

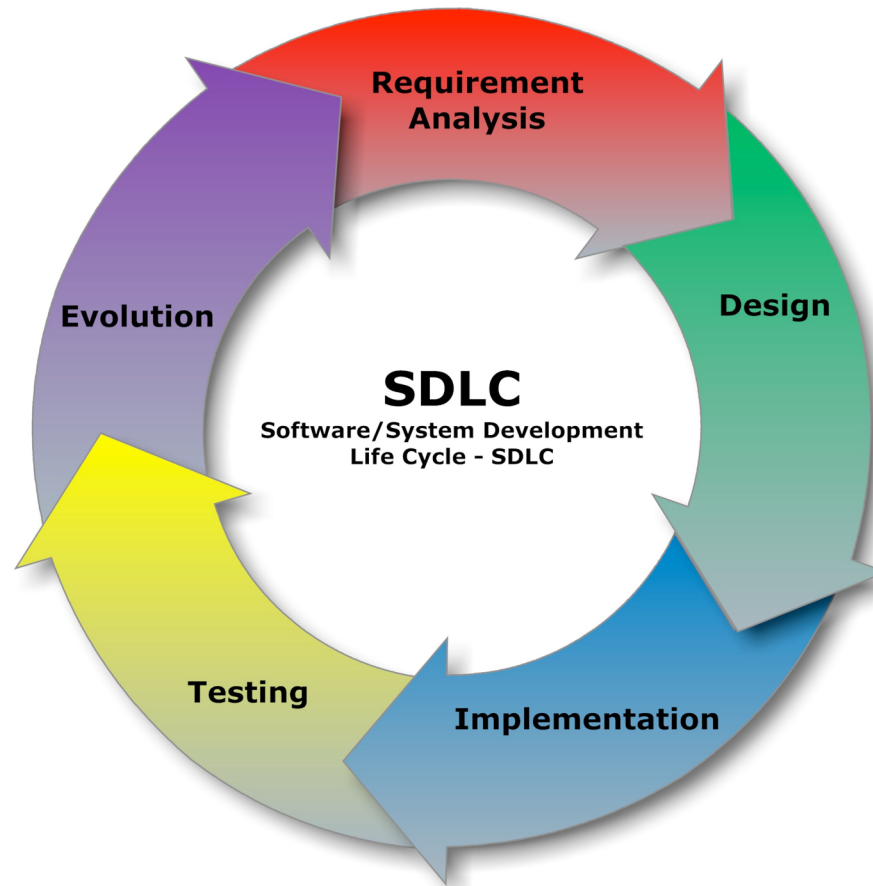
Anytime Algorithms for Robust Multi-Objective Next Release Problem



UNIVERSIDAD DE MÁLAGA

**Miguel Ángel Domínguez, Francisco Chicano,
Enrique Domínguez, Ana Belén Ruiz**

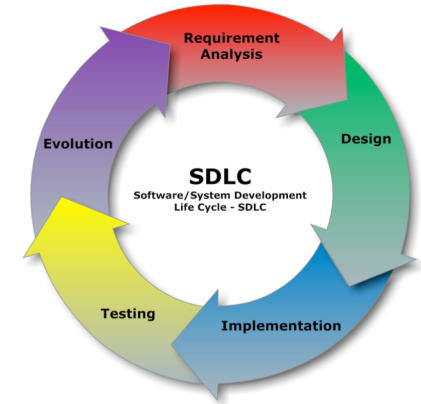
Next Release Problem (NRP)



Next Release Problem (NRP)

Given:

- A set of requirements $R = \{r_1, r_2, \dots, r_n\}$
- Each one with a cost c_j and a value w_j
- A set of functional relationships among them
 - **Implication** (r_i prerequisite of r_j): $r_i \Rightarrow r_j$
 - **Combination** (r_i at the same time as r_j): $r_i \odot r_j$
 - **Exclusion** (not together): $r_i \oplus r_j$



Find a set of requirements $X \subseteq R$ that fulfil the interactions and minimize the **cost** and maximize the **value**:

$$\min \quad cost(\hat{R}) = \sum_{j, r_j \in \hat{R}}^n c_j,$$

$$\max \quad value(\hat{R}) = \sum_{i=1}^m w_i \prod_{j, r_j \in \hat{R}} v_{ij}$$

