



CONSISTENCY-BASED DIAGNOSIS

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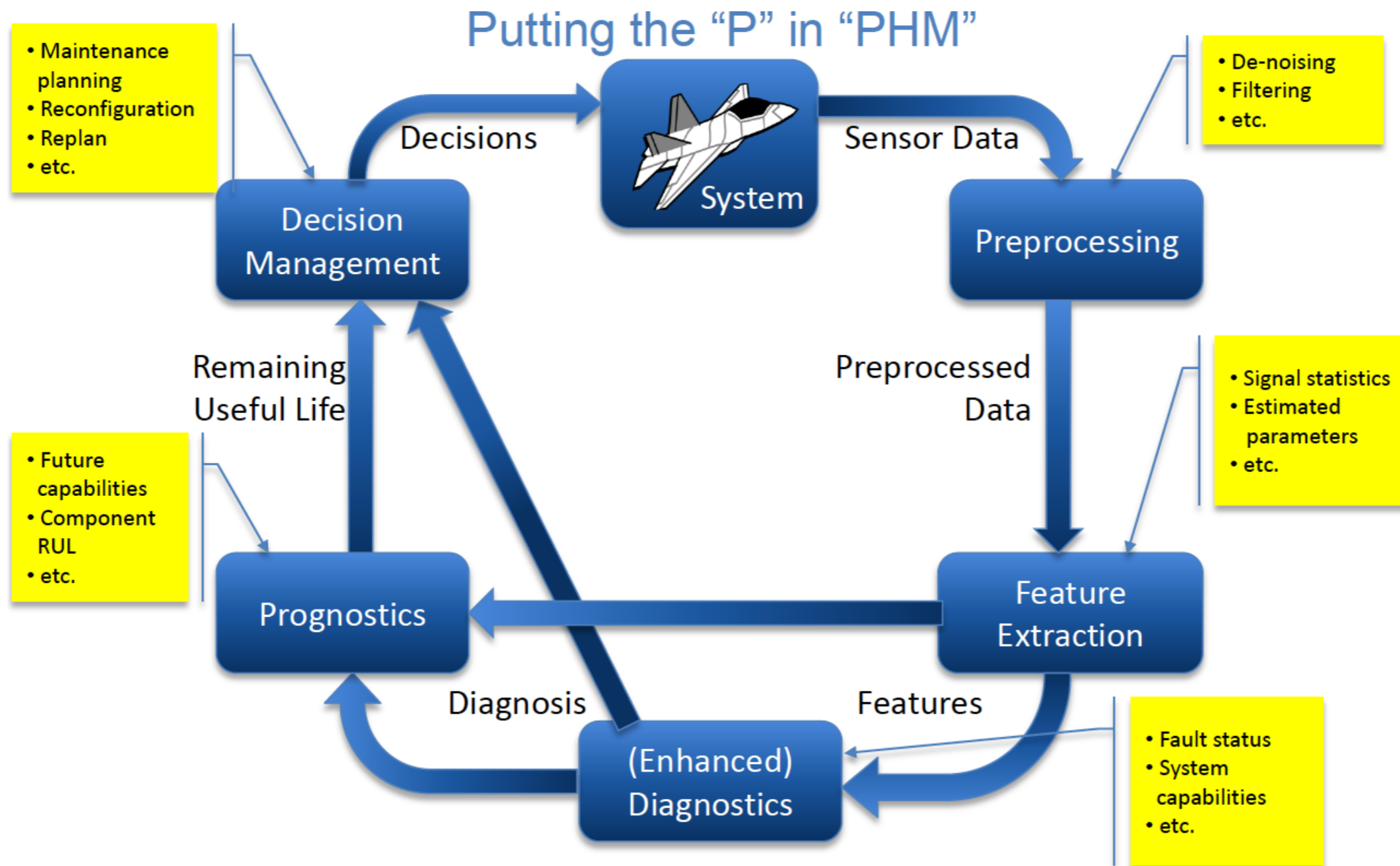
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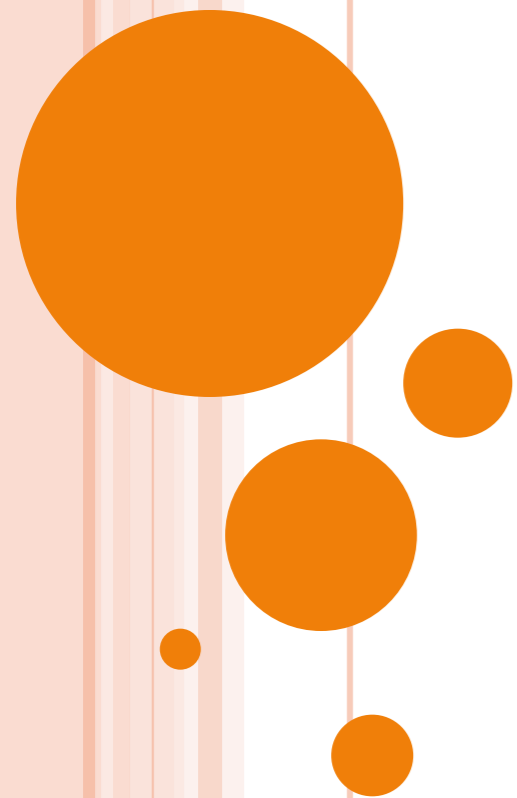


HOW DIAGNOSIS FITS INTO “PHM”?



