





Cancer Phase I trial design using drug combinations when a fraction of dose limiting toxicities is exclusively attributable to one agent

José L. Jiménez¹, Mourad Tighiouart², Mauro Gasparini¹

¹Politecnico di Torino, Turin, Italy ²Samuel Oschin Comprehensive Cancer Institute, Los Angeles, CA, USA

Barcelona, September 9, 2016

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 633567





- 2 Dose-toxicity Model
- Ose Escalation Algorithm
- Design Operations Characteristics
- **5** Simulation Results



Index

Motivation

- 2 Dose-toxicity Model
- 3 Dose Escalation Algorithm
 - 4 Design Operations Characteristics
 - 5 Simulation Results

6 Conclusions

• Clinician wants to design a phase I cancer trials with drug combinations.

• Clinician wants to design a phase I cancer trials with drug combinations.

• She can identify a certain toxicity from one of the drugs.

2 Dose-toxicity Model

- 3 Dose Escalation Algorithm
- 4 Design Operations Characteristics
- 5 Simulation Results

6 Conclusions

- Let *D* be the dose limiting toxicity (DLT) or toxicity binary indicator.
- Let A be the attribution binary indicator.
- Let (δ_1, δ_2) indicate to which drug the toxicity is attributed (i.e., $(\delta_1 = 1, \delta_2 = 0)$ represents a toxicity attributed to drug 1).

- Let *D* be the dose limiting toxicity (DLT) or toxicity binary indicator.
- Let A be the attribution binary indicator.
- Let (δ_1, δ_2) indicate to which drug the toxicity is attributed (i.e., $(\delta_1 = 1, \delta_2 = 0)$ represents a toxicity attributed to drug 1).

Depending on the outcomes, we have three different types of data.

- Let *D* be the dose limiting toxicity (DLT) or toxicity binary indicator.
- Let A be the attribution binary indicator.
- Let (δ_1, δ_2) indicate to which drug the toxicity is attributed (i.e., $(\delta_1 = 1, \delta_2 = 0)$ represents a toxicity attributed to drug 1).

Depending on the outcomes, we have three different types of data.

• Patients with no toxicity.

- Let *D* be the dose limiting toxicity (DLT) or toxicity binary indicator.
- Let A be the attribution binary indicator.
- Let (δ_1, δ_2) indicate to which drug the toxicity is attributed (i.e., $(\delta_1 = 1, \delta_2 = 0)$ represents a toxicity attributed to drug 1).

Depending on the outcomes, we have three different types of data.

- Patients with no toxicity.
- Patients with non attributable toxicity.

- Let *D* be the dose limiting toxicity (DLT) or toxicity binary indicator.
- Let A be the attribution binary indicator.
- Let (δ_1, δ_2) indicate to which drug the toxicity is attributed (i.e., $(\delta_1 = 1, \delta_2 = 0)$ represents a toxicity attributed to drug 1).

Depending on the outcomes, we have three different types of data.

- Patients with no toxicity.
- Patients with non attributable toxicity.
- Patients with attributable toxicity.

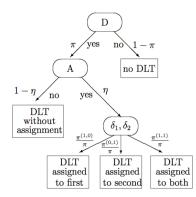
- Let *D* be the dose limiting toxicity (DLT) or toxicity binary indicator.
- Let A be the attribution binary indicator.
- Let (δ_1, δ_2) indicate to which drug the toxicity is attributed (i.e., $(\delta_1 = 1, \delta_2 = 0)$ represents a toxicity attributed to drug 1).

Depending on the outcomes, we have three different types of data.

- Patients with no toxicity.
- Patients with non attributable toxicity.
- Patients with attributable toxicity.

Assumption: When a toxicity is attributed, we assume that we are 100% sure about the attribution.

Dose-toxicity model (II)



• $Pr(D = 1) = \pi$, • $Pr(A = 1|D = 1) = \eta$, • $Pr(\delta_1 = 1, \delta_2 = 0|D = 1, A = 1) = \frac{\pi^{(1,0)}}{\pi}$, • $Pr(\delta_1 = 0, \delta_2 = 1|D = 1, A = 1) = \frac{\pi^{(0,1)}}{\pi}$, • $Pr(\delta_1 = 1, \delta_2 = 1|D = 1, A = 1) = \frac{\pi^{(1,1)}}{\pi}$,

where

$$egin{aligned} &\pi^{(\delta_1,\delta_2)} = (x^lpha)^{\delta_1} \, (1-x^lpha)^{1-\delta_1} \, (y^eta)^{\delta_2} \, ig(1-y^eta)^{1-\delta_2} \ &+ (-1)^{(\delta_1+\delta_2)} x^lpha \, (1-x^lpha) \, y^eta \, ig(1-y^eta) \, rac{e^{-\gamma}-1}{e^{-\gamma}+1}, \end{aligned}$$

and

$$\pi = \pi^{(1,0)} + \pi^{(0,1)} + \pi^{(1,1)}.$$
(2)

