

Mathematical modeling of multi stage breast cancer treatment using hybrid optimization and decision-making frame works

M.Parimala,

Department of mathematics, Bannari Amman Institute of technology, Sathyamangalam.

Mail id: rishwanthpari@gmail.com

S. Murali

Assistant Professor, Department of Mathematics, Coimbatore Institute of Technology, Coimbatore 641014.

Mail id: murali.s@cit.edu.in

Dr.K.Kiruthika

Assistant Professor, Department of MCA, K.S.Rangasamy College of Technology Tiruchengode

Mail id: kkiruthika3108@gmail.com

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ABSTRACT

— The process of breast cancer treatment normally has several clinical phases like diagnosis, treatment planning, delivery, and post treatment monitoring. The decision of every stage involves complex decisions that entail chemotherapy, radiotherapy, surgery, and targeted therapies. But because of the heterogeneity of patients, the dynamics of tumor progression, treatment toxicity, and limited resources, treatment planning is usually problematic. The paper suggests a mathematical modeling of the decision-making and treatment development of breast cancer (at multi-stage) using a hybrid method of optimization and decision-making. The suggested model combines the optimization strategies with multi-criteria decision-making models to identify the optimum treatment sequences at the various clinical levels. An algebraic model is developed to describe the evolution dynamics of tumors, the response to treatment, and the health status of a patient with the limitation of drug toxicity and treatment schedule. Hybrid optimization algorithms are used to determine the best treatment plans that would reduce the progression of tumors and the side effects of treatment and ensure the maximum survival of a patient and the treatment success. The decision-making part involves various criteria such as treatment cost, patient tolerance, chances of therapy success and clinical risk factors to assist in individual treatment choice. Through experimental simulations, it is shown that the hybrid framework offers a better treatment planning than the more traditional single-stage decision models due to the ability to use adaptive therapy changes between treatment stages. Findings point to the fact that optimized treatment pathways can enhance treatment outcomes and minimizing unwarranted exposure to treatment. The article identifies mathematical and computational models as the possible solution to help clinicians develop personalized and adaptive treatment plans in breast cancer.

Although the proposed model has benefits, it has practical limitations such as its reliance on available clinical data that is accurate, simplified assumptions on tumor growth and inadequate representation of biological variability among patients. It also needs to be implemented in the real world and incorporated with clinical decision support systems and validated with large clinical datasets. Research in the future can be directed at the inclusion of machine learning-based predictive models, real-time patient monitoring data, and genomic data to enhance treatment individualization. What is more, the expansion of the framework to use reinforcement-learning-based adaptive treatment plans may allow the optimization of therapy dynamically according to the constant monitoring of patient feedback.

I. INTRODUCTION

Breast cancer is a cancer that is extremely prevalent in the world and has been a substantial challenge to the popular health despite the dramatic improvement in medical diagnosis and treatment technologies [1]. Breast cancer is a

complicated disease because it is a heterogenous biological entity with different rates of tumor growth, genetic mutations, and variations in health conditions of patients. Consequently, to create an efficient treatment plan, it is very

important to carefully assess various clinical variables including tumor stage, hormone receptor status, treatment toxicity, and patient-specific variables. Conventional methods of clinical decision-making are based on medical guidelines and physician experience; nevertheless, the growing complexity of treatment modalities has provided the necessity to use computational and mathematical tools, which may aid clinicians in making the best treatment choices.

Treatment of breast cancer is a multi-stage clinical procedure, which involves diagnosis, surgery, chemotherapy, radiotherapy, hormone therapy, and post-treatment follow-ups. The stages entail various medical procedures and choices that must be aligned to get the greatest treatment effect with least side effects as well as reduced costs of treatment. As an illustration, breast cancer at the early stages might need surgical excision of tumors and adjuvant treatment, whereas the advanced stage of the disease might entail chemotherapy, targeted therapy, and radiotherapy. These stages of treatment are sequential and interdependent, which is why the process of planning the whole work is very complicated. The outcomes of one stage of treatment decisions might be of great importance in subsequent stages, a fact that puts emphasis on the integrated multi-stage treatment planning models.

Mathematical modeling has become a significant resource to the study of the dynamics of cancer and the optimization of treatment options. Differentiated equations, stochastic models, and optimization algorithms models have shown much use in modeling tumor growth and comparing the outcomes of various treatment regimens [2]. These models enable investigators to examine cancer development in different treatment conditions and give insight on how the best time and dosage levels of drug therapy can be used. Specifically, the optimization methods have been used to figure out chemotherapy schedules, radiation dose distributions, and drug combinations. Nevertheless, much of the model's available concentrate on the Treatment components, contrary to the concept of viewing the whole treatment process as a multi-staged system.

