



Nancy Research Centre of Automatic Control



SYSTEM APPROACH-BASED BAYESIAN NETWORK TO AID MAINTENANCE OF MANUFACTURING PROCESS

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CONTENT

- ☒ Motivations to develop aids for the maintenance of manufacturing process**
- ☒ Bayesian Network: a solution to represent the models for maintenance aid**
- ☒ From the complementary functioning-malfunctioning representation of the manufacturing process...**
- ☒ ... to an unified Bayesian Network representation to aid maintenance**
- ☒ Application: aid for the maintenance of lathe machine**
- ☒ Conclusion - Prospects**

New manufacturing context

- ☒ Extended Enterprise challenge: to optimise the quality of service of the product**
- ☒ Environment of the product manufacturing: not only technical but also social and economic**
- ☒ Product manufacturing system more en more complex: use of Communication and Information Technologies**
- ☒ The unavailability cost of such manufacturing systems (indirect costs) is widely superior to the repairing costs (direct costs)**

A challenge is to better master this cost / availability relation by decision-making aid successful in maintenance



New maintenance context

- ☒ From a cost centre to a profit centre: integration of the maintenance as a Enterprise domain**
- ☒ To master the system by measures, evaluations, decision-makings either only in off-line but also on-line (as soon as possible, degradation more than failure)**
- ☒ To assist the operator in his decision-making (diagnosis, prognosis...). To implement strategies integrating not only technical criteria but also economic, security, quality...**
- ☒ To propose relevant models for aid and representing the required strategic knowledge**

A challenge is to have models formalising this knowledge but allowing so easily to maintain it, to expand it, to reuse it... [Rao 98]



Bayesian Networks to support decision-making in Maintenance domain

Motivation

Bayesian network
From...
To...
Application
Conclusion

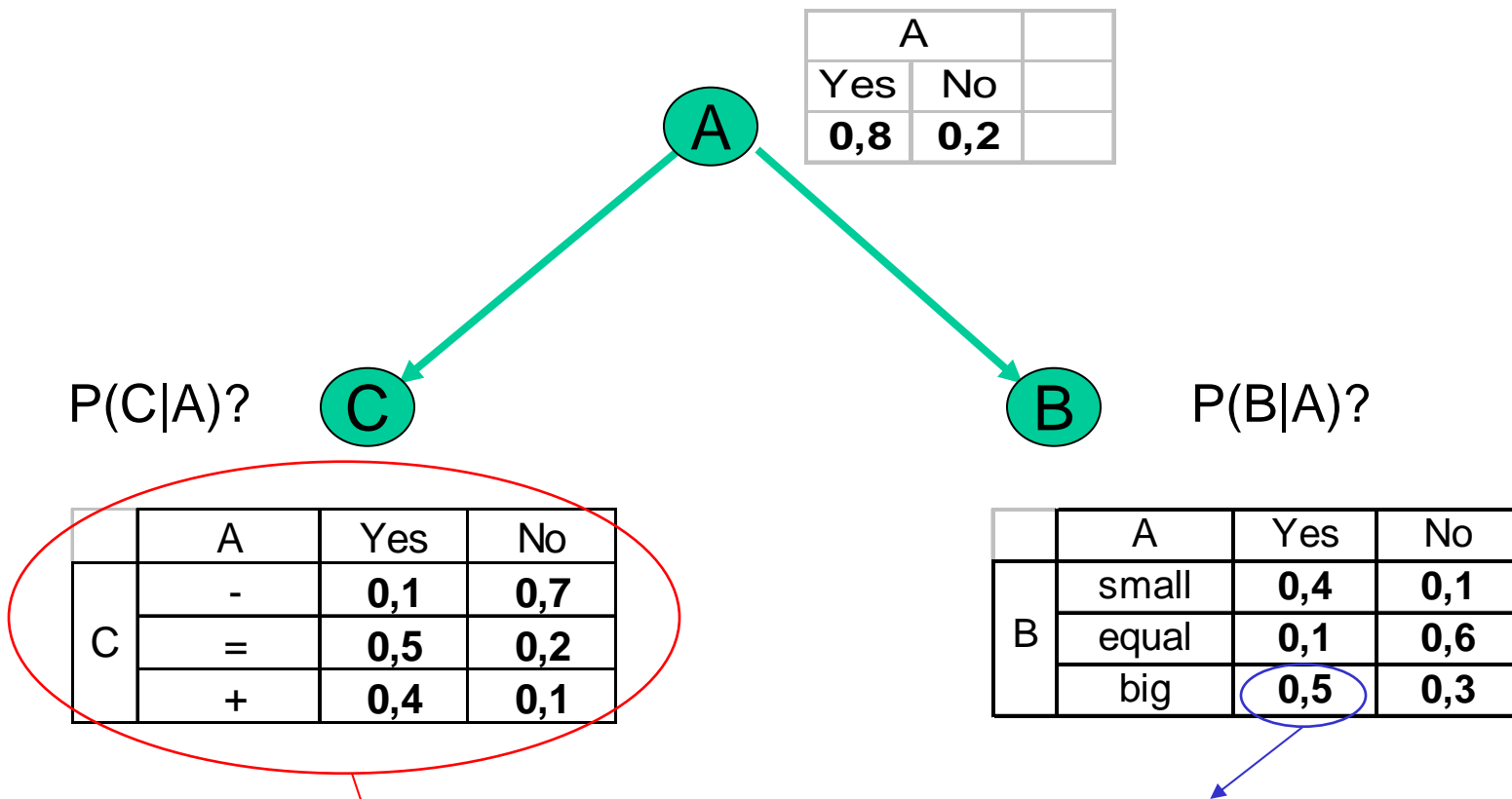
☒ Why Bayesian Networks (BN) ?

- In relation to knowledge-based systems tools, the uncertainty is handled in mathematically rigorous yet efficient and simple way
- In relation to probabilistic analysis tools, the network representation of problems use of Bayesian statistics, and the synergy between these
- Possibility to integrate some expert judgement, to extract knowledge from data...

☒ How BN are they built ?

- From a System Functioning Representation (using SADT graphical representation, system principles)
- To induce a System Malfunctioning Representation (FMECA and HAZOP study)
- By unifying functioning-malfunctioning approach in a representation in the terms of networks

What is a Bayesian Network ?



