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A MBSE probabilistic framework for preliminary lifecycle costing of mechanical products

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About

Industrial Management Group within IST's Department of Mechanical Engineering

- Team of circa 10 people working on lean manufacturing, cost methods, process modeling, etc.
- Several sectors of expertise: mould-making, automotive, aeronautics, etc.
- Regular interactions with Computer Science and Mathematics Departments

Presenter's short resume

- Aerospace engineer (MSc @ Supaéro Toulouse & Imperial College London, 2007)
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Context and motivation

Industrial context

- Competitive pressure, challenging customer requirements, demanding airworthiness regulations
- Development of quality and profitable products
- Trading lifecycle cost (LCC) with performance, weight, quality, etc.

Importance of LCC modeling in early design of jet engines [Haskins, 2010]

- Major part of the cost typically committed during this early phase [Barton, 2001]
- Multi-attributes decision problem requiring a Systems Engineering (SE) approach
- Ability to leverage large volumes of historical data to predict future LCC

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Industrial case study

Rolls-Royce's jet engines

- Working principle: suck-squash-bang-woosh
- Complex mechanical product: thousands of parts, exotic alloys, unique manufacturing processes
- Modular architecture facilitating LCC estimation

MBSE framework applied to compressor blades

- Engine components adapted to probabilistic approach
  - Many items in the engine (statistical significance)
  - Subject to diverse operating conditions
  - Made of different alloys (titanium, steel, nickel)
  - Variations around generic commonality
- MBSE framework extendable to virtually any mechanical product

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Definition of LCC

NASA's definition of LCC

« (LCC is) the total of the direct, indirect, recurring, nonrecurring, and other related expenses incurred, or estimated to be incurred, in the design, development, verification, production, operation, maintenance, support, and disposal of a project. » [NASA, 2010]

Categories of (LCC) modeling approaches [Asiedu, 1998]

- Parametric (regression on a few variables)
- Analogous (extrapolation from similar items)
- Analytical (detailed, based on activity or physics)

Challenges in LCC estimation in early design [Meisl, 1988]

- Insufficient details in requirements or contextual parameters
- Lack of quality data

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Current LCC approaches

Generic MBSE frameworks for LCC

- Process-based parametric (SEER-MFG, PRICE-H/HL)
- Parametric for SE-related activities (COSYSMO)
- Cost and efforts in software engineering (COCOMO II)
- Regression models for mechanical products (MISERLY)

MBSE frameworks of LCC targeted at early design

- Hybrid Activity-Based and Machine Learning applied to pressure vessels [Liu, 2008]
- Artificial Neural Networks applied to 150 products [Seo, 2002]

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- Often not based on actual data
- No probabilistic aspect

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Expression of LCC

Two-terms (simplified) equation of LCC

For a given mechanical component, at time t_0:
$LCC_{t_0} = MC_{t_0} + \sum_{i^{th} shop\ visit} R_{t_i} x MC_{t_i}$ where:

- MC_t: Manufacturing cost at a given time t
- R_{t_i}: Replacement rate at the i^{th} maintenance visit

Main features of the LCC model

- LCC as a function of time:
  - Manufacturing: materials rates, quantity, productivity...
  - Maintenance: engine deterioration, fleet structure...
- Simplified equation of LCC
  - No R&D (fuzzy) or disposal costs (negligible)
  - Manufacturing cost: no labor or consumables considered
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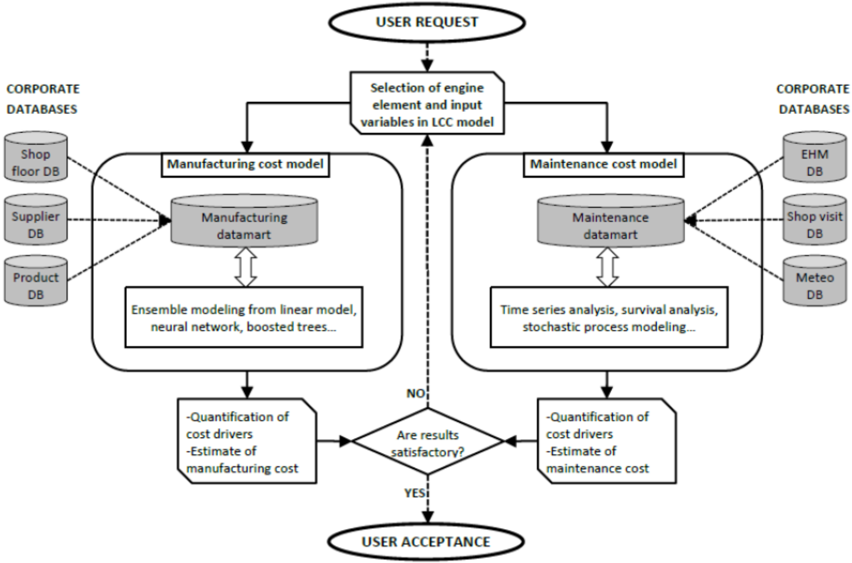
Architecture of MBSE LCC framework



Royce

Estimation of manufacturing cost

Probabilistic equation of manufacturing cost

For a given mechanical component, at time t:
$MC_t = f(L, W, P, A, M, Q_t, CR_t)$ where:

