Surv-CRM-12

A Bayesian Phase I/II Survival CRM for Right-Censored Toxicity Endpoints with Competing Disease Progression

<u>Anaïs Andrillon^{1,2}, Lucie Biard², Shing M. Lee³, Sylvie Chevret²</u>

¹ SARYGA, France ²ECSTRRA, INSERM U1153 CRESS, France ³ Columbia University, NY, USA





October 26th, 2023

- Delayed effects, including toxicities (extended observation windows)
 - → Depending on the patient accrual rate, generate **incomplete data**



- Delayed effects, including toxicities (extended observation windows)
 - → Depending on the patient accrual rate, generate **incomplete data**
- Intercurrent events: death, disease progression, consent withdrawal or physician discretion
 - → Alternative treatment off the protocol will be proposed
 - → Trial discontinuation, precluding complete toxicity assessment
 - → Define a competing risks framework



- Delayed effects, including toxicities (extended observation windows)
 - → Depending on the patient accrual rate, generate **incomplete data**
- Intercurrent events: death, disease progression, consent withdrawal or physician discretion
 - → Alternative treatment off the protocol will be proposed
 → Trial discontinuation, precluding complete toxicity assessment
 - \rightarrow Define a competing risks framework

New definition of the target dose (instead of the MTD)











→ Administrative censoring

incomplete observation at the time of dose-assignment

Inserm

SARYGA



 \rightarrow Administrative censoring

incomplete observation at the time of dose-assignment

→ Informative censoring due to trial discontinuations







HANDLE ADMINISTRATIVE CENSORING IN PHASE I DESIGNS

Mostly, weighting the observation with its partial follow-up time (binary endpoints)
 TITE-CRM (Cheung and Chappell 2000), TITE-BOIN (Yuan et al. 2018), TITE-mTPI (Lin and Yuan 2020)





HANDLE ADMINISTRATIVE CENSORING IN PHASE I DESIGNS

Mostly, weighting the observation with its partial follow-up time (binary endpoints)
 TITE-CRM (Cheung and Chappell 2000), TITE-BOIN (Yuan et al. 2018), TITE-mTPI (Lin and Yuan 2020)

HANDLE INFORMATIVE CENSORING DUE TO TRIAL DISCONTINUATIONS

- **1. Replacement** of non-evaluable patients
- 2. Practical strategies for managing partial observation
 - Weighted likelihood

 \rightarrow Impacting performance of dose-toxicity centered designs (Biard et al 2020)



PROPOSAL: BAYESIAN SURVIVAL MODELING FRAMEWORK



PROPOSAL: BAYESIAN SURVIVAL MODELING FRAMEWORK



PROPOSAL: BAYESIAN SURVIVAL MODELING FRAMEWORK



COMBOLA TRIAL*

- Patients with low-risk myelodysplastic syndrome (MDS)
- Dose finding trial of luspatercept in combination with erythropoietin
- Toxicity observation windows: 42 days
- 5 dose levels
- Phase I/II trial using the TITE-BOIN-ET design (Takeda et al. 2020)
- Progression free survival (PFS) was a secondary endpoint



*Groupe Francophone des Myélodysplasies (GFM), NCT05181735

SURVIVAL-CRM-12

- **Toxicity and progressoin endpoints** within the observation window (t*)
- *T*, the time-to-DLT or progression
- → Administrative censoring: during the trial and at the end of the observation window
- → Informative censoring: discontinuations due to progression



SURVIVAL-CRM-12

- **Toxicity and progressoin endpoints** within the observation window (t*)
- T, the time-to-DLT or progression
- → Administrative censoring: during the trial and at the end of the observation window

 \rightarrow Informative censoring: discontinuations due to progression

- Survival analysis framework with competing risks
- $h_1(.)$, the cause-specific instantaneous hazard function for DLT, d scaled dose

 $h_1(\beta_1, d) = \exp(d \exp(\beta_1))$

• $h_2(.)$, the **cause-specific instantaneous hazard function**, for progression, d scaled dose