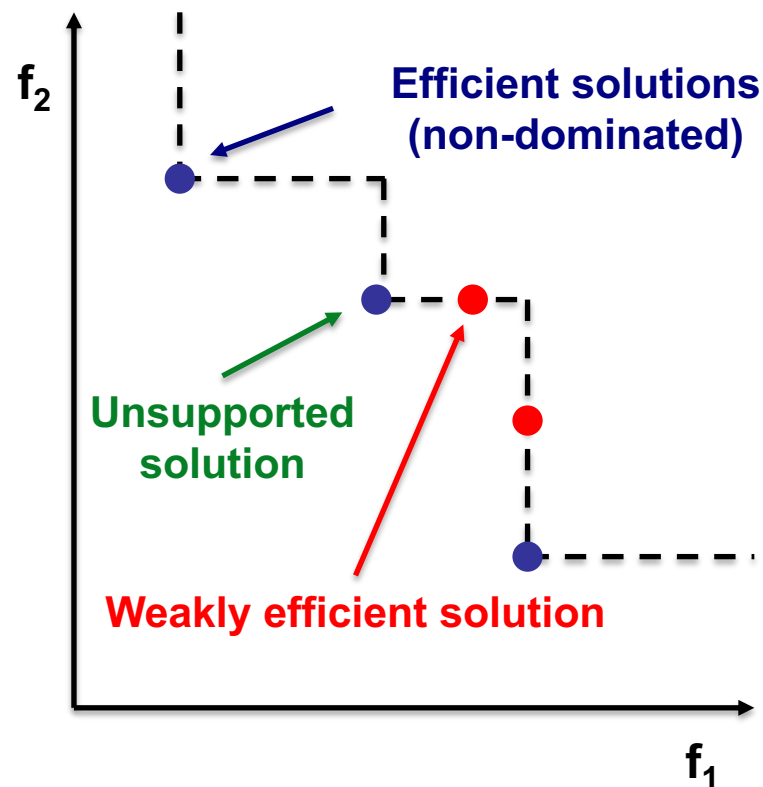
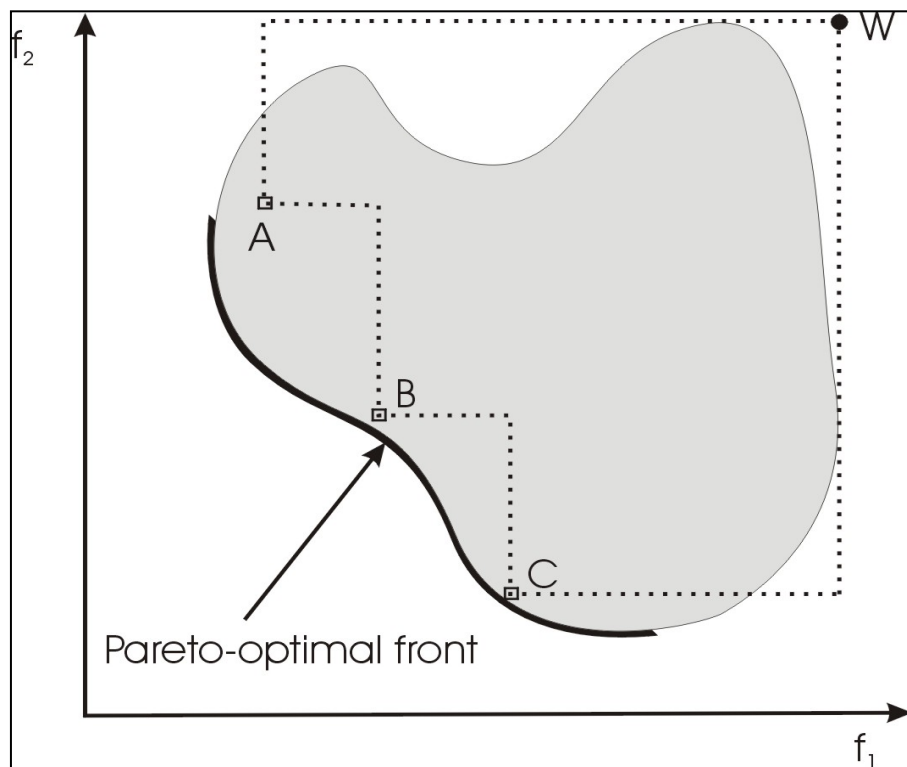
Xuan et al.

$$value(\hat{R}) = \sum_{j, r_j \in \hat{R}}^n s_j, \quad \sum_{i=1}^m w_i * \check{v}_{ij}$$

Del Sagrado et al.

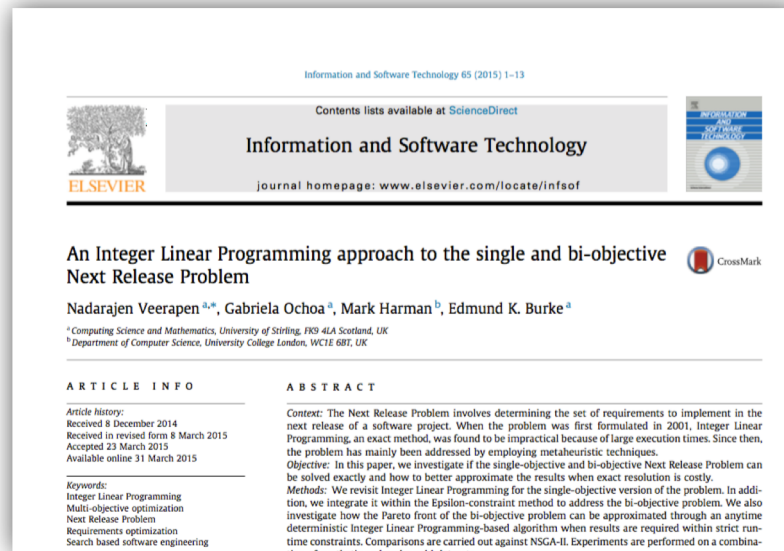
Multi-objective problems

- Several objective functions to optimize (we will assume minimization here)



Previous Work on NRP

- Initially solved using ILP in a single-objective version
- Later, metaheuristics (NSGA-II, GRASP, ACS)



- ϵ -constraint with ILP finds the whole Pareto front in less than 8 hours
- They propose dichotomic search and NSGA-II to reduce time

Previous Work on NRP

Sistedes
Biblioteca Digital

INICIO NOTICIAS ACERCA DE LA BIBLIOTECA CONTACTO

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Navegación

- Conferencias
 - Jornadas de Ingeniería del Software y Bases de Datos (JISBD)
 - JISBD 2015 (Santander)
 - JISBD 2016 (Salamanca)
 - Arquitecturas del Software y Variabilidad
 - Artículos Relevantes
 - Calidad y Pruebas
 - Comités
 - Conferencia Invitada: Prof. Dr. Andrei Voronkov
 - Desarrollo de Software Dirigido por Modelos
 - Gestión de Datos
 - Ingeniería del Software Guiada por Búsqueda

Dos estrategias de búsqueda anytime basadas en programación lineal entera para resolver el problema de selección de requisitos

