Online Diagnosis of Engine Dyno Test Benches: A Possibilistic Approach

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Engine dyno diagnostic
BEST project
Bench Expert System Tool

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Context

Automobiles are more and more complex and sophisticated

The tuning of an engine as well as the management is a tedious and difficult and costly task

Done on engine dyno. and refined on roll benches and vehicles

More and more information on the engine running state are available

Tuning engineers are faced with an increased data flow and are not able to tackle it in real time

Objectives

- To help the tuning engineer for control and validation tasks
- To increase the tests reliability (20% bad today)
- To optimize the use of heavy test means
- To shorten the development time

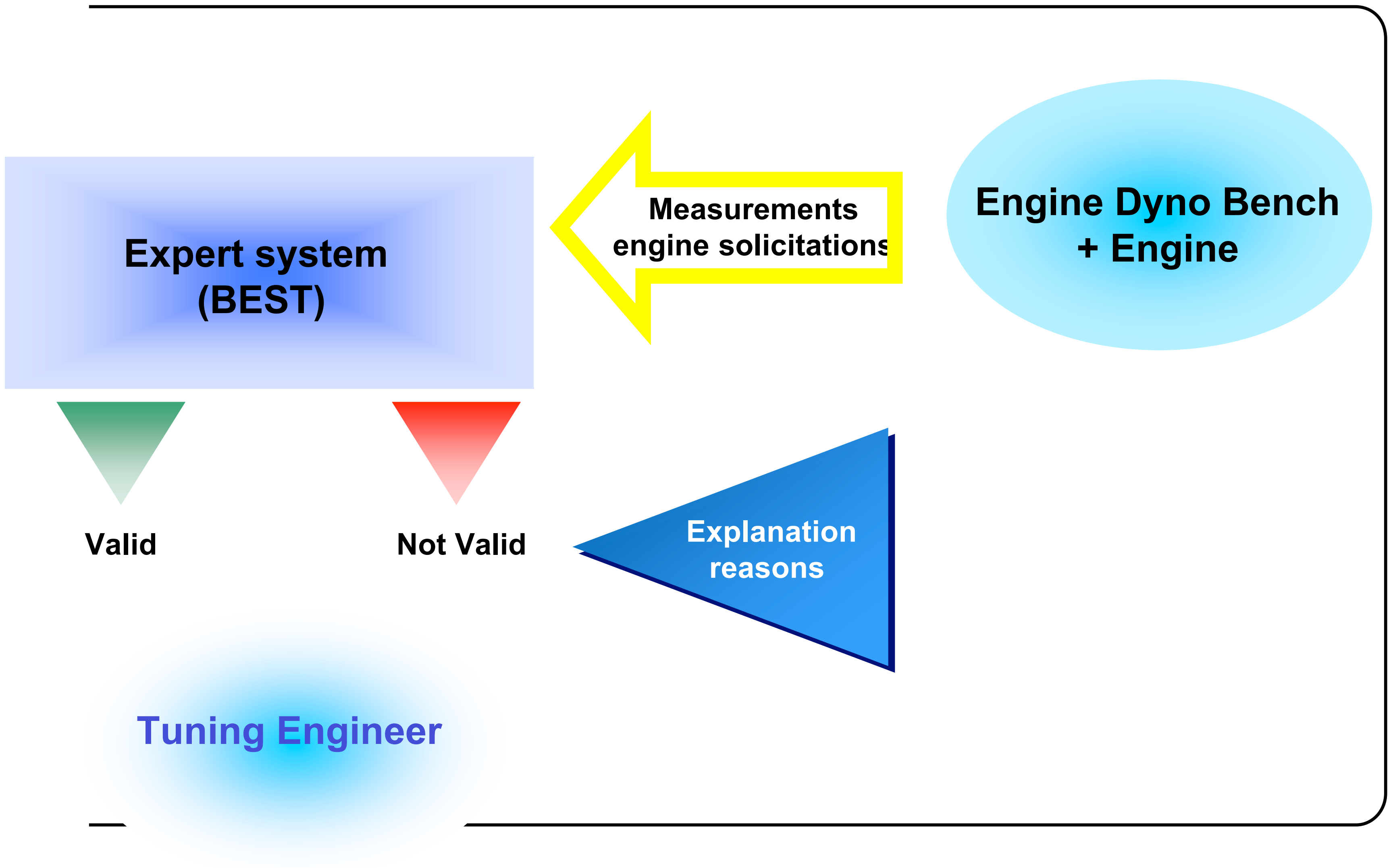
Development
of a diagnostic assistance
tool able to produce in real time
a synthetic information

Modify parameters

Stop the test

Development of a system for the automatic supervision of the tests, able to realize an on-line diagnostic and to take decisions in relation with the observations

Principles


Expert system
(BEST)
Measurements
engine solicitations
Engine Dyno Bench
+ Engine
Valid
Not Valid
Explanation
reasons
Tuning Engineer

Diagnostic assistance tool
Automatic supervision of the tests

Formalization of on line diagnostic problems based on temporal information

Development of scenario identification tools for continuous and discrete information

Development of operational methods based on abductive reasoning with uncertainty based on numerical and symbolic information

Formalization
of Siemens expertise

Which expert system?

- Very first ones'? (symptom is . . . Then cause is . . .)

  No because they lack flexibility and give false results.

- Bayesian Networks?

