Technische Universität Braunschweig

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Forecasting the Repair of HPT NGVs

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Content

1. Background & aims/objectives
2. Basics
3. Construction of a Bayesian belief network (BBN)
    1. Standard BBN
    2. Modified BBN
4. Verification & Evaluation
5. Conclusions

Background
Why using BBN for engine maintenance?

Main cost driver

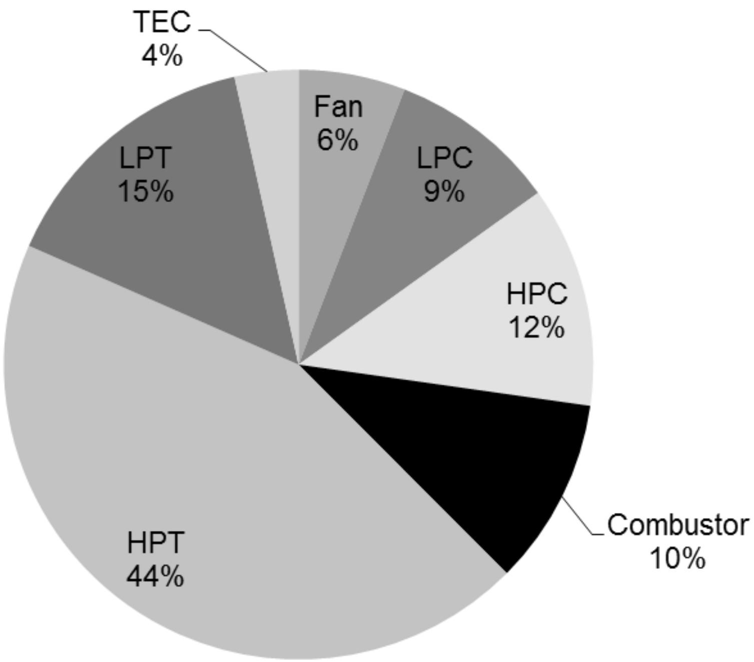

Fig. 1 Cost driver according to engine modules, modified by [1].

Business side: Contractual framework

1. „Time and Material“
2. „Fixed Price“
3. „Fly by Hour“

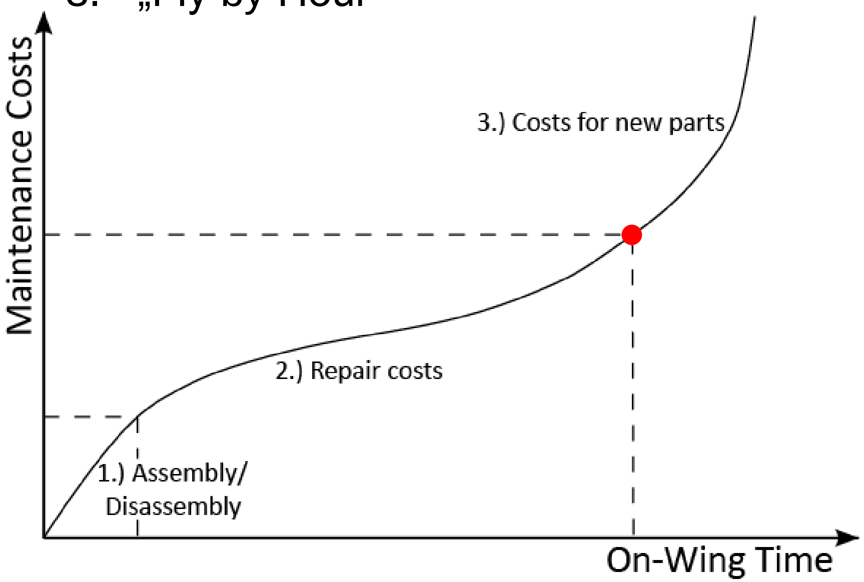

Fig. 2 The three degradation phases of an engine, modified by [2].