 $h_2(\beta_2, d) = \exp(-d \exp(\beta_2))$

17



SURVIVAL MODELS FOR COMPETING EVENTS



Observed cumulative incidence for event k = 1, 2 at time t^*

$$F_k(t^*, h_1, h_2, d) = \frac{h_k(t^*, d)}{h_1(t^*, d) + h_2(t^*, d)} \Big(1 - \exp\left(-\big(H_1(t^*, d) + H_2(t^*, d)\big)\Big)\Big)$$

with $h_k(.)$ the cause-specific hazard function, and $H_k(.)$ the corresponding cumulative hazards event k = 1 for DLT and k = 2 for progression [0; t^*]: observation window

SURVIVAL-CRM-12

Dose finding objective

The optimal dose :
$$d^* = \underset{d \in \mathcal{A}_{ccept}}{arg \min} F_2(t^*, h_1, h_2, d)$$

 $F_1(.)$ the cumulative incidence of toxicity and $F_2(.)$ the cumulative incidence of progression



SURVIVAL-CRM-12

Dose finding objective

The optimal dose :
$$d^* = \underset{d \in \mathcal{A}_{ccept}}{arg \min} F_2(t^*, h_1, h_2, d)$$

 $F_1(.)$ the cumulative incidence of toxicity and $F_2(.)$ the cumulative incidence of progression

Dose finding algorithm

 $\begin{aligned} \mathcal{A}_{ccept}, \text{ the set of acceptable doses}, \mathcal{A} &= \{d : d \leq \arg\min_{d \in D} |F_1(t^*, h_1, h_2, d) - \pi_{DLT}| \} \\ \mathcal{G}_{ood}, \text{ the set of good doses}, \ \mathcal{G} &= \{d \in \mathcal{A} : F_2(t^*, h_1, h_2, d) - \min(F_2(t^*, h_1, h_2, d)) \leq \delta_p, \\ \delta_p \geq 0 \} \end{aligned}$

Adaptive randomization

Randomization of the next inclusion at dose $d \in \mathcal{G}$ with probability $R = \frac{1 - F_2(t^*, h_1, h_2, d)}{\sum_{d \in \mathcal{G}_{ood}} 1 - F_2(t^*, h_1, h_2, d)}$



BAYESIAN INFERENCE

DATA PRIOR DISTRIBUTIONS OF β_k , $\phi(\beta_k)$ • *C* : Right-censored failure time Normal distribution with mean 0 and • Y : Observed outcome least informative prior variance* Y=1 if DLT, Y=2 if Progression, Y=0 otherwise D : Allocated doses Sy \mathbf{M} Inference on cause-specific hazard performed separately for toxicity and progression** **Posterior mean of** $\boldsymbol{\beta}_{k}$: $\widehat{\boldsymbol{\beta}_{k}} = \frac{\int_{-\infty}^{\infty} \beta_{k} L(B;C,Y,D) \phi(\beta_{k}) d\beta_{k}}{\int_{-\infty}^{\infty} L(B;C,Y,D) \phi(\beta_{k}) d\beta_{k}}$, with L(B;C, Y,D), the survival likelihood **Estimates of the cumulative incidences of DLT and Progression:** $\widehat{F}_k(t^*, h_1, h_2, d)$ for each dose level ſļ Apply the dose-finding objective * Lee and Cheung. Stat in Med 2011; **Benichou & Gail. Biometrics 1990

• TITE-BOIN-ET (Takeda et al. 2020)

- Handling pending data via a weighted likelihood
- <u>Obj:</u> the dose maximizing the efficacy probability among the doses lower or equal to the MTD



- TITE-BOIN-ET (Takeda et al. 2020)
 - Handling pending data via a weighted likelihood
 - <u>Obj:</u> the dose maximizing the efficacy probability among the doses lower or equal to the MTD
 - Nonparametric Benchmark for right censored endpoints (O'Quigley et al. 2002)



- TITE-BOIN-ET (Takeda et al. 2020)
 - Handling pending data via a weighted likelihood
 - <u>Obj:</u> the dose maximizing the efficacy probability among the doses lower or equal to the MTD
 - Nonparametric Benchmark for right censored endpoints (O'Quigley et al. 2002)