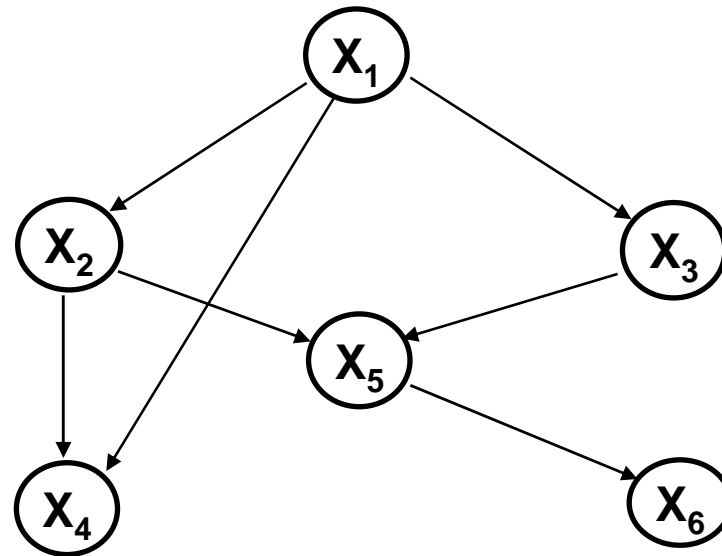
Conditional Probability Table

A Probability to estimate

- by learning
- **based on expert's judgement**

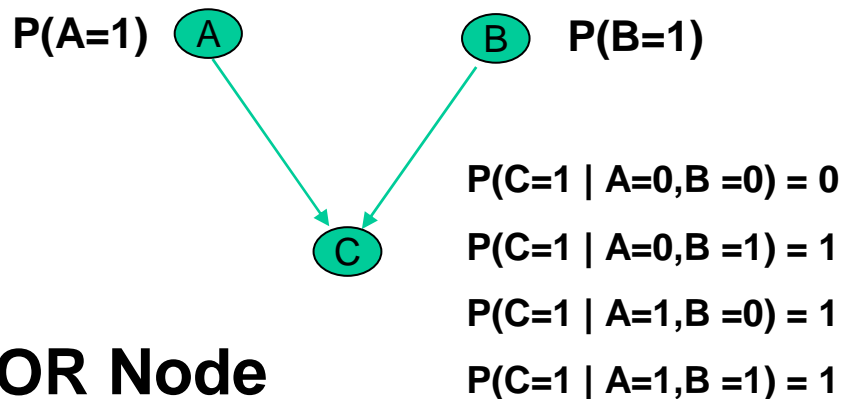
What is a Bayesian Network ?

Motivation
Bayesian network
From...
To...
Application
Conclusion

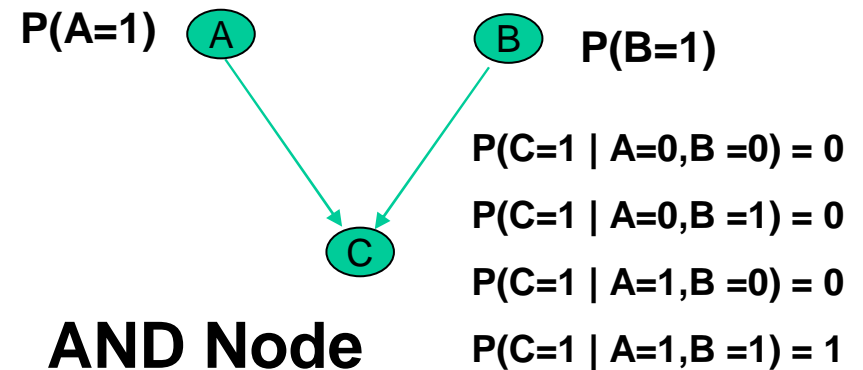


Joint distribution

$$P(x_1, x_2, x_3, x_4, x_5, x_6) = P(x_6 | x_5) P(x_5 | x_3, x_2) P(x_4 | x_2, x_1) P(x_3 | x_1) P(x_2 | x_1) P(x_1)$$

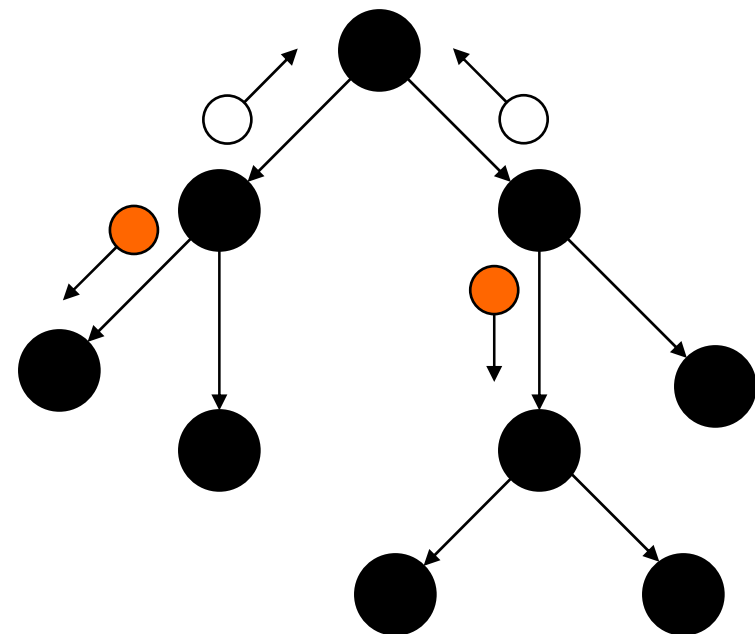
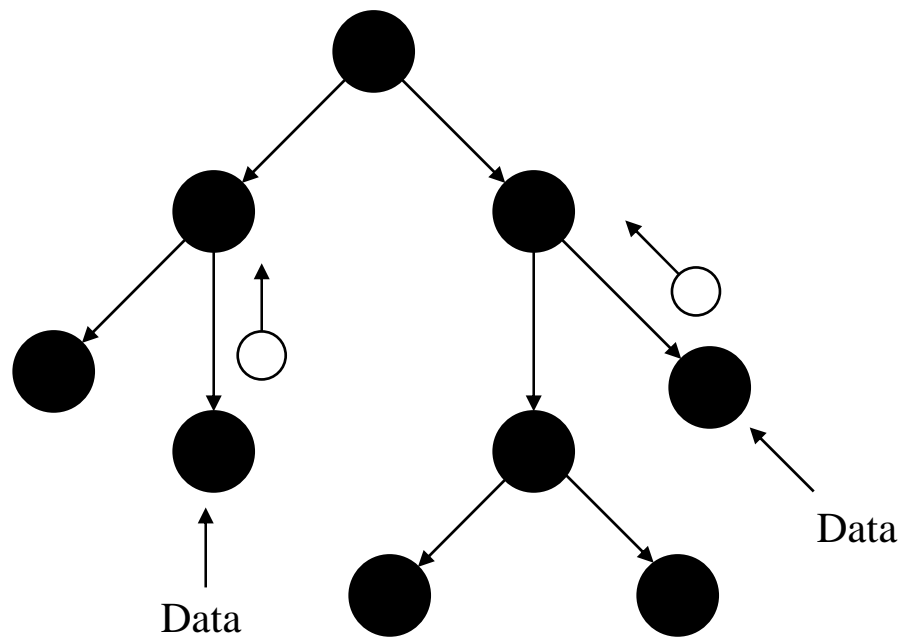