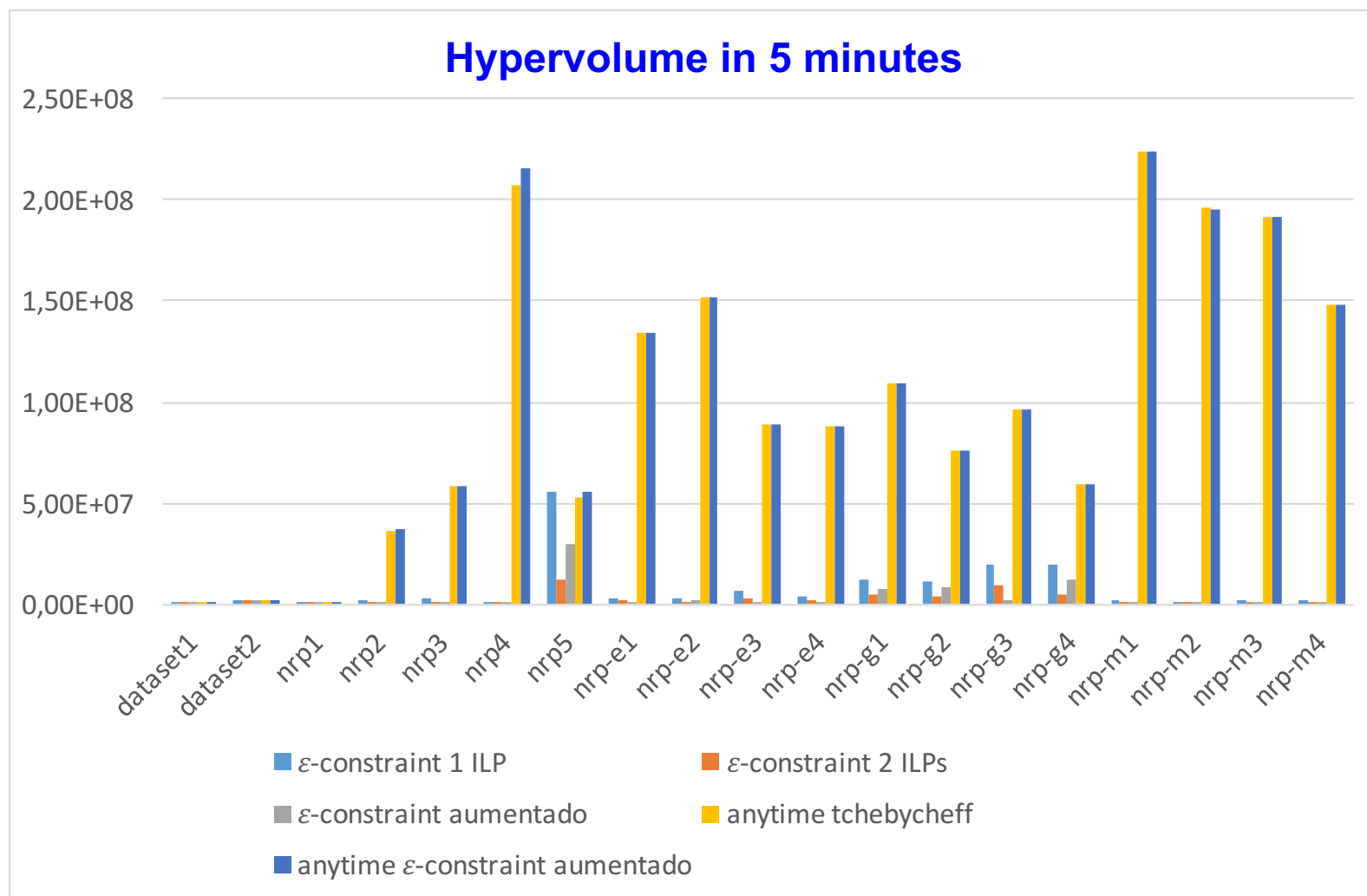
Resumen:

El problema de selección de requisitos (o Next Release Problem, NRP) consiste en seleccionar el subconjunto de requisitos que se va a desarrollar en la siguiente versión de una aplicación software. Esta selección se debe hacer de tal forma que maximice la satisfacción de las partes interesadas a la vez que se minimiza el esfuerzo empleado en el desarrollo y se cumplen un conjunto de restricciones. Trabajos recientes han abordado la formulación bi-objetivo de este problema usando técnicas exactas basadas en resolutores SAT y resolutores de programación lineal entera. Ambos se enfrentan a dificultades cuando las instancias tienen un gran tamaño, sin embargo la programación lineal entera (ILP) parece ser más efectiva que los resolutores SAT. En la práctica, no es necesario calcular todas las soluciones del frente de Pareto (que pueden llegar a ser muchas) y basta con obtener un buen número