		Doses					
		D1	D2	D3	D4	D5	
Incomplete information (Real clinical trial) {	<i>Y</i> ₁	*	*	0	*	*	



- TITE-BOIN-ET (Takeda et al. 2020)
 - Handling pending data via a weighted likelihood
 - <u>Obj:</u> the dose maximizing the efficacy probability among the doses lower or equal to the MTD
 - Nonparametric Benchmark for right censored endpoints (O'Quigley et al. 2002)

	Doses					
	D1	D2	D3	D4	D5	
Incomplete information (Real clinical trial) $\langle Y_1 \rangle$	0	0	0	*	*	



- TITE-BOIN-ET (Takeda et al. 2020)
 - Handling pending data via a weighted likelihood
 - <u>Obj:</u> the dose maximizing the efficacy probability among the doses lower or equal to the MTD
 - Nonparametric Benchmark for right censored endpoints (O'Quigley et al. 2002)

		Doses				
		D1	D2	D3	D4	D5
Incomplete information (Real clinical trial) {	<i>Y</i> ₁	0	0	0	*	*
Complete information (Framework of simulations) <i>{</i>	<i>Y</i> ₁	0	0	0	1	1



- TITE-BOIN-ET (Takeda et al. 2020)
 - Handling pending data via a weighted likelihood
 - <u>Obj:</u> the dose maximizing the efficacy probability among the doses lower or equal to the MTD
 - Nonparametric Benchmark for right censored endpoints (O'Quigley et al. 2002)

Gray (1988) estimator at t* from all generated complete data

		Doses				
		D1	D2	D3	D4	D5
Incomplete information (Real clinical trial) \langle	<i>Y</i> ₁	0	0	0	*	*
Complete information (Framework of simulations) {	<i>Y</i> ₁	0	0	0	1	1

→ Provide a scenario-specific assessment of the accuracy of dose-finding designs (PCS upper bound estimate)



SIMULATION STUDY: SCENARIOS

N = 10,000 trials; **n = 45 patients**; π_{DLT} = 0.25 Accrual rate of 4 patients per obs. window



Inserm

SARYGA

RESULTS: SURV-CRM-12; CYTOTOXIC SCENARIOS



RESULTS: SURV-CRM-12; PLATEAU SCENARIOS



Inserm

曲

RESULTS: SURV-CRM-12; SAFETY DURING THE TRIAL



CONCLUDING REMARKS

A FRAMEWORK FOR DOSE-FINDING (PHASE I & PHASE I/II)

WITH RIGHT CENSORED ENDPOINTS AND COMPETING RISKS ISSUES

\rightarrow Surv-CRM-12

- Desirable properties (statistical performance, safety, feasibility)
- Sensitivity analyses (patient accrual rate, sample size, variance specification, correlated time to toxicity and progression)







REFERENCES

Andrillon A, Chevret S, Lee S.M., Biard L (2020). Dose-finding design and benchmark for right censored endpoints. *Journal of Biopharmaceutical Statistics*.

Andrillon A, Chevret S, Lee S.M., Biard L (2022). Surv-CRM-12: A Bayesian phase I/II survival CRM for right-censored toxicity endpoints with competing disease progression. *Stat Med*; 1-14.

Biard, L., S. M. Lee, and B. Cheng (2021). Seamless phase I/II design for novel anticancer agents with competing disease progression". *Stat Med*; 40 (21), pp. 4568–4581.

Benichou J., Gail M.H. (1990). Estimates of absolute cause-specific risk in cohort studies. *Biometrics*; 46(3):813-826.

Beyersmann J., Latouche A., Buchholz A., Schumacher M. (2009) Simulating competing risks data in survival analysis. *Statistics in Medicine;* 28(6):956-971.

Jeong, J.-H. and Fine, J. (2006). Direct parametric inference for the cumulative incidence function. *Journal of the Royal Statistical Society: Series C (Applied Statistics);* 55(2):187–200.

Lee S.M., Cheung Y.K. (2009). Model calibration in the continual reassessment method. *Clinical Trials*; 6(3):227-38.