OUTLINE

- Introduction to Fault Diagnosis
- Consistency-based Diagnosis
- Consistency-based Diagnosis using GDE
- Inclusion of temporal information within CBD
- Possible Conflicts – a compilation technique for CBD
- Some Application Examples
 - Efficient fault identification – Advanced Water Recovery System
 - Distributed diagnosis – Planetary rover
 - The link between CBD and Prognosis
 - Distributed prognosis – Centrifugal pump (rapid propellant system)
- Current Challenges and Open Problems



INTRODUCTION TO
FAULT DIAGNOSIS
Fundamental concepts

WHAT IS (AUTOMATED) DIAGNOSIS?

- What is diagnosis?
 - The identification of the nature of an illness or other problem by examination of the symptoms (Concise Oxford English Dictionary, 2008)
 - It is very typical of the medical domain, but not exclusive: **finding the cause that something is wrong**



WHAT IS (AUTOMATED) DIAGNOSIS?

- How the diagnosis process works?

1. We observe (some) symptom(s)	I feel dizzy, and have nausea	Temperature at boiler over 140°C
2. We need to know that something is wrong	Dizziness is not a normal status	Temperature must be < 130°C
3. We enumerate the set of illness / malfunctions that fits the symptoms	<ul style="list-style-type: none">•Problems in your neck (muscles pulled in the cervix)•Vertigo•Etc...	<ul style="list-style-type: none">•Sensor fault: blocked exhaust pipe•Etc...
4. We perform additional tests to confirm or reject the diagnosis	<ul style="list-style-type: none">•Discomfort in the ear → vertigo•I was running for one hour at noon (36°C outside temperature, high humidity, high ozone concentration) → Heatstroke	<ul style="list-style-type: none">•Relation pressure/temperature abnormal => sensor fault



INTRODUCTION

FAULT DIAGNOSIS

- I will focus on automated **diagnosis of physical devices** (industrial, aerospace, etc...)
- R. Davies, 1982
 - Process of reasoning and acting
 - To identify the cause of a wrong behaviour
 - To restore the desire functionality
- L. Console, 2000
 - Task that given a **system** and a **set of observations** from an abnormal behaviour determines **what's wrong** in the system in order to **recover** its working order

INTRODUCTION

DIAGNOSIS STAGES



What crime was committed
and who committed it?

Isolation

Identification

How severe was the crime?

Detection

Has a crime been committed?

- **Fault Detection:** An abnormal event reported.
- **Fault Isolation:** Location of a fault.
- **Fault Identification:** Size and time of the fault (severity).



INTRODUCTION

DIAGNOSIS APPROACHES

- No universally accepted taxonomy
- Venkatasubramanian et al., 2003
- BalaKrishnan and Honavar, 1998
 - Knowledge based
 - Tzafestas 87; Guida y Tasso 94; Stefik 95; Jackson 98; Schreiber et al. 99.
 - Case Based Reasoning
 - Schank 82; Kolodner 93; Watson 97.
 - Machine learning
 - Goldberg 89; Quinlan 93; Venkatusugramanian and Chan 97; Mitchell 97; Muggelton 99.
 - **Model-based**
 - Hamscher, Console and de Kleer 92; Patton and Chen 1991; Isermann 93; Gertler 98; Patton 2000.

