



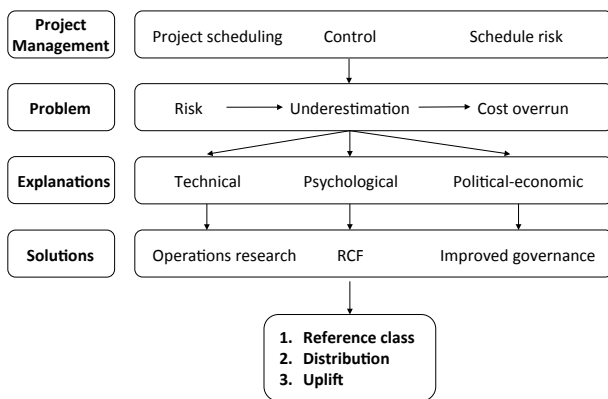
REFERENCE CLASS FORECASTING TO IMPROVE TIME AND COST FORECASTS

Empirical and statistical analysis

dr. Tom Servranckx
Prof. Mario Vanhoucke
Prof. Tarik Aouam

If you want to refer to this presentation, please refer to T. Servranckx, M. Vanhoucke and T. Aouam, "Practical application of reference class forecasting for cost and time estimations: Identifying the properties of similarity", European Journal of Operational Research, In Press.

INTRODUCTION



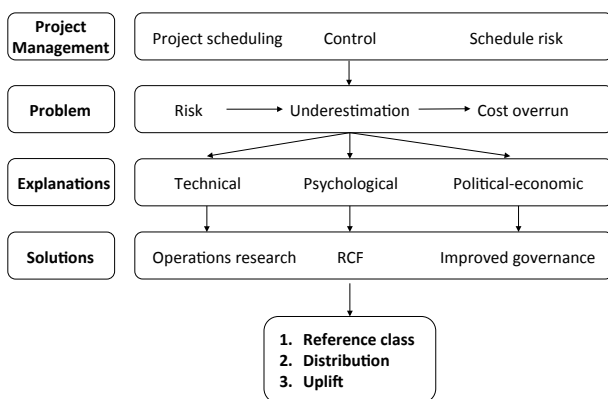
Project Monitoring and Forecasting:

- Earned Value Management (EVM)
- Critical Chain Buffer Management (CC/BM)
- Artificial Intelligence techniques
- Fixed contingency approach
- Risk-based estimating

Disadvantages:

- Highly uncertain and complex environments?
- Early stages of the project?

INTRODUCTION



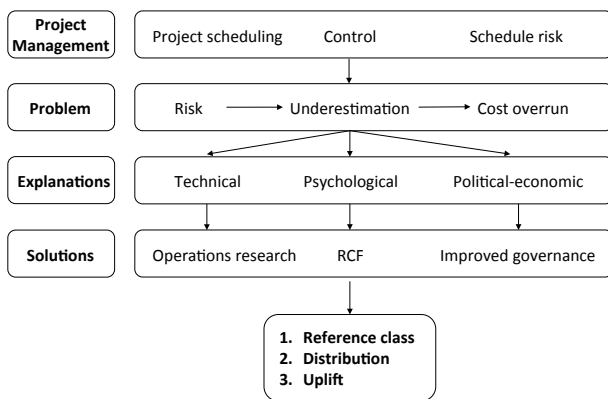
Project Monitoring and Forecasting:

- Earned Value Management (EVM)
- Critical Chain Buffer Management (CC/BM)
- Artificial Intelligence techniques
- Fixed contingency approach
- Risk-based estimating

Disadvantages:

- Systematic underestimation of project risks
- Subjective estimations of project managers

INTRODUCTION



Project Monitoring and Forecasting:

- Earned Value Management (EVM)
- Critical Chain Buffer Management (CC/BM)
- Artificial Intelligence techniques
- Fixed contingency approach
- Risk-based estimating

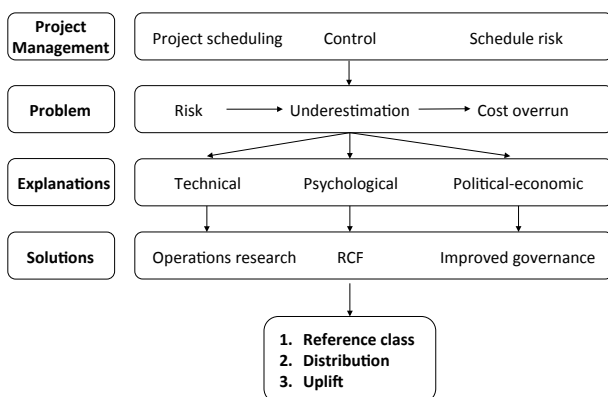
Inside view

Reference Class Forecasting (RCF)

