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Optimization of drug regimen in chemotherapy based on semi-mechanistic model for myelosuppression

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ABSTRACT

Based on the latest statistics on trends in cancer incidence and mortality worldwide, cancer burden is growing at an alarming pace. Many anticancer drugs have been proved effective against cancer cells as well as toxic to human tissues, which prevents sufficient doses from being administered to obtain a complete cure. In this paper we build an optimal control model to optimize the scheduling problem along one cycle of chemotherapy treatment using a single anticancer drug etoposide (VP-16). In the model, three mathematic models are adopted to mimic physiological response of body under chemotherapy: (i) Pharmacokinetic model of anticancer drug; (ii) A two-compartment tumor growth dynamic model under the influence of cell-cycle-specific anticancer drug; and (iii) A semi-mechanistic model for myelosup-pression. In this new integrated model clinically relevant objectives are proposed to gain a trade-off between efficacy and toxicity. Simulation results of clinical protocols are consistent with real-life clinical data. Furthermore, we find a new optimal drug regimen which can improve the efficacy without the risk of severe toxicity.

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42 1. Introduction

Cancer, also known as malignant tumor, is a group of diseases 43 involving abnormal cell growth with the potential to invade or 44 spread to other parts of the body. According to 'World Cancer 45 Report 2014' released by the International Agency for Research 46 47 on Cancer (IARC), in 2012 the worldwide burden of cancer rose to an estimated 14 million new cases per year, and the figure is 48 expected to rise to 22 million annually within the next two dec-49 ades. Over the same period, annual cancer deaths are predicted 50 51 to rise from an estimated 8.2 million to 13 million. As pointed out by the Director of IARC, Dr. Christopher, "the rise of cancer 52 worldwide is a major obstacle to human development and 53 54 well-being. These new figures and projections send a strong signal that immediate action is needed to confront this human disaster, 55 which touches every community worldwide, without exception". 56

57 Surgery, chemotherapy, radiotherapy, hormone therapy and 58 immunotherapy are the primary treatment options for cancer. 59 Since cancer cells can invade surrounding tissues and migrate to 50 the other parts of the body, chemotherapy is commonly employed

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http://dx.doi.org/10.1016/j.jbi.2015.06.021 1532-0464/© 2015 Published by Elsevier Inc. as a systemic treatment by clinicians. Combining with surgery, chemotherapy has been proven beneficial in many different types of cancer such as breast cancer, colorectal cancer, pancreatic cancer, osteogenic sarcoma, testicular cancer, ovarian cancer, and certain lung cancers. However, the effectiveness of chemotherapy is often limited by toxicity to other tissues in the body due to the interaction of the drug with normal cells. Clinicians need to put forward a drug regimen to balance the treatment efficacy with the toxic side effects.

Randomized clinical trials are the standard method for the evaluation of efficacy and toxicity of chemotherapy treatment plans. The current standard of practice of treatment is based on empirical evidence gathered from preclinical and clinical trials carried out during the drug development process. However, given the limited human and financial resources for clinical trials, optimal protocols cannot be determined empirically. To this end, mathematical modeling provides a low-cost method for evaluating different strategies more efficiently by describing the quantitative relations among several factors [1].

The optimal control model (OCM) constructed by Martin et al. [1,2] has been extensively used by the studies on chemotherapy treatment optimization problem. Martin et al. [1,2] use the Gompertz equation to describe tumor cell populations. Maximum tolerated dose (MTD) and area under concentration (AUC) are indicators of toxicity. A multiple characteristic time (MCT) constraint is

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used to ensure tumor population decrease at, or faster than, a given rate in a specified time interval. More recently, Liang et al. [3–5] modified the metabolism process of cumulative drug toxicity by introducing a new parameter representing the elimination rate of drug toxicity and applied several algorithms to the chemotherapy scheduling problem.

The Gompertz model is capable of capturing clinically observed tumor dynamics, but it cannot capture information regarding the progression of cells through the individual phases of the cell-cycle. Compartment models are developed to gain more insight into cell behavior [6]. Based on the previous research, Dua et al. [7] incorporate the cycle-specific chemotherapy effect mechanism into the optimal control model (OCM), in which they present two typical optimal control formulations that minimize the final tumor population subject to the constraints on toxicity and drug resistance. A more complex description of the system incorporates patient-specific parameters into their cell population growth model, where an approximately optimal treatment plan is found by applying simulated annealing algorithm [8].

Efforts have been made to shed light on interaction between 105 106 tumor and immune system. Villasana et al. [9,10] formulated the 107 action of a cycle-specific cytotoxic drug with the goal of maximiz-108 ing cell kill fraction and minimizing normal cell killing and 109 designed a heuristic algorithm to find optimal delivery schedules. 110 Furthermore, they incorporated a cytostatic drug which arrest cells 111 in a phase of their cycle. The problem of designing efficient com-112 bined chemotherapies is formulated as an optimal control problem 113 and tackled using three heuristic algorithms for real-parameter 114 optimization, namely, covariance matrix adaptation evolution 115 strategy, differential evolution, and particle swarm pattern search 116 method [11,12].