$\Rightarrow$ **precise hardware forecast is badly required**

Aim and Objectives

<u>Aim:</u>

- developing a method for forecasting the repair of the HPT NGV
- showing the potential benefit in case of inadequate data density

<u>Objectives/Methodology:</u>

Data set

- customer database
- engine manual
- inspection results
- workscopes
- summary of performance

Net architecture definition

- standard BBN
- quadratic convergence & expert knowledge

State determination

- Norsys Netica 4.16

Verification & evaluation

- trend forecasting
- jet engine data se

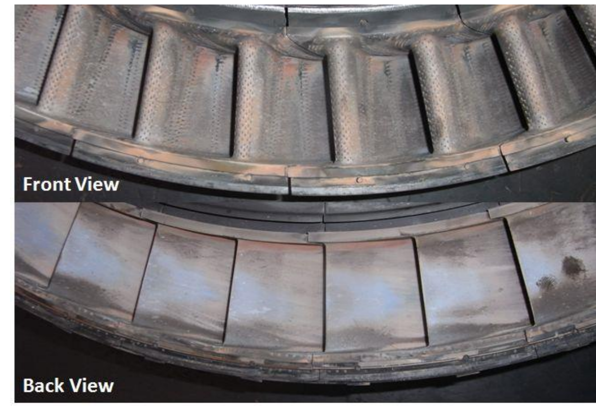

Fig. 3 Deposits on surfaces of HPT NGVs, [3].

Framework Conditions
Learning Data Set

<u>Boundary conditions:</u>

- piece-part repair level
- no unscheduled SV
- engines with recent modification levels
- complete data set

⇒ **~4500 NGV** data sets or **~195 jet engines**

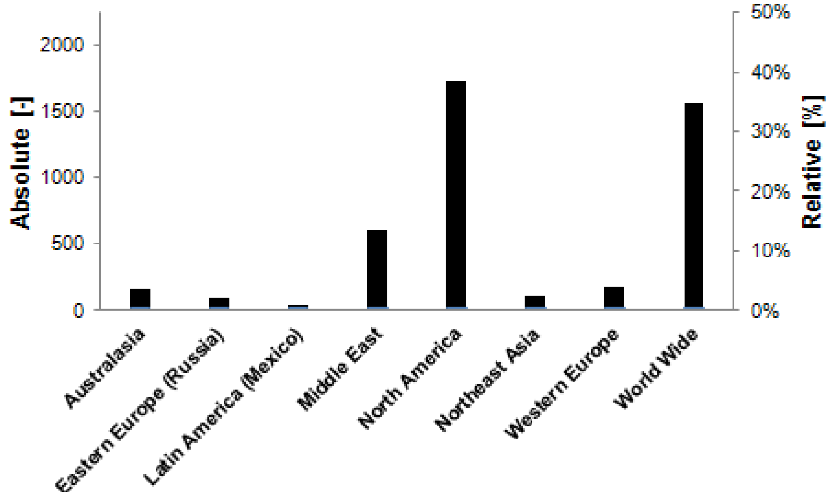

Fig. 4 Frequency distribution of the region, [3].

Framework Conditions
Bayesian Belief Net (BBN)

Why BBN?

- Shop Visits (SV) determined by various influence parameter which are not analytical acquired
- modifications and further developments shall require little time and effort
- implementing expert knowledge
- manageable in case of imprecise data