OR Node



AND Node

Propagation algorithm objective



System Functioning Representation

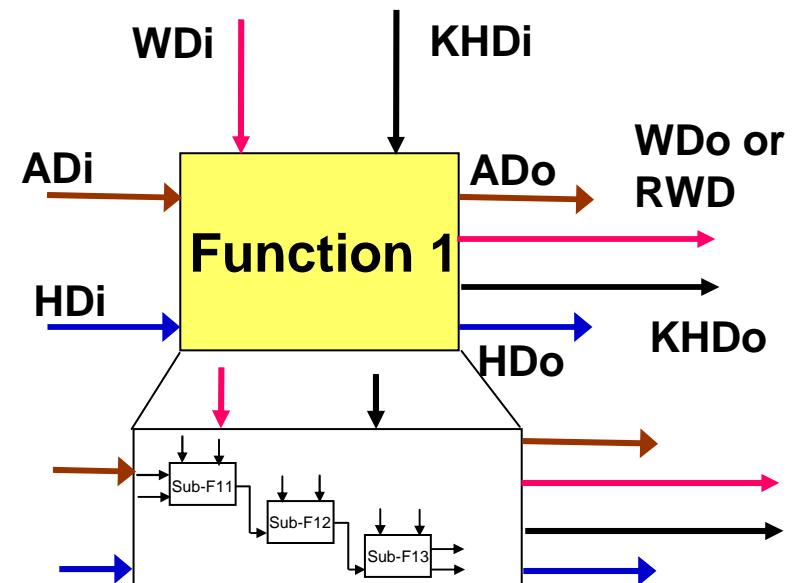
Motivation
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To...
Application
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☒ **Duality between Functioning - Malfunctioning**
(relation between normal and abnormal states,
between functioning mode and degradation-failure)

☒ **Functioning modelling (to produce):**

- finality
- function and sub-function
- flows
 - ⇒ **Having to Do (HD)**
 - ⇒ **Knowing How to Do (KHD)**
 - ⇒ **being Able to Do (AD)**
 - ⇒ **Wanting to Do (WD)**
- objects
- flow properties - object properties

SADT graphical representation



System Malfunctioning Representation

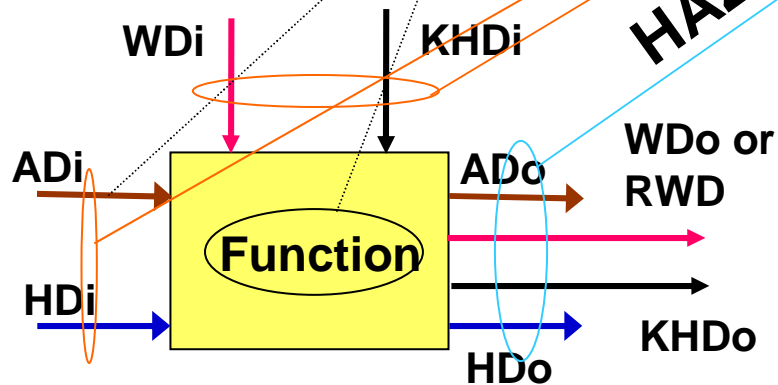
Motivation
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 From...
 To...
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FMECA

Functional Analysis level :

System : F = Frequency (Likelihood) S = Seriousness (Severity) ND = No Detection

Function	Element	Failure Mode	Causes	Effects	Checking	F	S	ND	Criticality



Assumption : RWD = activity state

R for fulfilled or Realised

NC for Not Conform (less than, more than...)

NR for Not Realised (no)

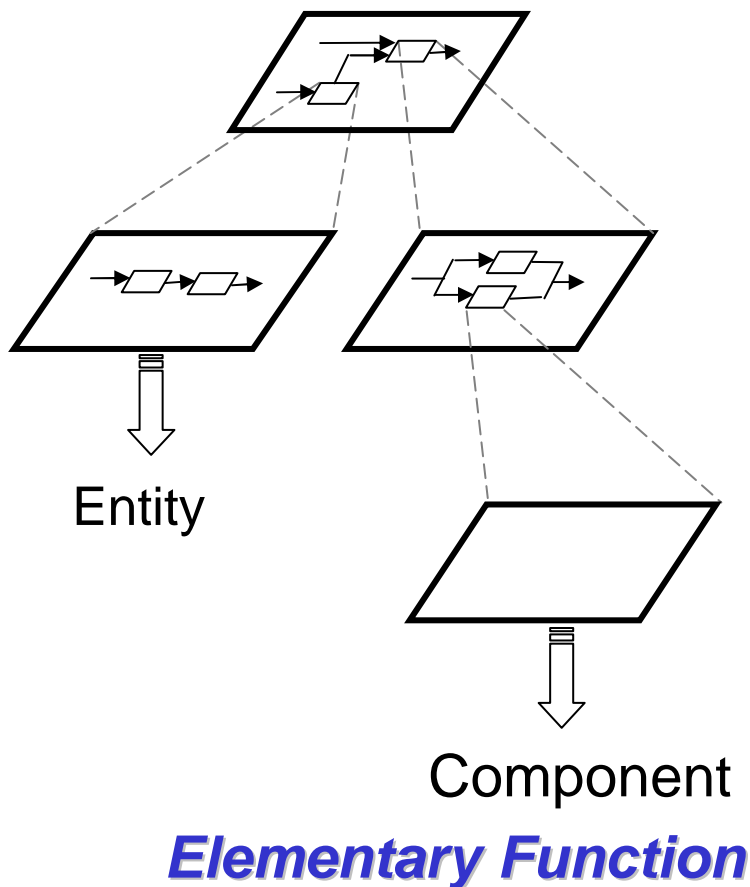
Internal Cause linked to the activity support flow (one ADi)