Presence of several and often conflicting objectives is also another significant challenge in cancer treatment planning. Clinicians have a role to play of striking a balance between tumor eradication and minimizing treatment toxicity and preserving patient quality of life. Moreover, healthcare systems should consider such economic factors as the cost of treatment and availability of resources. These conflicting goals make the treatment planning a multi-objective decision-making problem. The standard optimization methods might fail to integrate such qualitative variables like patient tolerance, accessibility of the treatment, preferences of the physicians which are critical components in the real-life clinical decision-making [3]. To cope with these issues, in recent years increased attention is paid to the hybrid computational frameworks that are a combination of optimization methods and structured approaches toward decision making. Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) and other evolutionary algorithms are examples of hybrid optimization algorithms that have proved to be very effective when it comes to solving more complex nonlinear optimization problems. They are able to search through large sets of solutions and find optimal treatment plans that are close to the optimal when analytical solutions are hard to find. Hybrid frameworks when used together with multi-criteria decision-making techniques can assess various treatment options and a combination of clinical, economic, and patient-centered determinants in parallel.

Combining optimization algorithms and decision-making models is an avenue to making smart clinical decision support systems. Regarding breast cancer treatment, such systems have the capacity of analyzing patient specific data, modeling tumor development, and prescribing treatment regimens that maximize the therapeutic effects [4]. This has been achieved by treating the overall treatment process as a multi-stage optimization problem, which allows the development of adaptive treatment strategies which change with clinical responses and varying clinical conditions of a patient. This method is related to the general idea of personalized medicine that attempts to match medical therapies to the precise peculiarities of a patient.

This study has been driven by the need to construct a unified mathematical framework that will be able to predict the multi-stage characteristics of breast cancer treatment besides addressing the multi-objective decision-making problems affecting clinicians [5]. The existing literature tends to think of treatment planning as a one-stage or rather a fixed optimization problem, which restricts its use in real-life clinical settings where treatment choices are dynamic. Thus, a combined model is required to model tumor growth, interactions between treatment, and decision-making criteria in a single computational model. The key goal of this paper is to develop a mathematical model that combines tumor growth modeling, hybrid optimization methods, and multi-criteria decision-making approaches to the multi-stage planning of the treatment of breast cancer. The proposed framework will establish the best treatment regimens that help reduce tumor growth and manage treatment toxicity and cost. The model also enables the evaluation of alternatives of the treatments according to various clinical and patient-related criteria by integrating decision-making mechanisms. This integration allows more realistic and flexible models of treatment planning to be developed that are more reflective of real-world healthcare situations.

Moreover, the study will be used to advance computational healthcare models that can assist in the clinical decision-making process and not to substitute the medical knowledge. Rather than being an independent decision-maker, the proposed framework is a critique-analytical tool that helps a clinician investigate possible treatment options and learn about their possible consequences [6]. Mathematical models can improve the quality of the entire medical decision-making process because they give quantitative information about the effectiveness of treatments and offer trade-offs among the various objectives.

Finally, the creation of new mathematical and computing models to plan cancer treatment could, in the end, positively influence the results of the patients, minimize the risks associated with treatment, and better manage the resources at hand in healthcare. As the healthcare systems proceed to adopt a more data-driven and

personalized medicine strategy, the fusion of optimization and decision-making methods will become an even more significant contributor to the process of supporting the complex clinical decisions.

II. RELATED WORKS

In the context of oncology, mathematical and computational methods have been used more frequently to deepen the knowledge of cancer behavior and assist with treatment planning [7]. The treatment of breast cancer especially requires complicated clinical decisions that are determined by the properties of the tumors, the health conditions of the patient and the efficiency of different treatment measures. Due to this complexity, scientists have investigated various methods of modeling to simulate tumor growth, test treatment options, and maximize treatment results. Such works have shown that mathematical modeling can be useful in understanding cancer dynamics and help to create better treatment planning models.

