Novel Clinical Trial Designs with Dose Optimization to Improve Long-term Outcomes

Peter F. Thall1, Yong Zang2, Andrew G. Chapple3, Ying Yuan1, Ruitao Lin1, David Marin4, and Pavlos Msaouel5,6,7

ABSTRACT

Conventional designs for choosing a dose for a new therapy may select doses that are unsafe or ineffective and fail to optimize progression-free survival time, overall survival time, or response/remission duration. We explain and illustrate limitations of conventional dose-finding designs and make four recommendations to address these problems. When feasible, a dose-finding design should account for long-term outcomes, include screening rules that drop unsafe or ineffective doses, enroll an adequate sample size, and randomize patients among doses. As illustrations, we review three designs that include one or more of these features. The first illustration is a trial that randomized patients among two cell therapy doses and standard of care in a setting where it was assumed on biological grounds that dose toxicity and dose–response curves did not necessarily increase with cell dose. The second design generalizes phase I–II by first identifying a set of candidate doses, rather than one dose, randomizing additional patients among the candidates, and selecting an optimal dose to maximize progression-free survival over a longer follow-up period. The third design combines a phase I–II trial and a group sequential randomized phase III trial by using survival time data available after the first stage of phase III to reoptimize the dose selected in phase I–II. By incorporating one or more of the recommended features, these designs improve the likelihood that a selected dose or schedule will be optimal, and thus will benefit future patients and obtain regulatory approval.

Introduction

Preclinical development of new targeted and immunotherapy agents for cancers and other diseases has created a pressing need for clinical trials to evaluate and optimize these agents. Members of the medical research community have become aware that conventional methods for choosing the dose or schedule of a new agent are inadequate (1–6). Shah and colleagues (7) provided examples of several agents with recommended doses that had high toxicity rates in trials or postmarketing samples following FDA approval. Failure of conventional designs to reliably identify safe and effective doses apply generally, and they are likely to perform poorly for cytotoxics, radiotherapy, and targeted agents (2, 5, 7).

We review problems with conventional dose-finding designs and recommend desirable design features to obtain better results. We review three practical dose-finding designs that reliably identify safe doses that maximize progression-free survival (PFS) time, overall survival time (OS) time, or response/remission duration (RD). Our goal is to motivate medical researchers to include these features in their dose-finding trials.

Background and Examples

The FDA initiated Project Optimus (7, 8), “to reform the dose optimization and dose selection paradigm in oncology drug development.” Despite widespread agreement that new dose-finding designs are needed for targeted or immunologic agents, it is unclear how to structure them for many medical settings. Conventional phase I designs choose a MTD by assigning doses to successive patient cohorts in a small trial using a 3+3 algorithm (9) or the continual reassessment method (CRM; refs. 10, 11), using dose-limiting toxicity (DLT) evaluated after one or two cycles of therapy. It is well known that a 3+3 algorithm is likely to produce poor decisions (2, 12, 13), with a high risk of an unacceptably high toxicity rate at the MTD in later trials (7, 13). Most phase I samples are too small to reliably choose an MTD or estimate its toxicity probability. For example, if two DLTs are observed in 6 patients treated at the MTD in phase I, a Bayesian posterior 95% credible interval for the probability of DLT at the MTD ranges from 8% to 71%. Treating an expansion cohort at the MTD does not solve this problem, because an MTD chosen based on a small sample has a high risk of being excessively toxic. Conventional designs assume that the risk of DLT increases with dose, “monotonicity,” which may be true for some agents but not others, and a careful analysis of all preclinical data should be done to adjudicate this before choosing a design. If the response probability is not monotone, dose escalation is inappropriate, because higher doses may be less safe or provide lower anticancer efficacy.