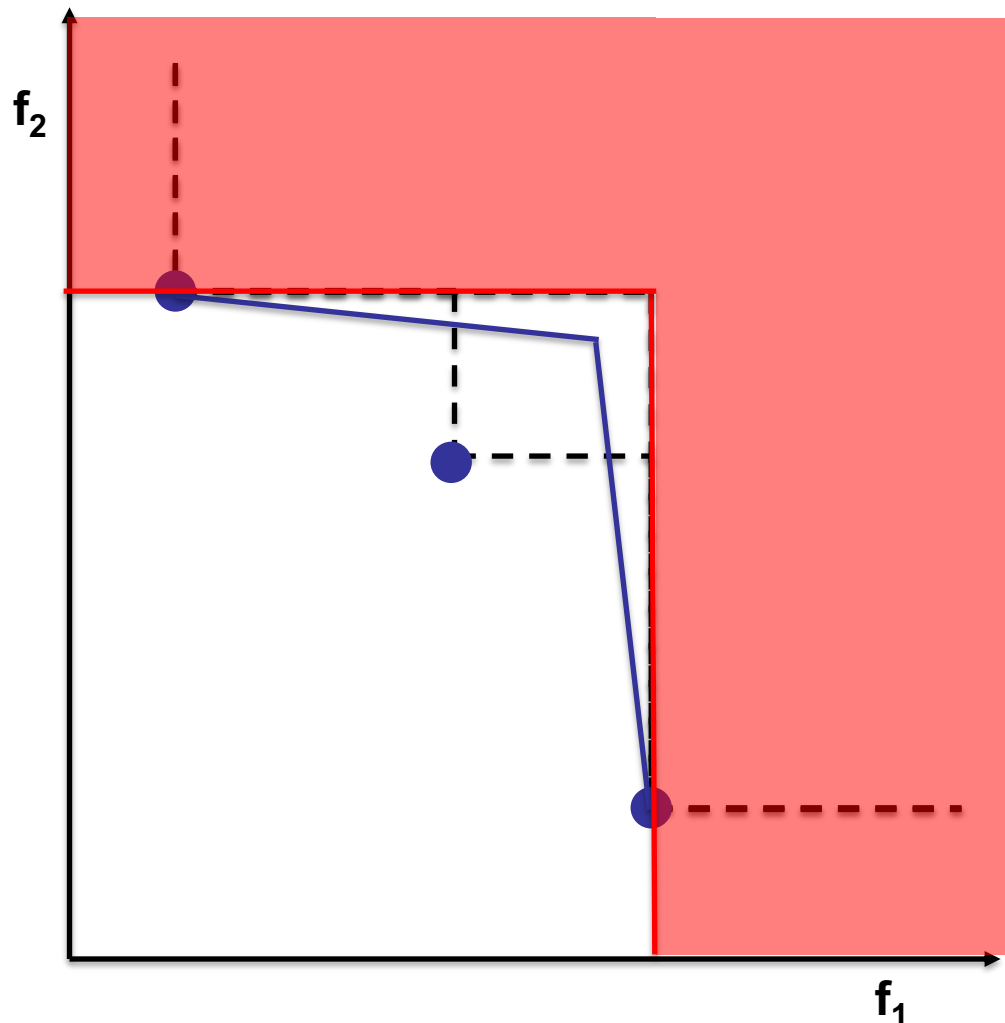
JISBD 2016

- We developed **anytime strategies** to find a spread set of solutions of the Pareto front at anytime
- More appropriate for **Software Engineers**