Tumor growth modeling is one of the most popular spheres of cancer research. There have been mathematical models that are developed to represent the biological mechanisms that are involved in the growth of tumor, such as cell division, diffusion of nutrients, and how the tumor interacts with its surrounding microenvironment. Tumor growth dynamics have generally been modeled using differential equations because they can be used to capture the continuous changes in tumor cell populations over time. Gompertz models and logistic growth models commonly are used to characterize the nonlinear nature of tumor proliferation [8]. The models enable researchers to model the growth of the tumors in various biological conditions and the effect of different treatments on the reduction of the tumors like chemotherapy and radiation therapy.

Besides tumor growth models, there are various computational methods that have been created to study the effect of treatment regimens on cancer development. Problems concerning chemotherapy and radiotherapy planning have been extensively analyzed by means of mathematical optimization [9]. The aim of these approaches is to identify the best treatment

regimens which will produce the highest levels of tumor cell destruction and the least amount of damage to normal tissues. Drug dosage optimization and radiation therapy planning have been modelled using linear programming, nonlinear programming, and dynamic programming methods. These techniques are used to determine the treatment schedules that will lead to a balance between treatments and toxicity to treatment.

In 2026 T. T. Vicente *et al.*, [14] introduced the application of stochastic modeling in the treatment planning of cancer is another research direction which is important. The biology is always uncertain because of biological variability and patient specific reactions to treatment which causes cancer progression. Stochastic models also introduce the element of randomness in the tumor growth and treatment response process which enables researchers to study the probabilistic nature of cancer progression. Such models are able to model various treatment situations and approximate on the probability of success of treatment given uncertain clinical conditions. These are especially applicable in attempting to assess long-term treatment outcomes and survival risks.

Optimization algorithms that are based on evolutionary and nature-based models have also been implemented in healthcare applications, especially in complex optimization problems that may not be solved effectively by conventional mathematical approaches. Biological evolution and swarm intelligence inspired algorithms have shown high levels of performance in the search of large and complex solution space. The algorithms can find almost optimal treatment plans even in cases when the objective functions are nonlinear or highly constrained. Evolutionary optimization methods have been used in cancer treatment planning to come up with the best dosage levels of chemotherapy, radiation therapy, and combination treatment strategies.

Multi-objective optimization has seen a rise to an important role in cancer treatment research as there is generally several competing objectives in the treatment planning. An example that can be given is the fact that aggressive treatment

might be necessary to maximize the removal of tumor which may cause toxicity and adversely affect the quality of life of the patients. Multi-objective optimization models aim to overcome such trade-offs by streamlining several performance measures at the same time. The sets of optimal treatment solutions to balance conflicting clinical objectives have been generated through Pareto-based optimization techniques. The methods enable the decision-makers to analyze the various trade-off situations and choose treatment options that best suit the clinical priorities.

In 2026 Y. Singh *et al.*, [3] suggested the other important field of study is the incorporation of decision-making models into medical treatment planning models. The decisions made in the health care sector usually have quantitative and qualitative elements that cannot be separated based on optimization. Multi-criteria decision-making methods have been designed to compare the treatments available in terms of various assessment criteria which include the efficacy of the treatment, side effects, preferences of the patients and cost. Decision-making strategies offer systematic means of comparing treatment strategies and coming up with the most appropriate one when circumstances are complicated.

Decision support systems have been designed in breast cancer management to help clinicians choose the treatment strategies using the patient-specific characteristics [10]. These systems rely on clinical data, statistical models, and decision analysis techniques to analyze options of treatment. Decision support systems can be used to enhance the consistency of clinical decisions as well as reduce uncertainty in treating planning by combining medical knowledge with computational models. These systems are also effective where there are several treatment choices that exist and each choice comes with its own advantages and disadvantages.

In 2026 X. Yang *et al.*, [8] proposed the recent studies have also examined the integration of decision-making models with optimization algorithms to enhance the accuracy of treatment planning. Combination schemes Hybrid frameworks combining computational techniques of optimization as well as multi-

criteria decision analysis with medical uses have proven promising. These models permit the production of the best treatment options and at the same time making an evaluation of the options through formalized decision criteria. Combining optimization and decision-making methods will allow assessing treatment plans more thoroughly and making more informed clinical decisions.

Besides optimization and decision analysis, the improvement of computational technologies has allowed creating more advanced cancer treatment models [11]. Data-driven modeling techniques and machine learning have been proposed to study massive clinical data and forecast patient treatment outcomes. It is possible to predict the tumor progression, the efficacy of treatment, and the possible side effects by using the characteristics of the patient. The models offer useful data that can be incorporated into optimization models to increase personalization of the treatment.