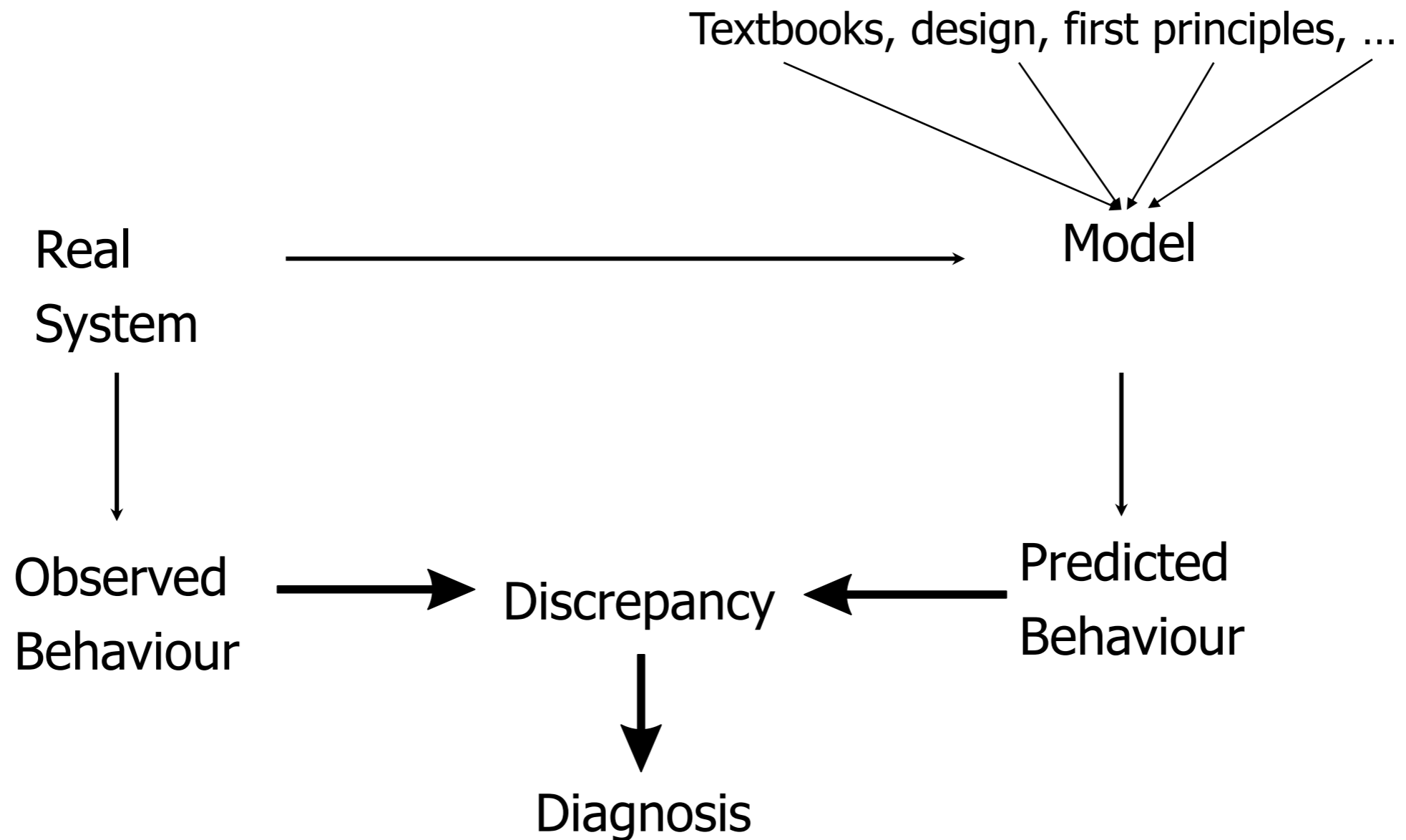
INTRODUCTION

MODEL-BASED DIAGNOSIS (MBD)

- Proposed in the early 80's to overcome limitations of the traditional expert systems approach
- Model-based diagnosis uses an objective model of the device (system) to be diagnosed. More specifically, different types of models can be considered:
 - structural (concerning the physical or logical structure of a device)
 - functional (describing the functions of a device)
 - behavioral (describing how a device works, i.e., how its functions are achieved)
 - teleological (describing the purposes of the use of a device)
 - or a combination of them

INTRODUCTION

MODEL-BASED DIAGNOSIS (MBD)



INTRODUCTION

WHY MODEL-BASED DIAGNOSIS?

- Reusable models; a library of component models can be built and the models in the library re-used for the diagnosis of different devices or for other tasks
- The models are “objective”
- Possibility of diagnosing “new” devices
- It is natural to deal with dynamic and time-varying behavior
- It is natural and simpler to deal with multiple faults and with fault masking
- Detailed explanations