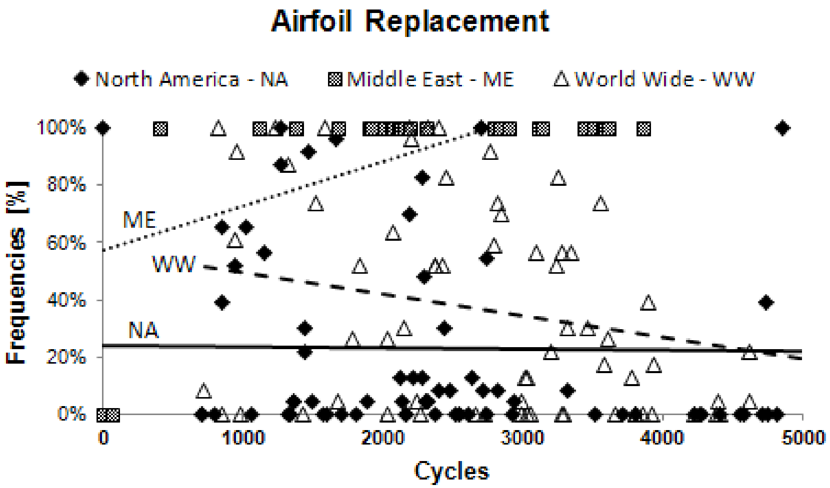

Fig. 5 Percentage of the AFR repaired components of the three main regions towards the cycles, [3].

High Pressure Turbine Nozzle Guide Vane 1 (HPT NGV 1)
Repair Possibilities – Simplification

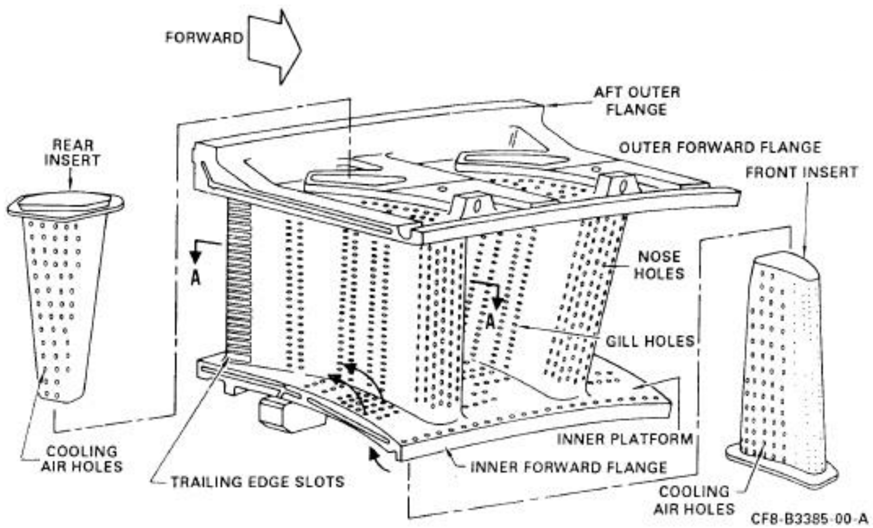

Fig. 6 HPT NGV 1, [4].