External Cause linked to deviations of the activity input flows (Wdi, KHDi, Hdi, others ADi)

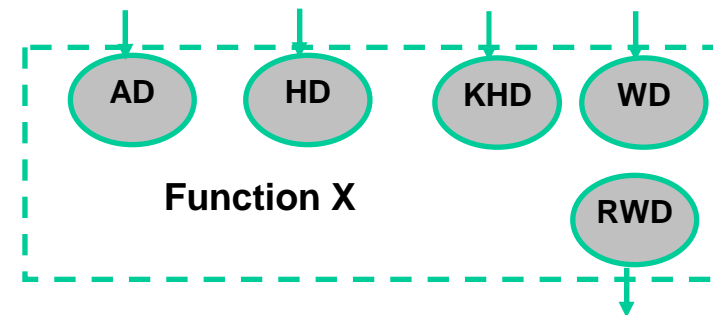
Bayesian Network Representation: Generic BN node structure

Motivation
Bayesian network
From...
To...
Application
Conclusion

Main Function



Generic model of a function

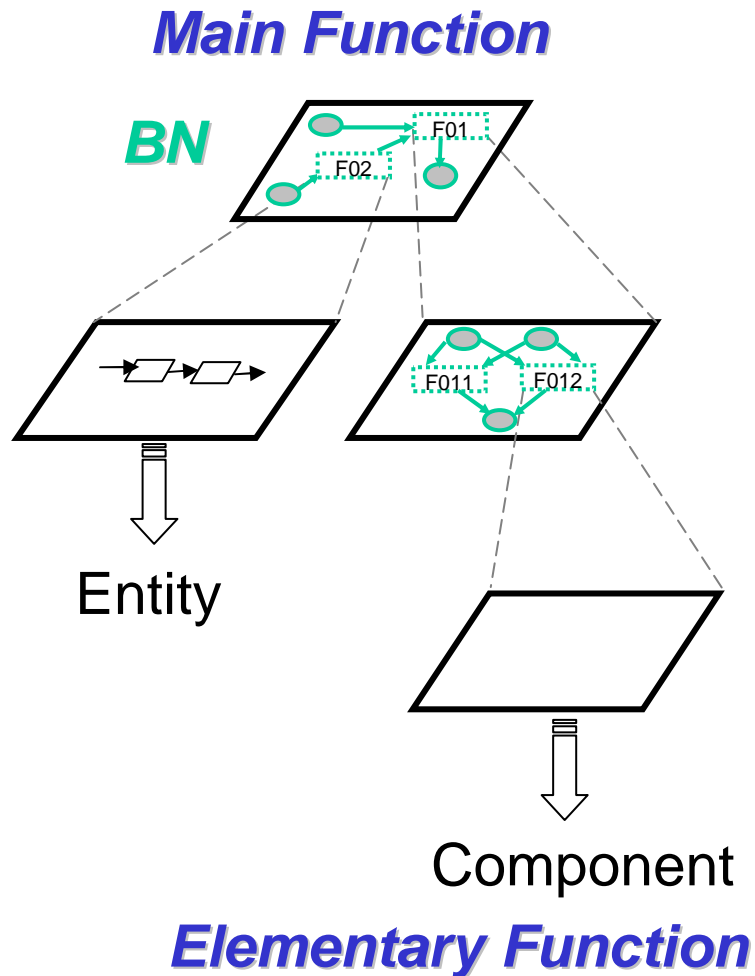


Report on Want to Do (RWD):
informational result of the Input WD
transformed by the function