Previous Work on NRP



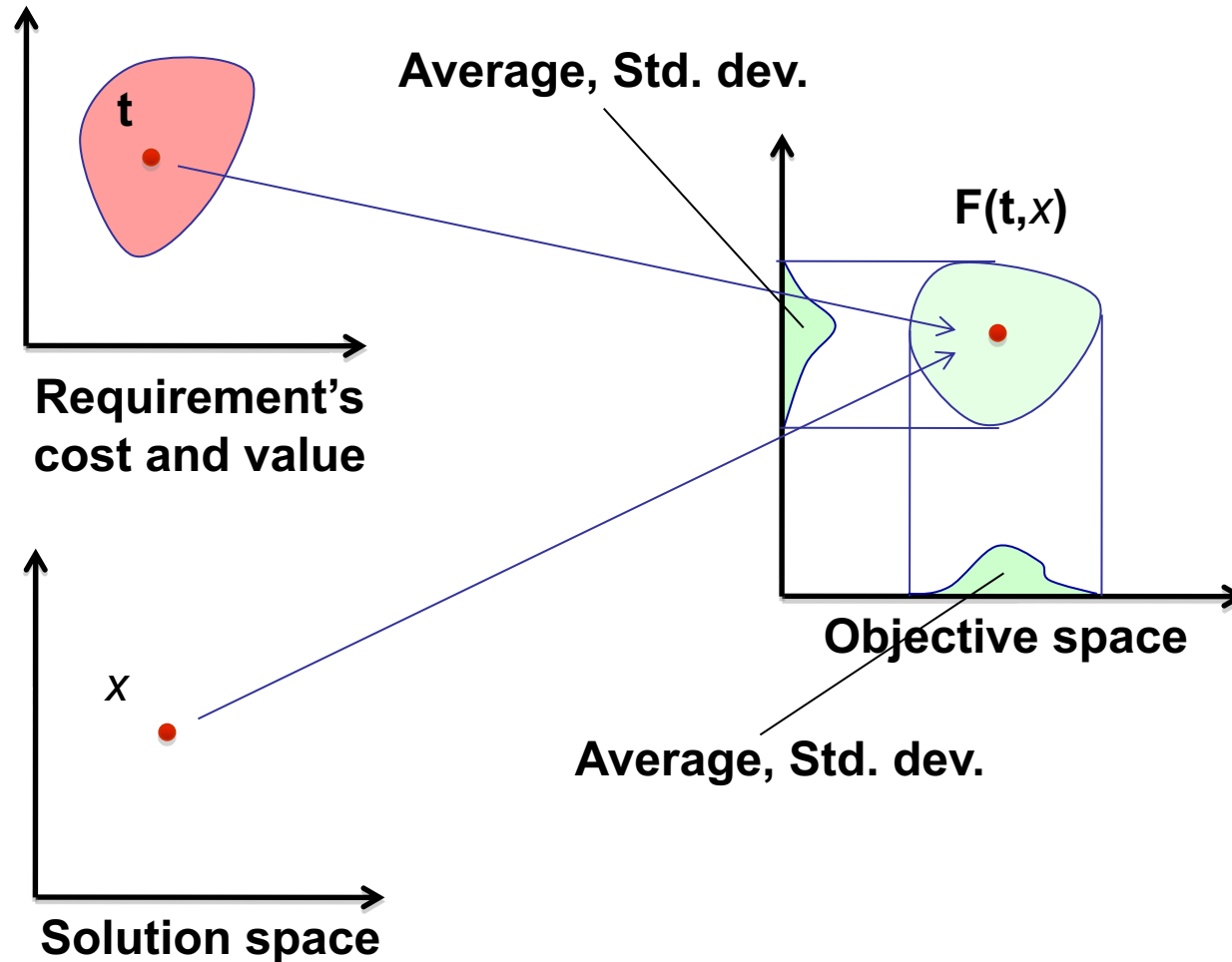
Anytime Augmented Weighted Tchebycheff



Algoritmo 4 *Anytime augmented weighted Tchebycheff*



- 1: $z^{(1)} \leftarrow$ calcular óptimo lexicográfico para el orden (f_1, f_2)
- 2: $z^{(2)} \leftarrow$ calcular óptimo lexicográfico para el orden (f_2, f_1)
- 3: $FP \leftarrow \{z^{(1)}, z^{(2)}\}$ // Frente de Pareto
- 4: $Cola \leftarrow \{(z^{(1)}, z^{(2)})\}$
- 5: **while** $Cola \neq \emptyset$ **do**
- 6: $(z^{(1)}, z^{(2)}) \leftarrow$ extraerParDeMayorArea(Cola)
- 7: $z \leftarrow$ resolverTchebycheff($(z^{(1)}, z^{(2)})$)
- 8: **if** z no dominado en $(z^{(1)}, z^{(2)})$ **then**
- 9: $FP = FP \cup \{z\}$
- 10: $Cola \leftarrow Cola \cup \{(z^{(1)}, z), (z, z^{(2)})\}$
- 11: **end if**
- 12: **end while**

Robustness



Previous Work on Robust NRP

Robust next release problem: handling uncertainty during optimization

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Authors: [Lingbo Li](#) [University College London, London, United Kingdom](#)
[Mark Harman](#)
[Emmanuel Letier](#)
[Yuanyuan Zhang](#)



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[ACM](#) New York, NY,
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The Value of Exact Analysis in Requirements Selection

Lingbo Li, Mark Harman, Fan Wu, and Yuanyuan Zhang

Abstract—Uncertainty is characterised by incomplete understanding. It is inevitable in the early phase of requirements engineering, and can lead to unsound requirement decisions. Inappropriate requirement choices may result in products that fail to satisfy stakeholders' needs, and might cause loss of revenue. To overcome uncertainty, requirements engineering decision support needs uncertainty management. In this research, we develop a decision support framework *METRO* for the Next Release Problem (NRP) to manage algorithmic uncertainty and requirements uncertainty. An exact NRP solver (*NSGDP*) lies at the heart of *METRO*. *NSGDP*'s exactness eliminates interference caused by approximate existing NRP solvers. We apply *NSGDP* to three NRP instances, derived from a real world NRP instance, RALIC, and compare with NSGA-II, a widely-used approximate (inexact) technique. We find the randomness of NSGA-II results in decision makers missing up to 99.95 percent of the optimal solutions and obtaining up to 36.48 percent inexact requirement selection decisions. The chance of getting an inexact decision using existing approximate approaches is negatively correlated with the implementation cost of a requirement (Spearman ρ up to -0.72). Compared to the inexact existing approach, *NSGDP* saves 15.21 percent lost revenue, on average, for the RALIC dataset.

Index Terms—Software engineering, exact multi-objective optimisation, simulation optimisation, next release problem

Lingbo Li work on robustness for NRP is based on Monte Carlo Simulation

Formulation

$$\min E [\text{cost}(r)] = E \left[\sum_{j=1}^n c_j r_j \right]$$

$$E [\text{cost}(r)] = \sum_{j=1}^n E[c_j] r_j$$

$$\min \text{Var} [\text{cost}(r)] = \text{Var} \left[\sum_{j=1}^n c_j r_j \right]$$

$$\min -E [\text{value}(t)] = -E \left[\sum_{i=1}^m w_i t_i \right]$$

$$-E [\text{value}(t)] = - \sum_{i=1}^m E[w_i] t_i$$

$$\min \text{Var} [\text{value}(t)] = \text{Var} \left[\sum_{i=1}^m w_i t_i \right]$$

Formulation

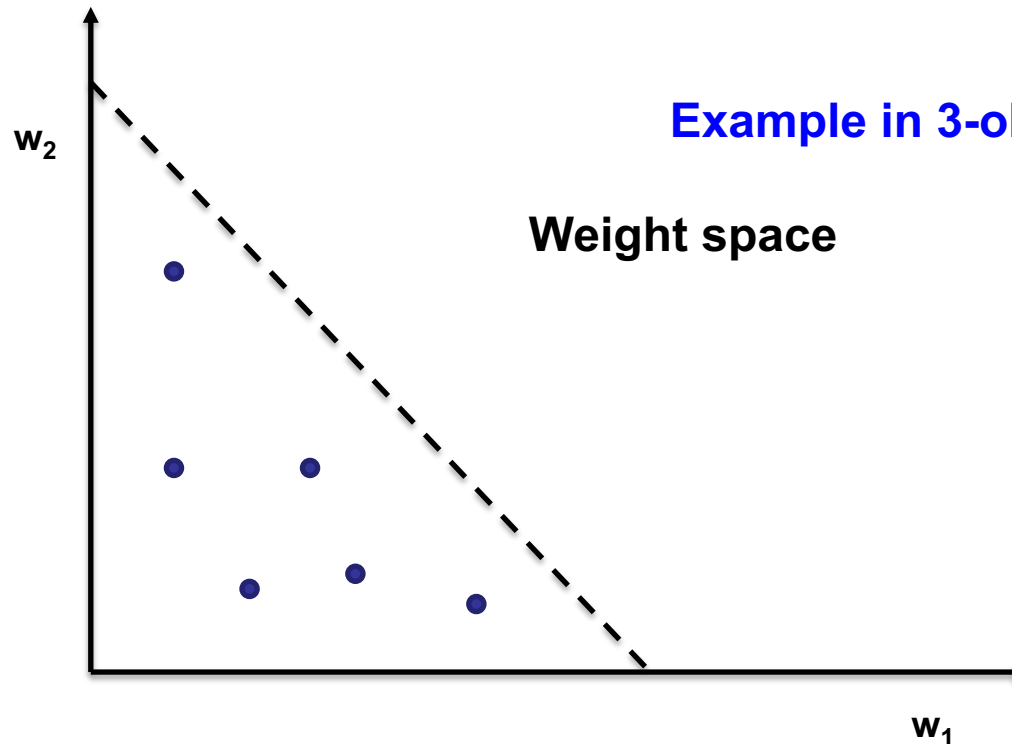
$$\begin{aligned} \text{Var} [\text{cost}(r)] &= \text{Var} \left[\sum_{j=1}^n c_j r_j \right] \\ &= \sum_{i,j=1}^n \text{Cov}[c_i, c_j] r_j r_i = \sum_{i=1}^n \text{Var}[c_i] r_i \end{aligned}$$

$$\begin{aligned} \text{Var} [\text{value}(t)] &= \text{Var} \left[\sum_{i=1}^m w_i t_i \right] \\ &= \sum_{i,j=1}^n \text{Cov}[w_i, w_j] t_j t_i = \sum_{i=1}^n \text{Var}[w_i] t_i \end{aligned}$$