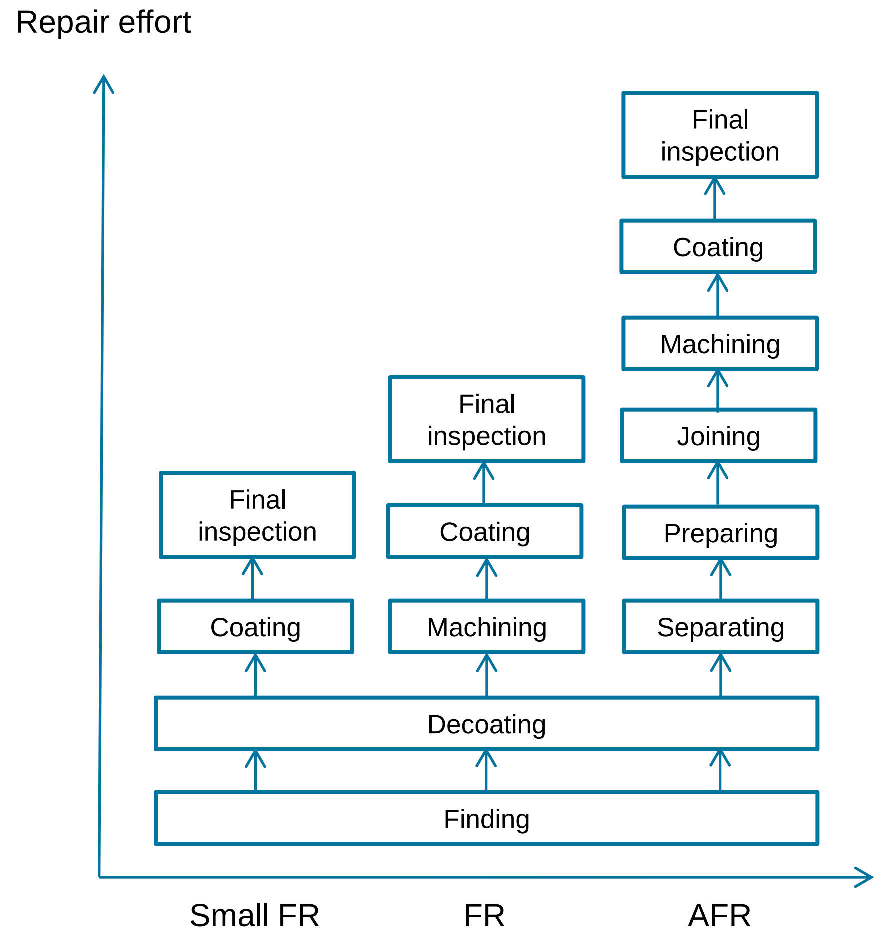

Fig. 7 Mögliche Reparaturen der HDT-Leitschaufel.

High Pressure Turbine Nozzle Guide Vane 1 (HPT NGV 1)

Degradation Mechanisms

Indirect influence

Direct influence

Fig. 14 Erosion of HPC rotors, [5].

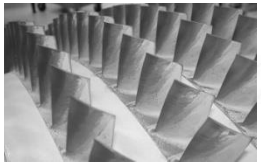

Fig. 9 Erosion of HPT vanes, [5].

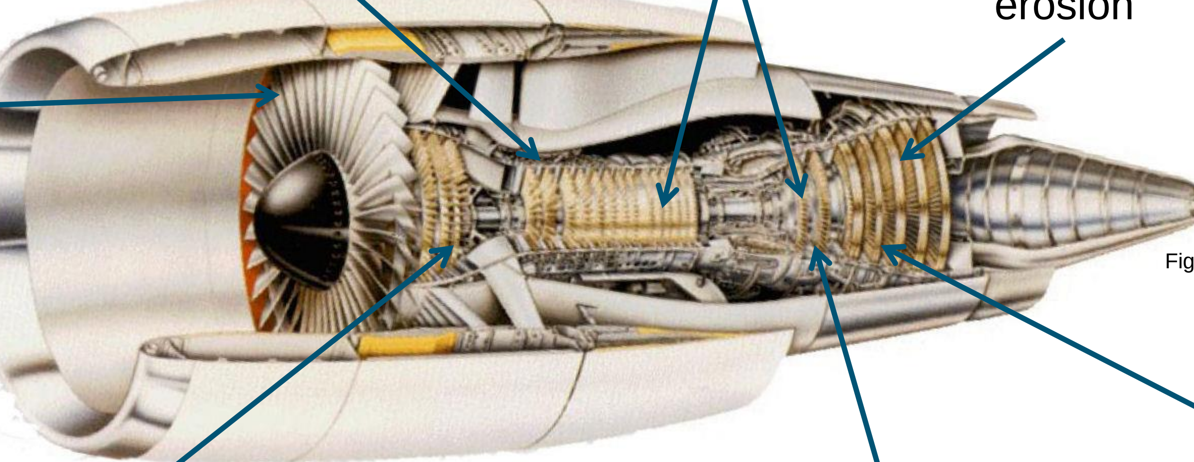

Fig. 8 Sectional drawing of GE CF6-80C2, [4].

Fig. 13 Fan damage.