INTRODUCTION

MODEL-BASED DIAGNOSIS APPROACHES

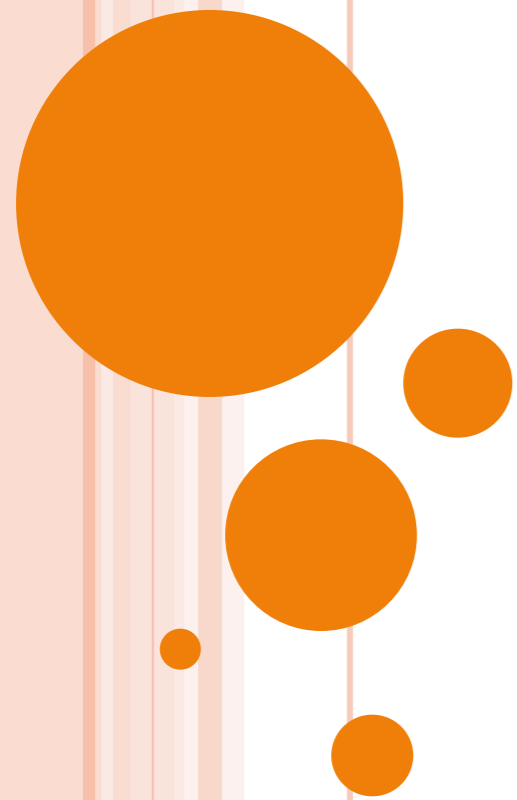
- Control Theory / Engineering (FDI community)
 - Robust Fault Detection and Isolation
 - Analytical Models, mainly
 - Generation and Analysis of Residuals (discrepancy)
 - Most commonly used techniques
 - State-observers
 - Parity-equations (Analytical Redundancy Relations)
 - Parameter Identification (or Estimation)



INTRODUCTION

MODEL-BASED DIAGNOSIS APPROACHES

- Artificial Intelligence (DX community)
 - Fault Isolation and Identification
 - (assumption: robust fault detection is available)
 - Qualitative/quantitative models
 - **Conflict detection and (diagnosis) candidates generation**
 - Diagnosis based on structure and behavior
 - **Consistency-based diagnosis**
 - Abductive diagnosis
 - Consistency-based Diagnosis with fault models
- BRIDGE (integration of DX and FDI)



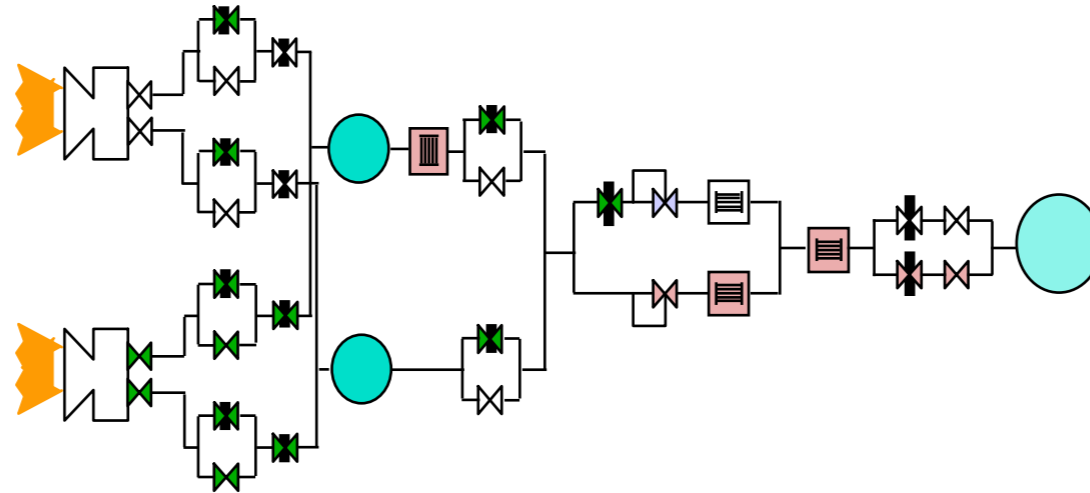
CONSISTENCY-BASED
DIAGNOSIS

CONSISTENCY-BASED DIAGNOSIS

- Main Model-based Diagnosis framework from DX community
- Historical background
 - Second generation Expert Systems (Davis, 1982-84)
 - First works in USA, late 70s – early 80s (@ MIT, Stanford Univ.)
 - Solid theoretical background (Reiter, 1987)
 - Computational paradigm - GDE (deKleer, 1987)
 - Early results:
 - mid/late-80s: static systems
 - late 80s, early 90s: dynamic systems
 - late 90s (mature) → large systems