→ Outside view

= Statistical **distribution** of **similar** historical projects to **correct** project forecast

INTRODUCTION



Project Monitoring and Forecasting:

- Earned Value Management (EVM)
- Critical Chain Buffer Management (CC/BM)
- Artificial Intelligence techniques
- Fixed contingency approach
- Risk-based estimating

Inside view

Reference Class Forecasting (RCF)

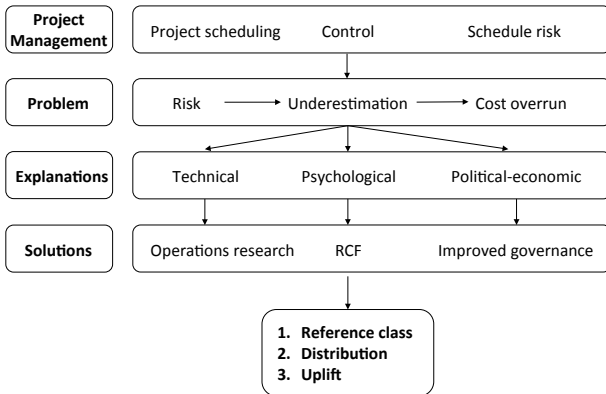
→ Outside view

= Statistical **distribution** of **similar** historical projects to **correct** project forecast

Research questions:

1. Which properties identify similar projects?
2. How much properties should be considered simultaneously?
3. What interaction effects do exist between similarity properties?

INTRODUCTION



Project Monitoring and Forecasting:

- Earned Value Management (EVM)
- Critical Chain Buffer Management (CC/BM)
- Artificial Intelligence techniques
- Fixed contingency approach
- Risk-based estimating

Inside view

Reference Class Forecasting (RCF)

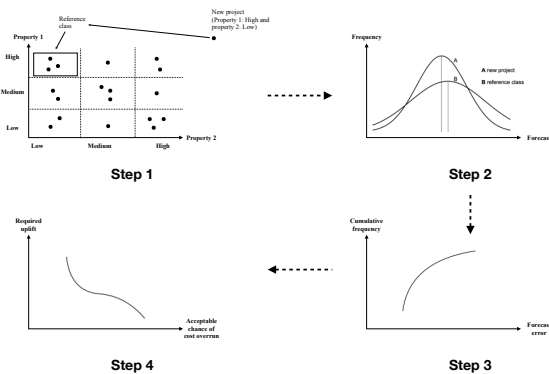
→ Outside view

= Statistical **distribution** of **similar** historical projects to **correct** project forecast

Main contributions

1. Interview project managers to explore similarity properties
2. Empirical analysis of risk underestimation (time and cost) in projects
3. Investigate the impact of RCF on the forecasting accuracy

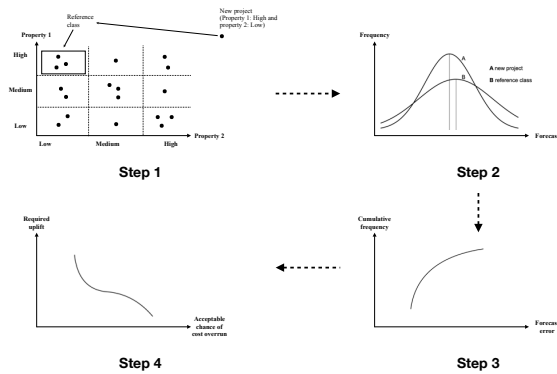
REFERENCE CLASS FORECASTING



Reference Class Forecasting (RCF)

= Statistical **distribution** of **similar** historical projects to **correct** project forecast

REFERENCE CLASS FORECASTING



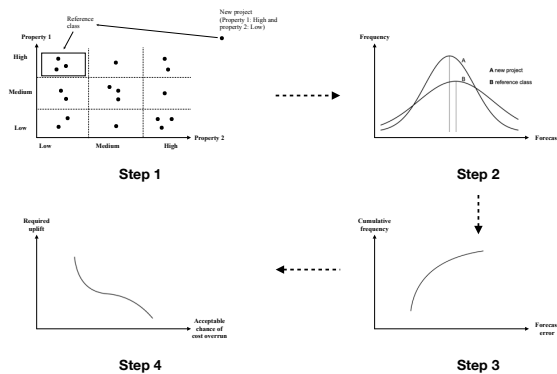
Reference Class Forecasting (RCF)

= Statistical **distribution** of **similar** historical projects to **correct** project forecast

