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Metaheuristic Algorithm for Constrained Optimization in Radiation Therapy Treatment Planning: Design and Performance Comparison

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Abstract

Radiation Therapy (RT) plays a pivotal role in the treatment of cancer, offering the potential to effectively target and eliminate tumor cells while minimizing harm to surrounding healthy tissues. However, the success of RT heavily depends on meticulous treatment planning that ensures the optimal balance between delivering a sufficiently high dose to the tumor and sparing nearby critical organs. This critical process demands a multidisciplinary approach that combines medical expertise, advanced imaging techniques, and computational tools. Optimization techniques have emerged as indispensable tools in refining RT planning, enabling the precise adjustment of radiation beam arrangements and intensities to achieve treatment objectives while adhering to strict dose constraints. This study focuses on constrained optimization within RT Treatment Planning, utilizing metaheuristic algorithms to improve this process. The research compares three widely-used optimization techniques: Bat Search Optimization (BSO), Bacterial Foraging Algorithm (BFA), and Artificial Bee Colony (ABC). These metaheuristic approaches are evaluated against traditional methods, with evaluation metrics including execution time, convergence, and Dose-Volume Histogram (DVH) outcomes. The experimental results demonstrate that the metaheuristic techniques significantly outperform traditional methods. Among them, BFA delivers the most favorable results, offering minimal convergence time and superior DVH performance. For the unconstrained case ($w_R = 0$, $w_B = 0$), BFA achieved superior tumor coverage with $D_{95}^{PTV} = 65.7$Gy, while maintaining rectum and bladder doses at 72.8Gy and 71.6Gy, respectively. Under constrained conditions ($w_R = 10$, $w_B = 10$), BFA effectively reduced rectum and bladder doses to 67.2Gy and 60.7Gy, with an acceptable $D_{95}^{PTV} = 59.5$Gy —outperforming traditional IMRT, ABC, and BSO in both dose sparing and target coverage. Moreover,

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BFA demonstrated faster execution times and reached convergence within 60 iterations, highlighting its suitability for efficient, high-quality RT treatment planning. These findings underscore BFA's potential for integration into clinical workflows, balancing tumor control and organ-at-risk protection.

Keywords: Metaheuristic Optimization, Beamlet, Organs at Risk, Tumor

1. INTRODUCTION

Intensity-Modulated Radiation Therapy (IMRT) is a widely adopted technique in the field of radiation therapy (RT) [1]. The core principle of radiotherapy involves directing localized radiation toward malignant tumor cells to induce DNA damage, thereby inhibiting their proliferation [2]. IMRT represents an advanced treatment modality that employs external megavoltage radiation beams from linear accelerators, with precise modulation of beam intensity.

IMRT is particularly effective in treating cancers such as prostate and nasopharyngeal malignancies, as it enables the delivery of a concentrated radiation dose to the tumor while minimizing exposure to surrounding healthy tissues [3]. Unlike traditional three-dimensional conformal radiotherapy (3DCRT), which utilizes uniform large beams, IMRT varies the radiation dose across the treatment area by subdividing the radiation field into grid-like units called beamlets [4, 5]. During RT planning, specific dose constraints are established for both the target area and adjacent healthy structures. These constraints are generally defined by overall parameters, such as maximum or minimum allowable doses and dose-volume limits, rather than point-specific doses. Subsequently, an inverse optimization process is applied using numerical methods to determine the optimal beamlet intensities in accordance with the prescribed dose objectives [6].

One of the primary advantages of IMRT is its ability to ensure that the Planning Target Volume (PTV) receives the full prescribed radiation dose, while minimizing the dose delivered to Organs at Risk (OARs) [7]. This is achieved by conforming the radiation beams to the tumor's geometry and adjusting the spatial intensity of the beams to account for both tumor shape and proximity to critical structures. A Multi-Leaf Collimator facilitates this shaping process. In IMRT, the optimization of weight factors is a key aspect of inverse planning. Beamlets, which are small, rectangular segments of the radiation field, serve as the variables in beamlet-based inverse planning. These fluence intensities, often numbering in the thousands, are optimized to ensure appropriate dose distribution while adhering to clinical constraints for OARs.

Optimization algorithms for RT treatment planning can be broadly classified into two categories. The first includes deterministic algorithms, which follow a fixed computational path from a given starting point. Despite their predictability, these algorithms often struggle to escape local minima. Examples include gradient-based methods, such as the Newton-Raphson method, and non-gradient methods, like the Nelder-Mead method. Both have been employed in IMRT and volumetric modulated arc therapy (VMAT) planning [8]. The second category comprises heuristic algorithms, which use adaptive, non-deterministic search strategies. These algorithms enhance the search process by balancing exploration and exploitation, thereby reducing the risk of stagnation in local optima [9].

Traditional RT planning techniques, including inverse planning for IMRT, commonly rely on gradient-based or deterministic algorithms. While effective in some scenarios, these methods may converge prematurely to suboptimal solutions, especially in complex, non-convex search spaces. Moreover, they often demand significant computational resources and may not adequately accommodate patient-specific anatomical variations or evolving clinical requirements.

The present study addresses these limitations by exploring the application of three metaheuristic optimization techniques—BSO, BFA, and ABC—to RT treatment planning. The novelty of this research lies in the integration of these metaheuristic algorithms within the RT planning workflow, enabling a more robust exploration of the solution space. A systematic comparison of the algorithms is conducted, evaluating their performance based on execution time, convergence behavior, and dose-volume histogram (DVH) outcomes.