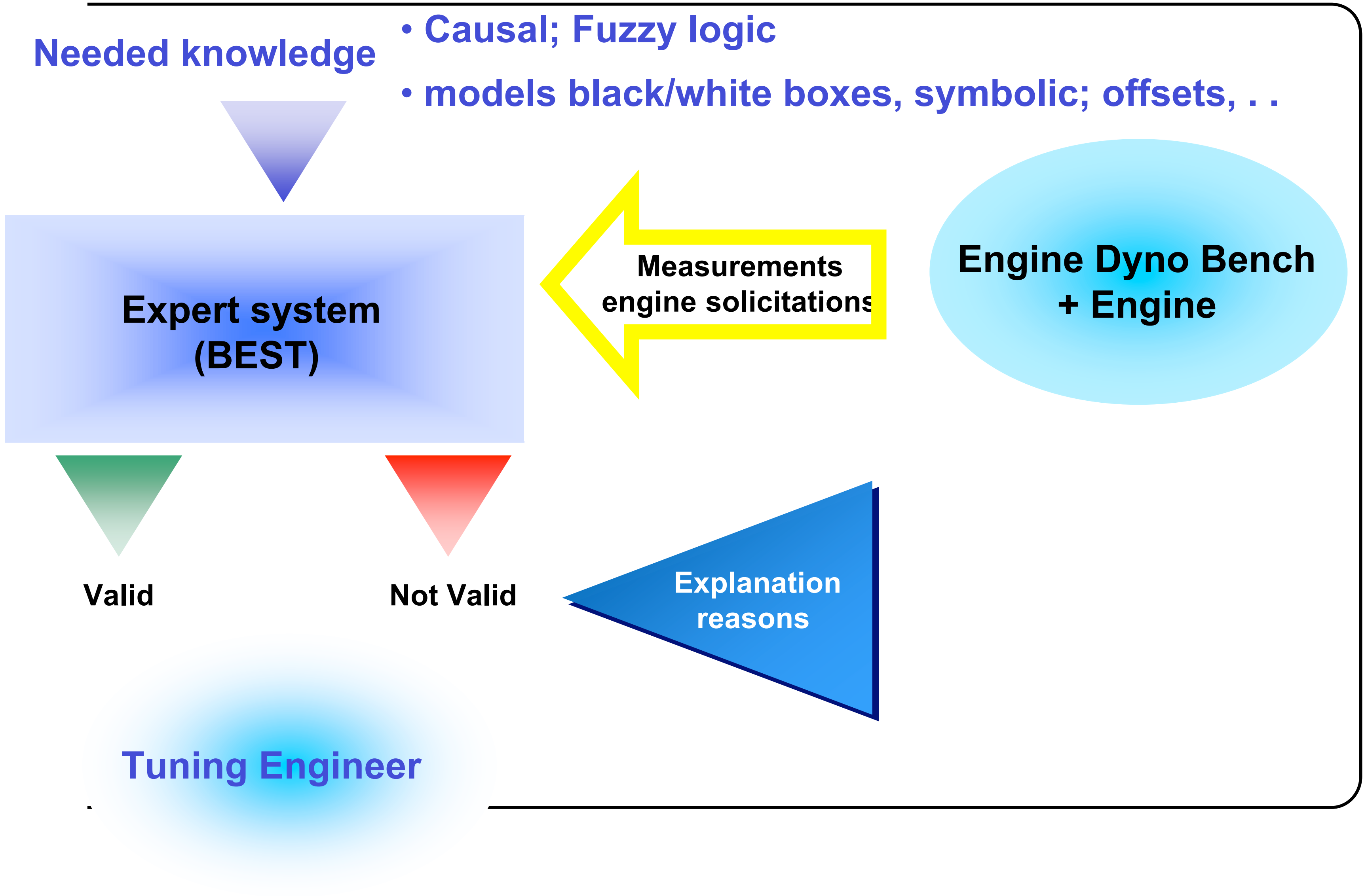
  More expressive, give very precise results, but lack flexibility and need 'a priori' knowledge (probabilities of presence of each malfunction, which makes sense only when statistics are available).

A fuzzy expert system based on possibility theory

- fuzzy logic is expressive and makes it more natural for experts to formalize their knowledge.
- no 'a priori' knowledge is needed and flexibility is reached.
- the outputs are good and better understandable (closer to human beings' thinking process and they can be justified).

BEST knowledge formalization

Principles



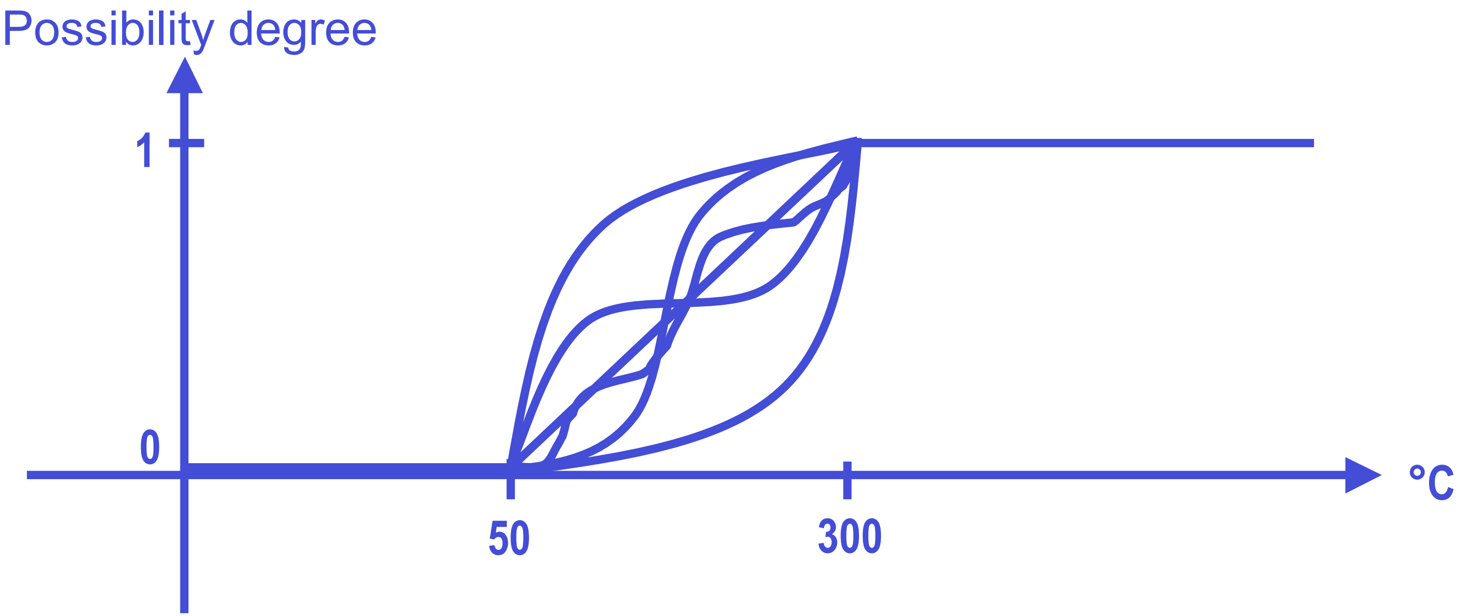
• Causal; Fuzzy logic
Needed knowledge
• models black/white boxes, symbolic; offsets, . .
Measurements
engine solicitations
Engine Dyno Bench
+ Engine
Expert system
(BEST)
Valid
Not Valid
Explanation
reasons
Tuning Engineer