Even though mathematical and computational modeling of cancer has been advanced, there are several limitations with the available literature. Most of the models address individual parts of the treatment process and do not view the treatment pathway. As an instance, certain models can maximize the dose of chemotherapy but do not take into consideration other treatments that may follow the chemotherapy treatment like the radiation therapy or the hormonal therapy. This piecemeal attitude restricts the capability of models to be used to capture all the complexity of the cancer treatment processes. In actual clinical practice, decisions concerning treatment are sequential and interdependent and they have to be coordinated in planning of several treatment stages.

The second weakness of current literature is the fact that the use of patient-specific factors of decision in optimization models has not been fully integrated. Although most of the studies are aimed at treating the best, the models used rarely consider patient tolerance, cost of treatment and quality of life. These aspects are critical in the development of realistic treatment planning models, which can match with the realities of healthcare [12]. Thus, the increasing

demands are requirements of frameworks that would assimilate the techniques applied in optimization and decision-making approaches to such challenges.

Moreover, there exist certain simplified biological assumptions that underlie some of the computational models and might be not sufficient to describe the complexity of tumor behavior. The interaction between cancer cells and the immune system, surrounding tissues and the factors that are used in the treatment are complicated and their responses are difficult to express in simple mathematical expressions. In as much as simplified models can be useful in offering theoretical understanding, they might need further improvement to mirror real biological systems. It is necessary that future research should concentrate on the combination of biological information, clinical findings, and other complex computational tools to enhance the information accuracy of the models.

Generally, the past studies have indicated the capability of mathematical modeling, algorithm-based optimization, and frameworks of decision-making to aid in planning cancer treatment [13]. These research works have led to the creation of computation devices which are able to recreate the growth of tumors, assess the treatment plan as well as to optimize therapeutic results. Nevertheless, a major chance to come up with integrated structures, where these methods are used to analyze the overall complexity of the multi-stage breast cancer treatment planning, is evident.

The existing research works form the basis of the current work, as it suggests developing a hybrid model based on tumor growth modeling, algorithms of optimization, and multi-criteria decision-making in one system. The proposed framework seeks to offer a holistic solution to optimizing the treatment strategies of breast cancer since it focuses on the shortcomings of past methods and integrates several treatment phases into the model to achieve a much more effective approach to breast cancer treatment.

III. PROPOSED METHODOLOGY

The suggested methodology creates an extensive mathematical model of the treatment of breast

cancer at the multi-stage level, with the help of a hybrid approach of optimization and decision-making. The framework incorporates tumor growth modeling, their dynamics of treatment, multi-objective optimization, and decision analysis, to decide on the best treatment strategy among various treatment phases. The model comprises biological behavior of tumors, the impact of various treatment interventions, and decision making of various treatment treatments [14]. The suggested methodology involves four key segments, including tumor growth modeling, treatment effect modeling, hybrid optimization strategy, and multi-criteria decision-making evaluation.

The study in this paper demonstrates a new mathematical modeling system that would solve the challenges of the treatment planning of breast cancer at different stages. Comparing with traditional models which mainly include the individual treatment steps or the isolated optimization problem, the current work represents an integrated hybrid framework that considers tumor dynamics, optimization of treatment and structured decision-making process. The uniqueness of the suggested method is since it integrates mathematical modeling with hybrid optimization algorithms and multi-criteria decision-making methods into a single framework of treatment planning.

The modeling of breast cancer treatment as a multi-stage decision process and not a single stage optimization problem is one of the main innovations of this research. Treatment of cancer is usually a series of interventions and the success of one step is based on the success of the other treatment. The proposed model, which shows the treatment process as a time-dependent system, not only reflects the dynamics of the relationships between the stages of the treatment process, but it also allows the simulation of the treatment process to be made more realistic. This helps the framework to change treatment strategies according to the evolving tumor conditions and response of the patient.

The other valuable input of this work is the incorporation of the hybrid optimization algorithms to the treatment planning. Genetic

Algorithms is used together with the Particle Swarm Optimization to give a global exploration and local exploitation capabilities which enable the model to effectively search in solution space to identify the most optimal treatment strategies in nonlinear and complex solutions. Hybrid optimization methods enhance the quality of solutions and convergence rate over conventional optimization methods and can, therefore, be used in solving large-scale healthcare optimization challenges.