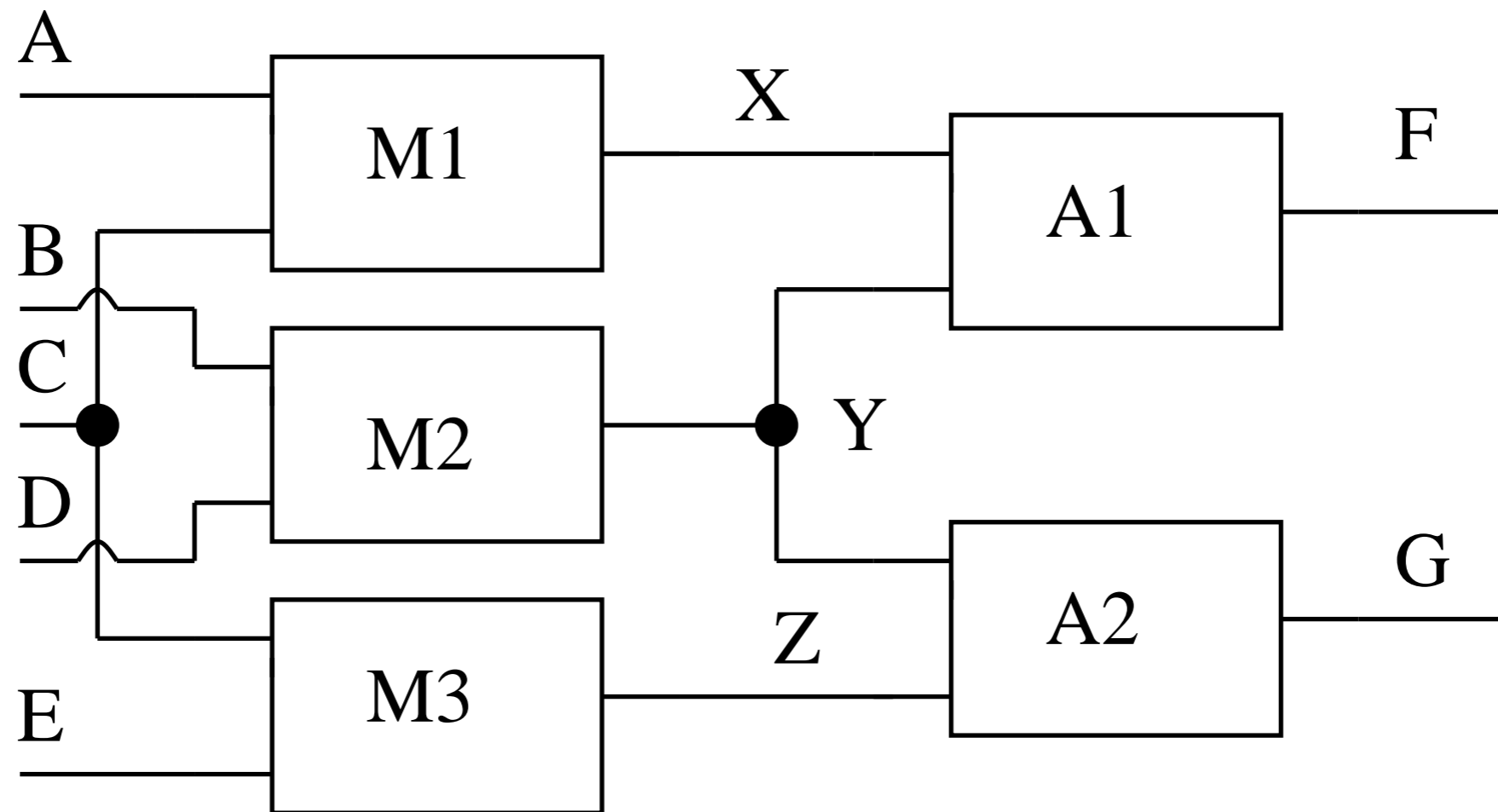
CONSISTENCY-BASED DIAGNOSIS

BASIC ASSUMPTIONS (DE KLEER 03)