(1)

Dose-toxicity model (IV)

Toxicity (D)	Attribution (A)	δ_1	δ_2	Contribution to the Likelihood
0	-	-	-	$egin{aligned} 1-\pi &= 1-\left[x^lpha+y^eta-x^lpha y^eta-x^lpha^eta^eta-x^lpha^eta^eta-x^lpha^eta^eta-x^lpha^eta^eta^eta-x^lpha^eta^eta^eta-x^lpha^eta^eta^eta^etaeta^eta^etaeta^etaeta^eta^$
1	0	-	-	$\pi imes (1-\eta) = \left[x^{lpha} + y^{eta} - x^{lpha}y^{eta} - x^{lpha}y^{eta} - x^{lpha} y^{eta} \left(1 - x^{lpha} ight) y^{eta} \left(1 - y^{eta} ight) rac{e^{-\gamma} - 1}{e^{-\gamma} + 1} ight] imes (1-\eta)$
1	1	1	0	$\pi imes\eta imesrac{\pi^{(1,0)}}{\pi}=\etaig[x^lphaig(1-y^etaig)-x^lphaig(1-x^lphaig)y^etaig(1-y^etaig)rac{e^{-\gamma}-1}{e^{-\gamma}+1}ig]$
1	1	0	1	$\pi imes\eta imesrac{\pi^{(0,1)}}{\pi}=\etaig[y^eta(1-x^lpha)-x^lpha(1-x^lpha)ig)-x^lpha\left(1-x^lpha ight)y^eta\left(1-y^eta ight)rac{e^{-\gamma}-1}{e^{-\gamma}+1}ig]$
1	1	1	1	$\pi \times \eta \times \frac{\pi^{(1,1)}}{\pi} = \eta \left[x^{\alpha} \times y^{\beta} + x^{\alpha} \left(1 - x^{\alpha} \right) y^{\beta} \left(1 - y^{\beta} \right) \frac{e^{-\gamma} - 1}{e^{-\gamma} + 1} \right]$

Prior distribution of the model parameters:

- $Pr(\alpha) = Uniform(0.2,2).$
- $Pr(\beta) = Uniform(0.2,2).$
- $Pr(\gamma) = Gamma(0.1, 0.1).$

Posterior distribution of the model parameters:

$$\Pr(\alpha, \beta, \gamma \mid \mathsf{data}) \propto \\ \Pr(\alpha, \beta, \gamma) \times \prod_{i=1}^{n} \left[\left(\eta \times \pi_{i}^{(\delta_{1}, \delta_{2})} \right)^{A_{i}} \left(\pi_{i} \left(1 - \eta \right) \right)^{1 - A_{i}} \right]^{D_{i}} (1 - \pi_{i})^{1 - D_{i}}.$$

$$\tag{3}$$

2 Dose-toxicity Model

Ose Escalation Algorithm

Design Operations Characteristics

5 Simulation Results

6 Conclusions

- The first cohort in the trials receives the same dose combination. Hence (x₁, y₁) = (X_{min}, Y_{min}) and (x₂, y₂) = (X_{min}, Y_{min}).
- In the second cohort.
 - Patient 3 receives doses (x_3, y_3) , where $y_3 = y_1$ and x_3 is equal to the dose $x \in C$ such that

$$|\operatorname{Prob}(D=1|x, y=y_1) - \theta|$$

is closer to zero. If a toxicity was cause by drug A, then x_3 cannot be higher than x_1 .

• Patient 4 receives doses (x_4, y_4) where $x_4 = x_2$ and y_4 is equal to the dose $y \in C$ such that

$$|\mathsf{Prob}(D=1|x=x_2,y)-\theta|$$

is closer to zero. If a toxicity was cause by drug B, then y_4 cannot be higher than y_2 .

Skeep adding patients until the maximum sample size is reached.

- 2 Dose-toxicity Model
- 3 Dose Escalation Algorithm
- 4 Design Operations Characteristics
- **5** Simulation Results

6 Conclusions

Safety:

- Average % of toxicities.
- % of trials with toxicity rate greater that $\theta + 0.05$ and $\theta + 0.10$.

Efficiency:

- Continuous doses:
 - Pointwise average relative minimum distance between the true MTD and the estimated MTD curves (average bias).
 - 2 Pointwise percent selection.
- Discrete doses:
 - Percentage of MTD selection.