The paper is organized as follows: Section I outlines the objectives of the study; Section II presents a comprehensive literature review to establish the research context; Section III describes the methodology and the implementation of the optimization algorithms in RT planning; Section IV discusses the results and evaluates the comparative performance of the methods; and Section V concludes with key findings and suggestions for future research directions.

2. LITERATURE SURVEY

This research draws from a thorough examination of recent academic journals and studies that have informed its development. Several of these pivotal works are outlined below, contributing significantly to the study's foundation and direction.

In the journal [10], the authors elaborate on the creation, execution, and resolution of a dependable Direct Aperture Optimization (DAO) model intended for IMRT planning in cancer treatment. Their notable contribution to operations research is reflected in the introduction of an innovative mixed-integer programming model that incorporates both mechanical and clinical prerequisites relevant to modern treatment equipment. Considering the model's complexity, a novel heuristic is proposed to generate feasible treatment plans efficiently, demonstrated on five clinical patient datasets. In the study [11], an automated treatment planning approach is presented through the MetaPlanner (MP) algorithm. This algorithm automates the planning process by optimizing hyperparameters using meta-optimization. A derivative-free method is employed to search for weight configurations that minimize a meta-scoring function designed to mimic clinical decision-making, prioritizing dose uniformity, conformity, spillage, and OAR sparing. The algorithm's effectiveness is validated on clinical datasets for both IMRT and VMAT planning, demonstrating comparable or improved outcomes compared to manual VMAT planning.

The idea of superiorization in IMRT treatment planning is introduced in the study [12]. To guide a feasibility-seeking projection method toward a feasible point, superiorization uses linear voxel dose inequality constraints. A nonlinear objective function is optimized through gradient descent steps. The matRad toolbox is used for implementation, providing a foundation for this approach. The framework's effectiveness is evaluated in comparison with feasibility-seeking and nonlinearly constrained optimization methods. DAO in IMRT planning is presented with a mixed-integer nonlinear mathematical framework in the journal [13]. Metaheuristic techniques such as Differential

Evolution (DE) and Particle Swarm Optimization (PSO) are applied to handle the problem's complexity, with the Taguchi method used for algorithm parameter tuning. PSO surpasses DE in treatment quality and computational efficiency, based on experiments with real patient data involving liver tumors.

The journal [14], introduces a novel method called direct angle and aperture optimization, which integrates decisions related to beam directions, intensities, and aperture shapes. DE-based metaheuristic algorithms are developed, and their parameters are optimized using the Taguchi design of experiments. Evaluations on liver cancer cases demonstrate the superiority of the ahdDE-PSO algorithm in generating high-quality treatment plans. In the study [15], the issue of limited solution diversity in IMRT planning is addressed by framing it as a massive combinatorial many-objective optimization problem. A co-evolutionary technique is proposed, combining fine and rough encoding for local exploitation and global exploration, with customized local search algorithms implemented. The suggested approach shows improved performance and faster convergence compared to state-of-the-art algorithms.

The study [16], examines the application of contemporary Bayesian Optimization (BO) techniques in robotic therapy planning. Various BO methods, including Gaussian Process with Expected Improvement (GPEI) and Sparse Axis Aligned Subspace BO (SAAS-BO), are evaluated using IMRT treatment cases and compared with clinical plans and other optimization strategies, focusing on both quality and efficiency. An Intelligent Treatment Planner Network (ITPN) is introduced in the journal [17], utilizing Deep Reinforcement Learning for treatment planning. ITPN adjusts dwell times by mimicking human decision-making to enhance plan quality. The network is trained to optimize dwell times based on a hybrid equivalent uniform dose objective function. The performance of ITPN is shown to surpass that of Inverse Planning Simulated Annealing (IPSA) through comparative analysis. The reviewed journals and studies emphasize notable advancements in IMRT treatment planning, such as the development of DAO models, automated hyperparameter tuning algorithms, superiorization frameworks, and the application of various metaheuristic and deep learning techniques. However, a common limitation across these works is the dependence on deterministic or single-strategy metaheuristic methods, often constrained by computational complexity, limited scalability, or lack of clinical adaptability. Several approaches focus on specific aspects, like beam angle selection or dose distribution, without presenting a comprehensive optimization strategy that balances execution time, convergence efficiency, and clinical feasibility.

Addressing these gaps, the present study systematically evaluates and compares three metaheuristic algorithms—BFA, BSO, and ABC—for constrained IMRT optimization. Unlike previous works, this research emphasizes both computational performance (execution time and convergence speed) and treatment quality metrics (PTV coverage and OAR sparing) using realistic simulated datasets.

3. METHOD

This study aims to enhance the IMRT treatment planning process by integrating a metaheuristic optimization framework within a clinically relevant computational environment. The Computational Environment for Radiotherapy Research (CERR) is employed for RT data generation, treatment plan modeling, and dose calculation. CERR provides a flexible, MATLAB-based framework for simulating realistic clinical scenarios with controllable parameters, making it suitable for comparative optimization studies. Several studies [18, 19], have adopted CERR for similar research purposes, including dose optimization, treatment plan comparison, and evaluation of algorithmic performance in IMRT and other advanced radiotherapy techniques. CERR, built on MATLAB§, enables direct access to dose matrices, anatomical structures, and planning tools essential for research-grade RT planning. In the treatment planning setup, the number and orientation of 6 MV photon beams are determined based on tumor location and patient anatomy, utilizing CT imaging data. To ensure optimal dose delivery, constraints are defined for both the tumor—represented by the PTV—and surrounding critical structures, or OARs. The goal is to achieve maximum dose conformity to the PTV while minimizing exposure to OARs.