If costs and values are uncorrelated the expression is simplified

Algorithm

- We implemented an algorithm exploring only supported solutions
- It picks random weights until time is over



Results: Instances

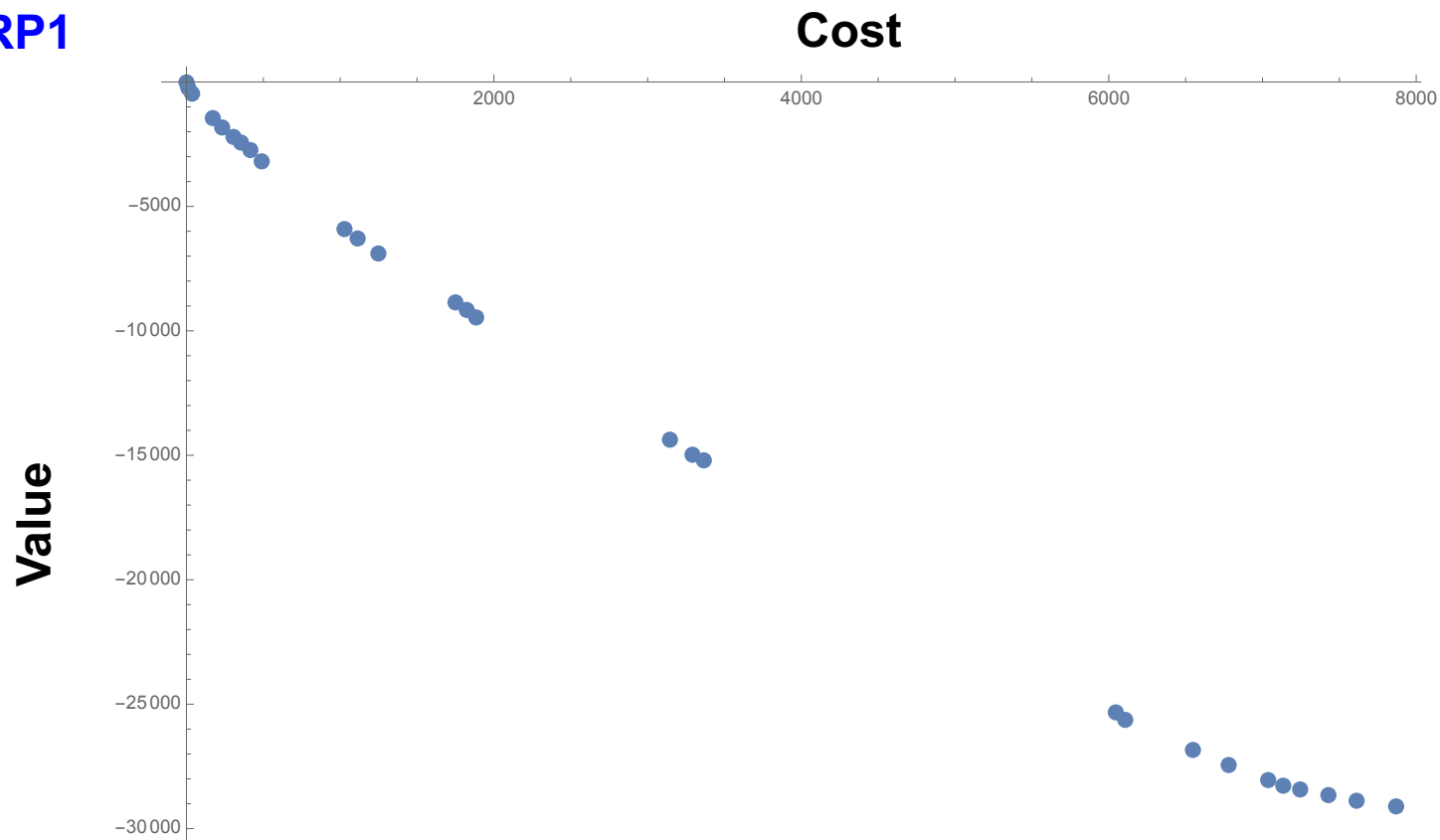
- 17 instances by Xuan et al.
- Only implication relation

We included variance information to the instances

Instance	Requirements	Stakeholders
nrp1	140	100
nrp2	620	500
nrp3	1500	500
nrp4	3250	750
nrp5	1500	1000
nrp-e1	3502	536
nrp-e2	4254	491
nrp-e3	2844	456
nrp-e4	3186	399
nrp-g1	2690	445
nrp-g2	2650	315
nrp-g3	2512	423
nrp-g4	2246	294
nrp-m1	4060	768
nrp-m2	4368	617
nrp-m3	3566	765
nrp-m4	3643	568

