Queen's University Belfast

PACES

Adaptive uncertain information fusion to enhance plan selection in BDI agent systems

Modelling sensor information

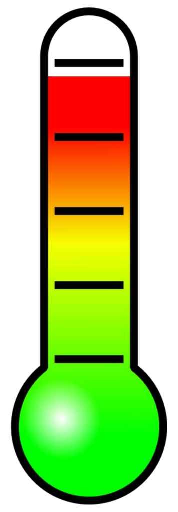
Dempster-Shafer (DS) theory is capable of dealing with **incomplete** and **uncertain** information

Frame of discernment $\Omega = \{\omega_1,\ldots,\omega_n\}$

Set of possible events — One true at a particular time

Mass function $m: 2^\Omega \rightarrow [0,1]$

2 properties: $m(\emptyset) = 0$ and $\sum_{A \subseteq \Omega} m(A) = 1$



70°C → ¬normal
...
40°C
... → normal
0°C

Information **sources**
(e.g., sensors, expert opinions, etc):

S_1 (80% reliable),
S_2 (70% reliable),
...

Information from sources: **S_1** : [30°C, 35°C], **S_2** : [50°C, 55°C], ...

Model (uncertain) sensor information as mass functions: $m_1(\{normal\}) = 1$, $m_2(\{\neg normal\}) = 1$, ...

Discount information with respect to reliability of source:
$m_1^{0.8}(\{normal\}) = 0.8$, $m_1^{0.8}(\{normal, \neg normal\}) = 0.2$,
$m_2^{0.7}(\{\neg normal\}) = 0.7$, $m_2^{0.7}(\{normal, \neg normal\}) = 0.3$,
...

Context-dependent information fusion

Conjunctive merging: use if low degree of conflict
Disjunctive merging: use if high degree of conflict

Merging with LPMCSes (largely partially maximal consistent subsets): a contextual approach using both merges

a. start with highest quality source (i.e. most specific source)

b. merge with those closest (i.e. in agreement)

1. merge sources conjunctively until contradiction is too high (depends on sources)
2. merge conjunctive results disjunctively
3. transform the merge result into a probability distribution for plan selection

$m_1 \wedge m_2$

∨

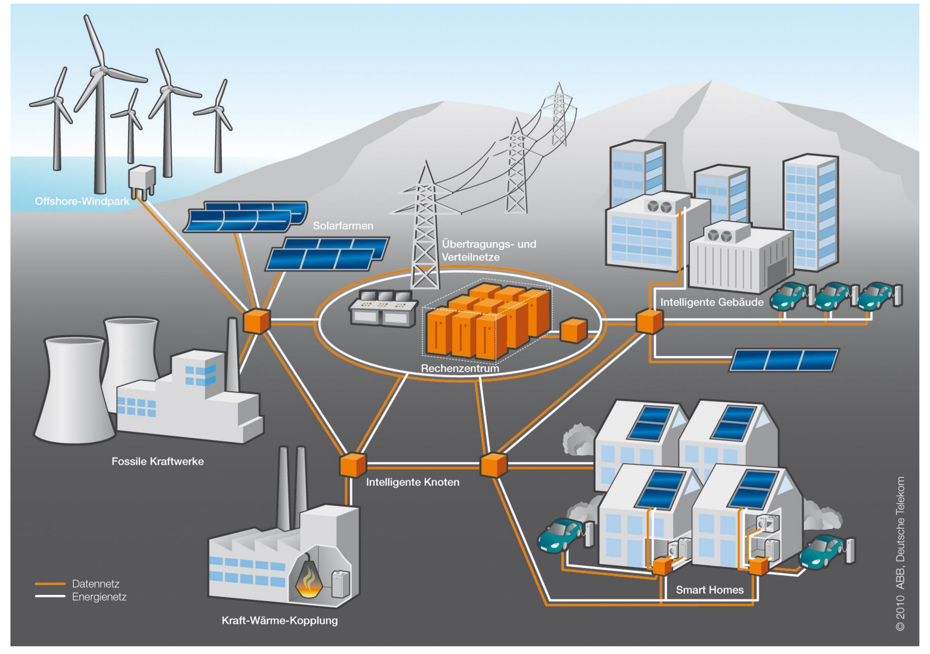
$m_3 \wedge m_4 \wedge m_5$

∨

m_6

Applications

Smart grid



→ voltage, frequency, temperature, vibration, etc

Transportation

→ speed, automatic doors, temperature, vibration, CCTV, etc

Sensors: to collect data

SCADA systems monitor and control plant or equipment through gathering and analysing real time data