Conventional phase I designs ignore efficacy, such as tumor shrinkage or complete remission in cancers such as leukemias, which makes it impossible to choose doses based on risk–benefit trade-offs. Phase I–II designs use both toxicity and early efficacy to select doses and are well-known to be superior to phase I designs (2, 12, 13). Phase I–II designs accommodate dose–response curves with a plateau due to saturation of pharmacokinetic exposure in the patient, whereby the response rate does not increase for higher doses, and a selected dose on a plateau by conventional phase I designs may expose patients unduly
Translational Relevance

We address limitations of conventional trial early-phase designs that hinder clinical translation of promising new agents by choosing suboptimal doses. These designs may select doses that are either unsafe or ineffective and do not optimize outcomes such as progression-free survival time, overall survival time, or remission duration. We highlight four strategies to improve this process, which include accounting for long-term outcomes, excluding doses that are unsafe or ineffective, ensuring adequate sample size, and using randomization in dose selection. Three illustrative designs are discussed, each incorporating one or more of these recommendations. The examples provided underscore the potential of these methodologies to optimize the selected dose or schedule of a therapeutic intervention, thus enhancing patient outcomes and increasing the likelihood of securing regulatory approval. Such strategies, when effectively applied, could substantially improve dosage determination in oncology by maximizing long-term efficacy and patient safety.

to a higher risk of toxicity (2). For example, if five doses have toxicity probabilities 1%, 5%, 30%, 45%, and 50%, and response probabilities 20%, 50%, 50%, 50%, and 50%, a plateau is reached at dose 2. A 3+3 algorithm or CRM with target toxicity probability 30% both are most likely to select dose 3, while dose 2 has the same response probability of 50% but much lower toxicity probability of 5%. Although superior to conventional phase I, most phase I–II designs ignore PFS time, OS time, and RD evaluated over longer follow up. Because early outcomes seldom are reliable surrogates for long-term outcomes (14, 15), a dose chosen in phase I or phase I–II often fails to maximize PFS, OS, or RD (16, 17). Table 1 gives examples and solutions provided by novel designs (1, 18–24). For example, writing R = response and T = toxicity, the phase I trial of niraparib for ovarian cancer in Table 1 might be replaced by a phase I–II trial based on the utilities U(R, No T) = 100 and U(No R, T) = 0 for the best and worst possible outcomes, with U(R, T) = 80 and U(No R, No T) = 40 for the intermediate outcomes, using estimated values of U as a basis for evaluating doses. This could be extended further to use response duration to choose a best dose, by applying the generalized phase I–II design, described below.

As an illustration, a phase I trial of allogeneic stem cell transplantation for acute leukemia (25) studied six doses of vorinostat added to a standard preparative regimen, using the time-to-event CRM (26) with target toxicity probability 30%. Because very few DLTs were observed, the design rapidly escalated and selected the highest dose, level 6, as the MTD, where an expansion cohort was treated, giving per-dose sample sizes of 3, 3, 4, 4, and 31. Longer follow up showed that patients treated with dose 6 had shorter OS than patients treated at doses 1–5. This effect persisted after accounting for prognostic variables (25, 27). Because dose 6 is undesirable, but a lower dose maximizing OS cannot be determined from the small samples at dose levels 1–5, it is unclear what dose to use in clinical practice, or how to design a future study. This trial suggests that, in general, longer term outcomes should be considered, along with toxicity and early response, when selecting a dose.

A second illustration is a phase I–II trial conducted to optimize the dose of sitravatinib, a tyrosine kinase inhibitor, + a fixed dose of nivolumab, an anti–programmed death agent, in clear cell renal cell carcinoma (ccRCC; ref. 1). The “Late Onset Efficacy-Toxicity (LO-ET) design (28) was used to choose among 60-, 80-, 120-, and 150-mg doses of sitravatinib, which had final respective LO-ET desirability scores of 0.622, 0.787, 0.755, and 0.630. However, longer outcomes including PFS time and later patient-reported outcomes measuring depression, quality of life, and hope for the future all indicated that the 120-mg dose was best, rather than the nominally optimal LO-ET dose of 80 mg (1).

Recommended Features of a Dose-Finding Design

To address limitations of conventional dose-finding methods, and respond to Project Optimus, we recommend that, when feasible

Table 1. Examples of flaws with conventional designs and solutions provided by novel designs.