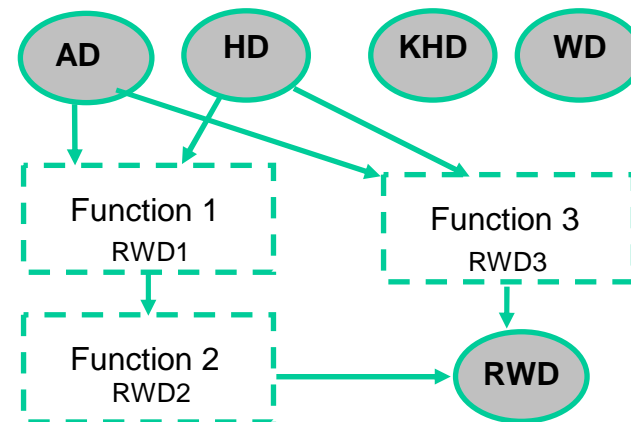
States: R NC NR

Bayesian Network Representation: Main functions

Motivation
Bayesian network
From...
To...
Application
Conclusion

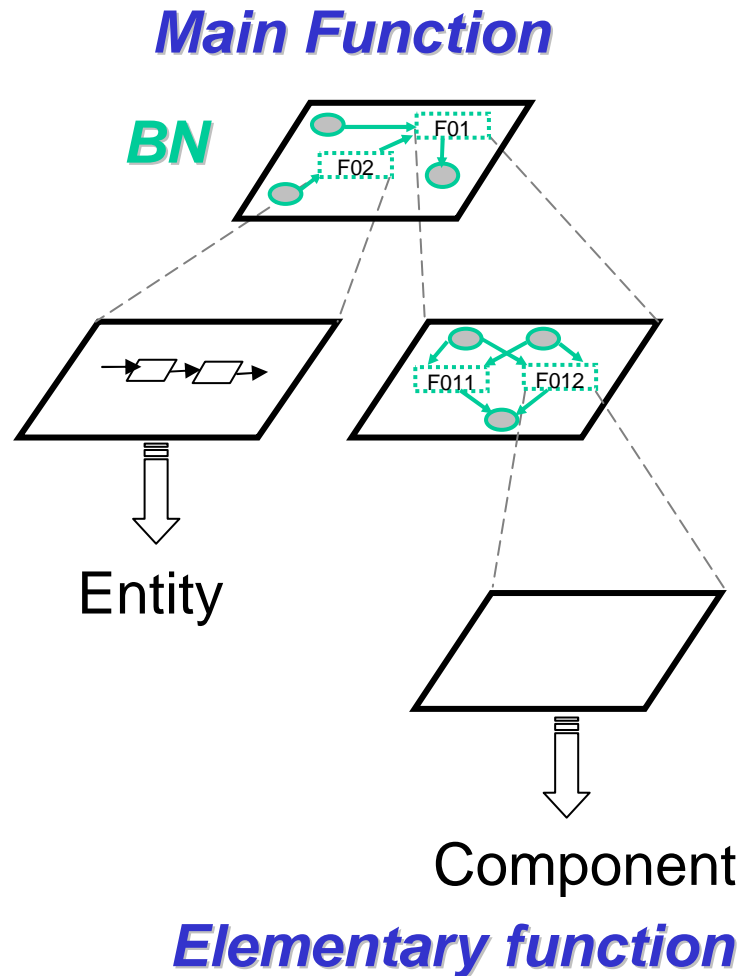


Higher level

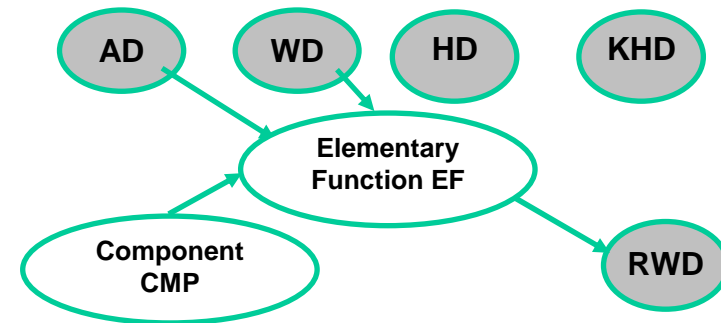


Bayesian Network Representation: Elementary function

Motivation
Bayesian network
From...
To...
Application
Conclusion



Lower level (link with component)



Bayesian Network Representation: Component probabilities evaluation

Motivation
Bayesian network
From...
To...
Application
Conclusion

Node CMP

CMP = P1 the component failure P1

CMP = P2 the component failure P2

CMP = OK the component working

Prior Probabilities

The computation is performed at a given mission time T

Hypothesis: the component reliability is exponentially distributed

$$P(\text{CMP} = \text{P1}, T) = 1 - \exp(-\lambda_{\text{P1}} T)$$

λ_{P1} is the failure rate of component failure P1 $\lambda_{\text{P1}} = 1/\text{MTBF}_{\text{P1}}$

$$P(\text{CMP} = \text{P2}, T) = 1 - \exp(-\lambda_{\text{P2}} T)$$

λ_{P2} is the failure rate of component failure P2

$$P(\text{CMP} = \text{OK}, T) = 1 - [P(\text{CMP} = \text{P1}, T) + P(\text{CMP} = \text{P2}, T)]$$

Bayesian Network Representation: Function probabilities evaluation

Motivation
Bayesian network
From...
To...
Application
Conclusion

Elementary function

AD		R			NC			NR
CMP		OK	P1	P2	OK	P1	P2	*
EF	R	1	0.2	0	0	0	0	0
	NC	0	0.8	0	1	0.2	0	0
	NR	0	0	1	0	0.8	1	1

- ☒ The probabilistic dependence is included in the CPT
- ☒ The dependence relations among variables in a BN are not restricted to be deterministic

Bayesian Network Representation: Prognosis strategy

Motivation
Bayesian network
From...
To...
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☒ Specification and design:

NO EVIDENCE

Computation of the overall unreliability of the system:

this corresponds to computing the prior probability of the variable

$$P(\text{RWD Main function} = R, NR, NC)$$

Computation of the unreliability of each identified function:

this corresponds to computing the prior probability of the variable

$$P(\text{RWD Function} = R, NR, NC)$$

☒ Operation:

EVIDENCE: component or function NR

Propagation and estimation of posterior probabilities

$$P(\text{RWD Function} = R, NR, NC \mid \text{Evidence})$$

Bayesian Network Representation: Diagnostic strategy (1)

Motivation
Bayesian network
From...
To...
Application
Conclusion

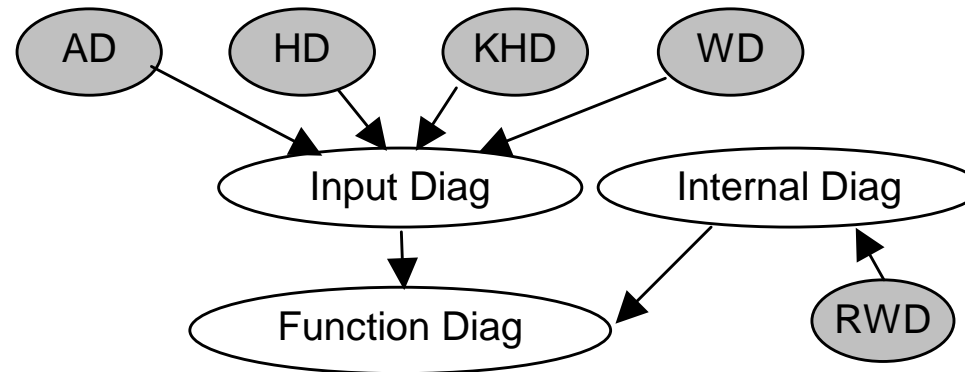
- ☒ Possibility of performing diagnostic problem-solving on the modeled system**

- ☒ Classical diagnostic inference on a BN:**
computation of the posterior marginal probability distribution on each component

- ☒ Scenarios involving more variables:**
 - computation of the posterior joint probability distribution on subsets of components
 - computation of the posterior joint probability distribution on the set of all nodes, but the evidence ones

Bayesian Network Representation: Diagnostic strategy (2)

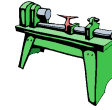
Motivation
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From...
To...
Application
Conclusion



Rules to define the CPT of the node « Function Diagnosis »:

Function Diagnosis = Internal	if Internal Diagnosis = NC or NR and Input Diagnosis = R
Function Diagnosis = Upstream	if Internal Diagnosis = NC or NR and Input Diagnosis = R, NC or NR
Function Diagnosis = Downstream	if Internal Diagnosis = R and Input Diagnosis = R