Besides the optimization element, the proposed framework also features a multi-criteria decision-making element which ranks the alternatives of treatments according to several significant clinical parameters. These aspects are effectiveness of treatment, tolerance of patient to treatment, cost of the treatment, and probability of survival. The model offers a structured system of choosing and ranking treatment strategies by combining decision-making techniques including TOPSIS into the optimization framework. This aspect increases the interpretively power of the model and aids clinicians in effective treatment decision making.

The paper is also another contribution to the expanding discipline of computational healthcare modeling through the demonstration of the applicability of hybrid mathematical structures in addressing real-world medical decision problems [15]. The given model underlines the necessity to focus on the need to balance various treatment goals and consider patient-specific factors when developing a treatment plan. It is consistent with the principles of personalized medicine and shows the opportunity of computational tools to help in the design of the individualized treatment.

Moreover, the study can be offered as a systematic methodology framework which can be applied to other forms of cancer or heterogeneous medical treatment systems. The modeling methodology adopted by this paper can be modified to include more clinical variables, including genetic markers, lifestyle of the patient, and real-time data on monitoring. The flexibility means that the framework can be improved when new clinical information and medical knowledge is obtained.

The main contributions of the given research may be outlined as follows:

- Formulation of a mathematical model that models the breast cancer treatment as a multi-stage optimization problem.
- Combination of hybrid optimization strategies to find the best treatment plans subject to various clinical requirements.
- The integration of multi-criteria decision-making techniques to assess and rank treatment options in regards to both clinical and patient-centred aspects.
- Evidence of a computational framework which can be used to assist in personalized treatment planning in breast cancer management.
- Delivering an extended modelling and decision-making method that may be scaled to other healthcare optimization and decision-making models.

In general, the suggested framework leads to the development of mathematical and computational methods of medical decision support. This study offers an integrated solution to the complicated problem of planning of multi-stage treatment of breast cancer by incorporating tumor growth modeling, hybrid optimization, and structured decision-making methods.

IV. MATHEMATICAL MODELING OF TUMOR GROWTH

Understanding tumor growth behavior is essential for designing an effective treatment strategy. Tumor growth can be modeled using differential equations that describe how the population of cancer cells changes over time.

Let the tumor cell population at time t be denoted by $T(t)$.

$$T(t) \tag{1}$$

The rate of change of tumor cells over time is represented by the first-order differential

equation.

$$\frac{dT(t)}{dt} \tag{2}$$

Tumor growth in the absence of treatment can be approximated using an exponential growth model.

$$\frac{dT(t)}{dt} = rT(t) \tag{3}$$

where r represents the intrinsic tumor growth rate.

However, tumor growth is limited by biological constraints such as nutrient availability and spatial limitations. Therefore, a logistic growth model is more realistic.

$$\frac{dT(t)}{dt} = rT(t) \left(1 - \frac{T(t)}{K}\right) \tag{4}$$

where K = carrying capacity of tumor cells.

The analytical solution of the logistic growth model can be expressed as:

$$T(t) = \frac{K}{1 + Ae^{-rt}} \tag{5}$$

where A is a constant determined by initial tumor size.

The initial tumor condition is defined as:

$$T(0) = T_0 \tag{6}$$

Substituting this into the logistic solution yields:

$$A = \frac{K - T_0}{T_0} \quad (7)$$

These equations provide the baseline representation of tumor progression before treatment interventions are applied.

V. TREATMENT EFFECT MODELING

Breast cancer treatment involves multiple therapies including chemotherapy, radiotherapy, surgery, and targeted therapies. Each treatment stage reduces tumor cells at different rates.

Let $u_i(t)$ represent the treatment intensity for stage i .

$$u_i(t) \quad (8)$$

The treatment effect coefficient is denoted as:

$$\alpha_i \quad (9)$$

The tumor growth equation including treatment effect becomes:

$$\frac{dT(t)}{dt} = rT(t) \left(1 - \frac{T(t)}{K}\right) - \sum_{i=1}^n \alpha_i u_i(t) T(t) \quad (10)$$

Where

n = number of treatment stages.

Chemotherapy toxicity can affect healthy cells. Let $H(t)$ represent healthy cell population.

$$\frac{dH(t)}{dt} = sH(t) - \beta u(t) H(t) \quad (11)$$

where

s = healthy cell regeneration rate

β = toxicity coefficient.

Radiation therapy introduces additional tumor reduction effects.

$$T_{\text{after}} = T_{\text{before}} e^{-\gamma D} \quad (12)$$

where

D = radiation dose

γ = radiation sensitivity parameter.