Following plan initialization, the intensity of individual beamlets—small subdivisions of radiation beams—is optimized. The dose deposition for each voxel is computed using the Dose Deposition Matrix (DDM), enabling the calculation of voxel-wise dose distributions. The primary objective of this optimization process is to minimize the dose deviation within the PTV while adhering to clinically defined OAR constraints. To optimize beamlet intensities and improve overall treatment quality, three metaheuristic algorithms are applied: ABC, BSO, and BFA. These algorithms are evaluated based on key performance indicators such as execution time, convergence rate, and the quality of the resulting DVH. The best-performing algorithm is selected for further analysis and comparison. Additionally, to improve methodological clarity, a detailed workflow of the proposed method has been presented in the form of a flowchart in FIGURE 1, outlining each step from data preparation to optimization and evaluation.

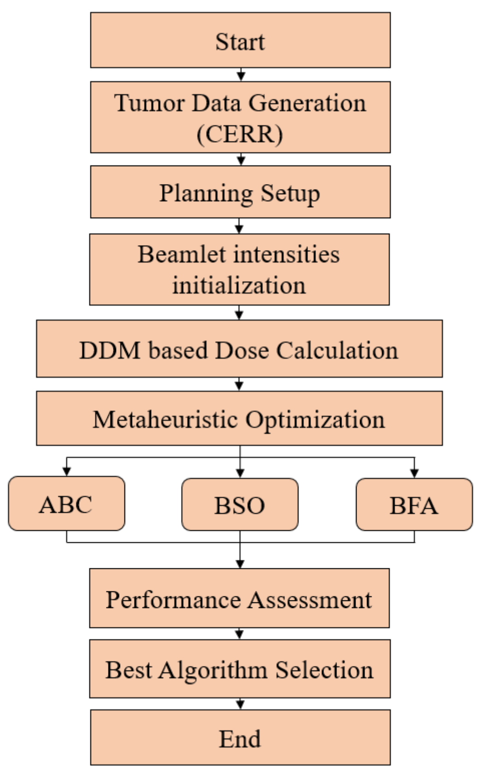


Figure 1: IMRT plan for the prostate as seen on an axial CT scan.

3.1 Treatment Planning Preparation

In our study, we employed the CERR [20], as the treatment planning system. CERR is a software built on MATLAB§that provides a comprehensive package for RT treatment planning. Merits of CERR include its user interface, access to matrices describing dosage deposition, the integration of specialized programming modules, and the availability of MATLAB toolboxes. Based on the specified target and structures of the anatomy, the planner chooses the number and orientation of 6 MV photon beams for treatment with the help of the planning CT scan.

Beams are deliberately arranged in an environment of conformal therapy with uniform radiation fields to avoid beam collisions and reduce overlap with normal OARs. Beams in IMRT plans are broken down into a series of smaller units, usually measuring 0.5 cm × 0.5 cm, but can be as small as 0.2 cm × 0.2 cm. The intensity of these beamlets is then determined using an optimization method. The primary objective of this optimization approach is to maximize the dose delivered to the PTV while restricting the dose absorbed by OARs. FIGURE 2 illustrates a treatment approach for prostate cancer, utilizing a single anterior beam. The beam's upper section illustrates the intensity distribution of its constituent beamlets.

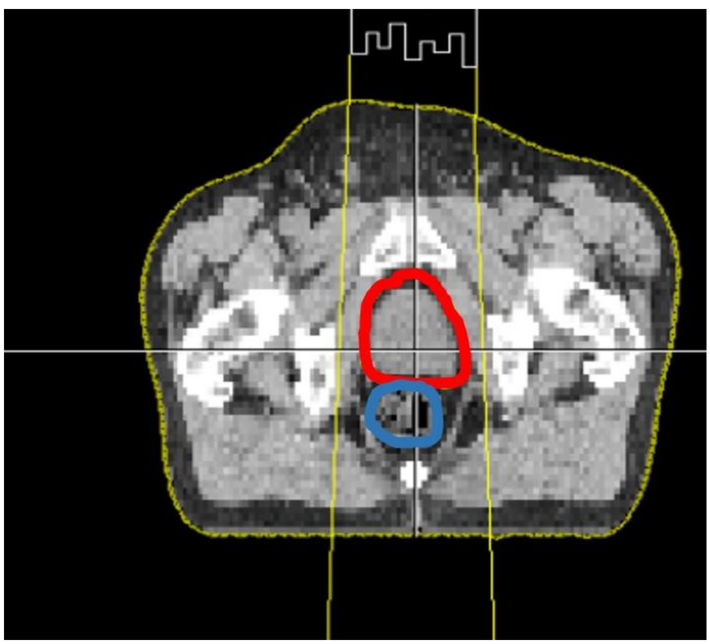


Figure 2: IMRT plan for the prostate as seen on an axial CT scan.

During the process of IMRT treatment planning, it's necessary to define a two-dimensional photon fluence map for each beam. This fluence map consists of controllable individual beamlet intensities. Subsequently, the optimization process involves calculating the dose delivered to each voxel within all structures, thereby providing optimization feedback.