<table>
<thead>
<tr>
<th>Disease</th>
<th>Agent</th>
<th>Design</th>
<th>References</th>
<th>Flaw</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Philadelphia chromosome-</td>
<td>Ponatinib (oral tyrosine</td>
<td>3+3</td>
<td>18, 19</td>
<td>Pick an unsafe dose of 45 mg PO daily</td>
<td>Include a dose toxicity rate safety monitoring</td>
</tr>
<tr>
<td>positive leukemias</td>
<td>kinase inhibitor)</td>
<td></td>
<td></td>
<td>continuously (38), which later was</td>
<td>rule</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>modified to starting with 45 mg PO</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>daily then 15 mg PO daily once ≤1%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>BCR-ABL is achieved (19)</td>
<td></td>
</tr>
<tr>
<td>Non-small cell lung cancer</td>
<td>Onartuzumab (monoclonal</td>
<td>3+3</td>
<td>20, 21</td>
<td>Pick a dose with a low response rate</td>
<td>Include a dose response rate safety monitoring</td>
</tr>
<tr>
<td></td>
<td>antibody against MET)</td>
<td></td>
<td></td>
<td>‒ Phase III failure</td>
<td>rule</td>
</tr>
<tr>
<td>Ovarian Cancer</td>
<td>Niraparib (PARP inhibitor)</td>
<td>Accelerated titration</td>
<td>22, 24</td>
<td>Pick a dose with a high grade 3</td>
<td>Account for toxicity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3+3 design</td>
<td></td>
<td>hemato genomic toxicity rate</td>
<td>grades and response using a utility function</td>
</tr>
<tr>
<td>High risk acute leukemia</td>
<td>Vorinostat (histone</td>
<td>Time-to-event</td>
<td>25</td>
<td>Pick a dose that yielded a worse</td>
<td>Account for long-term</td>
</tr>
<tr>
<td></td>
<td>deacetylase inhibitor)</td>
<td>continual</td>
<td></td>
<td>overall survival than the other</td>
<td>overall survival and</td>
</tr>
<tr>
<td></td>
<td></td>
<td>reassessment</td>
<td></td>
<td>doses. Limited sample size to</td>
<td>enroll adequate sample size for reliable</td>
</tr>
<tr>
<td></td>
<td></td>
<td>method (CRM)</td>
<td></td>
<td>choose among the other doses</td>
<td>dose selection</td>
</tr>
<tr>
<td>Clear cell renal cell</td>
<td>Sitravatinib (oral tyrosine</td>
<td>Late-onset efficacy-</td>
<td>1</td>
<td>Unable to choose a dose giving better</td>
<td>Account for long-term</td>
</tr>
<tr>
<td>carcinoma</td>
<td>kinase inhibitor) in</td>
<td>toxicity</td>
<td></td>
<td>long-term survival</td>
<td>PFS or survival time when choosing a dose</td>
</tr>
<tr>
<td></td>
<td>combination with</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>nivolumab immunotherapy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Downloaded from http://aacrjournals.org/clincancerres/article-pdf/29/22/4549/3380588/4549.pdf by MD Anderson Cancer Center Cancer Center user on 14 November 2023
depending on the setting, a dose-finding design should include one or more of the following features:

**Feature 1.** To choose an optimal dose, in addition to using short-term response and toxicity, a long-term outcome, such as PFS time, OS time, or RD, evaluated over longer follow up should be used.

**Feature 2.** Include screening rules that drop unsafe or ineffective doses. If some doses are dropped, enrich the sample sizes of remaining doses rather than reducing overall sample size.