Knowledge

A fuzzy expert system based on possibility theory and causal knowledge :

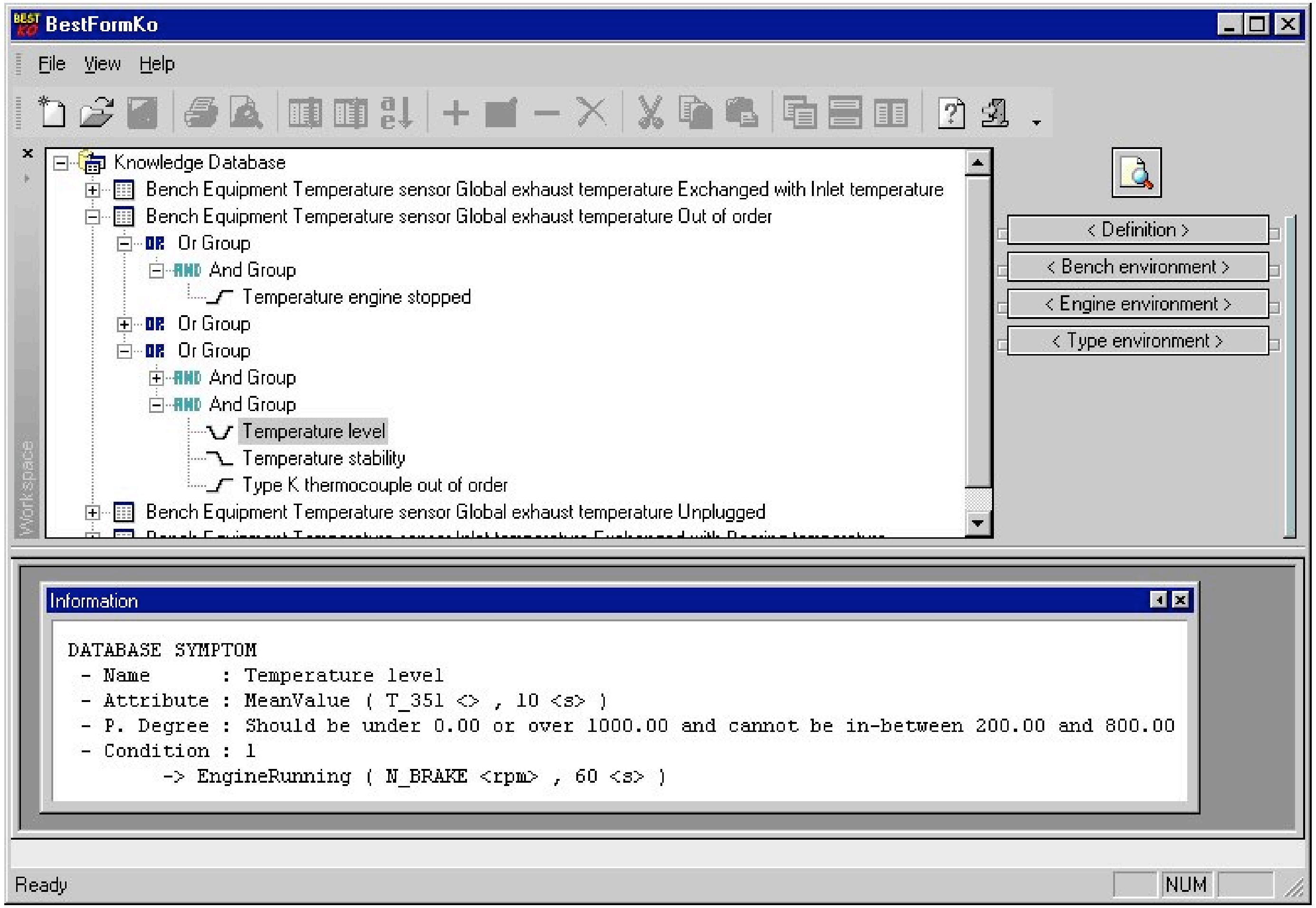
- No statistics or stored data available.
- Fuzzy logic is expressive and makes it more natural for experts to formalize their knowledge.
- No ‘a priori’ knowledge is needed and flexibility is reached.
- The outputs are good and better understandable (closer to human beings’ thinking process and they can be justified).
- From a computational point of view the min-max based diagnosis algorithm is efficient.

Fuzzy causal information



When inlet and exhaust temperature sensors are exchanged, the inlet temperature indication is high

Experts' knowledge formalisation: off-line tool



Conclusion

This knowledge formalization tool enables us to:

• Define malfunctions

• Define symptoms for a malfunction.

The symptoms can be made of one or several channels.

Some environment configurations (e.g., Bench 5, diesel engine…) may be specified.

Also, some conditions may be linked to a symptom in order to be able to observe its presence or its absence.

Conclusion

- Enhances the malfunctions with a confidence level

- Deals with Qualitative information (uncertain information coming from human expertise)

- Deals with imprecise measurements (sensors errors)

- Allows to re-build the human reasoning methodology thus this information is available for users

BEST diagnosis system

BEST: How does it think?