In the IMRT optimization, the objective is to deliver the prescribed dose to the PTV while respecting the maximum dose limits for the OARs. This is mathematically formulated by minimizing the difference between the delivered dose and the prescribed dose for all voxels within the PTV, as shown in Equation (1). Additionally, the maximum dose to each OAR is constrained by its allowable limit, as expressed in Equation (2).

$$f(x) = \arg\min \sum_{i \in T} \frac{(D_i - D_{PTV})^2}{N_T}, \qquad i \in PTV \tag{1}$$

$$s.t\ maxD_j \leq D_{max,OAR_j}, \qquad \forall j \in OAR_j \tag{2}$$

Here, let N_T represent the total voxels within the target structure, also referred to as the PTV. D_{PTV} signifies the recommended dose assigned to the target structure. Within this context, D_j denotes the dose of each specific voxel labelled as "j", while $D_{max,j}$, stands for the maximum permissible dose designated for the respective OAR$_j$. Additionally, "D_i" corresponds to the dose received by voxel "*i*" within the PTV. Equation 1 captures the extent to which the PTV is covered by the required prescription dose, D_{PTV}. The dose attributed to voxel "*i*" demonstrates a linear relationship with the Dose Deposition Matrix (DDM) and can be expressed in Equation (3):

$$D_i = \sum_{k=1}^{M} \sum_{j=1}^{N} A^i_{k,j}.x^i_{k,j} \tag{3}$$

Within this framework, $A_{k,j}$ represents the DDM that characterizes the contribution of dose to pertinent voxels within the structure of interest for unit fluence. The index "*k*" signifies the beam number, while $x_{k,j}$, represents the beamlet intensity "*j*" for beam "*k*". Notably, "*M*" and "*N*" denote the total count of beams, and beamlets associated with "*k*". At its core, the process of IMRT treatment planning can be seen as an optimization problem aimed at minimization. The optimization process revolves around the continuous fluence intensities represented as $x_{k,j}$, for the beamlets. These fluence intensities serve as the decision variables in this context. The DDM was computed using the ORART (Operations Research Applied to RT) toolbox, a CERR extension. The computation relies on Ahnesjo's pencil beam approach [21].

3.2 Optimization Algorithms

Here, we introduce the utilization of metaheuristic algorithms to tackle the challenges of constrained optimization in the realm of RT treatment planning. This approach aims to enhance the effectiveness of IMRT planning by optimizing the arrangement of radiation beams. The goal is to achieve precise tumor targeting while concurrently minimizing the impact on adjacent healthy tissues. The working of optimization techniques are detailed below.

Bat Search Optimization (BSO): BSO, inspired by the behaviours of bats in their search for prey [22], is employed to tackle the complexities of constrained optimization in this medical context. The algorithm mimics the echolocation and movement patterns of bats to navigate through the search space and converge toward optimal solutions. The procedure of BSO for constrained optimization in RT treatment planning can be outlined as follows:

- The optimization process begins with the initialization of a population of virtual "bats" [23]. Each bat represents a potential solution in the search space, which corresponds to different combinations of beamlet intensities.

- Just as bats emit ultrasonic signals for navigation, each bat in the algorithm sends out pulses that represent its potential solution. These pulses are adjusted according to a specified loudness and pulse rate. Bats with louder pulses are more likely to find better solutions.
- Bats perform both local and global searches [24]. In the local search, bats explore around their current positions to identify promising areas. In the global search, some bats randomly explore the entire search space to enhance diversity and discover potentially better solutions.
- After exploring, bats adjust their positions towards more promising solutions. This adjustment is influenced by the best solutions found so far, as well as the echolocation process.
- One of the key challenges in RT treatment planning is dealing with constraints. BSO handles constraints by penalizing infeasible solutions, ensuring that the optimization process adheres to the specified dose constraints and other physical limitations.
- The above steps are iteratively executed to allow bats to refine their solutions over multiple generations. The optimization process terminates after a predefined number of iterations or when convergence criteria are met.
- Hyperparameters such as pulse frequency range, loudness, pulse rate, and population size are carefully tuned to balance exploration and exploitation. Adaptive adjustment of loudness and pulse rate during iterations enhances convergence toward constraint-compliant solutions.

Artificial Bee Colony Optimization (ABC): ABC is inspired by the foraging behaviour of honeybee colonies [25]. It imitates the process of honeybee scouts searching for food sources and sharing information with other bees in the hive. The algorithm leverages this natural behaviour to navigate the solution space and identify optimal solutions that fulfil both dose requirements and physical constraints. The working process of ABC Optimization for constrained optimization in RT treatment planning can be explained below:

- The optimization starts with an initial population of artificial bees, each representing a potential solution. These solutions correspond to various configurations of beamlet intensities [26].
- In this phase, employed bees evaluate the quality of their solutions based on an objective function, which integrates both the prescribed dose to the target and constraints related to maximum doses at OARs. Bees adjust their solutions by exploring nearby regions in the solution space.
- Other bees, referred to as onlooker bees, select their solutions based on the quality information shared by employed bees. Better-performing solutions are more likely to be chosen, while solutions that do not adhere to constraints are less favoured.
- Occasionally, a solution may not yield improvement for an extended period. In such cases, the solution is abandoned, and the corresponding bee becomes a scout bee. Scout bees then explore new, unexplored areas of the solution space.
- ABC Optimization addresses constraints by adjusting the selection probabilities of solutions based on their feasibility [27]. Infeasible solutions are penalized to encourage adherence to dose limits and other physical constraints.

- The optimization process iteratively progresses through the employed bees, onlooker bees, and scout bees phases. This iterative approach allows the algorithm to refine solutions over multiple cycles. The optimization process reaches its conclusion either after a specified number of iterations have been completed or when the predefined convergence criteria have been satisfied.
- Key hyperparameters such as the colony size, limit value (for scout behavior), and number of employed/onlooker bees are adjusted to promote effective convergence. Increasing the number of onlooker bees improves local search, while tuning the limit value helps maintain diversity in constrained environments.