Fig. 12 Deposits on surfaces of an HPC.

Fig. 11 Hot gas corrosion of an HPT rotor, [6].

Fig. 10 Deposits on surfaces of HPT NGVs.

Main Influence Parameter
Input Data

Material	Region	Wing Position	Rating Level	Repairhistory	Customer Segment	Cycles
DSR'142	Australasia	Twin Engine	Low	New	AT/BJ – Business Jet Operator	<1500
X-40	Eastern Europe	Four Engine – Inside	Medium	Small FR	AT/CA – Charter Airlines	1500 to 2000
N5	Latin America (Mexico)	Four Engine – Outside	High	1st FR	AT/FA – Freight Airlines	2000 to 2500
	Middle East	Three Engine – Upper		…	AT/LC – Low Fare Carrier	2500 to 3000
	North America	Three Engine – Outside		5th FR	AT/MA – Major Airlines	3000 to 3500
	Northeast Asia			AFR	AT/SEC – Secondary Airlines	3500 to 4000
	Western Europe					4000 to 4500
	World Wide					4500<

Tab. 1 Parameter influences with its characteristics.

Construction of a BBN
Standard BBN

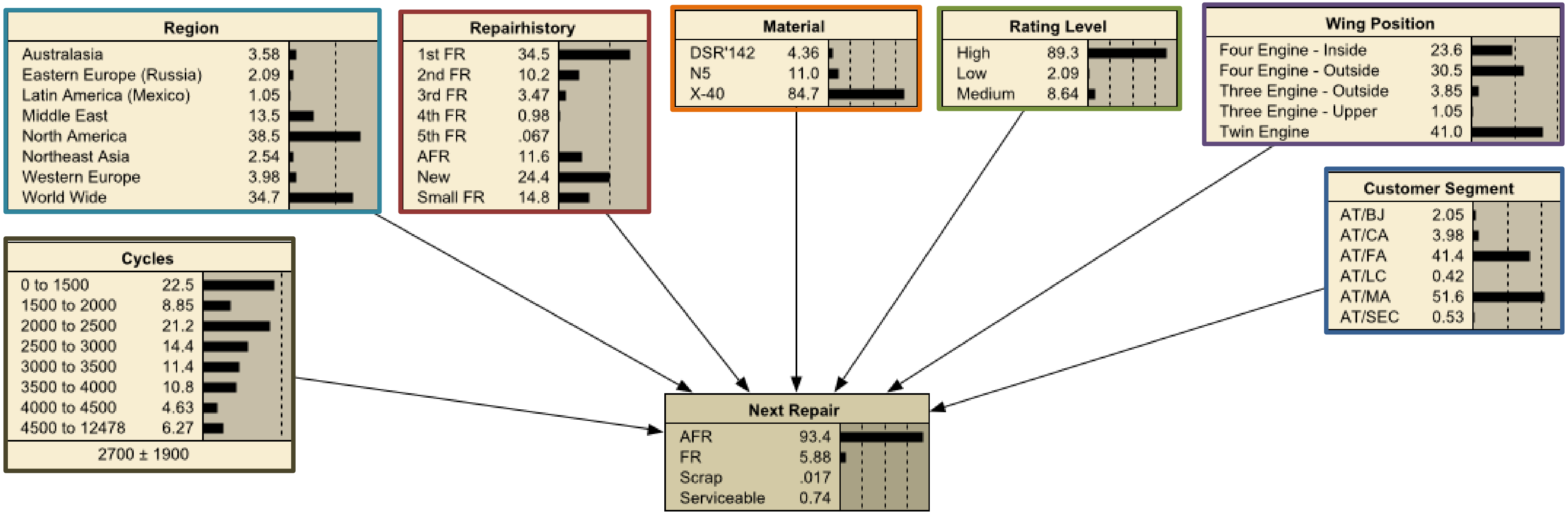

Fig. 15 The standard net, [3].