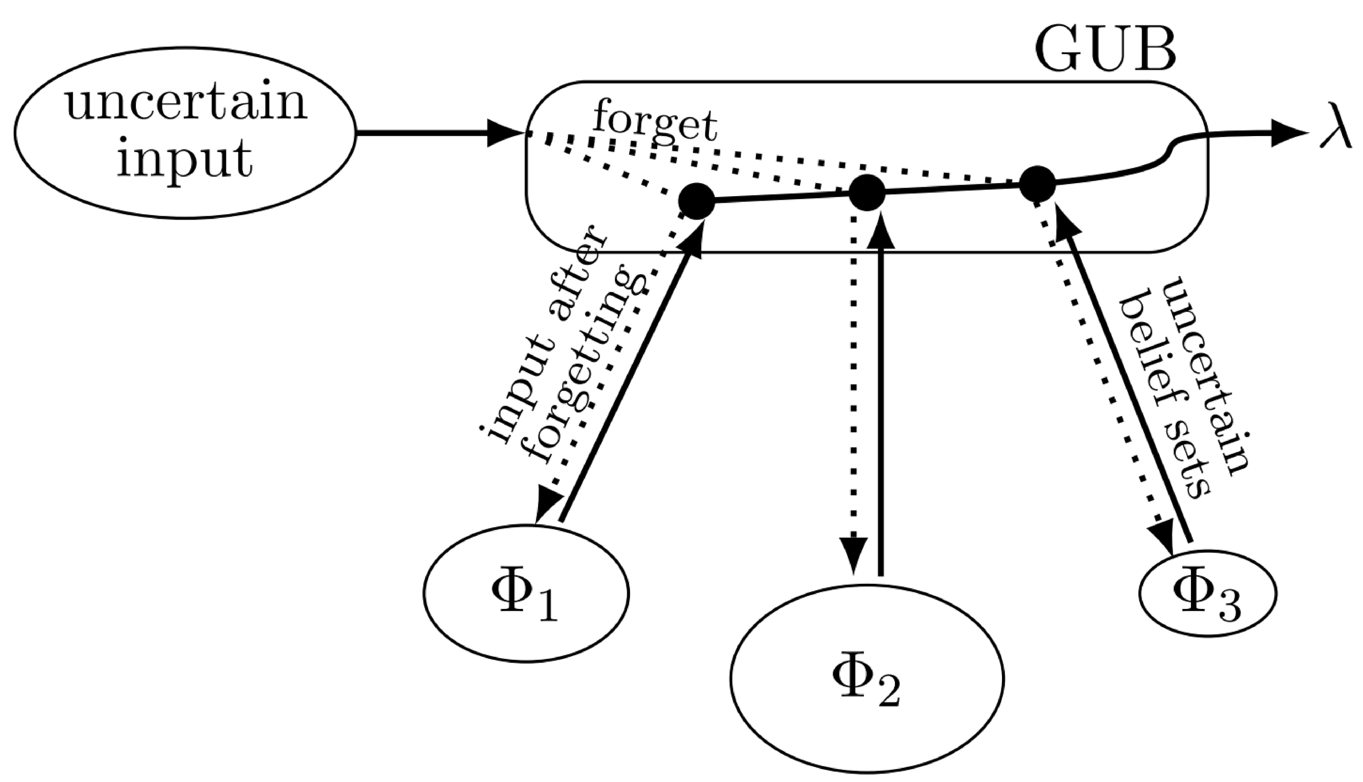
Goal: To achieve situational awareness in dynamic, complex and uncertain environments to aid decision making

Types of Uncertainty

- noisy sensor measurements
- unreliable sensors
- malicious/accidental damage to sensors
- component failure
- etc

Sensors can generate faulty measurements with power failure, physical damage, miscalibration, etc

Handling uncertain beliefs in BDI



Each **epistemic state** Φ represents uncertainty over a distinct subset of beliefs, e.g., **probabilistic** beliefs about the world, **possibilistic** beliefs about trust, etc

A **global uncertain belief set (GUB)** is used to model and reason about all the epistemic states of an agent

Based on the combined sensor information, the agent believes it is more plausible that the temperature is normal than not normal: ***normal*** > ***¬normal***

(P1) *+!run_transformer : normal > ¬normal ← !step_down_power; !distribute_power; ...*

(P2) *+!run_transformer : ¬normal > normal ← !generate_alert.*