Bacterial Foraging Algorithm (BFA): BFA draws inspiration from the foraging behaviour of bacteria in search of nutrients [28]. It models the interactions between bacteria and their environment to navigate through solution spaces and locate optimal solutions that satisfy both dose requirements and physical constraints. The operational process of Bacterial Foraging Optimization for constrained optimization in RT treatment planning can be outlined as follows:

- The algorithm begins with an initial population of virtual bacteria, each representing a potential solution [29]. These solutions represent different arrangements of beamlet intensities.
- Bacteria undergo chemotactic movement, which simulates their exploration of the environment for nutrients. Solutions are adjusted based on the concept of bacterial movement toward areas with higher nutrient concentrations. In the context of RT, nutrient concentration correlates with optimal solution quality.
- Bacteria that have explored regions with higher nutrient concentrations are more likely to reproduce, generating new solutions [30]. Meanwhile, bacteria that have not found promising solutions undergo elimination-dispersal, simulating the concept of bacteria dispersing when resources are scarce.
- Bacteria communicate and share information about their exploration. This fosters cooperation and enables the algorithm to collectively converge towards optimal solutions.
- BFA Optimization addresses constraints by incorporating them into the optimization process. Solutions that violate constraints are penalized, and the algorithm guides the exploration towards feasible regions of the solution space.
- The optimization process iterates through chemotactic movement, reproduction, elimination-dispersal, and communication phases. This iterative approach refines solutions over multiple generations. The optimization process concludes after a predetermined number of iterations or when convergence criteria are met.
- Hyperparameters such as chemotactic step size, swim length, reproduction rate, elimination-dispersal probability, and population size are tuned to regulate exploration intensity and convergence rate. A dynamic adjustment of swim length based on local improvement ensures fine-grained search under constraint-heavy conditions.

3.3 Constraints

Constraints in the optimization problem are commonly divided into two categories: "geometrical" constraints and "physical" constraints. Limits on the range of the design variables might be thought of as upper and lower bounds for the geometric constraints. Contrarily, physical constraints impose bounds on physical quantities that can only be evaluated numerically. Equation 1 is a constrained optimization problem; an approach was used to prevent constraint violations by transforming the problem into an unconstrained one. This was accomplished by punishing computationally expensive infeasible objective function solutions [31], rather than attempting to correct them. Dose-based constraints for OARs were preferred in this investigation. Dose-based constraints were chosen because of their conceptual simplicity and widespread application in clinical practice [30]. The optimization problem with dose constraints used the following pseudo-objective function, as expressed in Equation (4):

$$\emptyset(x) = f(x) + \sum_{i=1}^{N}\left[w_j H\left(maxD_{OAR_j} - D_{max,OAR_j}\right).maxD_{OAR_j}\right] \tag{4}$$

Here, "x" denotes the intensities of the beamlets, while "$f(x)$" and "$H(\cdot)$" represent the quadratic dose and Heaviside function associated with the PTV. The index "j" encompasses the various OARs. "$maxD_{OAR_j}$" signifies the maximum permissible dose for the OAR_j and "$maxD_{OAR_j}$" indicates the maximum dose at OAR_j, iteratively computed throughout the optimization phase. Additionally, "w_j" is a weight factor linked to the OARs, and "N" represents the total count of OARs. Then, a repair function "$g(x_i)$" was employed, as given in Equation (5), to ensure that each individual beamlet's intensity "x_i" falls within an acceptable range. This repair function addresses geometrical constraints, ensuring that the beamlet intensities remain within predefined limits. Specifically:

$$g\ (x_i) = \begin{cases} lower\ bound & if \quad x_i < lower\ bound \\ upper\ bound & if \quad x_i < upper\ bound \end{cases} \tag{5}$$

In this context, the lower and upper bounds were established through empirical experimentation, set at 0 and 20 respectively.

4. RESULTS AND DISCUSSION

In this study, synthetic radiotherapy datasets were generated using the CERR platform to simulate realistic treatment planning scenarios. A total of five distinct prostate cancer cases were modeled, each varying in target volume size, organ-at-risk (OAR) proximity, and anatomical complexity. These variations were designed to reflect common clinical scenarios encountered in radiotherapy practice. The performance of three metaheuristic optimization algorithms—BFA, ABC, and BSA—was then evaluated against traditional IMRT inverse planning without optimization. The comparison focused on constrained optimization within RT treatment planning, using two primary criteria: execution time and convergence behavior.

4.1 Execution Time

FIGURE 3 presents the absolute execution times of the metaheuristic algorithms and traditional IMRT techniques in relation to the number of pencil beams (PBs) utilized. The RT planning with optimization performs better than the traditional IMRT without optimization. Among the three metaheuristic techniques – BFA, ABC, and BSA – BFA exhibited superior performance. Notably, the execution time of the optimization approaches demonstrated a linear relationship with the number of PBs.