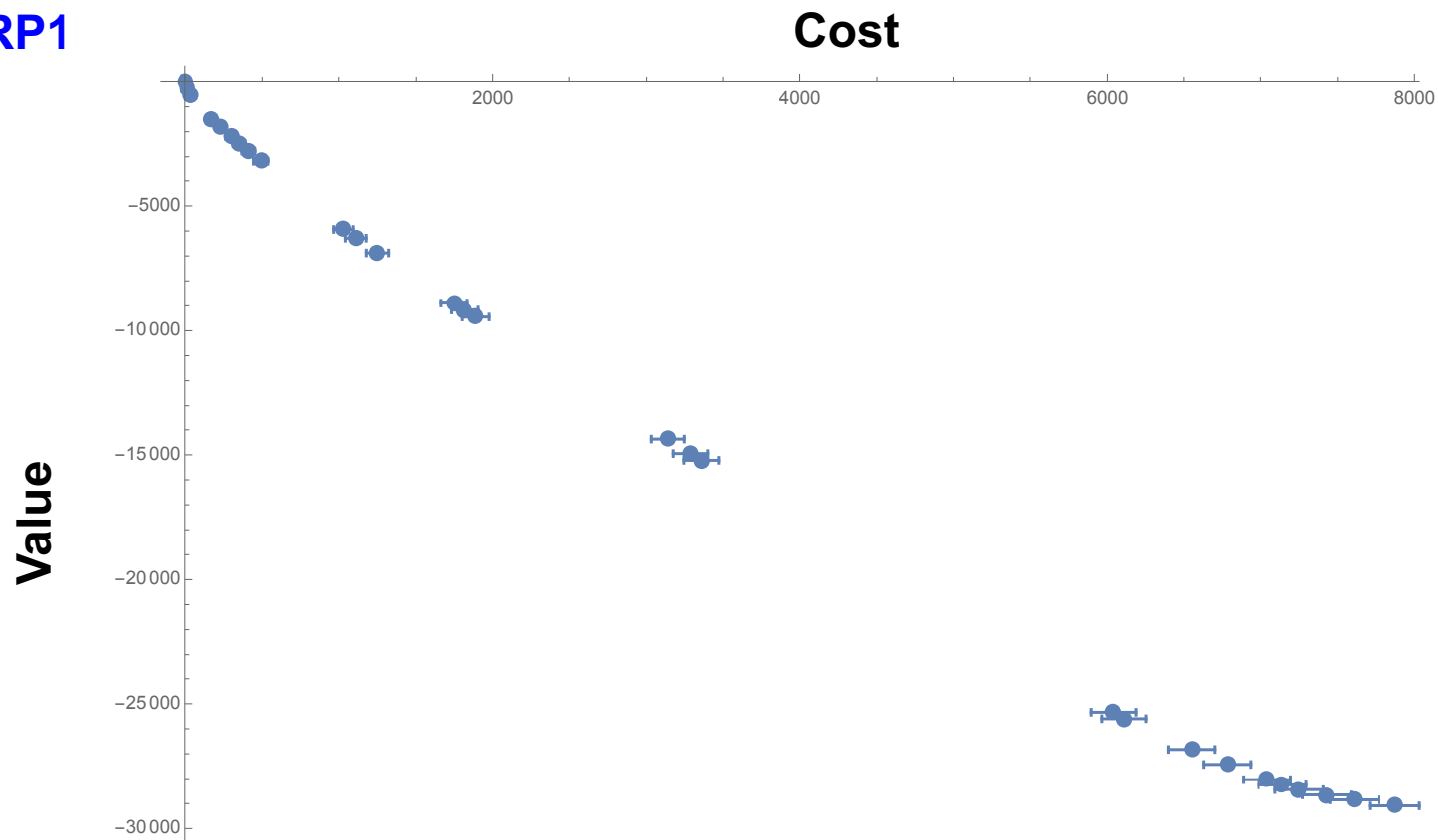
Original 2-obj. Supported Non-Dominated Set

NRP1



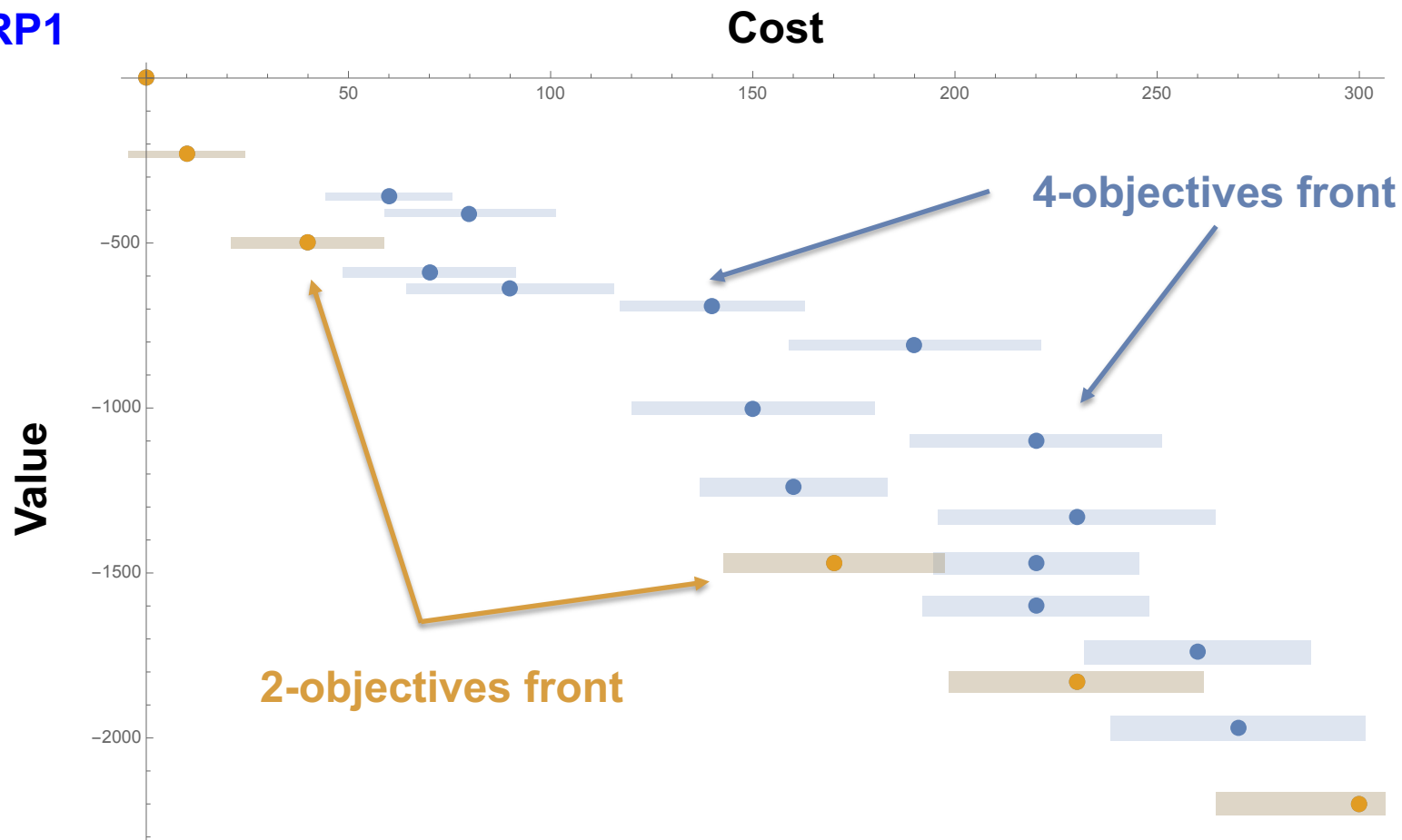
Original 2-obj. Supported Non-Dominated Set