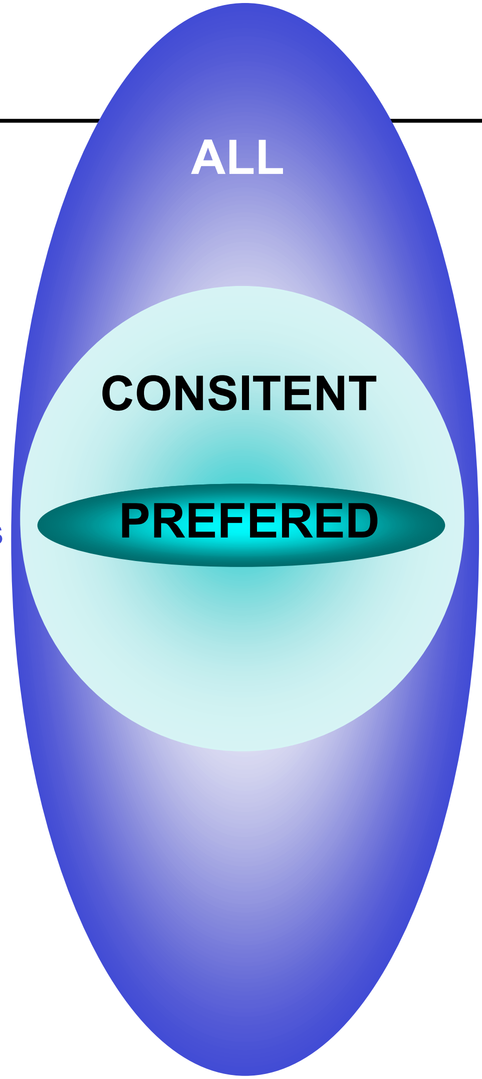
BEST is based on a quite simple and efficient thinking process:

a) discarding malfunctions

the effects of which are more or less inconsistent with the observations

b) selecting malfunctions

the effects of which are more or less certainly observed



Causal reasoning

If $\underbrace{\text{bad connection of Sensor}}_{\text{malfunction}}$ then $\underbrace{\underbrace{\text{temperature}}_{\text{attribute}}\text{ too high}}_{\text{symptom}}$

Causal information:

if malfunction m *then* symptom s.   Observation of symptoms

Diagnosis: Information on malfunctions

Consistency-based Diagnosis:

Symptom s is not present

---

malfunction m is discarded

Abductive inference [Polya]:

If m then s   s is true (observed)

---

m is a plausible explanation for s.

Causal reasoning: from crisp to fuzziness

Consistency-based Diagnosis:

$$\frac{\text{Symptom s is not present}}{\text{malfunction m is discarded}}$$

Abductive inference [Polya]:

$$\frac{\text{If m then s} \qquad \text{s is true (observed)}}{\text{m is a plausible explanation for s.}}$$

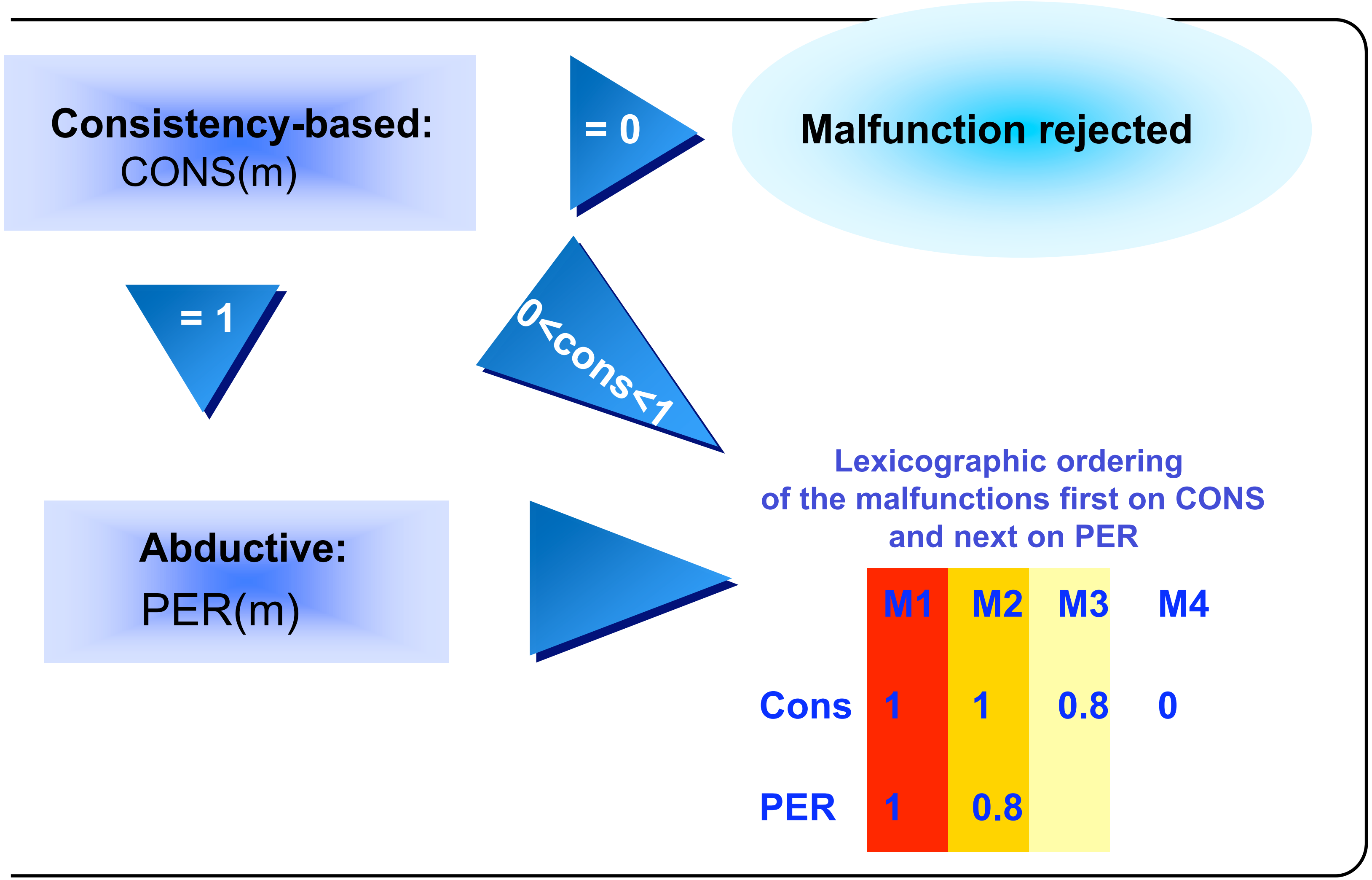
$\mu_{CONS}(m) = \min_{i=1..n} \sup_{u \in Ui} \min(\mu_{Oi}(u), \pi_m^i(u))$