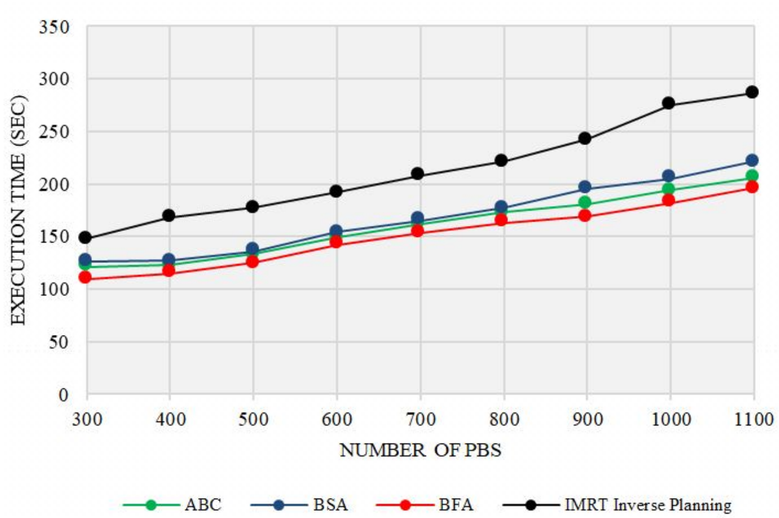


Figure 3: Execution time comparison

4.2 Convergence

Convergence is a critical aspect of optimization, as it determines the ability to reach optimal or near-optimal solutions efficiently. The metaheuristic algorithms (BSA, ABC, and BFA), along with traditional IMRT, were evaluated for their convergence properties. These iterative methods allowed for comparisons by tracking the best solution at each iteration. In practice, the metaheuristic algorithms converged effectively, generally requiring fewer than 60 iterations to reach stability. This demonstrates their ability to explore the solution space and rapidly identify high-quality solutions. FIGURE 4 showcases the evolution of the objective function $\varphi(x)$ over 100 iterations for the three optimization techniques and a traditional technique, focusing on a prostate case. The traditional method shows slightly slower convergence than the metaheuristic method. From the figure, it is evident that BFA displayed a quicker convergence rate compared to the other optimization methods. The blue plot corresponds to BSA's convergence, the red plot depicts BFA's convergence, the green plot represents ABC's convergence, and the black plot shows the convergence of traditional IMRT inverse planning.

From FIGURE 3 and FIGURE 4, it is evident that the BFA outperforms other techniques in RT planning, particularly in terms of convergence speed and execution time. This observation is further supported by the comparative analysis presented in TABLE 1, which provides a detailed and structured evaluation of four distinct RT treatment planning techniques. The comparison is based

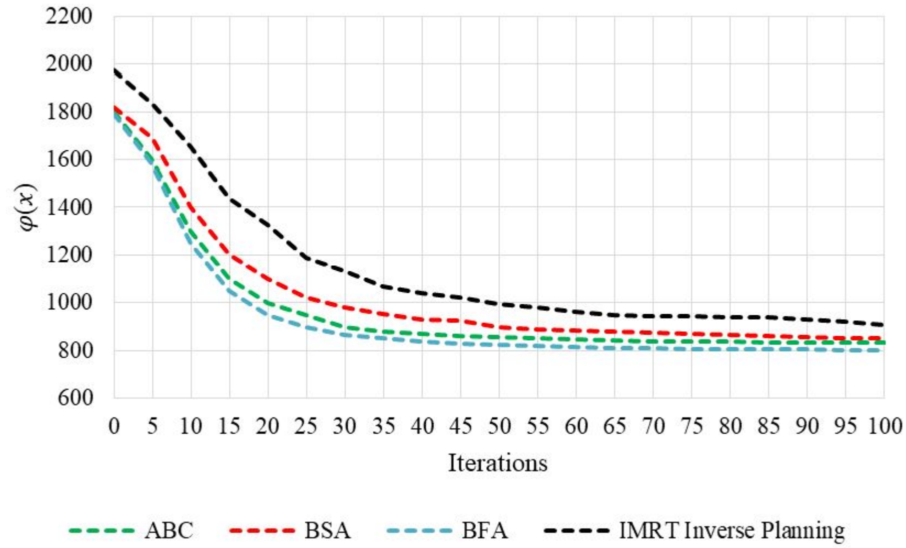


Figure 4: Convergence comparison

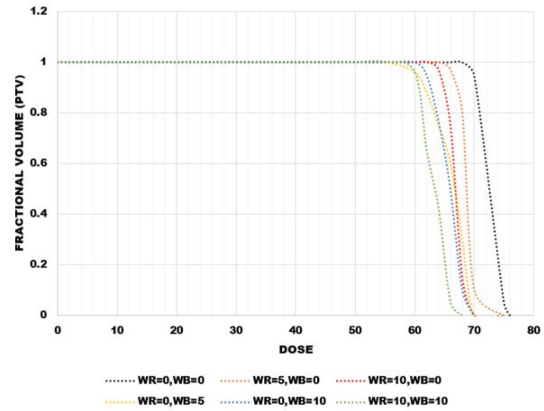
on six essential performance criteria: execution time, convergence speed, optimization quality, computational complexity, scalability, and ease of implementation. Traditional IMRT, while easy to implement and clinically validated, suffers from high execution time and slow convergence, making it less suitable for complex or time-sensitive treatment plans. On the other hand, BFA demonstrates superior performance, offering the fastest convergence and lowest execution time, coupled with high optimization quality. This makes it highly effective for dynamic and high-resolution treatment planning.

Table 1: Comparison of traditional RT and metaheuristic-based RT techniques

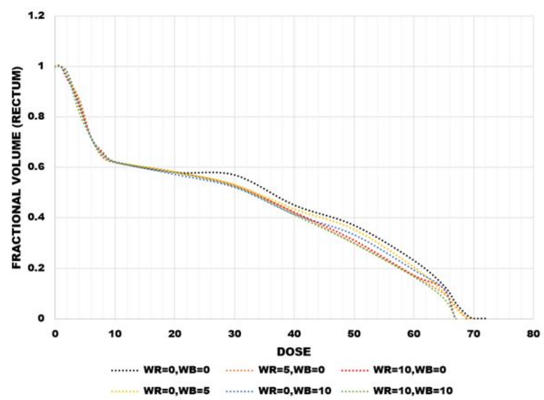
Technique	Execution Time	Convergence Speed	Optimization Quality	Computational Complexity	Scalability	Implementation
Traditional IMRT	High	Slow	Moderate	Low	Limited	Easy
BFA	Low (fastest among all)	Fastest	High	Moderate	High	Moderate
ABC	Moderate	Moderate	Good	Moderate	High	Moderate
BSA	Moderate–High	Moderate	Good	Moderate–High	High	Moderate