O'Quigley, J., Paoletti, X., and Maccario, J. (2002). Non-parametric optimal design in dose findingstudies. *Biostatistics*; 3(1):51–56.

Putter H., Fiocco M., Geskus R.B. (2006). Tutorial in biostatistics: competing risks and multi-state models. *Statistics in Medicine*; 26(11):2389-430.

Zhang Y., S. Cao, et al. (2021). A Bayesian adaptive phase I/II clinical trial design with late-onset competing risk outcomes". *Biometrics*; 77 (3), pp. 796–808.



BACK-UP



Marginal cause-specific cumulative incidences of event k = 1, 2 at time t^* (unobserved)

 $1 - \exp(H_k(t^\star, d))$

Observed cumulative incidence for event k = 1, 2 at time t^*

$$F_k(t^*, h_1, h_2, d) = \frac{h_k(t^*, d)}{h_1(t^*, d) + h_2(t^*, d)} \Big(1 - \exp\left(-\big(H_1(t^*, d) + H_2(t^*, d)\big)\Big)\Big)$$

with $h_k(.)$ the cause-specific hazard function, and $H_k(.)$ the corresponding cumulative hazards event k = 1 for DLT and k = 2 for treatment discontinuation [0; t^*]: observation window



OBJECTIVE

- Black lines (solid and dashed) : Causespecific marginal cumulative incidences of event at t*
- Gray lines (solid and dashed): Observed cumulative incidences of events at t*



SURV-CRM-12: DATA GENERATION

Competing risks data generation (Beyersmann et al. 2009)

- Cause-specific risks back computed from scenarios cumulative incidence at t*
- Time to any event sampled from exponential distribution with rate (h1+h2)
- Event case determined by a random drawn from a Bernouilli (h1/h1+h2) for toxicity
- Administrative censoring applied at t*

- Dose skeletons calibration: indifference intervals (Lee and Cheung 2009)
- Least informative prior variance for β_1 and β_2 (Lee and Cheung 2011)



RESULTS: SURV-CRM-12; SENSITIVITY ANALYSES

% Correct selection Surv-CRM-12

% Correct selection Benchmark



Clayton model for data generation

When $c \rightarrow 0$ the correlation approaches 1 and, when $c \rightarrow \infty$ the correlation converges to 0



Competing Risk-CRM (Biard et al. 2021)

Survival framework, targeting theoretical marginal incidence of events

<u>Obj</u>: a dose or a set of doses associated with the **minimum progression marginal risk within an admissible set**

Bayesian data augmentation design (Zhang et al. 2021)

- Late-onset competing risks outcome modeled by the cause-specific hazard rate
- Piecewise exponential model
- Pending data during the trial are treated as missing data

Obj: the dose yielding the highest posterior mean utility within an admissible set



COMPETING RISKS CRM DESIGNS

CR-CRM

- Likelihood estimation
- 3 stage design
- Target unobserved cause specific incidences
- Non monotone dose progression relationship

Surv-CRM-12:

- Bayesian
- One-stage design
- Target observed cumulative incidence of events
- Monotonicity assumption



DOSE SKELETONS

- Surv-CRM {0.069, 0.151, 0.250, 0.346, 0.426}.
- iSurv-CRM, best guess prior. Polley (2011),
 - Toxicity: {0.05, 0.10, 0.25, 0.35, 0.50}
 - Trial discontinuation: {0.50, 0.45, 0.40, 0.35, 0.35}
- TITE-CRM: {0.043; 0.124; 0.250; 0.398; 0.542}. Lee and Cheung (2009)
- Surv-CRM-12
 - Toxicity: {0.055, 0.130, 0.250, 0.406, 0.571}
 - Progression {0.666, 0.541, 0.400, 0.266, 0.158}.



RESULTS: ISURV-CRM

🖐 Inserm

SARYGA

N = 10,000 trials; n = 25 patients; π_{DLT} = 0.25 Accrual rate of 4 patients per obs. window



43

PATIENTS WHO EXPERIENCED NEITHER DISEASE PROGRESSION NOR DLT AT T* \rightarrow ADMINISTRATIVE CENSORING?