1. Identify relevant class of historical projects

Property A key project characteristic that is a good indicator for the similarity between projects

REFERENCE CLASS FORECASTING



Reference Class Forecasting (RCF)

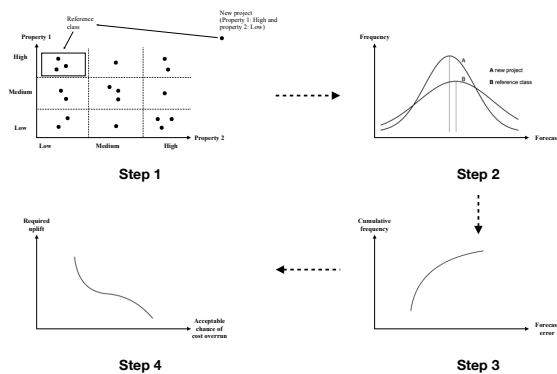
= Statistical **distribution** of **similar** historical projects to **correct** project forecast

1. Identify relevant class of historical projects

Property A key project characteristic that is a good indicator for the similarity between projects

2. Determine distribution for the reference class

REFERENCE CLASS FORECASTING



Reference Class Forecasting (RCF)

= Statistical **distribution** of **similar** historical projects to **correct** project forecast

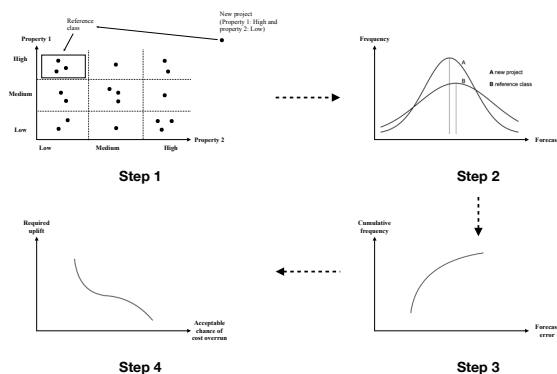
1. Identify relevant class of historical projects

Property A key project characteristic that is a good indicator for the similarity between projects

2. Determine distribution for the reference class
3. Cumulative frequency in function of forecast error

e.g. **80%** of the **historical projects** have a **forecast error** of **15%**

REFERENCE CLASS FORECASTING



Reference Class Forecasting (RCF)

= Statistical **distribution** of **similar** historical projects to **correct** project forecast

1. Identify relevant class of historical projects

Property A key project characteristic that is a good indicator for the similarity between projects

2. Determine distribution for the reference class
3. Cumulative frequency in function of forecast error

e.g. **80%** of the **historical projects** have a **forecast error** of **15%**

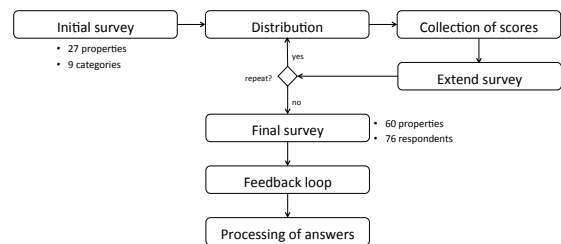
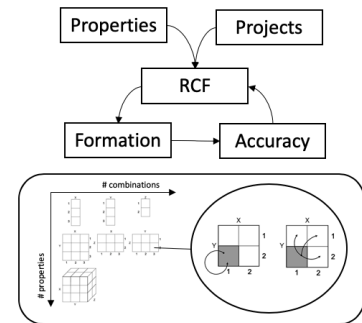
4. Inverse cumulative distribution to determine uplift

e.g. **10% uplift** of budget/timing required to have a **5% chance** of cost/time **overrun**

METHODOLOGY

1. Data Collection - Properties

- Interviews with 76 project managers:
 - Cross-country: Belgium and Italy
 - Cross-industry: Construction, consulting, energy, IT, etc.
 - Experience: Belgium (13.6 years) and Italy (9.5 years)
- Combination of literature review and input participants
 - 60 possible properties in 9 categories
 - 10% best scoring properties are identified:
 1. Type of deliverable
 2. Project complexity
 3. Company experience
 4. Project definition
 5. Governmental law
 6. Impact employees

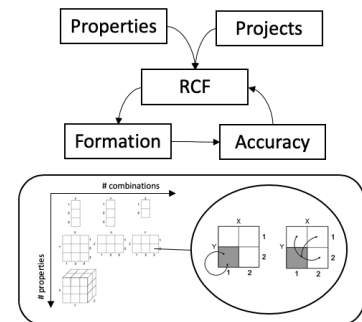


METHODOLOGY

1. Data Collection - Properties

2. Data Collection - Projects

- Data of 52 projects was collected
 - 63% of projects have cost overruns (average = 16%)
 - Average cost underestimation is 30.5%
 - Average cost overestimation is only 9.2%
- Important information for RCF
 - Forecasted and actual cost/duration = *Forecast error*
 - Values for the similarity properties