4.3 Correlation between Weight Factors and Plan Quality

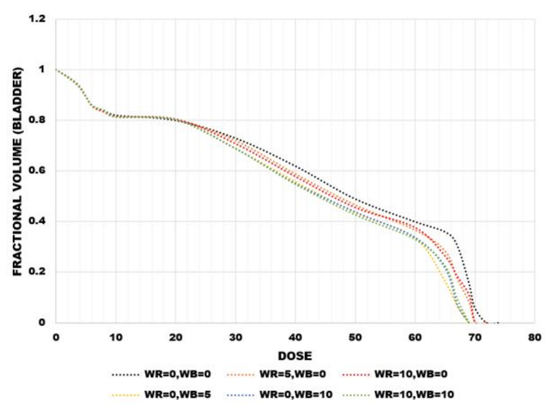
Based on the comparison of execution times and convergence properties, the BFA emerged as the optimal solution for treatment planning. Using the BFA optimization approach, we investigate the impact of penalizing weight factors (w_j) through the total quality of prostate cancer treatment plans. To perform a qualitative assessment of treatment plan quality, we adopted the cumulative Dose



a) DVHs for PTV



b) DVHs for Rectum



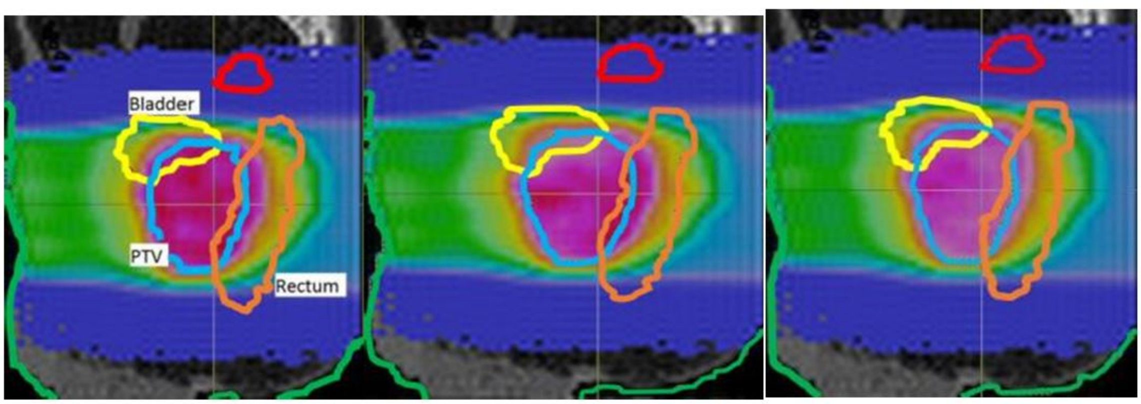
c) DVHs for Bladder

Figure 5: DVHs with various combinations of penalizing weight factors.

Volume Histogram (DVH), a commonly employed metric in the field of RT. The DVH serves to condense the three-dimensional dose distribution into a concise two-dimensional visual format.

FIGURE 5 displays the overall DVHs for the PTV when various penalizing factors, w_B and w_j, on the bladder and rectum are used. The horizontal and the vertical axis indicates the desired dose level, and the volume of the PTV acquiring that dose or above. An ideal DVH for the PTV exhibits a steep drop-off, indicating excellent tumor coverage. The appearance of a step-like drop at the prescribed dose (D_0) signifies that the entire volume received the prescribed dose. For the PTV, this steep drop-off is crucial to ensure comprehensive tumor coverage. Moreover, dose constraints impact the DVH curve's shape for each Volume of Interest (VOI). It is important to note that optimizing a treatment plan involves balancing the quality of the DVHs for various VOIs. The optimizer may slightly compromise the DVH quality for some VOIs to enhance those of others. The w_j in the optimization algorithm (Equation 4) indicate the amount of priority assigned for each dose constraint.

FIGURE 5 (a) illustrates the DVH for the unconstrained plan ($w_R = 0$, $w_B = 0$), showing a sharp curve that signifies thorough coverage of the prostate cancer. However, as the w_j are elevated, as demonstrated in FIGURES 5 (b) and (c), the PTV coverage becomes affected. Meanwhile, there is a reduction in the dose administered to OARs. This trend can be attributed to the intersection of the bladder and rectum volumes with the volume of the tumor. In conclusion, this section delves into the significance of w_j in influencing treatment plan quality. The utilization of cumulative DVHs sheds light on the impact of these factors on the trade-offs between optimal tumor coverage and adherence to dose constraints for various structures. This comprehensive analysis contributes to a deeper understanding of the interplay between penalizing factors and the resulting treatment plan characteristics.



(a) w_R=w_B=0 (b) w_R=10, w_B=0 (c) w_R=0, w_B=10

Figure 6: Sagittal dose distribution view of unconstrained IMRT optimization.