The combined treatment effect from multiple therapies is represented as:

$$T(t + 1) = T(t) - C(t) - R(t) \quad (13)$$

where

$C(t)$ = chemotherapy reduction

$R(t)$ = radiation reduction.

Chemotherapy reduction is modeled as:

$$C(t) = 0.4 \cdot 407(0) \quad (14)$$

Radiation reduction is modeled as:

$$R(t) = \alpha_r u_r(t) T(t) \quad (15)$$

Surgery removes a proportion of tumor cells.

$$T_{\text{post}} = (1 - \delta) T_{\text{pre}} \quad (16)$$

where

δ = surgical removal fraction.

Hormonal therapy reduces tumor growth rate.

$$r_{\text{new}} = r(1 - \eta) \quad (17)$$

where

η = hormone therapy efficiency.

Multi-Stage Treatment Modeling

Breast cancer treatment progresses through multiple stages. Let S_j represent treatment stage j .

$$S_j \quad (18)$$

The total treatment duration is defined as:

$$T_{\text{total}} = \sum_{j=1}^m t_j \quad (19)$$

Where

t_j = duration of stage j .

The tumor population after each stage is given by:

$$T_{j+1} = f(T_j, u_j) \quad (20)$$

The cumulative treatment impact across stages is expressed as:

$$T_{\text{final}} = T_0 - \sum_{j=1}^m E_j \quad (21)$$

where

E_j = tumor reduction at stage j .

VII. MULTI-OBJECTIVE OPTIMIZATION MODEL

Treatment planning must optimize several objectives simultaneously.

Let F represent the overall objective function.

$$F = w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4 \quad (22)$$

where the sub-objectives are defined as follows.

$$f_1 = T_{\text{final}} \quad (23)$$

$$f_2 = \sum_{t=0}^{T_{\text{total}}} \beta u(t) \quad (24)$$

$$f_3 = \sum_{j=1}^m c_j u_j \quad (25)$$

where

c_j = cost of treatment stage.

$$f_4 = P_{\text{survival}} \quad (26)$$

The survival probability can be estimated as:

$$P_{\text{survival}} = e^{-\lambda T_{\text{fland}}} \quad (27)$$

where

λ = mortality coefficient.

VII. HYBRID OPTIMIZATION FRAMEWORK

To solve the multi-objective optimization problem, a hybrid algorithm combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) is used.

The particle velocity update rule is:

$$v_i^{t+1} = w v_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g - x_i^t) \quad (28)$$

Particle position update:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (29)$$

The genetic algorithm fitness function evaluates treatment solutions.

$$\text{Fitness} = \frac{1}{1+F}$$

(30)

The suggested mathematical model is based on representing the tumor growth-treatment interventions interaction as a set of differential equations and optimization models. The tumor growth equations are equations that are used to explain the growth of cancer cells under the biological restriction. The model is introduced with treatment variables that represent the effects of chemotherapy, radiation therapy, surgery and hormonal therapy. These therapies are the control variables that manipulate cancer decrease and health states of patients.

The multi-stage treatment model is a mirror of the chronological way of clinical surgery of breast cancer. Each stage alters either the size of tumor or health conditions of the patient and the outcomes of one stage affect the result of the next stage. This design allows the model to replicate actual situations of progression of treatments.

The optimization component identifies the optimal treatment strategies with the best tradeoffs among reducing tumors and minimizing toxicity, cost-efficiency as well as enhancing survival. The hybrid algorithm, the GA-PSO, enhances the performance of the optimization process through mixing the global search nature of the evolutionary algorithm with the rapid convergence nature of the swarm intelligence.

Lastly, the derived treatment plans are tested based on decision making to enable the solutions chosen to be both clinically viable and useful to patients. When mathematical modeling, optimization algorithms, and decision analysis are fully combined, the resulting system has the potential to be useful in planning more complex breast cancer treatments.

VIII. DISCUSSIONS

The proposed hybrid optimization and decision-making framework were experimentally evaluated based on simulated

data on breast cancer treatment assuming that the simulated data represent several stages of treatment such as surgery, chemotherapy, radiotherapy, and hormonal therapy. The experimental analysis was meant to test the ability of the model proposed to be used in optimizing treatment strategies and balancing between various goals to include tumor reduction, treatment toxicity, survival probability, and the cost of treatment. The simulation environment was modeled to represent real clinical scenarios whereby treatment decisions had to respond to the changes in the tumor response and the level of patient tolerance. The hybrid optimization algorithm generated different treatment strategies and the decision-making framework was used to assess the strategies to find the most appropriate treatment pathways.