117 Research in the last five decades has led to the development of 118 Medical Decision Support (MDS) applications using a variety of 119 modeling techniques, for a diverse range of medical decision prob-120 lems, such as diagnostic decision support [13] and management of 121 hospital resources [14,15]. In this paper we focus on cancer 122 chemotherapy and dose schedule optimization using mathemati-123 cal methods.

124 Although extensive efforts have been invested in the theoretical 125 investigation of chemotherapy control methods, we find several 126 limitations to practical application. In most previous studies, the toxicity of a treatment is measured both by maximum tolerated 127 dose and maximum drug exposure expressed as area under curve 128 129 (AUC). It relies on the assumption that today's chemotherapy treat-130 ments achieve the maximum efficacy. However, we find this 131 approach clinically unrealistic. In practical chemotherapy con-132 stantly suffers from the inability to control the efficacy-toxicity 133 balance. More importantly, AUC as an indicator of toxicity is argu-134 able, since it induced unreasonable timing for the first treatment in 135 the optimization problem in Martin et al.'s work [1,2]. Liang et al. 136 [3–5] attempted to fix this by introducing a new parameter. While Agur et al. [9] tried to model the interaction of drugs with normal 137 138 cells. Nevertheless, those methods cannot be applied directly because parameters in their models are clinically unavailable. In 139 140 order to reduce the gap between theoretical investigation and medical practice, we propose a more practical approach by inte-141 142 grating a physiology-based model, i.e., the semi-mechanistic model for myelosuppression proposed by Friberg et al. [16], 143 into the chemotherapy dose scheduling problem. This semi-144 145 mechanistic model effectively captures the main physiological pro-146 cesses and predicts the whole time course of leukopenia. Based on 147 this new model we are able to find optimal drug regimen, and 148 identify new strategies to split the total drug dose so that toxicity 149 will be reduced without compromising efficacy.

The rest of the paper is organized as follows: Section 2 gives a brief introduction on biomedical background and describes the

pharmacokinetic model of VP-16, tumor growth dynamic model152and chemotherapy-induced myelosuppression model in detail.153Section 3 is the simulation results of different clinical protocols154and Section 4 works on optimizing dose regimens in cancer155chemotherapy. Conclusions and discussions are presented in156Section 5.157

2. Problem formulation

2.1. Biomedical background

In cancer treatment, measurement of tumor growth is neces-160 sary for preclinical and clinical assessment of efficacy. To model 161 untreated tumor growth, exponential, Gompertz and logistic 162 growth models are commonly used but cell-cycle models provide 163 more insight into cell behavior. Cell cycle is a chain of phases that 164 both normal and cancer cells undergo from their birth to death. In 165 general, the cycle comprises of five stages which are G0, G1, S, G2 166 and M. G0 stands for resting phase, representing cell is quiescent. 167 Cycling cell has four phases, including the gap period (G1), the syn-168 thetic period (S), the second gap period (G2), and mitosis (M). 169 Usually, cancer drugs work by damaging the RNA or DNA to halt 170 division. Anticancer drugs that are able to kill all cancer cells are 171 called cell-cycle non-specific; while drugs that only kill cancer cells 172 when they are dividing are called cell-cycle specific. 173

Since anticancer drugs attack both normal and cancer cells, their usage often lead to severe side effects. Side effects of anticancer chemotherapy include hematological toxicity, nausea, vomiting, diarrhea, fatigue, alopecia, and cardiac, neurological, and renal toxicity. The main toxicity of most anticancer drugs is hematological. Thus, the ability to anticipate hematological toxicity could be of great value for optimizing treatment and predicting complication for patients who undergo prolonged periods of myelosuppression [17].

Etoposide (VP-16) is a cell-cycle specific anticancer drug that has been widely used in chemotherapy treating childhood leukemia, testicular tumors, Hodgkin's disease, large cell lymphomas and small cell lung cancer (SCLC). The activity of VP-16 is dose- and schedule-dependent, and efficacy might be improved markedly with repeated drug administration. However, myelosuppression as the dose-limiting toxicity for VP-16 should be taken into account when planning the chemotherapy regimen. The chemotherapy treatment is given in cycles, attacking cancer cells at their most sensitive periods, and allowing normal body cells time to recover [18].

2.2. PK–PD model

Cancer progression in a patient undergoing chemotherapy is a very complex process. Engineers have considered the development of drug administration schedules for simulated cancer patients constrained by pharmacokinetic (PK) and pharmacodynamic (PD) models to meet the challenge [19] (see Fig. 1).

2.2.1. Pharmacokinetic model

Pharmacokinetic models can include the distribution of drugs by the circulatory system, the elimination of drug, and the amount of drug present at the site of action. Systems of linear ordinary differential equations (ODEs) are commonly used to describe the dynamic relationship between the kinetic behavior of the drug administered and corresponding concentration. Regarding VP-16, a two-compartment PK model (as in Fig. 2) has the best fit [20].

The mathematical models are as follow:

$$\dot{X}_c = K_{21} \times X_p - (K_{12} + K_{10}) \times X_c + X_0 \tag{1}$$

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