- simplest net architecture
- equal weighting of parameters

Construction of a BBN
Quadratic Convergence

Cramer's contingency coefficient:

$$C = \sqrt{\frac{\phi^2}{\min\{k-1, m-1\}}}, \qquad 0 \leq C \leq 1$$

ϕ^2: Mean value of quadratic convergence

Maximum value of
k: row
m: column

- Min. / Max.values:
  1. $C = 0$ $\rightarrow$ statistical independence
  2. $C = 1$ $\rightarrow$ ideal statistical dependence
- $C \geq 0.5$: strong correlation between two parameters

Results:

Strong correlation between region and…

- …rating level ($C = 0.84$)
- …customer segment ($C = 0.64$)
- …material ($C = 0.57$)
- …wing position ($C = 0.49$)

Strong correlation between material and wing position ($C = 0.48$)

Construction of a BBN
Expert Knowledge

- in average almost 20 years of experience per person
- up to almost 30 years of experience for one person

<u>Procedure:</u>

- rank the main influences which affect the next repair

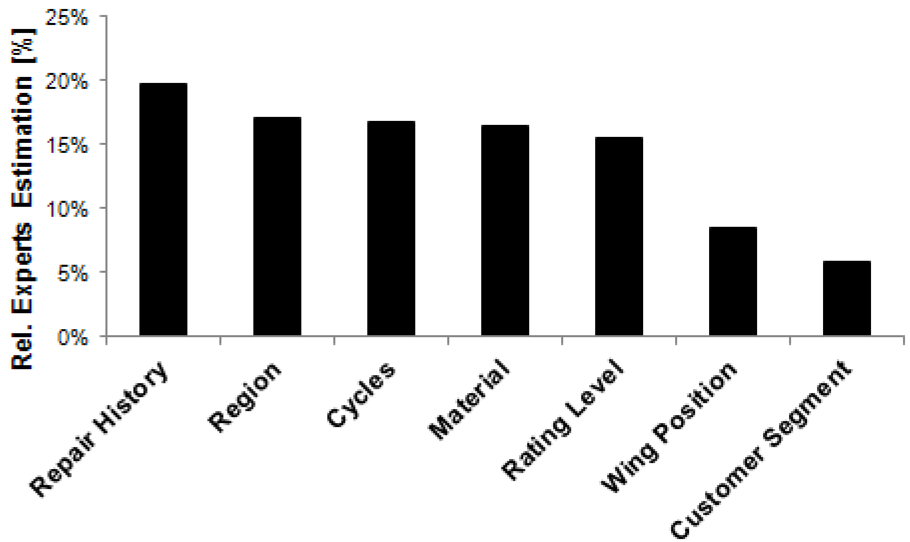

Fig. 16 Expert knowledge presentation, [3].