**Feature 3.** Enroll a sample large enough to make reliable inferences.

**Feature 4.** If appropriate, randomize patients among doses and compare them with standard of care (SOC).

Feature 1 addresses the problem that early outcomes are imperfect surrogates for PFS, OS, or RD, so a dose-maximizing response rate often does not optimize long-term outcomes. Feature 1 requires longer follow-up, often 6 or 12 months, to evaluate the long-term outcome. Screening rules in Feature 2 protect patients from unsafe or ineffective doses, and enrichment increases dose selection reliability. Feature 3 is motivated by the fact that the precision of any inference increases with sample size. Feature 4 ensures that between-dose comparisons are fair and, to protect patient safety, a monitoring rule that stops accrual to an excessively toxic dose should be included.

Each of the following three designs has one or more of the recommended features. The randomized controlled selection design, which is well established, is the least complex. The other two designs are novel. The generalized phase I–II design has intermediate complexity, and the phase I–II/III design is most complex. Properties of these designs are summarized in Table 2, which may provide a basis for choosing among them in a particular setting.

### A Randomized Controlled Selection Trial to Study Cellular Therapy in COVID-19

If assuming monotonicity is not valid, randomization is more appropriate because it gives unbiased comparisons between doses. The following study (29) used a three-arm randomized controlled design (16, 17) to select a best dose. This design is not new (19, 30), and it offers a scientifically attractive alternative to cohort-by-cohort dose-finding. The trial studied T-regulatory NK cells for treating COVID-19–related acute respiratory distress syndrome (ARDS; ref. 29). DLT was any regimen-related grade 3 or worse toxicity within 48 hours of infusion, and response was defined as the patient being alive and extubated at day 28. Because there was no biological or medical reason to assume monotonicity, 45 patients were randomized to 10^8 cells, 3 × 10^8 cells, or SOC, with 15 patients per arm. DLT and response were coprimary outcomes, and OS was evaluated over longer follow up. Safety monitoring rules were included to shut down a dose showing excessive toxicity compared with SOC. A schematic of the trial is given in Fig. 1.

No toxicities were observed, and the response rate was highest for 10^8 cells (9/15, 60%) and SOC (9/15, 60%) and lowest for 3 × 10^8 cells (6/15, 40%) (29). Similarly, estimated 100-day survival probabilities were 86.2% for 10^8 cells, 77.9% for SOC, and 45.1% for 3 × 10^8 cells. Because a conventional phase I design would have escalated to the 3 × 10^8 cell arm, randomizing saved nearly 30 patients from being treated with the higher dose, 3 × 10^8 cells, which had the shortest estimated OS, and it prevented this dose from being selected.

---

**Table 2.** Comparisons between the three dose-finding designs.

<table>
<thead>
<tr>
<th>Design</th>
<th>Sample size requirement*</th>
<th>Time requirement</th>
<th>Phases included</th>
<th>Advantages</th>
<th>Limitations</th>
<th>Recommended clinical scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td>Randomize all doses versus an active control and select the best dose</td>
<td>(K+1) n</td>
<td>Phase I–II</td>
<td>1 + 2</td>
<td>Unbiased dose-vs.-control comparisons. Can be expanded seamlessly to phase 3</td>
<td>Appropriate if Pr (response) and Pr (toxicity) are not monotone in dose</td>
<td>Randomization of all doses versus an active control is acceptable and selecting an optimal dose is the goal</td>
</tr>
<tr>
<td>Gen 1–2</td>
<td>K n + 10 m</td>
<td>Phase I–II + 10m more patients to estimate response/ remission duration</td>
<td>1 + 2</td>
<td>Uses safety, response, and response/ remission duration to optimize dose</td>
<td>Requires 10m more patients and 6 to 12 months longer follow up than phase I–II</td>
<td>A phase I–II trial is planned, including longer follow-up to assess duration of response/remission</td>
</tr>
<tr>
<td>Phase 1–2/3</td>
<td>K n + phase 3 sample size</td>
<td>Phase I–II + Phase 1 –II/III</td>
<td>1 + 2 + 3</td>
<td>Uses survival time to re-optimize the phase 1–2 dose and to do phase 3 comparison</td>
<td>Requires time and resources for conducting both phase 1–2 and phase 3.</td>
<td>A phase III trial is being considered, but better dose optimization is desired</td>
</tr>
</tbody>
</table>

*K = number of doses considered, n = average number of patients per dose in phase I–II, m = number of candidate doses chosen in stage 2 of a Gen 1–2 trial.