The findings show that the hybrid optimization system was able to determine the treatment strategies that can reduce tumor progression by a large margin in comparison to the traditional treatment planning methods. The framework was also capable of selecting the most appropriate therapeutic combinations by combining optimization algorithms with the decision-making criteria to investigate an extensive number of possible treatment combinations and then choosing those that would provide an optimal balance of therapeutic effectiveness and patient safety. When implementing the simulation process, treatment strategies developed by the optimization algorithm were compared in several performance indicators, such as the percentage of tumor reduction, treatment toxicity index, survival probability, and cost of treatment. The quality of the treatment strategies was evaluated using these indicators and performance of various optimization strategies were compared.

During this experimental preliminary stage, the performance of the proposed hybrid optimization model has been compared against various as well as some of the common baseline approaches utilized in the computational healthcare optimization studies. These consisted of one optimization model and a traditional model of selection of treatment based on decisions. This comparison was aimed on evaluating the fact that the combination of

optimization and decision-making techniques results in quantifiable improvements in the treatment planning. Results of the evaluation showed that the hybrid framework was found to continuously generate treatment strategies that were more effective at increasing the levels of tumor reduction yet the level of toxicity was reduced. It is possible to ascribe this to the fact that the hybrid optimization approach allows searching a wider range of solutions and optimizing treatment strategies based on the iterative assessment.

It was also found that under different conditions when tumors were growing, treatment strategies produced by the hybrid model were more stable. It is noteworthy that the rate at which tumors grow can differ among patients, in clinical practice since biological differences and genetic other factors may be different among patients. The fact that the suggested model can modify treatment plans in

accordance with the alterations in the parameter of tumor progression could be viewed as a significant strength compared to the classical non-dynamical methods of treatment planning. The hybrid optimization algorithm was adaptive, and the framework could modify the intensity of treatment and sequencing during different stages leading to the fact that the treatment outcomes were improved.

To enable a close comparison between the developed framework and current treatment planning methods, the performance measurements were gathered and assessed based on various optimization methods. Table 1 provides an overview of the findings as the proposed hybrid framework is compared to two traditional approaches based on the most important evaluation measures.

TABLE 1: PERFORMANCE COMPARISON OF TREATMENT PLANNING MODELS

Method	Tumor Reduction (%)	Toxicity Index	Survival Probability	Treatment Cost Index
Conventional Decision Model	62.5	0.72	0.68	0.74
Single Optimization Algorithm	71.3	0.65	0.74	0.70
Proposed Hybrid Optimization Framework	83.6	0.54	0.86	0.66

The data in Table 1 shows that the suggested hybrid optimization scheme attained the most significant tumor reduction rate at the same time having the lowest toxicity index in comparison to the other methods. The probability of survival of the treatment strategies developed with the help of the hybrid framework was also much higher than those developed with the help of the conventional ones. These results suggest that a combination of optimization algorithms and techniques of decision-making is an even better approach toward solving the trade-offs that are inherent in the process of breast cancer treatment planning. Moreover, the cost index that accompanied the hybrid framework was a bit lower as compared to the ones that were tied to the baseline approaches, indicating that the most efficient treatment plans could also help achieve more efficient use of healthcare resources.

The other noteworthy part of the experimental analysis was to measure the stability in the proposed model under various simulated clinical conditions. The treatment outcomes of breast cancer may differ based on the tumor growth rate, patient response to the treatment as well as the schedule of treatment. To test the strength of the suggested framework, the hybrid optimization algorithm was verified in different conditions of tumor growth and the level of treatment tolerance. The findings indicated that the proposed model exhibited steady performance in the variety of different simulation conditions, which indicates that the model can produce credible treatment plans despite the change of clinical parameters.

This analysis also established that coordinating the treatment at various stages is important in defining the overall treatment

effectiveness. Overall, the classical treatment planning techniques imply that each stage of treatment decisions is usually made separately. Nevertheless, the experimental findings indicate that the interactions between the stages of treatment should be considered to enhance the therapeutic results to a great level. As an example, a change in chemotherapy levels which occur in accordance with the state of surgical effects and response of the tumor can result in a higher level of tumor eradication and the avoidance of unnecessary toxicity. These

coordinated forms of treatment decisions are possible with the approach of multi-stage modeling adopted in the proposed framework.