- 2 Dose-toxicity Model
- 3 Dose Escalation Algorithm
 - 4 Design Operations Characteristics

5 Simulation Results

6 Conclusions

Simulation Results (I)

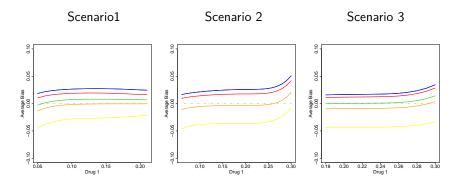
Safety results:

		Average % of toxicities	% of trials with toxicity rate $> \theta + 0.05$	% of trials with toxicity rate $> \theta + 0.10$	
	$\eta = 0.00$	33.62	25.90	4.10	
	$\eta=$ 0.10	32.67	22.60	4.80	
Scenario 1	$\eta = 0.25$	31.55	17.60	2.70	
	$\eta = 0.40$	30.70	13.30	2.00	
	$\eta=1.00$	27.87	4.70	0.20	
	$\eta = 0.00$	30.64	9.40	0.90	
Scenario 2	$\eta = 0.10$	29.69	7.30	0.40	
	$\eta = 0.25$	28.76	5.00	0.20	
	$\eta = 0.40$	28.04	4.10	0.30	
	$\eta = 1.00$	25.60	1.80	0.10	
	$\eta = 0.00$	27.47	2.00	0.00	
	$\eta = 0.10$	26.80	1.80	0.00	
Scenario 3	$\eta = 0.25$	25.99	1.30	0.00	
	$\eta = 0.40$	25.37	0.70	0.00	
	$\eta = 1.00$	23.57	0.20	0.00	

Jiménez, Tighiouart, Gasparini

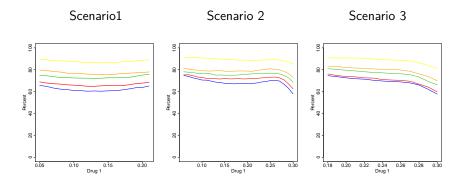
Efficiency results:

Average bias:



Efficiency results:

Average percent of selection:



Simulation Results (IV)

Discrete dose levels scenarios (dose levels probability of toxicity generated with our own model):

	1	2	3	4	1	2	3	4	5	6
Scenario 1				Scenario 4						
4	0.39	0.46	0.52	0.58	0.39	0.43	0.47	0.51	0.55	0.58
3	0.31	0.38	0.46	0.52	0.30	0.35	0.40	0.44	0.48	0.52
2	0.22	0.31	0.38	0.46	0.22	0.27	0.32	0.37	0.41	0.46
1	0.13	0.22	0.31	0.39	0.13	0.19	0.24	0.29	0.34	0.39
Scenario 2				Scenario 5						
4	0.30	0.36	0.42	0.48	0.30	0.33	0.37	0.40	0.44	0.48
3	0.22	0.28	0.35	0.42	0.22	0.26	0.29	0.33	0.38	0.42
2	0.14	0.21	0.28	0.36	0.14	0.18	0.22	0.27	0.31	0.35
1	0.07	0.14	0.22	0.30	0.07	0.11	0.16	0.20	0.25	0.30
Scenario 3				Scenario 6						
4	0.23	0.27	0.33	0.39	0.23	0.25	0.28	0.32	0.35	0.39
3	0.16	0.21	0.26	0.33	0.16	0.18	0.22	0.25	0.29	0.33
2	0.09	0.14	0.21	0.27	0.09	0.12	0.16	0.19	0.23	0.27
1	0.04	0.09	0.16	0.23	0.04	0.07	0.11	0.14	0.19	0.23

Jiménez, Tighiouart, Gasparini

Simulation Results (V)

Percentage of MTD selection:

		a		
		% of MTD		% of MTD
		selection for		selection for
		$ heta\pm 0.10$		$ heta\pm 0.10$
$\eta = 0.00$		91.40		90.00
$\eta = 0.10$		92.50		91.30
$\eta = 0.25$	Scenario 1	90.90	Scenario4	89.40
$\eta = 0.40$		90.90		89.80
$\eta = 1.00$		84.90		84.40
$\eta = 0.00$		78.10		82.90
$\eta = 0.10$		79.80		82.80
$\eta = 0.25$	Scenario2	83.00	Scenario 5	85.00
$\eta = 0.40$		83.50		85.70
$\eta = 1.00$		80.90		81.90
$\eta = 0.00$		99.10		98.80
$\eta = 0.10$		99.30		98.60
$\eta = 0.25$	Scenario 3	97.10	Scenario 6	96.20
$\eta = 0.40$		95.90		94.00
$\eta = 1.00$		86.90		84.80

- 2 Dose-toxicity Model
- 3 Dose Escalation Algorithm
 - 4 Design Operations Characteristics
- **5** Simulation Results



• Bayesian adaptive design for drug combination trials that includes toxicity attributions.

• Improvement of safety results (reduction of average % of toxicities up to 5%) while maintaining high percentage of MTD selection (always > 78%).

• Best overall results obtained when attributing around 40% of the toxicities.

Thanks for your attention! Any questions?

Hope you slept comfortably!