Construction of a BBN

Final Net Architecture – Modified Net

- multi-level architecture
- different weighting of parameters

3. level

2. level

1. level

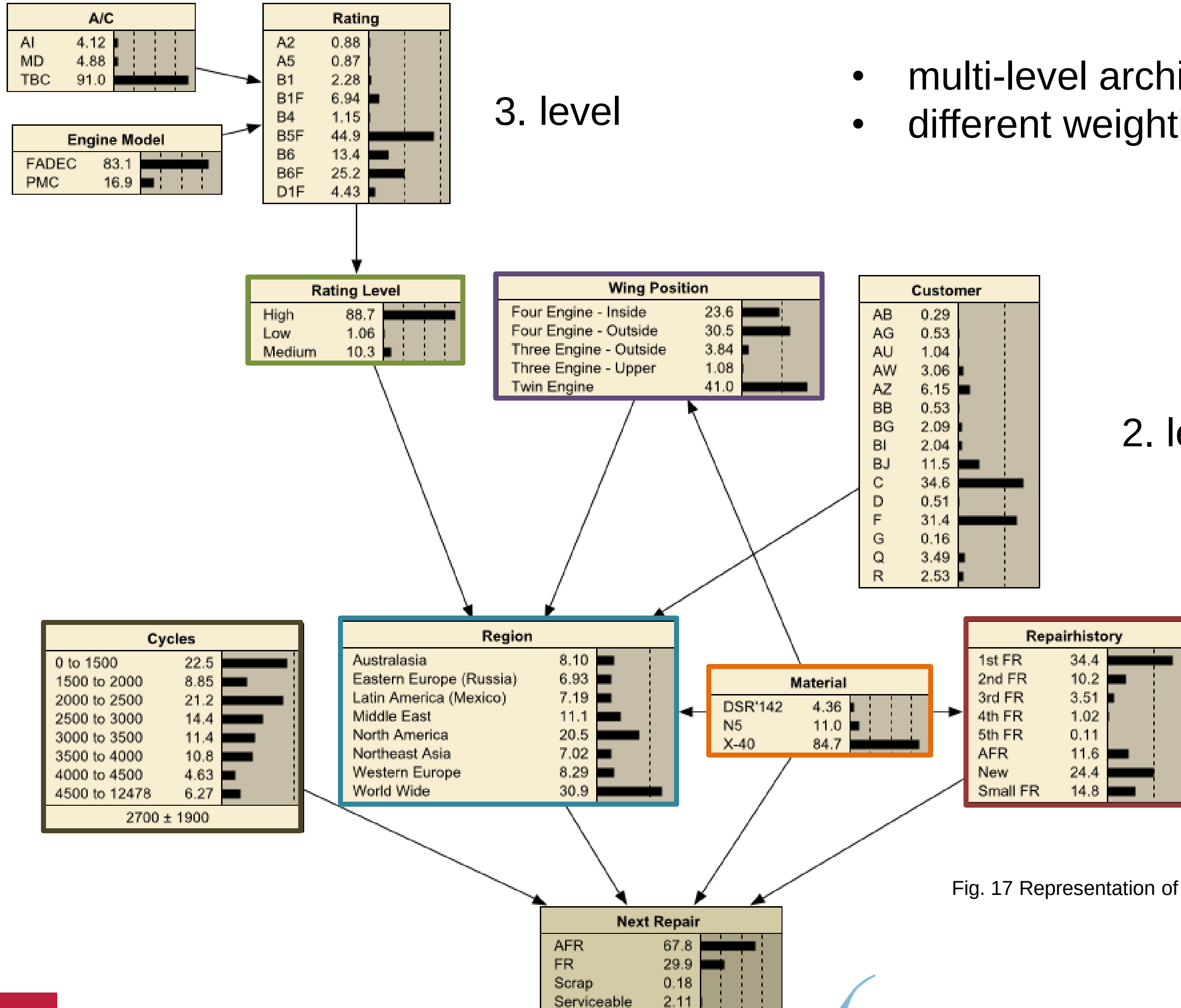

Fig. 17 Representation of the modified BBN, [3].

Verification
Trend Forecasting Test Cases

Case	Evidences	Expected	Standard net	Modified net
1	2nd FR	~ 100% AFR	✓	✓
2	Middle East, N5, High	~ 100% AFR	✓	✓
3	North America, 2nd FR, X-40	~ 100% AFR	✓	✓
4	Middle East, Cycles ↑	AFR ↑	0	0
5	North America, Cycles ↑	AFR ↑	0	✓
6	Cycles ↑	$AFR_{Outside} > AFR_{Inside}$	X	X
7	Cycles>3000, DSR'142, High	~ 100% AFR	✓	✓
8	North America, Cycles>2500	70% AFR, 30% FR	X	✓
9	High, AT/FA	75% AFR, 25% FR	X	✓
10	New	10% Serviceable	0	0
11	AFR	Serviceable ↓, AFR ↑	0	0

Legend: ✓ good forecast quality
0 medium forecast quality
X poor forecast quality

Tab. 2 Trend forecasting test cases, [3].

