Adaptive designs - an overview and some examples

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North West Hub

Attrition rates for new developments (Arrowsmith 2011a, 2011b)



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- phase III & submission: ~50%



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Reasons for failure (Arrowsmith & Miller 2013)



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Phase II (2011-2012)

Efficacy





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• taking forward futile treatments



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- studying the wrong patient population



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- taking forward futile treatments
- studying the wrong patient population
- poor precision (optimal dose, maximum tolerated dose, safety)



Can we do better?



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avoid going straight into large and expensive phase III



Can we do better?

- avoid going straight into large and expensive phase III
- take more care during phases I and II



Can we do better?

- avoid going straight into large and expensive phase III
- take more care during phases I and II
- consider adaptive and Bayesian designs



2. Adaptive Designs



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Modify an ongoing trial





Modify an ongoing trial by design or ad hoc





Modify an ongoing trial

by design or ad hoc

based on reviewing accrued data at interim





Modify an ongoing trial by design or ad hoc based on reviewing accrued data at interim to enhance flexibility





Modify an ongoing trial by design or ad hoc based on reviewing accrued data at interim to enhance flexibility

without undermining the study's integrity and validity.

(Chow et al. 2005)



Pros and cons

- + highly flexible
- + very efficient
- + reflects medical practice
- + shorter trial and/or more accurate estimates
- + ethical

- highly flexible
- inefficient
- time-consuming to design
- simple estimates may be biased
- interim analyses may require unblinding



Fixed sample design





Fixed sample design



• total sample size known in advance



Fixed sample design



- total sample size known in advance
- no adjustment possible



(Group-)sequential design





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(Group-)sequential design



At each interim:

decide whether or not to stop



(Group-)sequential design



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(Group-)sequential design



- decide whether or not to stop
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(Group-)sequential design



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At each interim:

- decide whether or not to stop
- and many other options ...
- Iarger maximum sample size
- Iower expected sample size
- possibly more relevant answer



How and what can we adapt?



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Prospectively ("by design")

adaptive randomization



- adaptive randomization
- early stopping (safety, futility, efficacy)



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- drop-the-loser(s), pick-the-winner



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Concurrently ("ad hoc")

modify inclusion/exclusion criteria



Prospectively ("by design")

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- modify inclusion/exclusion criteria
- change primary endpoint



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- extend treatment duration



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- sample size re-estimation (to achieve desired power)

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- change primary endpoint
- modify doses
- extend treatment duration
- change trial objective (e.g., non-inferiority → superiority)



A single-stage design





Simon's two-stage design





















Example 1: Sample size re-estimation

Problem:

sample size formulae depend on nuisance parameters e.g., σ^2



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- exact (with unblinding) or approximate (without unblinding) (Gould 1995)



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Methods:

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- negligible effect on type I error



Sample size re-estimation Example: DEVELOP-UK trial

- transplantation of reconditioned vs. standard donor lungs
- ex vivo lung perfusion (EVLP)
- phase III, multi-centre, unblinded, non-randomised, non-inferiority observational study
- primary endpoint: 12 months survival
- uncertainty in design parameters (only 50 transplants worldwide)



Example 1: Sample size re-estimation

- 408 patients randomised to EVLP and standard
- 3:1 in favour of standard to ensure all available lungs are used
- interim analyses after 1/3 and 2/3 of total sample size
 - first: early stopping
 - second: early stopping, sample size re-assessment
- significance levels: 0.005 (first), 0.014 (second), 0.045 (final)



Example 2: Phase I cancer trials

Dilemma:

low doses inefficient \longleftrightarrow high doses toxic



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Goal:

find a **maximum tolerated dose** (MTD) where a prespecified proportion p_0 of patients

experience dose-limiting toxicities (DLTs)



Example 2: Phase I cancer trials

Designs:



Example 2: Phase I cancer trials

Designs:

- 3 + 3 design (Carter 1973)
- ... and variations (A + B, rolling 6, ...)
- other 1- or 2-stage up-and-down designs
- accelerated titration design (Simon et al. 1999)
- Continual reassessment method (O'Quigley et al. 1990)



Example 2: Phase I cancer trials

Designs:

- 3 + 3 design (Carter 1973)
- ... and variations (A + B, rolling 6, ...)
 rule-based
- accelerated titration design (Simon et al. 1999)
- continual reassessment method (O'Quigley et al. 1990) model-based



Dose-finding / Phase I

Do NOT use rule based designs



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Adaptive trials

Example 2: Phase I cancer trials

Continual reassessment method (CRM):



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Continual reassessment method (CRM):

Bayesian adaptive design


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Example 2: Phase I cancer trials

Continual reassessment method (CRM):

- Bayesian adaptive design
- model-based
- synthesizes prior belief about MTD and accumulating data
- uses information from all previous patients ("memory")



Example 2: Phase I cancer trials

A CRM design:





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Example 2: Phase I cancer trials

CRM vs. 3 + 3:

- more likely to identify the correct dose
- more patients receive doses near MTD
- fewer overdoses
- clearly defined MTD
- MTD estimated with a measure of precision
- efficient use of all data
- flexible choice of toxicity levels
- easily extendable



Example 2: Phase I cancer trials

Seamless phase I/II designs:

• phase I study "with a phase II flavour" (O'Quigley et al. 2001)



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 - CRM-like (O'Quigley et al. 2001, Zohar & O'Quigley 2006)



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 - efficacy-toxicity trade-off (Thall & Russell 1998, Thall & Cook 2004)
 - CRM-like (O'Quigley et al. 2001, Zohar & O'Quigley 2006)
 - decision procedure for continuous response (Zhou et al. 2006)



Example 3: Multi-arm multi-stage trials (MAMS) TAILOR trial (Pushpakom et al. 2015)

- Phase II study to evaluate treatment for side effect of HIV tri-regimen treatment (TAILoR)
- Superiority trial
- Several possible doses
- Normal distributed endpoint



Example 3: Multi-arm multi-stage trials (MAMS) Design (Magirr et al, 2012)

- 3 active arms compared to control
- Equal randomization between actives and control
- one interim analysis
 - Stop for superiortiy
 - Stop if no active arm appears promising
 - Drop any active arms that are not sufficiently promising
- In the trial we underestimated drop-out and could adjust at interim



General considerations

- New methods either get results faster or are more accurate
- Tend to take more time to develop upfront
 - How can this cost be covered?
- Are the ideas sensible to implement?
 - Is an interim analysis feasible?
 - Can Bayesian methods be updated online?