Functioning/Malfunctioning representation of the Lathe

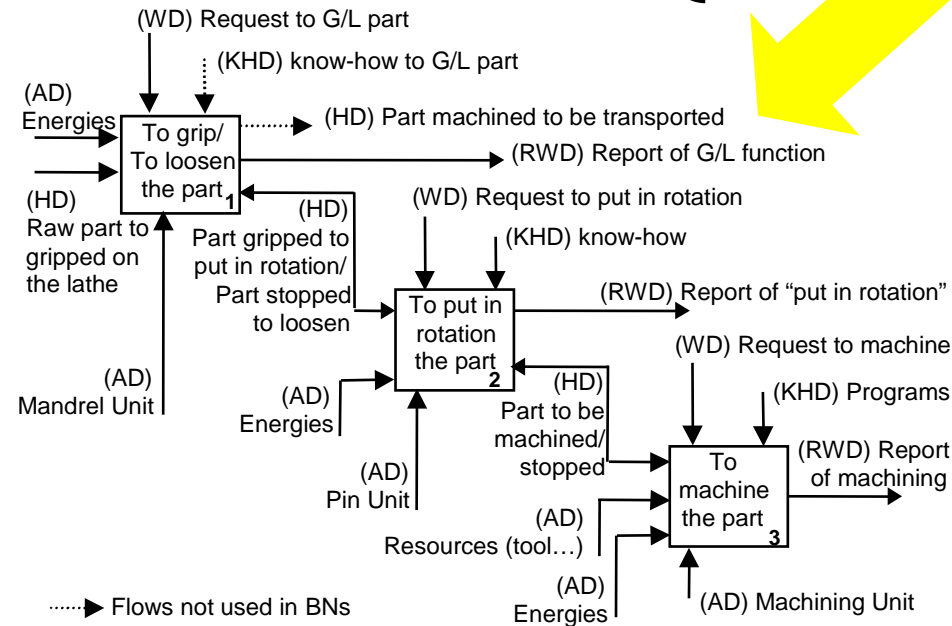
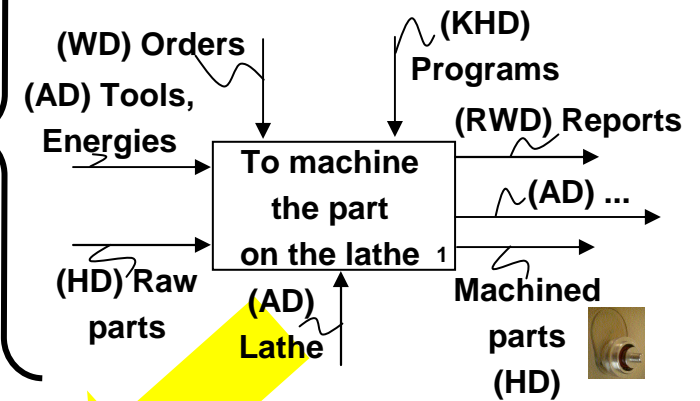