$\mu_{REL}(m) = \mu_{PER}(m) = \min_{i=1..n} \inf_{u \in Ui} \mu_{Oi}(u) \rightarrow \pi_m^i(u))$

$\mu_{CONS}(m)$ is 1 when all observations are consistent with the expected symptoms of m (on the n considered attributes).

$\mu_{REL}(m) = \mu_{PER}(m)$ is 1 when all expected symptoms of m (on the n considered attributes) are relevant/pertinent to the observations.

Possibilistic approach



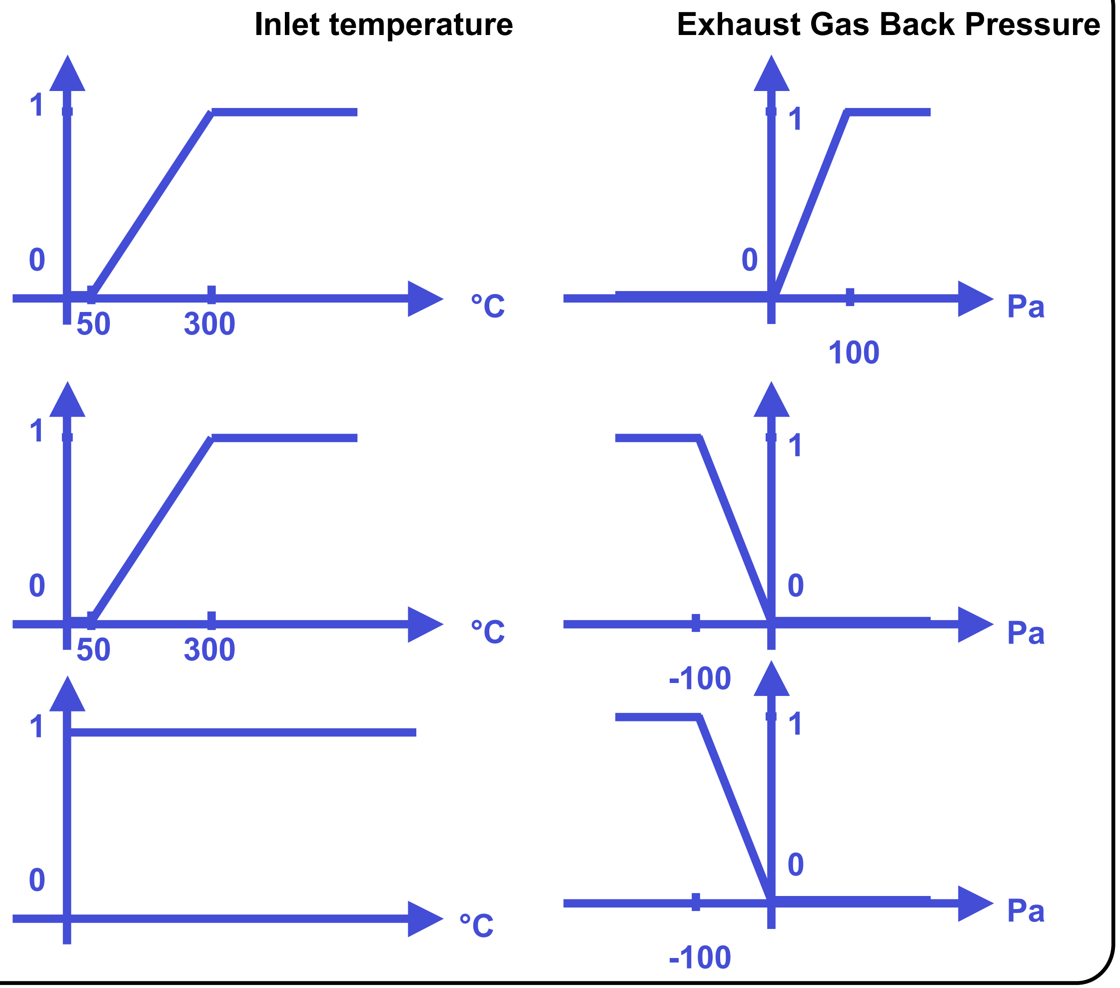
	M1	M2	M3	M4
Cons	1	1	0.8	0
PER	1	0.8		

Example

When Malfunction 1
then
inlet temperature is high and exhaust gas back pressure is positive