NRP1

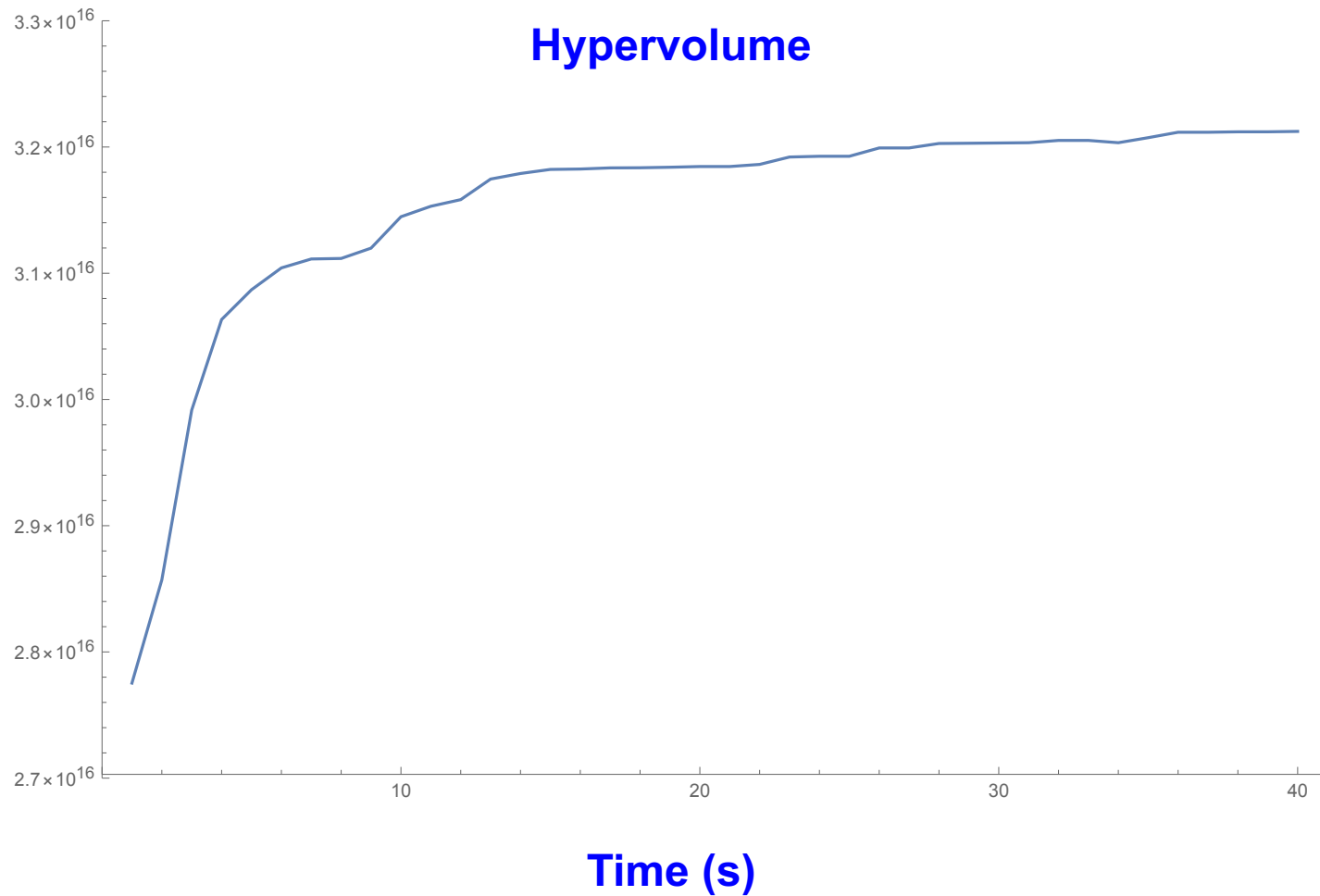


4-obj. Supported Non-Dominated Set

NRP1



Evolution of Hypervolume



Conclusions & Future Work

Conclusions

- A robust version of NRP has been modeled using ILP
- Anytime algorithms offer a well-spread set of non-dominated solutions

Future Work

- Apply other algorithms:
 - Przybylski, Gandibleux, Ehrgott (2010)
 - Dächert and Klamroth (2014)

Thanks for your Attention !!!



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EXHAURO Project



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