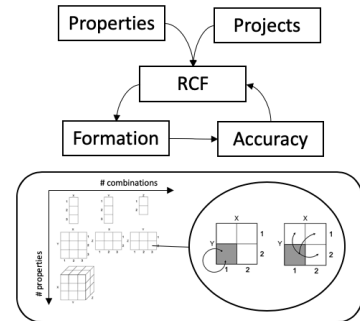


Property	Scale	Property values			
(A) Type of deliverable	Nominal	Product	Service	Combination	
	Absolute (#)	7	9	36	
	Relative (%)	13	17	69	
(B) Project complexity	Ordinal	High	Average	Low	
		Absolute (#)	17	25	10
		Relative (%)	33	48	19
(C) Experience of company	Ordinal	≤ 10	> 10, < 40	≥ 40	
		Absolute (#)	17	18	17
		Relative (%)	33	35	33
(D) Project definition	Nominal	New	Modification	Redo	
		Absolute (#)	19	24	9
		Relative (%)	37	46	17
(E) Governmental law	Ordinal	High	Average	Low	
		Absolute (#)	14	23	15
		Relative (%)	27	44	29
(F) Impact on the employees	Ordinal	High	Average	Low	
		Absolute (#)	14	19	19
		Relative (%)	27	37	37



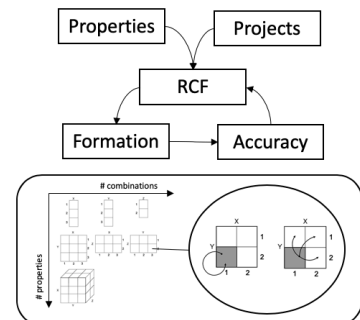
METHODOLOGY

1. **Data Collection - Properties**
2. **Data Collection - Projects**
3. **RCF - Construct reference classes**
 - Different # properties
 - Different combinations of properties



METHODOLOGY

1. **Data Collection - Properties**
2. **Data Collection - Projects**
3. **RCF - Construct reference classes**
4. **RCF - Determine forecasting accuracy**
 - K-fold cross-validation with 100 iterations
 - Training set: Determine the accuracy of a reference class
 - Test set: Validate the accuracy of a reference class
 - Accuracy computation
 - **Intra-accuracy** = Average improvement forecast based on uplift of projects in the **same** reference class
 - **Inter-accuracy** = Average improvement forecast based on uplift of projects in **other** reference classes



RESULTS

1. General findings

- Average forecasting accuracy improves with **2.41** %points
- 'Project definition': **+ 3.90** %points
- 'Governmental law' and 'Impact employees': **- 0.19** %points and **-0.57** %points
- Best combination (**+5.47** % points): 'Type of deliverable' + 'Project definition' + 'Governmental law'

“RCF improves the forecasting accuracy, but its performance depends on the properties”

	Number of properties						Total
	1	2	3	4	5	6	
A	1.63	AX 1.83	AXX 3.33	AXXX 4.02	AXXXX 3.97	AXXXXX 3.24	3.24
B	0.27	BX 0.36	BXX 1.70	BXXX 3.18	BXXXX 3.98	BXXXXX 3.24	3.24
C	1.82	CX 1.76	CXX 2.27	CXXX 3.08	CXXXX 3.61	CXXXXX 3.24	3.24
D	3.90	DX 3.77	DXX 3.43	DXXX 3.52	DXXXX 3.79	DXXXXX 3.24	3.24
E	-0.19	EX 0.72	EXX 1.43	EXXX 3.10	EXXXX 3.97	EXXXXX 3.24	3.24
F	-0.57	FX 0.81	FXX 1.78	FXXX 2.72	FXXXX 3.71	FXXXXX 3.24	3.24
Average	1.14	1.54	2.32	3.27	3.84	3.24	2.41
Exclude Worst	1.49	1.91	2.87	4.38	4.49	-	-
Exclude 2 Worst	1.90	2.75	4.33	4.50	-	-	-
Exclude Best	0.58	0.40	1.19	2.95	3.82	-	-
Exclude 2 Best	0.26	-0.19	0.20	1.63	-	-	-

RESULTS

2. Impact # properties

- Accuracy improves with the number of properties
- 5 properties results on average in the highest accuracy
- Trade-off between higher similarity (more properties) and larger size of reference class (fewer properties)