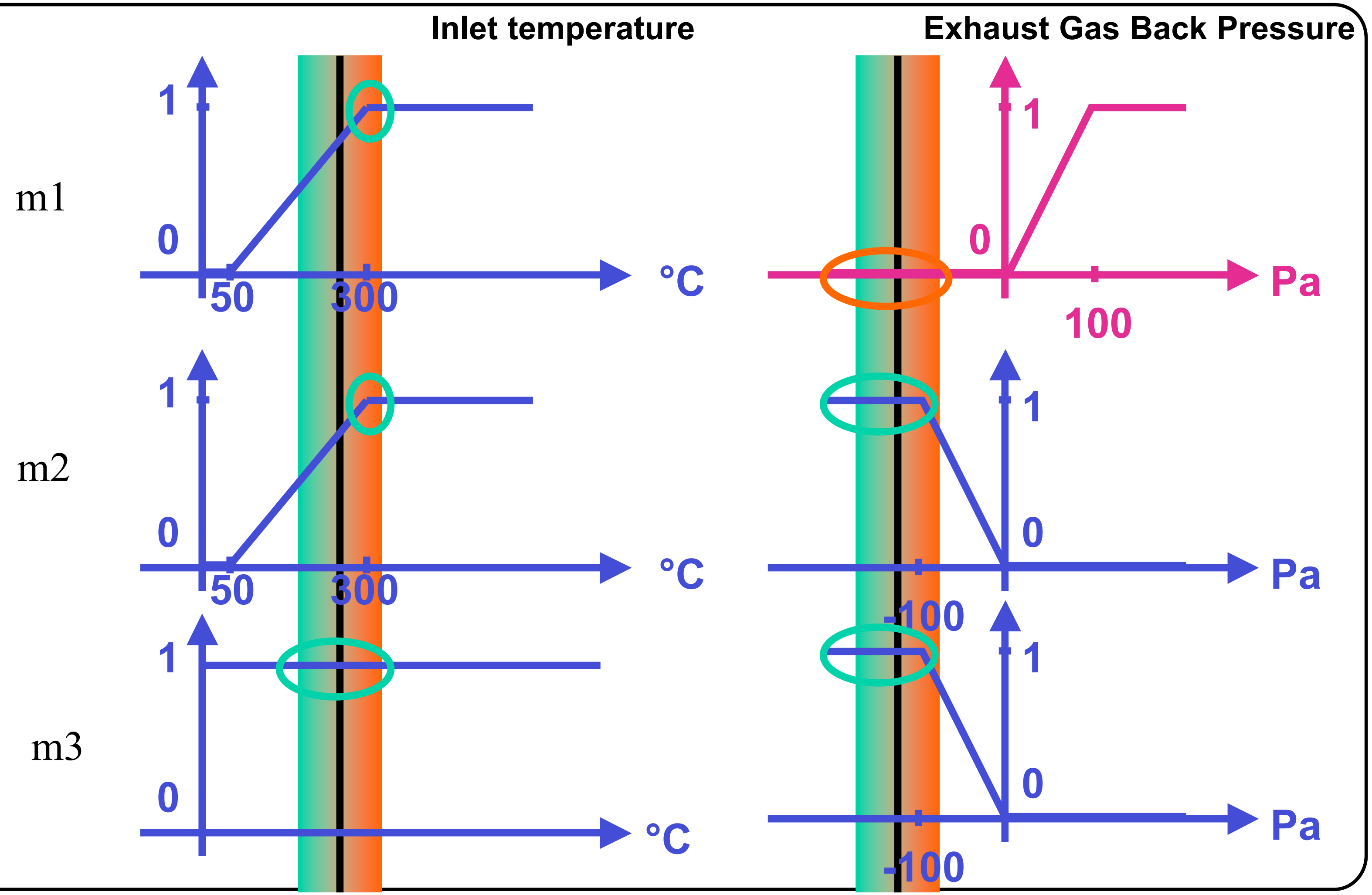
When Malfunction 2
then
inlet temperature is high and exhaust gas back pressure is negative

When Malfunction 3
then
exhaust gas back pressure is negative (no effect on inlet temperature)