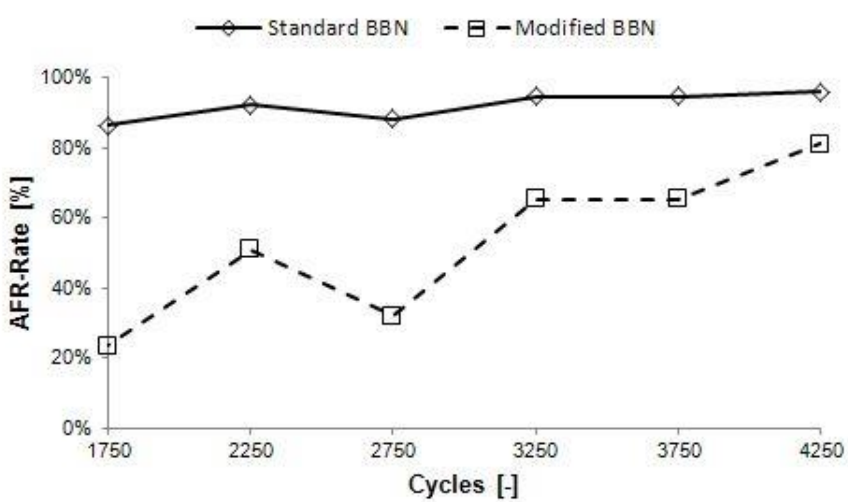

Fig. 18 Plausibility case five, [3].

Evaluation
Results

<u>Evaluation data set:</u>

- percentage distribution correspond to training data
- limited data used
- **41 test engines:**
    1. 29 **current** engines from August 2012 till January 2013
    2. 2 **unusual** engines
    3. 10 **representative** engines from 2010 till 2012

Jet engines	Standard BBN	Modified BBN
All	77%	83%
Current	80%	85%
Unusual	50%	50%
Representative	73%	85%

Tab. 3 List of high accuracy per net, [3].

⇒ With up to **85%** the repair of the HPT NGV has been correctly forecasted!

Conclusion

- identification of relevant **input parameter** and setting appropriate **boundary conditions** are of great significance

- **modified BBN: quadratic convergence** and **Cramer's** contingency coefficient combined with **expert knowledge** has been developed

  $\Rightarrow$ **very statisfactory behaviour** by **forecasting trends**

  $\Rightarrow$ **forecast accuracy** of **83%** for all investigated engines

- very promising potential for contract proposals and capacity planning

<u>Outlook:</u>

- combining BBN with other artificial intelligence methods
- investigating other modules
- determing the business value

Thanks for Listening!

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[1] Rupp, O. C., 2000. “Vorhersage von Instandhaltungskosten bei der Auslegung ziviler Strahltriebwerke”. PhD thesis, Lehrstuhl für Flugantriebe, Technische Universität München.

[2] Berkholz, D., Schmidt, M., and Nyhuis, P., 2008. “From volatile maintenance data forecasting to reliable capacity planning”. Proceedings of the World Congress on Engineering and Computer Science, October.

[3] Giesecke, D., Friedrichs, J., Kenull, T., Binner, M. and Siegert, M., 2014. “A Method for Forecasting the Condition of HPT NGV‘s by using Bayesian Belief Networks and a Statistical Approach“, Proceedings of ASME Turbo Expo(GT2014-25464), June 3-7.

[4] MTU Maintenance Hannover GmbH.

[5] Ebmeyer, C., Wensky, T., Friedrichs, J., and Zachau, U., 2011. “Evaluation of total engine performance degradation based on modular efficiencies”. Proceedings of ASME Turbo Expo(GT2011-45839), June 6-11.

[6] Kurz, R., 2005. “Gas Turbine Performance”. In: 34th Turbomachinery Symposium Proceedings, Turbomachinery Laboratory, Texas A&M University, College Station, Houston, September, pp. 131-146.