---

**Figure 1.**

Schematic of the randomized trial of cellular therapy for ARDS in COVID-19. Patients were randomly assigned to different doses of cellular therapy or standard of care.
This design is appropriate for any oncology trial of an agent when monotonicity in dose cannot be assumed. Two advantages of randomization are that the comparison between each dose of the agent and the active control is unbiased and, after the trial, patient cohorts treated with the selected dose or control may be expanded seamlessly to conduct a confirmatory randomized phase III trial, thus reducing phase III sample size. While two cell doses were considered in the COVID-19 ARDS trial, the randomized selection design is quite general. A larger number of doses, say K, may be included, and any endpoint may be used, subject to the practical requirement that the maximum sample size of \((K+1)^n\) must be feasible, where \(n\) is number of patients per dose.

A Generalized Phase I–II Design to Optimize Response Duration

The following design extends phase I–II to include a long-term outcome. For many therapies, responders have a substantial risk of relapse. Clinical investigators aware of this problem often include a longer follow-up period in a phase I–II dose-finding trial protocol to estimate response/remission duration. A generalized phase I–II design, Gen 1–2, exploits this practice to identify a dose that maximizes the probability of long-term RD (27). The Gen 1–2 paradigm can incorporate any phase I–II design and tailor trials to accommodate a variety of clinical settings. Early outcomes may be binary or ordinal variables, such as toxicity grade and disease severity levels, and numerical utilities of \((R,T) = (\text{response, toxicity})\) may be used for choosing doses (2, 3, 31–35). A Gen 1–2 design schematic is given in Fig. 2.

To illustrate a Gen 1–2 design, let one month be the follow up to evaluate response and toxicity, with long-term therapeutic success defined as the patient being alive with stable disease or better at 6 months. Stages 1 and 2 consist of a phase I–II trial based on toxicity and response, including rules to drop any dose having an unacceptably high toxicity or low response rate. In stage 1, doses are assigned to patient cohorts using the phase I–II design’s rules. Stage 2 randomizes patients among acceptable doses and identifies a set of nearly optimal candidate doses, rather than one dose. In stage 3, additional patients are randomized among the candidates, and all patients are followed to six months. The dose with largest six-month RD rate is selected as optimal. The stage 3 sample size is determined by computer simulation to obtain a desired level of reliability. Computer simulations showed that a Gen 1–2 design has optimal dose selection rates up to an order of magnitude larger than those of conventional phase I–II designs (27). Computer software for implementing a Gen 1–2 design is available from https://github.com/yongzang2020.

A Hybrid Seamless Phase I–II/III Design

Korn and colleagues (36) considered the timing of dose optimization in drug development, and recommended that it should be done during or after phase III. This solves the issues described above but produces the problem that reliably comparing the rates of an outcome among multiple doses and a control in phase III requires a large multi-arm trial. Seamless phase II–III designs (37–39) address this problem by combining randomized dose selection with confirmatory testing in a large-scale trial, with reliability defined by generalized power (GP), the probability of (i) selecting a truly optimal dose that provides a meaningful survival improvement over standard therapy, and (ii) concluding in a final test that the new agent at the selected dose is superior to the standard. GP quantifies how well the entire process of dose selection and comparative testing behaves.