FIGURE 6 provides a graphical representation of this phenomenon by displaying the dosage distribution in a sagittal plane for three distinct sets of weight components. FIGURE 6(a) shows the dose distribution when both the w_R and w_B are set to zero. FIGURE 6(b) illustrates the scenario where the w_R is increased to 10, while the w_B remains at zero. FIGURE 6(c) demonstrates the case where the w_B is increased to 10, with the w_R remaining zero. It's worth highlighting that as the weight factor increases, the dose administered to the OARs decreases. Additionally, the PTV overlaps with both the bladder and rectum, as demonstrated in the image. The results of the experiments related to prostate cancer are detailed in TABLE 2. Adhering to the recommendations of ICRU-50 [32, 33], it's important to emphasize that the presented findings have not been normalized to achieve the prescribed dose for the specified volume or point. Normalization involves a straightforward procedure in which the PTV dosage, along with other components, is progressively escalated for each set of penalized weights. The dose values are expressed in units of Gy.

Table 2: Performance metrics of PTV, Rectum, and Bladder by using the BFA-based RT

(w_R, w_B)	D_{95}^{PTV}	D_{max}^{Rectum}	$D_{max}^{Bladder}$
(0,0)	65.7	72.8	71.6
(5,0)	63.5	67.3	68.9
(10,0)	61.2	67.1	68.6
(0,5)	59.8	70.8	61.3
(0,10)	59.6	70.5	60.9
(10,10)	59.5	67.2	60.7

TABLE 3 presents a comprehensive evaluation of four treatment planning models—Traditional IMRT, ABC, BSO, and BFA—based on Tumor Coverage and OAR dosage. From this comparison, the BFA model demonstrates superior overall performance, achieving an optimal balance between high tumor coverage and low doses to critical organs. Other models like ABC and BSO provide moderate improvements over the Traditional method but fall short of BFA's efficiency.

The experimental outcome, underscore the importance of metaheuristic optimization in RT planning. The optimization techniques not only enhance the speed and efficiency of treatment planning but also improve the overall quality of the plans, ensuring better tumor control and minimized side effects, which are critical for the successful treatment of cancer. However, the trade-off between execution time and optimization accuracy is crucial, as high optimization accuracy may sometimes require longer computation times. Therefore, selecting the appropriate balance between speed and accuracy is essential for successful integration into real-world clinical workflows.

5. CONCLUSION

In conclusion, this study has showcased the significant potential of metaheuristic algorithms in addressing constrained optimization challenges within RT Treatment Planning. Through a comparative analysis of three optimization techniques, BFA emerged as a standout performer, characterized by superior execution time and convergence capabilities. The BFA achieved the highest PTV coverage of 65.7Gy with rectum and bladder maximum doses of 72.8Gy and 71.6Gy, respectively, at ($w_R = 0$, $w_B = 0$), outperforming Traditional IMRT, ABC, and BSO models under identical settings. Furthermore, the influence of penalizing weight factors on treatment plan quality was effectively illustrated using BFA. While higher weight factors enhance the sparing of OAR, they entail a trade-off with compromised PTV coverage. This intricate balance highlights the complex nature of RT treatment planning, where optimal outcomes must be achieved within safety constraints.

Although the study highlights strong computational potential for metaheuristic algorithms like BFA in RT planning, their clinical application remains limited. Current research has primarily been conducted in controlled simulation environments, with no integration into real-time clinical workflows. Radiation oncologists may consider approving BFA-optimized treatment plans if they are validated to meet clinical standards for accuracy, safety, and interpretability. For successful clinical

Table 3: Comparison of Tumor Coverage and Critical Organ Doses across Various Treatment Models

Model	(w_R, w_B)	D_{95}^{PTV}	D_{max}^{Rectum}	$D_{max}^{Bladder}$
Traditional IMRT	(0,0)	64.2	74.2	73.5
	(5,0)	62.1	69.5	70.5
	(10,0)	60.6	70.3	71.7
	(0,5)	58.6	73.1	66.1
	(0,10)	57.5	72.5	65.5
	(10,10)	57	70.7	64
ABC	(0,0)	63.5	72.5	72.2
	(5,0)	61.6	68.8	69.5
	(10,0)	59.2	69.2	70.3
	(0,5)	57.5	72.5	64.9
	(0,10)	57.4	71.5	63.5
	(10,10)	56.1	69.1	62.5
BSO	(0,0)	62.2	71.2	71.5
	(5,0)	60.6	66.3	67.5
	(10,0)	58.4	67.2	68.5
	(0,5)	57.8	69	62.5
	(0,10)	56.5	68.5	62.7
	(10,10)	55.9	66.3	61.3
BFA	(0,0)	**65.7**	**72.8**	**71.6**
	(5,0)	**63.5**	**67.3**	**68.9**
	(10,0)	**61.2**	**67.1**	**68.6**
	(0,5)	**59.8**	**70.8**	**61.3**
	(0,10)	**59.6**	**70.5**	**60.9**
	(10,10)	**59.5**	**67.2**	**60.7**

translation, BFA must be integrated into existing planning systems with minimal disruption and must consistently deliver reliable, high-quality outcomes.

Future work should prioritize clinical validation through pilot studies in real-world settings. Collaborations with oncology centers can help assess the feasibility and performance of clinical practices. Additionally, hybrid metaheuristic approaches could be explored by combining the strengths of different optimization techniques. Such integration may yield even more efficient and optimized solutions for RT treatment planning. Specifically, incorporating deep learning or multi-objective optimization with BFA could enhance its capabilities. Deep learning could offer data-driven insights, improving adaptability and accuracy, while multi-objective optimization could help better balance competing goals, such as PTV coverage and OAR sparing. Further research may also extend to more complex scenarios, such as adaptive therapy planning that updates treatment plans in real time based on patient data—an approach that holds promise for enhancing both treatment efficacy and patient outcomes.

6. CONFLICT OF INTEREST STATEMENT:

The authors have no conflict of interest to disclose.

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