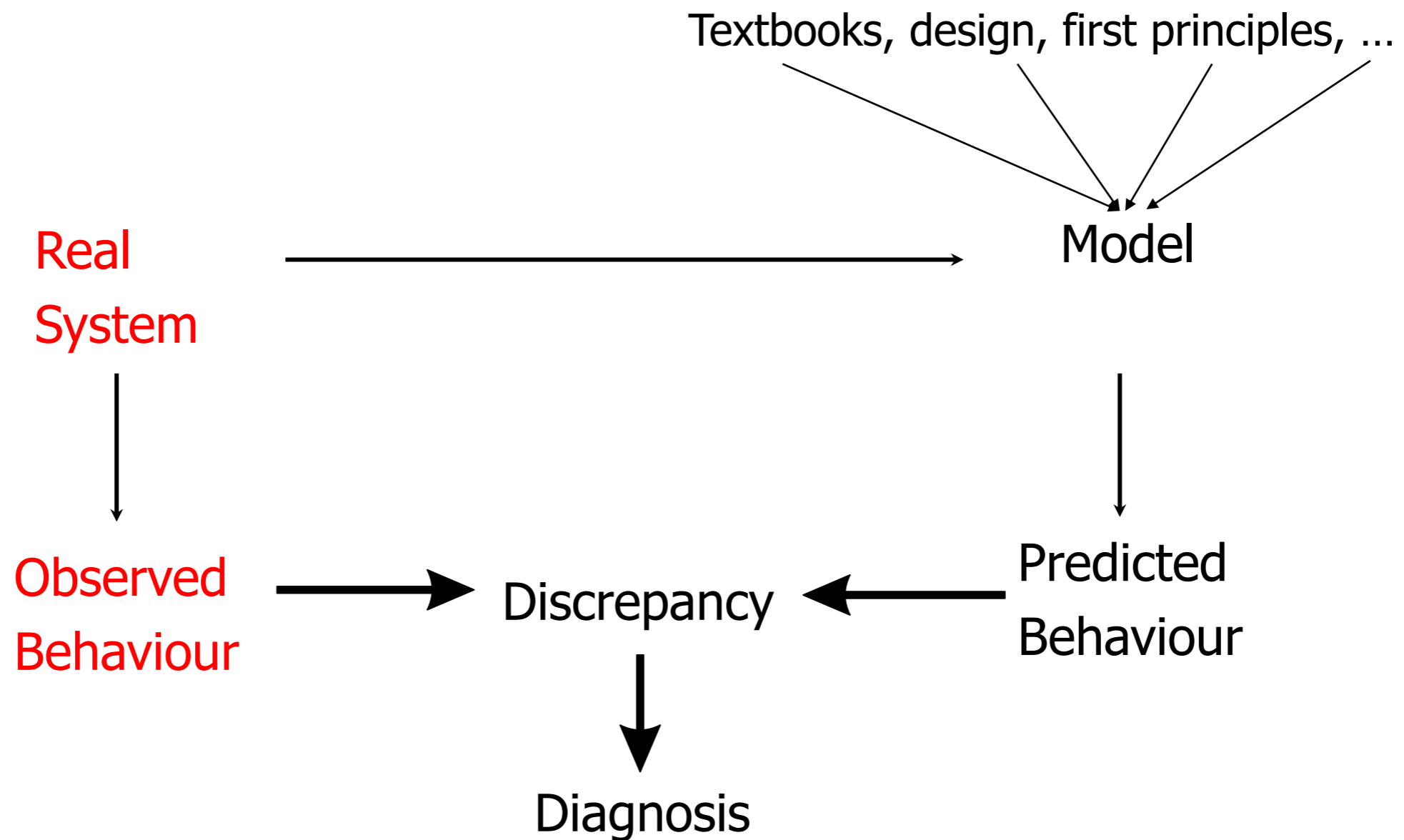


- Physical system
 - Set of interconnected components
 - Known desired function
 - Design achieves function
 - System is correct instance of design
- All malfunctions caused by faulty component(s)
- Behavioural information

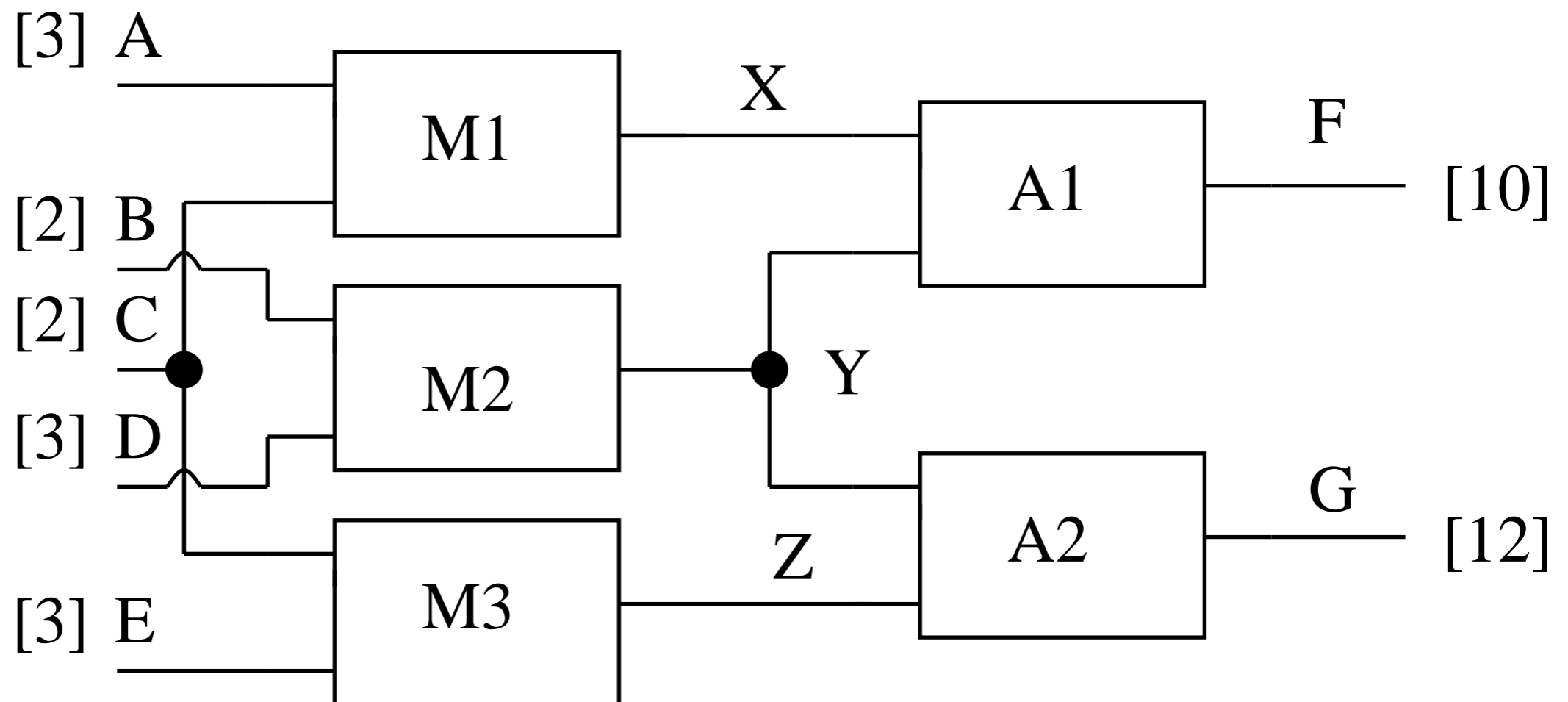
A CLASSIC EXPOSITORY EXAMPLE: THE POLYBOX (DE KLEER 87, 03)