“As more properties are added, the positive interaction effects between the properties increase”

	Number of properties						Total
	1	2	3	4	5	6	
A	1.63	AX 1.83	AXX 3.33	AXXX 4.02	AXXXX 3.97	AXXXXX 3.24	3.24
B	0.27	BX 0.36	BXX 1.70	BXXX 3.18	BXXXX 3.98	BXXXXX 3.24	3.24
C	1.82	CX 1.76	CXX 2.27	CXXX 3.08	CXXXX 3.61	CXXXXX 3.24	3.24
D	3.90	DX 3.77	DXX 3.43	DXXX 3.52	DXXXX 3.79	DXXXXX 3.24	3.24
E	-0.19	EX 0.72	EXX 1.43	EXXX 3.10	EXXXX 3.97	EXXXXX 3.24	3.24
F	-0.57	FX 0.81	FXX 1.78	FXXX 2.72	FXXXX 3.71	FXXXXX 3.24	3.24
Average	1.14	1.54	2.32	3.27	3.84	3.24	2.41
Exclude Worst	1.49	1.91	2.87	4.38	4.49	-	-
Exclude 2 Worst	1.90	2.75	4.33	4.50	-	-	-
Exclude Best	0.58	0.40	1.19	2.95	3.82	-	-
Exclude 2 Best	0.26	-0.19	0.20	1.63	-	-	-

RESULTS

3. Impact relations between properties

- Excluding worst properties improves the forecasting accuracy
- Excluding best properties reduces the forecasting accuracy

“A careful selection of the properties allows us to obtain even better results”

	Number of properties						Total				
	1	2	3	4	5	6					
A	1.63	AX	1.83	AXX	3.33	AXXX	4.02	AXXXX	3.97	AXXXXX	3.24
B	0.27	BX	0.36	BXX	1.70	BXXX	3.18	BXXXX	3.98	BXXXXX	3.24
C	1.82	CX	1.76	CXX	2.27	CXXX	3.08	CXXXX	3.61	CXXXXX	3.24
D	3.90	DX	3.77	DXX	3.43	DXXX	3.52	DXXXX	3.79	DXXXXX	3.24
E	-0.19	EX	0.72	EXX	1.43	EXXX	3.10	EXXXX	3.97	EXXXXX	3.24
F	-0.57	FX	0.81	FXX	1.78	FXXX	2.72	FXXXX	3.71	FXXXXX	3.24
Average	1.14	1.54	1.54	2.32	3.27	3.84	3.24	2.41			
Exclude Worst	1.49	1.91	2.87	4.38	4.49	-	-	-	-	-	
Exclude 2 Worst	1.90	2.75	4.33	4.50	-	-	-	-	-	-	
Exclude Best	0.58	0.40	1.19	2.95	3.82	-	-	-	-	-	
Exclude 2 Best	0.26	-0.19	0.20	1.63	-	-	-	-	-	-	

RESULTS

4. Impact uplift computations

- Average uplifts neglect the information in the standard deviation of the forecast errors
- Combined approach with prediction interval is only better when outliers are removed

“Changing the uplift computations to consider variability in reference classes should be done with care”

# Properties	AVG	50%CI	90%CI	95%CI	99%CI	ADAPT
ALL	2.41	-2.31	-9.12	-11.19	-14.97	2.95
1	1.14	-4.86	-14.36	-16.94	-21.57	1.73
2	1.54	-2.51	-9.76	-11.94	-15.87	1.92
3	2.32	-2.57	-9.33	-11.29	-15.02	2.68
4	3.27	-1.57	-7.68	-9.69	-13.42	3.85
5	3.84	-0.65	-6.04	-7.80	-10.83	4.68
6	3.24	0.24	-4.48	-6.03	-8.70	4.33

CONCLUSIONS

1. Main observations

- An average improvement in accuracy was obtained using RCF
- A careful selection of properties may lead to a better accuracy
- The performance of RCF might reduce when the method is based on poor-performing properties

2. Critical comments

- Data collection: As the number of properties increases, the size of the reference class decreases
- Subjectivity: Selecting the similarity properties and historical data is still subject to project managers' preferences
- Flaw of averages: The average uplift might increase the forecast error for certain projects and introduce budget reserves

3. Future research

- Combine inside and outside view: Incorporate expert judgement and allow customisation of uplift for specific projects
- Present objective guidelines on similarity property selection and reference class construction


dr. Tom Servranckx

Post doctoral researcher

BUSINESS INFORMATICS AND
OPERATIONS MANAGEMENT

 Universiteit Gent

 @ugent

 Ghent University

tom.servranckx@ugent.be

www.ugent.be