural networks and learning machines. 3rd ed: Pearson; 2009.
10. IAEA. Review of radiation oncology physics: A handbook for teachers and students. IAEA publication; 2012.
11. Blake SW. Artificial neural network modelling of megavoltage photon dose distributions. Phys Med Biol. 2004;49(12):2515-26.
12. Mathieu R, Martin E, Gschwind R, Makovicka L, Contassot-Vivier S, Bahi J. Calculations of dose distributions using a neural network model. Phys Med Biol. 2005;50(5):1019-28.
13. Vasseur A, Makovicka L, Martin E, Sauget M, Contassot-Vivier S, Bahi J. Dose calculations using artificial neural networks: a feasibility study for photon beams. Nuclear Instruments and Methods in Physics Research Research. 2008;266:1085-93.
14. Kalantzis G, Vasquez-Quino LA, Zalman T, Pratx G, Lei Y. Toward IMRT 2D dose modeling using artificial neural networks: a feasibility study. Med Phys. 2011;38(10):5807-17.
15. Hadad K, Moshkriz M, Nedaie H. SU-E-T-703: An Artificial Neural Network Treatment Planning System Based on Monte Carlo Calculation for VARIAN 2100C LINAC. Medical Physics. 2011;38(6):3652.
16. Varian Medical system. Treatment Planning Systems.Available from: www.varian.com.
17. Saeedimoghadam M, Zeinali B, Kazempour M, Jalli R, Sina S. Monte Carlo Study of Several Concrete Shielding Materials Containing Galena and Borated Minerals. Iranian Journal of Medical Physics. 2017;14(4):241-50.
18. Zeinali-Rafsanjani B, Faghihi R, Mosleh-Shirazi M, Saeedi-Moghadam M, Jalli R, Sina S. Effect of age-dependent bone electron density on the calculated dose distribution from kilovoltage and megavoltage photon and electron radiotherapy in paediatric MRI-only treatment planning. The British journal of radiology. 2018;91(1081):20170511.
19. Zeinali-Rafsanjani B, Mosleh-Shirazi MA, Haghighatafshar M, Jalli R, Saeedi-Moghadam M. Assessment of the dose distribution of Minibeam radiotherapy for lung tumors in an anthropomorphic phantom: a feasibility study. Technology and Health Care. 2017;25(4):683-92.
20. Tayebi M, Shooli FS, Saeedi-Moghadam M. Evaluation of the scattered radiations of lead and lead-free aprons in diagnostic radiology by MCNPX. Technology and Health Care. 2017;25(3):513-20.
21. Hadad K, Saeedi-Moghadam M, Zeinali-Rafsanjani B. Voxel dosimetry: Comparison of MCNPX and DOSXYZnrc Monte Carlo codes in patient specific phantom calculations. Technology and Health Care. 2017;25(1):29-35.
22. Kazempour M, Saeedimoghadam M, Shooli FS, Shokrpour N. Assessment of the radiation attenuation properties of several lead free composites by Monte Carlo simulation. Journal of biomedical physics & engineering. 2015;5(2):67.
23. Zeinali-Rafsanjani B, Faghihi R, Mosleh-Shirazi M, Mosalaei A, Hadad K. Revision of orthovoltage chest wall treatment using Monte Carlo simulations. Technology and Health Care. 2017;25(3):413-24.
24. Zeinali-Rafsanjani B, Mosleh-Shirazi M, Faghihi R, Karbasi S, Mosalaei A. Fast and accurate Monte Carlo modeling of a kilovoltage X-ray therapy unit using a photon-source approximation for treatment planning in complex media. Journal of Medical Physics/Association of Medical Physicists of India. 2015;40(2):74.
25. Zeinali Rafsanjani B, Faghihi R. Calculating of Dose Distribution in Tongue Brachytherapy by Different Radioisotopes using Monte Carlo Simulation and Comparing by Experimental Data. Iranian Journal of Medical Physics. 2011;8(2):35-44.
26. Mathieu R, Martin E, Gschwind R, Makovicka L, Contassot-Vivier S, Bahi J. Calculations of dose distributions using a neural network model. Physics in Medicine & Biology. 2005;50(5):1019.
27. IAEA. Commissioning of radiotherapy treatment planning systems: Testing for typical external beam treatment techniques. Austria: TECDOC-1583; 2008.
28. Fraass B, Doppke K, Hunt M, Kutcher G, Starkschall G, Stern R, et al. Quality assurance for clinical radiotherapy treatment planning. Medical Physics. 1998;25(10):1773-829.