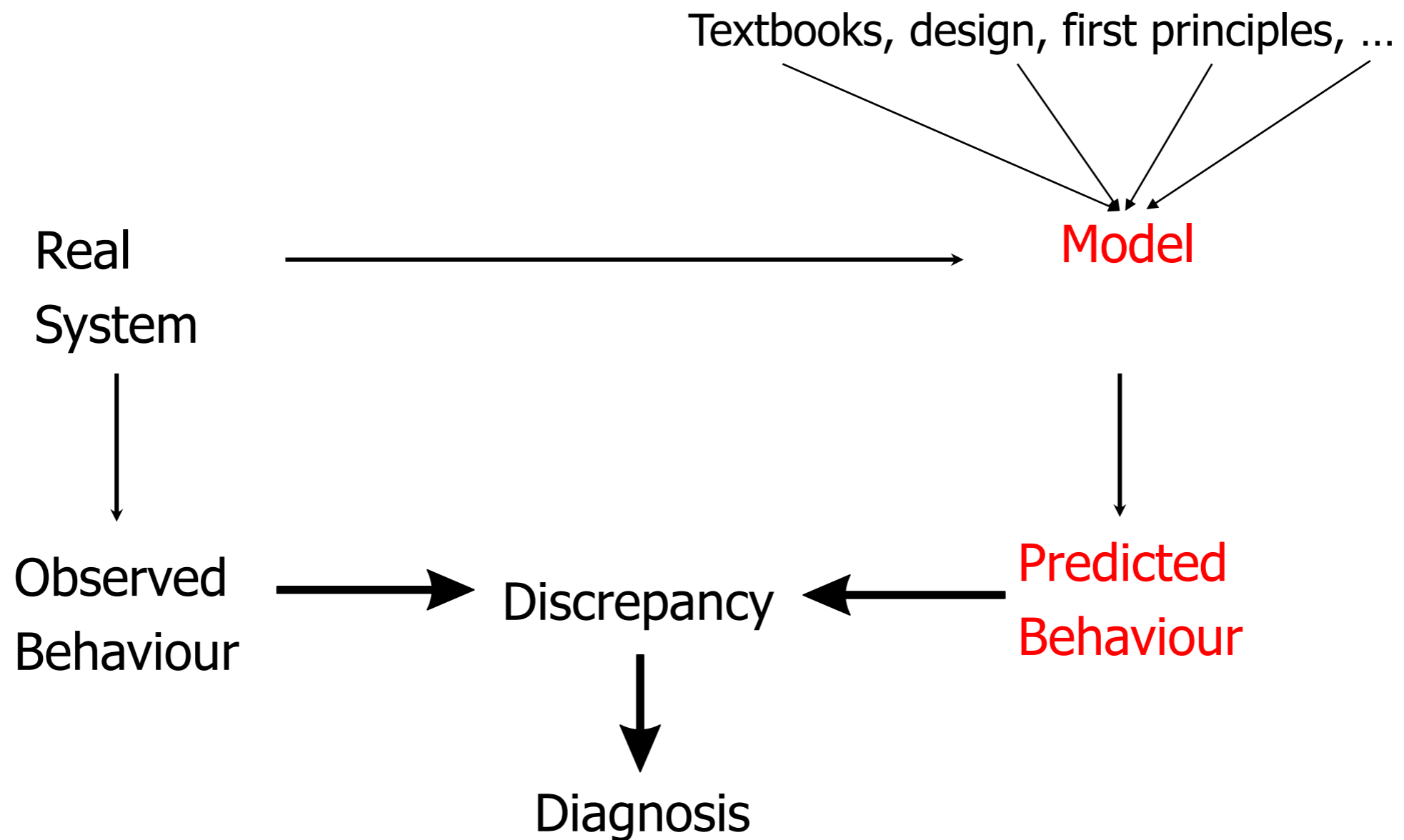
MODEL-BASED APPROACH TO DIAGNOSIS