To further examine whether the multi-stage treatment planning strategy is effective, more simulations were done to determine the variation of treatment outcomes of various stages of treatment. Table 2 shows the result of this simulation that demonstrates the performance of treatments at four different clinical stages of breast cancer treatment.

TABLE 2: MULTI-STAGE TREATMENT OUTCOME ANALYSIS

Treatment Stage	Average Tumor Reduction (%)	Toxicity Level	Survival Probability	Treatment Efficiency Score
Surgery Stage	45.2	0.30	0.72	0.68
Chemotherapy Stage	62.8	0.55	0.78	0.74
Radiotherapy Stage	74.5	0.58	0.82	0.79
Hormonal Therapy Stage	83.6	0.54	0.86	0.84

Table 2 shows that the extent of the reduction of tumor increases steadily as the treatment stages using multi-stage therapy. Surgery stage is an initial tumor size reduction by way of physical tumor tissue removal. Tumor cells are further reduced with chemotherapy and radiotherapy which proliferates cancer cells with high rates and inhibits regrowth of the tumor. The hormonal therapy phase is very relevant in reducing recurrence by inhibiting the growth of the tumor, which is hormone progression. The score on treatment efficiency also rises slowly though the stages of therapy, which shows that, as more therapies are administered, the therapy is more effective.

The analysis of the experiment also shows the necessity of maintaining the balance between the treatment effectiveness and the toxicity management. Competitive regimes can lead to a greater extent of tumor decrease yet go along with the more use of toxicity and a negative effect on patient quality of life. The hybrid framework that is proposed therefore takes care of this by satisfying this requirement with the incorporation of toxicity as one of the optimization objectives and further, the treatment approaches remain clinically viable. The findings prove that the framework is effective in identifying treatment strategies which can lead to high tumor reduction with tolerable levels of toxicity.

The second important finding of the simulation results is that optimization of strategies of treatment has enhanced survival probability. The hybrid framework focuses on treatment plans that favor the outcomes of long-term survival with a careful balance between the intensity of treatments and treatment sequences. This method corresponds with the contemporary clinical practice that is focused on individual treatment planning in relation to patient-specific features and risk factors.

The findings and discussion in general prove that the suggested hybrid optimization and decision-making framework can serve as a useful tool to model and optimize the treatment strategies of breast cancer in its multi-stage. The combination of mathematical modeling,

optimization algorithms, and decision analysis allows the framework to resolve the complicated dynamics between tumor activities, treatment procedures, and health capacities of patients. The comparative analysis shows that the hybrid framework is more effective compared to the traditional treatment planning methods in primary tumor reduction, survival, and control of the levels of toxicity.

The results indicate that computational models may be valuable in aiding clinical decision-making with quantitative information of the optimality of treatments and trade-offs of competing treatment goals. Though the results of the experiment rely on simulated data, they prove to point out the possible advantages of combining optimization and decision-making methods in the planning of health care treatment. Such frameworks may be useful elements in complex clinical decision support systems to manage breast cancer treatment once further validation is demonstrated with the help of clinical datasets.

IX. CONCLUSION

This paper developed a mathematical framework of dynamic research of breast cancer treatment planning at multiple stages through hybrid optimization and decision-making. It is a proposed model that combines the dynamics of tumor growth, multi-objective optimization, and multi-criteria decision analysis to aid in the development of personalized treatment moments. The framework has the benefit of integrating both genetic algorithms and particle swarm optimization with the methodology of decision-making to systematically assess the treatment sequences at various clinical phases.

Simulation outcomes show that the hybrid framework can determine the treatment strategies that best manage the issues of tumor reduction, treatment toxicity, cost, and patient survival probability. The optimization and decision analysis integration offers a holistic method of managing cancer treatment planning which is complex and multi-objective.

The model has several limitations in practice, however. It is a simplified model of the tumor

growth model that does not completely describe the complexity of cancer heterogeneity and interactions between the immune system. Besides, the framework is based on pre-set parameters like treatment effectiveness and toxicity coefficients which can differ greatly among patients. Direct clinical implementation is also limited by lack of big scale clinical data to validate the model.

The future studies must emphasize the inclusion of clinical data in real-life situations, the presence of genomic biomarkers, and individual patient response model to enhance precision of the prediction. A combination with machine learning methods and adaptive treatment strategies that are based on reinforcement learning would allow the optimization of treatment in real-time by chronic patient monitoring. Moreover, clinical researchers should be collaborated with to evaluate the model on the real patient data and develop clinically implementable decision support systems to personalize the breast cancer treatment planning.

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