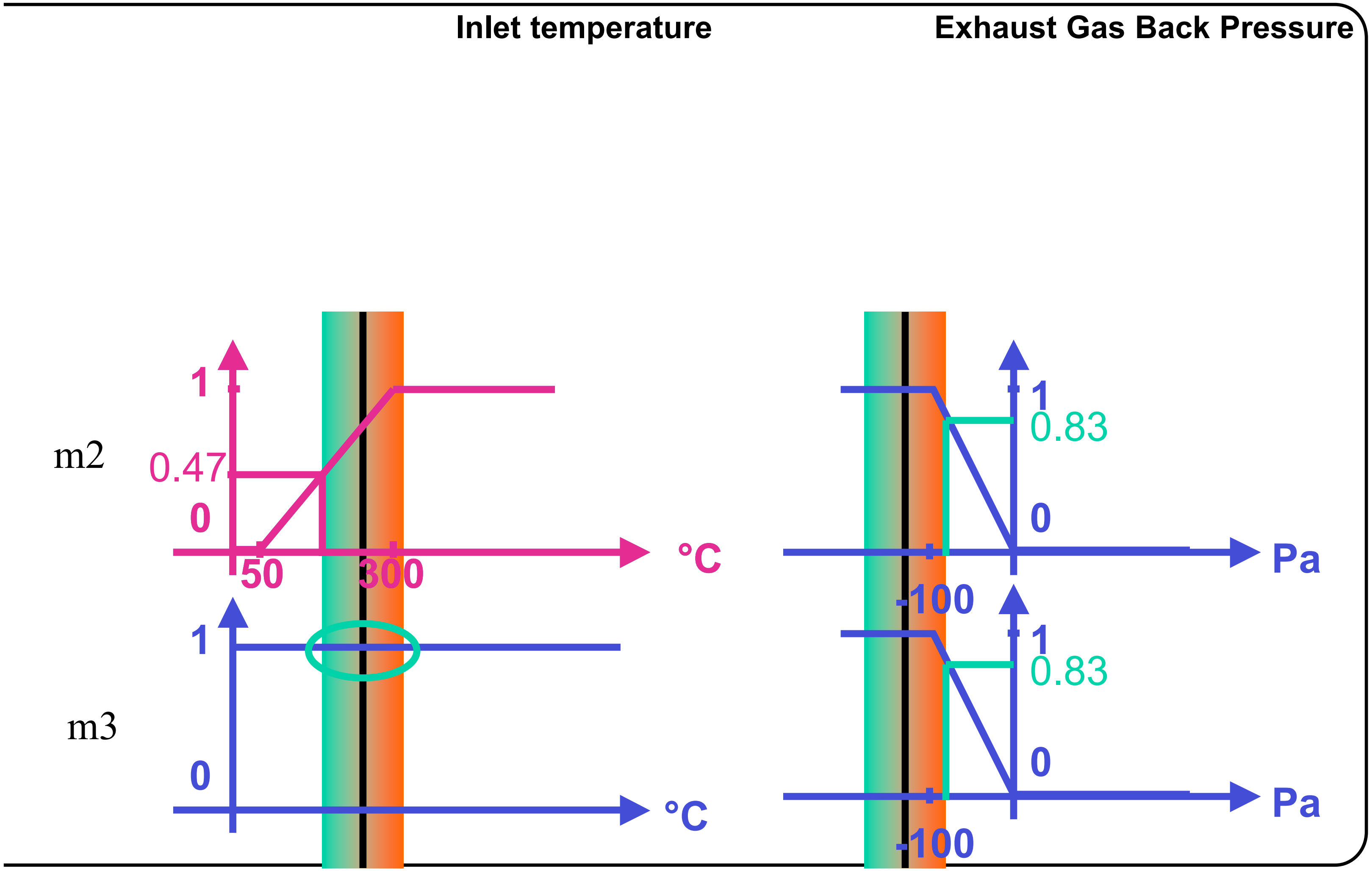


Example

CONS: discarding malfunctions the effect of which are more or less inconsistent with the observations



Example



PER: selecting malfunctions the effect of which are more or less certainly observed

Example

Malfunction 1 is rejected because there is no symptom related with back pressure

Malfunction 2 is possible but with a low confidence level (0.47)

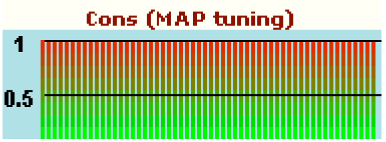
Malfunction 3 is is likely (confidence level 0.83)

BEST: How does it think?

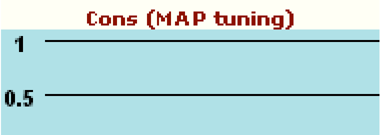
BEST is based on a quite simple and efficient thinking process:

a) discarding malfunctions

the effects of which are more or less inconsistent with the observations



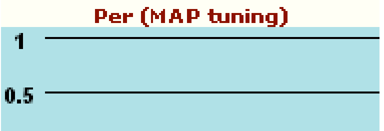
No information to discard this malfunction (see Per, below).



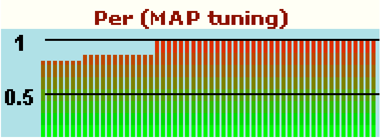
Malfunction discarded (at least an expected symptom is missing).

b) selecting malfunctions

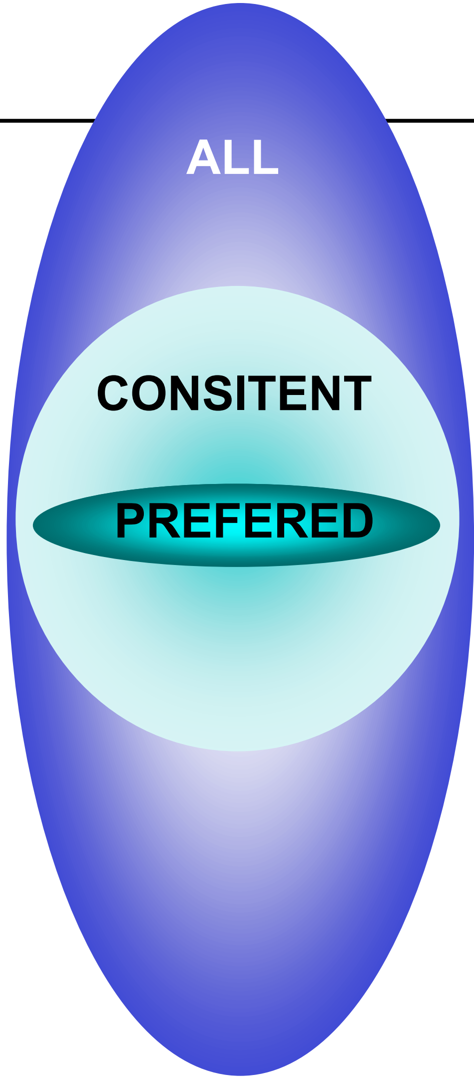
the effects of which are more or less certainly observed