• Patients who experienced neither disease progression nor DLT at t* \rightarrow informative censoring

- → Trinomial response outcomes (Zhang et al. 2021)
- → Cure rate models: a fraction of subjects in the population will never experience the event of interest (Berkson and Gage, 2006)

'GA

🖐 Inserm

			Model-based	Model-assisted
		Phase I	TITE-CRM (Cheung and Chappell 2000)	TITE-mTPI (Lin and Yuan 2020)
1. Weight the observations		Phase I/II	Seamless phase I/II TITE-CRM (Yan et al. 2019), Robust Bayesian EffTox design (Liu and Johnson 2016) Phase I/II MTA (Riviere et al. 2016)	TITE-BOIN-ET (Takeda et al. 2020)
2. Time-to-event	Time-to-event	Phase I	fCRM (Yin et al. 2013)	
endpoint		Phase I/II	Survival joint model (Yuan and Yin, 2009), Survival EffTox (Koopmeiners and Modiano 2014)	
3.	Missing data	Phase I	EM-CRM (Yuan and Yin 2011), DA-CRM (Liu et al. 2013)	TITE-BOIN (Yuan et al. 2018)
	methodology	Phase I/II	LO-EffTox (Jin et al. 2014)	TITE-BOIN-12 (Zhou et al. 2022)
				(.1

SURVIVAL-CRM

- Toxicity endpoint: DLT within the observation window (t*)
- T, the time-to-DLT
- → Administrative censoring: during the trial and at the end of the observation window
 - Independent from the time-to-DLT
- Survival analysis framework
 - Instantaneous hazard of toxicity for DLT, d scaled dose: $h(\beta, d) = exp(d exp(\beta))$
 - Cumulative hazard, $H(\beta, d)$
 - Cumulative incidence of DLT at the end of the observation window, t*

$$F(d, t^*, h) = 1 - \exp(-h(\beta, d)t^*)$$



CRM dose finding-algorithm

Identify the MTD, d^* , the dose with the probability of toxicity at time t^* closest to a prespecified target π_{DLT} (e.g., 0.25), among the set D of candidate dose levels

$$d^* = \arg\min_{d \in D} |F(d, t^*, h) - \pi_{DLT}|$$

With F(d, t*, h), the cumulative incidence of toxicity at time t*



CRM dose finding-algorithm

Identify the MTD, d^* , the dose with the probability of toxicity at time t^* closest to a prespecified target π_{DLT} (e.g., 0.25), among the set D of candidate dose levels

$$d^* = \arg\min_{d \in D} |F_1(t^*, h_1, h_2, d) - \pi_{DLT}|$$

With F₁(.), the observed cumulative incidence for toxicity at time t^{*}



RESULTS: SURV-CRM-12; U-SHAPE SCENARIOS

% Correct selection





曲

True Toxicity probability by dose : {0.08, 0.14, 0.25, 0.40, 0.57}



SIMULATION STUDY: COMPARATORS

Nonparametric Benchmark (O'Quigley et al. 2002, Cheung 2014, Mozgunov et al. 2020)

Inserm

SARYGA

DISCUSSION AND PERSPECTIVES

Surv-CRM-12 Optimal Dose definition: $d^* = \arg \min_{d \in \mathcal{A}} F_2(t^*, h_1, h_2, d)$

- 'Optimus' FDA project recommendations
- \rightarrow OD: lowest safe dose that achieves the highest efficacy
- Extension of the efficacy working model to strictly nonmonotone relationship

Cause-specific instantaneous hazard function, for progression

$$h_2(\beta_2, d) = \exp(\beta_{02} + \exp(\beta_{12}) d + \exp(\beta_{22}) d^2)$$





DISCUSSION AND PERSPECTIVES

Intention To Treat (ITT) approach

> Treatment decision at the time of the patient's inclusion in the trial

Repeated treatment administration over several cycles

Estimation of the MTD associated to some cumulative risk of DLT over a predefined number of treatment cycles (Altzerinakou, 2019, Ursino, 2021)