Chapple and Thall (37) proposed a three-stage ‘phase I–II/III’ design that combines phase I–II and phase III in one trial. In stage 1, any phase I–II design based on response or toxicity may be used, with patients adaptively randomized among acceptably safe doses. A best acceptable dose is selected, and stage 2 begins with a phase III trial based on OS time, with patients randomized between a control and the new agent at the selected phase I–II dose. After a prespecified number of deaths in stage 2, dose is reoptimized to maximize estimated mean survival time, and phase III is completed with patients randomized between the control and the new agent at the re-optimized dose. A final treatment comparison is based on all response, toxicity, and survival time data (40). A phase I–II/III design schematic is given in Fig. 3. Computer simulations showed that a phase I–II/III design is greatly superior to conducting phase III without re-optimizing dose (37). Across a range of scenarios, dose re-optimization increases GP by 9% to 73%, and provides a substantial increase in expected survival time for patients enrolled in the trial. The price of dose re-optimization is that a phase III trial with \(N = 500\) patients may require 10 to 100 additional patients to do phase I–II/III. If eligibility criteria of the phase I–II and phase III cohorts differ, to account for heterogeneity so that patient prognosis is not conflated with dose effects, regression models for early response, toxicity, and survival time must be extended to...
include prognostic covariates. A similar approach can be taken in a Gen 1–2 design by extending regression models for early response and RD to include covariates. The main elaboration for phase I–II/III is dose re-optimization and dose switching during phase III. The most demanding requirement is trial planning, which requires extensive computer simulations. A freely available software package, Phase123, to implement the design is available in an R package archive at https://cran.r-project.org/web/packages/Phase123/.

To use Table 2 for choosing between the three designs in a given setting, one may compute each design’s expected sample size and trial duration for particular design parameters. For example, if K = 4 doses are to be studied, with on average n = 15 patients per dose, then the randomized controlled selection design would require up to (4+1)15 = 75 patients. The Gen 1–2 design would require 4 × 15 + 10 m = 70, 80, 90, or 100 patients, respectively, if m = 1, 2, 3 or 4 candidate doses are chosen in stage 2. The phase I–II/III design would require up to 60 + (N – phase III sample size) patients, where N varies with the phase III design. For anticipated accrual rate of 10 patients per month, the respective accrual durations would be approximately 75/10 = 7.5 months for the randomized selection design, 70/10 = 7 to 100/10 = 10 months for Gen 1–2, and, if N = 500 for phase III, 60/10 + (10 to 100)/10 + 500/10 = 57 to 66 months for phase I–II/III, plus final additional follow up time added to each of these durations.

Future Research

Many important issues remain, including evaluating schedules or (dose, schedule) combinations (41). A complex issue is how best to give a therapy repeatedly over multiple cycles, with later doses chosen based on each patient’s previous doses and outcomes (42, 43). Additional challenges include accounting for late onset toxicity or response, and low-grade toxicities. A major issue is incorporating pharmacokinetic and pharmacodynamic parameters when evaluating doses, because the area under a pharmacokinetic curve quantifies systemic exposure for a given dose. This requires additional pharmacokinetic and pharmacodynamic analyses that may greatly complicate adaptive decision making during a trial. The ultimate goal is to choose personalized doses to account for patient heterogeneity (31–33, 44). Several designs for personalized dose-finding have been proposed (3, 45–48). Future research will integrate precision medicine approaches with the designs discussed here to incorporate information from long-term outcomes, use randomization to fairly compare doses, and conduct Gen 1–2 or phase I–II/III studies.

Authors’ Disclosures

R. Lin reports personal fees from Merck Sharp & Dohme, I.T.M Oncologics GmbH, and Monte Rosa Therapeutics outside the submitted work. P. Msaouel reports personal fees from Mirati Therapeutics, Bristol Myers Squibb, Exelixis, and Pfizer and grants from Takeda, Bristol Myers Squibb, and Mirati Therapeutics outside the submitted work. P. Msaouel also reports leadership or fiduciary roles as a Medical Steering Committee member for the Kidney Cancer Association and a Kidney Cancer Scientific Advisory Board member for KCCure. No disclosures were reported by the other authors.

The publication costs of this article were defrayed in part by the payment of publication fees. Therefore, and solely to indicate this fact, this article is hereby marked “advertisement” in accordance with 18 USC section 1734.

Received July 26, 2023; revised August 25, 2023; accepted September 14, 2023; published first September 19, 2023.

References

44. Thall PF, Bayesian cancer clinical trial designs with subgroup-specific decisions. Contemp Clin Trials 2020;90:105860.