Motivation
Bayesian network
From...
To...
Application
Conclusion

FLOWS OF
Energy
Resource
Information
Material

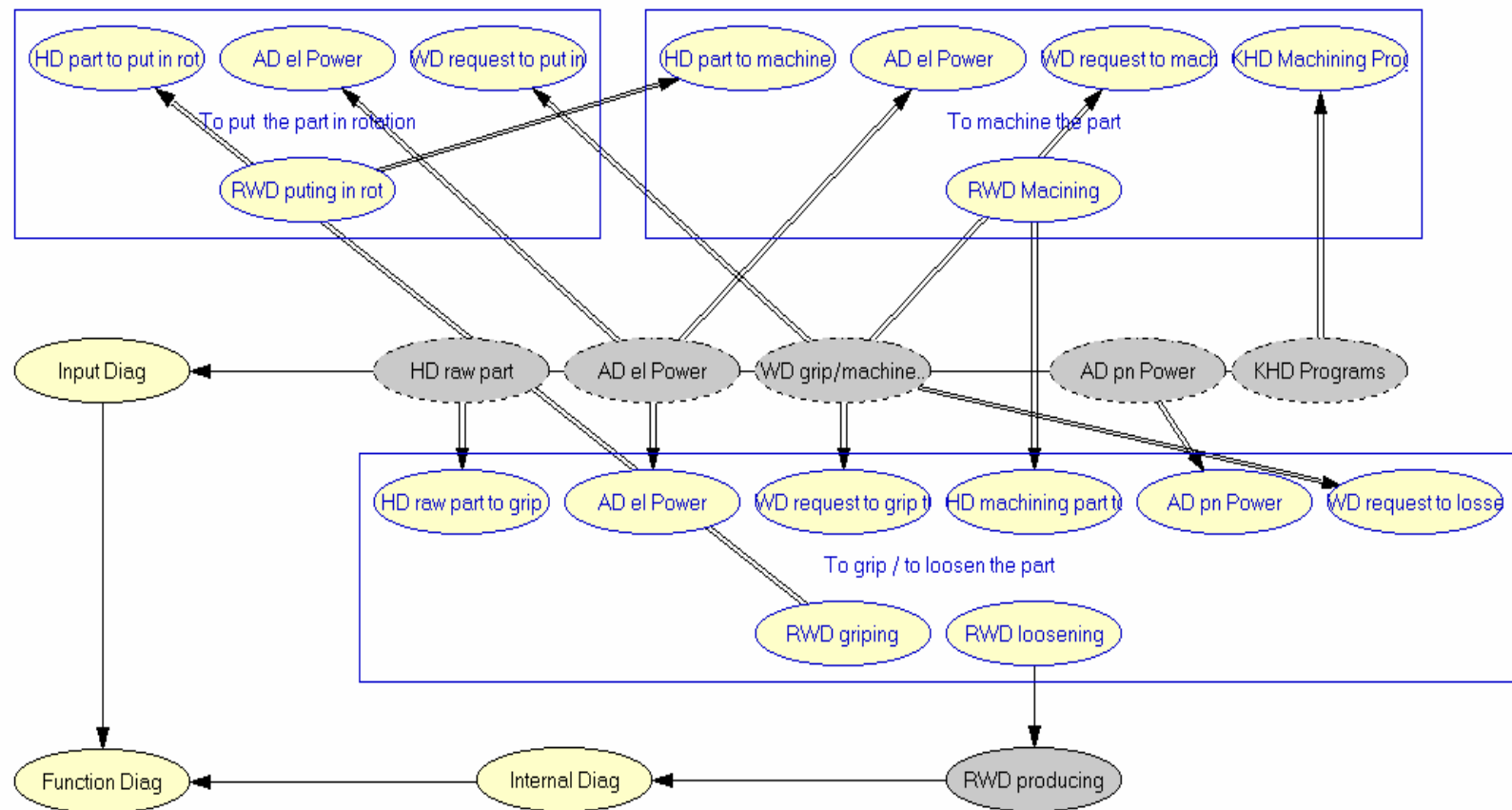


TO MACHINE THE PART ON THE LATHE

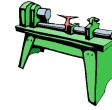


BN of the Lathe

Motivation
Bayesian network
From...
To...
Application
Conclusion



Functioning/Malfunctioning representation of the Lathe

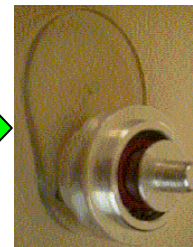


Motivation
Bayesian network
From...
To...
Application
Conclusion

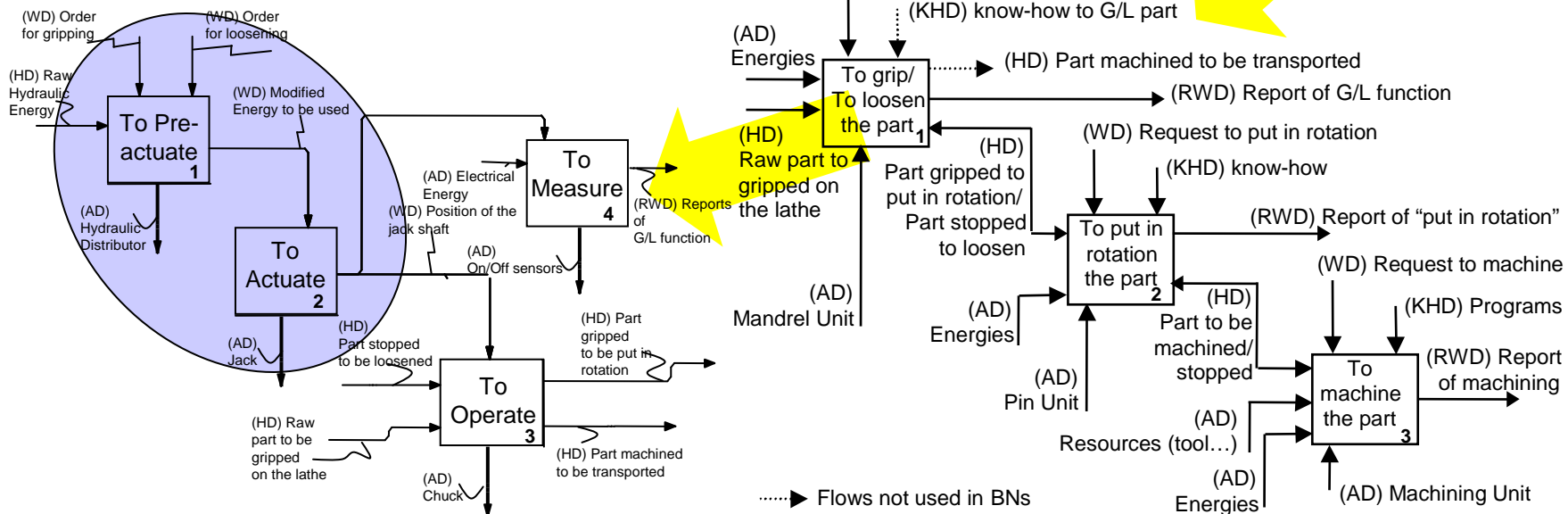
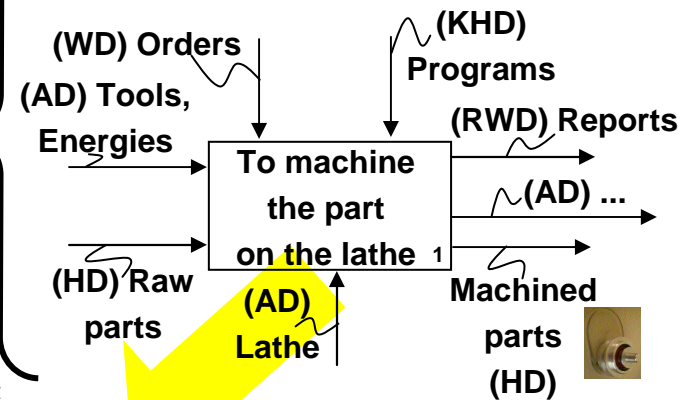
FLOWS OF
Energy
Resource
Information
Material