- MC_t: Manufacturing cost (continuous output variable)
- $f(.)$: Complex nonlinear function to estimate (non time dependent)

Important preliminary remarks

- Model at the component level
- Time dimension due to economic-related variables
- Probabilistic aspect due to variability in the input variables

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Characteristics of the manufacturing cost model

Seven input variables depending on each mechanical component

- Technical input variables
  - Component length L and width W
  - Manufacturing process P
  - Alloy type A and machinability M
- Economics-related input variables
  - Accumulated production volume Q_t
  - Materials cost rate CR_t

Aggregation of complementary models (Ensemble Models)

Model	Advantages	Drawbacks
Multiple Linear Regression (MLR)	Simple, interpretable	Inaccurate (linear only)
Neural Networks	Accurate (nonlinear)	Training and interpretation («black box» models)
Boosted trees	Very accurate (highly non parametric) Easy to train	Less interpretable than MLR

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Results

Procedure for model assessment

- Training the model with the data on 80% of the dataset
- Evaluate the generalization (i.e. predictive accuracy) on remaining 20% of the dataset

Criteria for model assessment

- Goodness-of-fit measured by coefficient of determination R^2 (total variance of the dataset explained by the model)
- Prediction accuracy measured by percentage of good prediction on new data (i.e. held out of the training set)

Goodness-of-fit (R^2)	**Accuracy ($MAPE$)**
>0.80	>90%

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Estimation of the maintenance cost

Probabilistic equation of maintenance cost

For a given mechanical component, at time t_i:
$R_{t_i} = g(T_T^j, P_T^j, S_T^j, V_T^j, ..., AT_T, AP_T, H_T, C_T, ...)$ where:

- R_{t_i}: Average replacement rate of the part (binary output)
- $g(.)$: Complex nonlinear function to estimate
- $T = [t_{i-1}, t_i]$: Time between two maintenance visits

Important remarks

- Hundreds of input variables extracted from complex time series (air temperature AT_T or pressure AP_T...)
- Six binary classifiers used as statistical models: logistic regression, support vector machines, decision trees, random forests, boosted trees, neural networks

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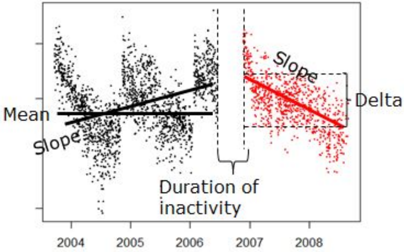
Characteristics of the maintenance cost model

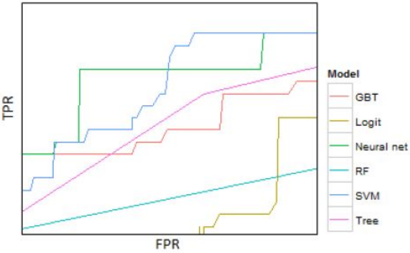
Pre-processing to extract features from raw historical sensor data

- Min/max, mean, variance
- Curve trend
- Discontinuities
- Class based on patterns
- 'Signature analysis' (wavelets, splines)

Criteria assessing model performance

- % of correctly predicted outcomes
- Area Under the ROC curve (AUC) more robust





Results

Procedure and criteria for model assessment similar to the ones used for manufacturing cost

- Training with 80% of the data and prediction accuracy on remaining 20%

Binary classifiers *in lieu* of regression models in manufacturing cost

- Goodness-of-fit measured by TPR
- Prediction accuracy measured by AUC

Goodness-of-fit (TPR)	**Accuracy (AUC)**
>85%	>85%

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Goodness-of-fit (*TPR*)	**Accuracy (*AUC*)**
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Take-home messages

A valid innovative framework

- Validity of the data-driven, statistics-based approach
- Scalable, reusable, maintainable model of LCC
- Contribute to structure the data within the IT system

Satisfactory results

- Complementary insights from ensemble models
- Good fit ($R^2 > 0.8 \& TPR > 85\%$) and prediction accuracy ($MAPE > 0.8 \& AUC > 85\%$) on new data, for manufacturing and maintenance costs
- Ranking of most relevant drivers LCC, challenging traditional engineering approach (results not presented today)

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Benefits and limits of the MBSE framework

Benefits

- Generic framework
  - Applicable at system, subsystem and component levels
  - Applicable to many (mechanical) products and sectors
- Probabilistic, data-driven approach
  - Risk in decision-making and financial evaluation
  - Estimation based on actual data (no dubious assumptions needed)

Limits

- Data-driven (!)
  - Requires sufficient amount of actual data
  - Pre-existing databases and data-rich IT infrastructure
  - Lack of statistical training amongst engineers
- Less applicable to families of products with low commonality

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What remains to be done

Refine the models

- Add more input variables, better extracted from time series (maintenance cost)
- Use more sophisticated models (Dynamic Bayesian networks, Functional Data Analysis, Markov-like models...)
- Interactions between drivers of manufacturing and maintenance costs

Benchmark and extend the results

- Compare with accuracy and variable importance obtained from current «manual» estimates of LCC by Rolls-Royce cost engineers
- Verify validity on different components or sectors

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