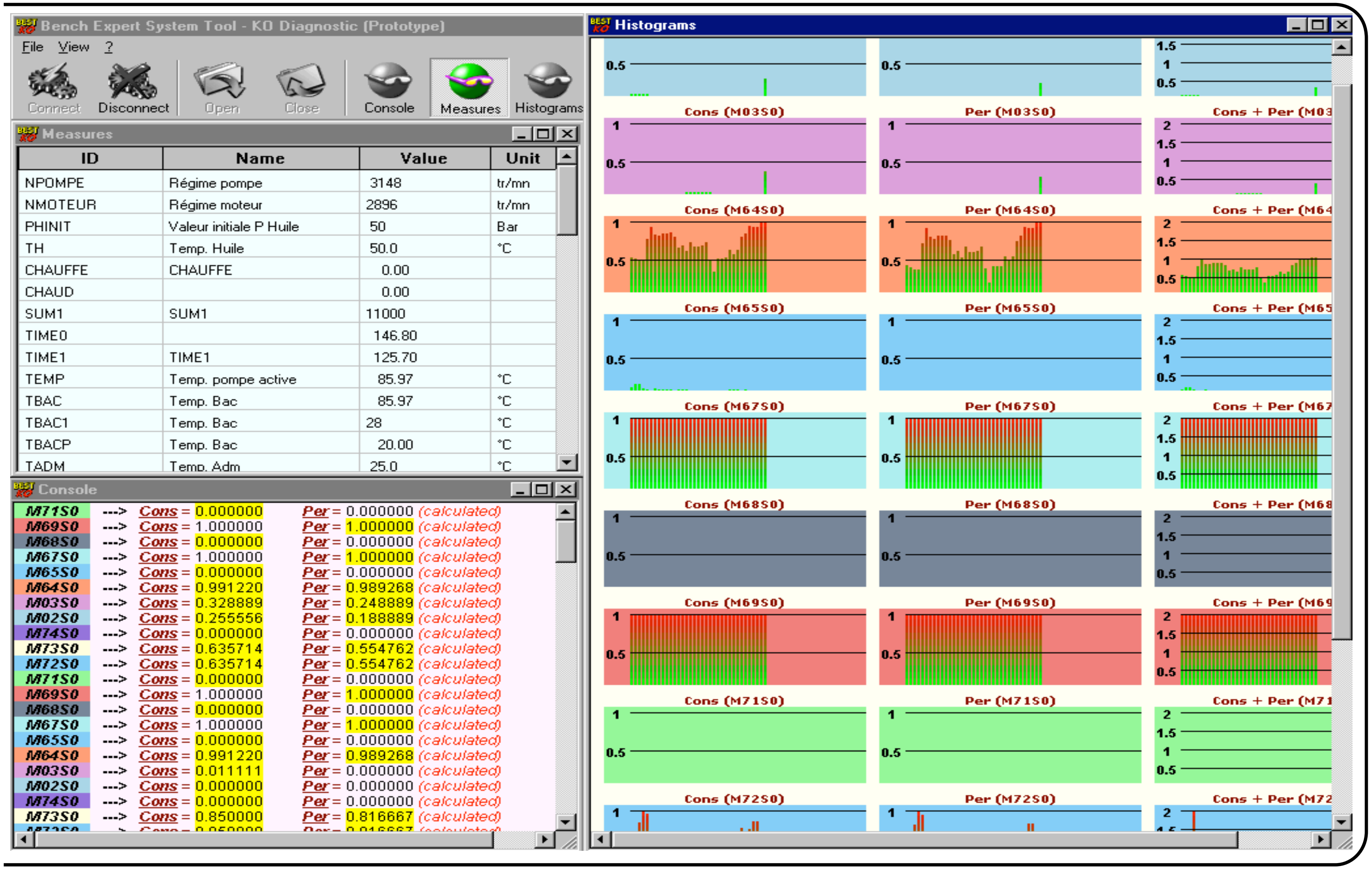
No information to prefer this malfunction.



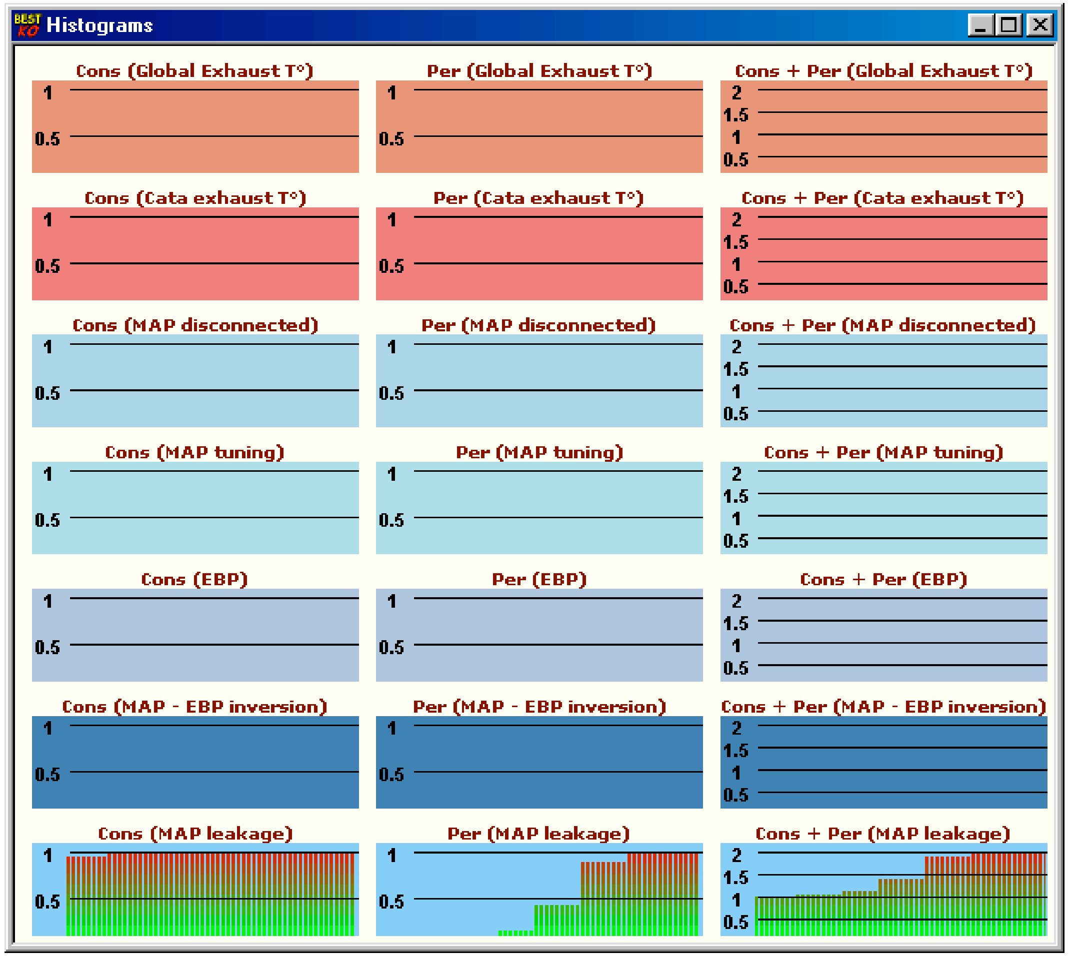
Malfunction highly suspected (all its expected symptom are present).



On-line diagnosis tool



Example: Mass Air Pressure leakage



Conclusions

- Malfunctions are detected and identified on-line.
- Very little false alarms. They are due to lack of information.
- The main point is then to be able to feed easily the knowledge base, which is now possible through the formalization off-line tool.

WHAT ARE THE PERSPECTIVES ?

Future work and development

- Being able to detect multiple and “cascading” malfunctions
- Introducing users’ rights in the formalization tool
- Industrialization and commercialization.