Environment



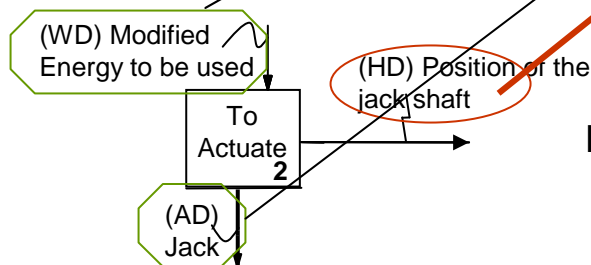
TO MACHINE THE PART ON THE LATHE



Functioning/Malfunctioning representation of the Lathe

Motivation
Bayesian network
From...
To...
Application
Conclusion

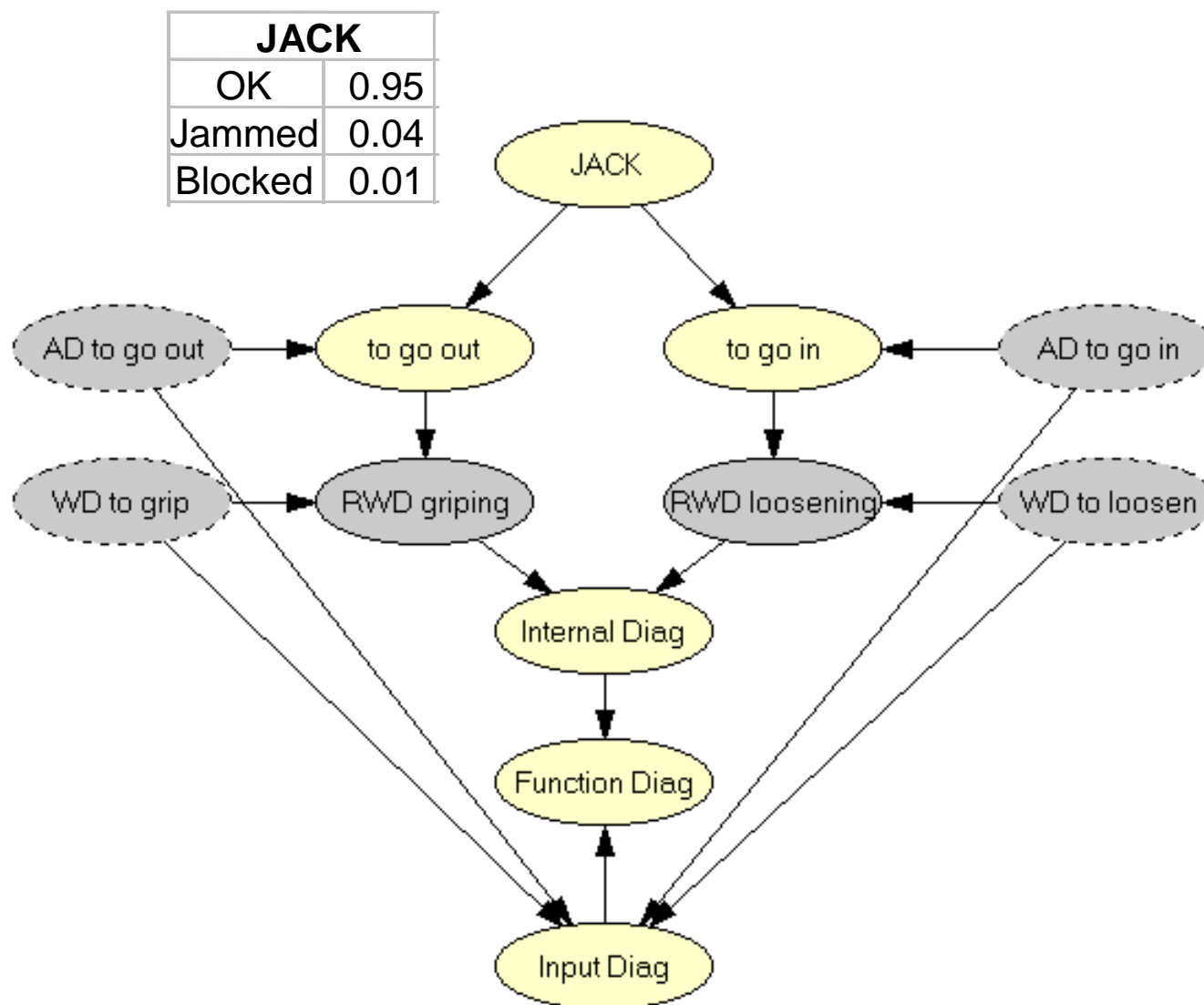
Function	Element	Failure Mode	Effects	Causes	F	S	ND
To pre-actuate	Distributor	No functioning	No modified energy (HD)	No order (WD) No input energy (HD) Distributor failed (AD)	3	2	3
To actuate	Jack	No functioning for "going in" moving	Jack shaft is not moving (HD)	No input energy (WD) Jack blocked failed (AD)	1	4	2
		No functioning for "going out" moving	Jack shaft is not moving (HD)	No input energy (WD) Jack blocked failed (AD)	1	4	2
		Going out action is too slow	Jack shaft is moving too slow (HD)	No enough energy (WD) Jack shaft is jammed (AD)	3	2	2
		Going in action is too slow	Jack shaft is moving too slow (HD)	No enough energy (WD) Jack shaft is jammed (AD)	3	2	2
To operate	Chuck	Chuck does not grip enough	Part fell (HD)	Jack shaft is moving too slow (WD) Raw Part not conform Chuck is bad regulated (AD)	2	4	3
To measure	On/Off sensors	...					



HAZOP Study: no flow, less flow than, too much flow than

BN of the Lathe (elementary activity)

Motivation
Bayesian network
From...
To...
Application
Conclusion



BN inference diagnosis of the Lathe Example

Motivation
Bayesian network
From...
To...
Application
Conclusion

$P(\text{RWD Main function}=\text{NR}) = 1$

EVIDENCE

INFERENCE

To check Function Diagnosis:

$P(\text{Function Diagnosis}=\text{Internal, Upstream, Downstream})$

To check Input Flows:

$P(\text{Input Flows}=\text{OK}) = 1$

EVIDENCE

INFERENCE

→ **To check Function Diagnosis of each function:**

$P(\text{Function Diagnosis To grip/to loosen}=\text{Internal}) = 0.6$

→ **To check Function Diagnosis of each sub-function:**

$P(\text{Function Diagnosis To Actuate}=\text{Internal}) = 0.8$

→ **To check the state of the components of the sub-function selected:**

If $P(\text{Jack}=\text{Jammed}) = 1$

If $P(\text{Jack}=\text{OK}) = 1$

END

EVIDENCE

INFERENCE

→ **To check another component, sub-function or function...**

Conclusion

- ☒ BN formalises the knowledge issued both from system functioning and malfunctioning to propose a decision-making aid**
- ☒ BN is easier to design from the generic mechanisms used in analysis phase (less the intuitive one; more explicit)**
- ☒ BN is initialised, from the design phase, with estimated values which can be adapted in operation phase (integration of the operating experience)**
- ☒ The approach feasibility has been made on a part of the lathe tool**

Prospects

- ☒ To extend the feasibility of this approach on the whole of the case study**
- ☒ To use algorithms of diagnosis dedicated to the BN**
- ☒ To implement the BN on site to be used by the operator in terms of decision-making assistance in the diagnosis field (to show its added value)**
- ☒ To integrate within the BN other knowledge such as aptitudes for detection, the components costs**
- ☒ To formalise this new knowledge within the BN (network with N dimensions, N strategies) in terms of new nodes (cost nodes, decision nodes...)**