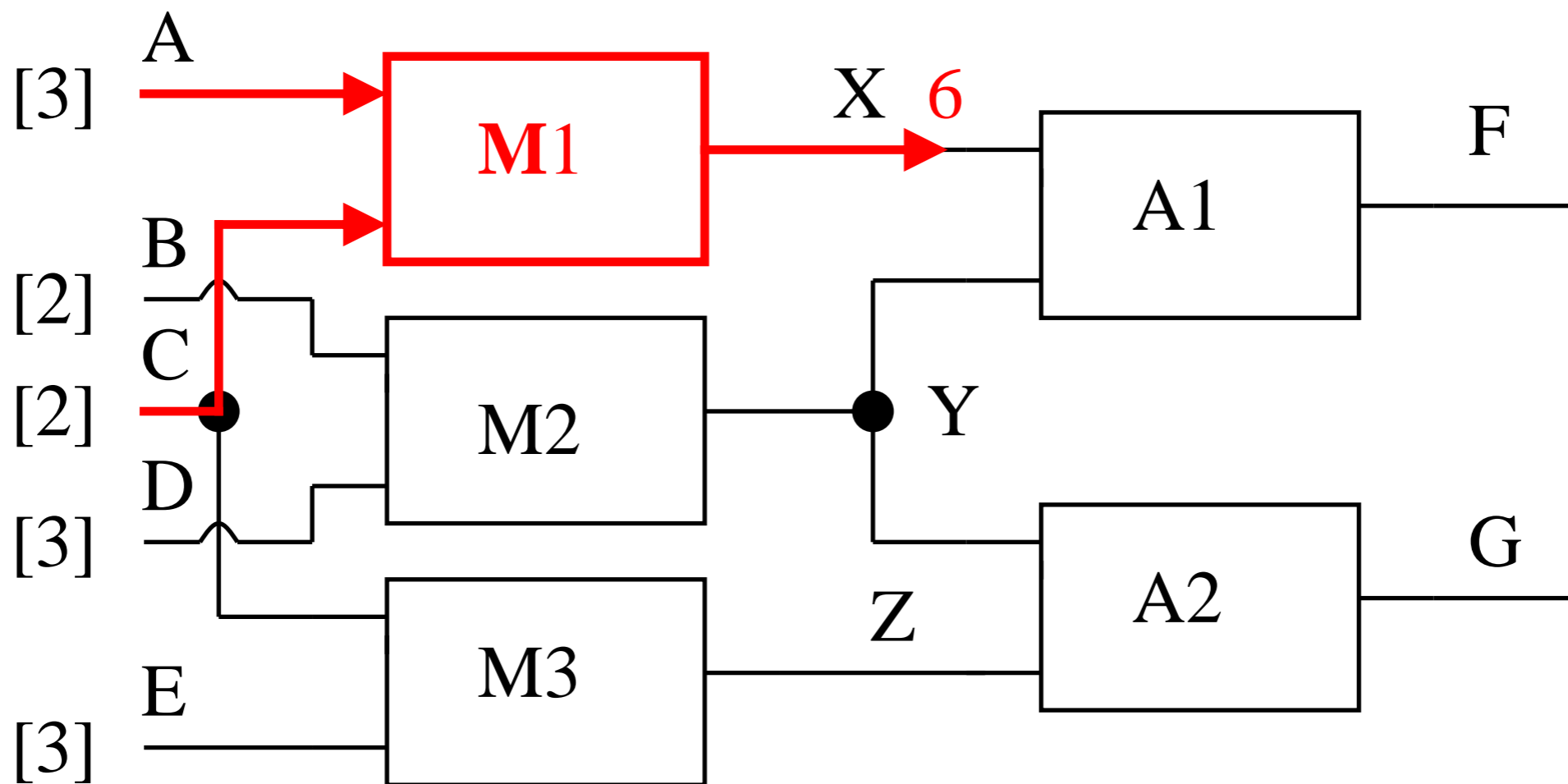
OBSERVED BEHAVIOUR



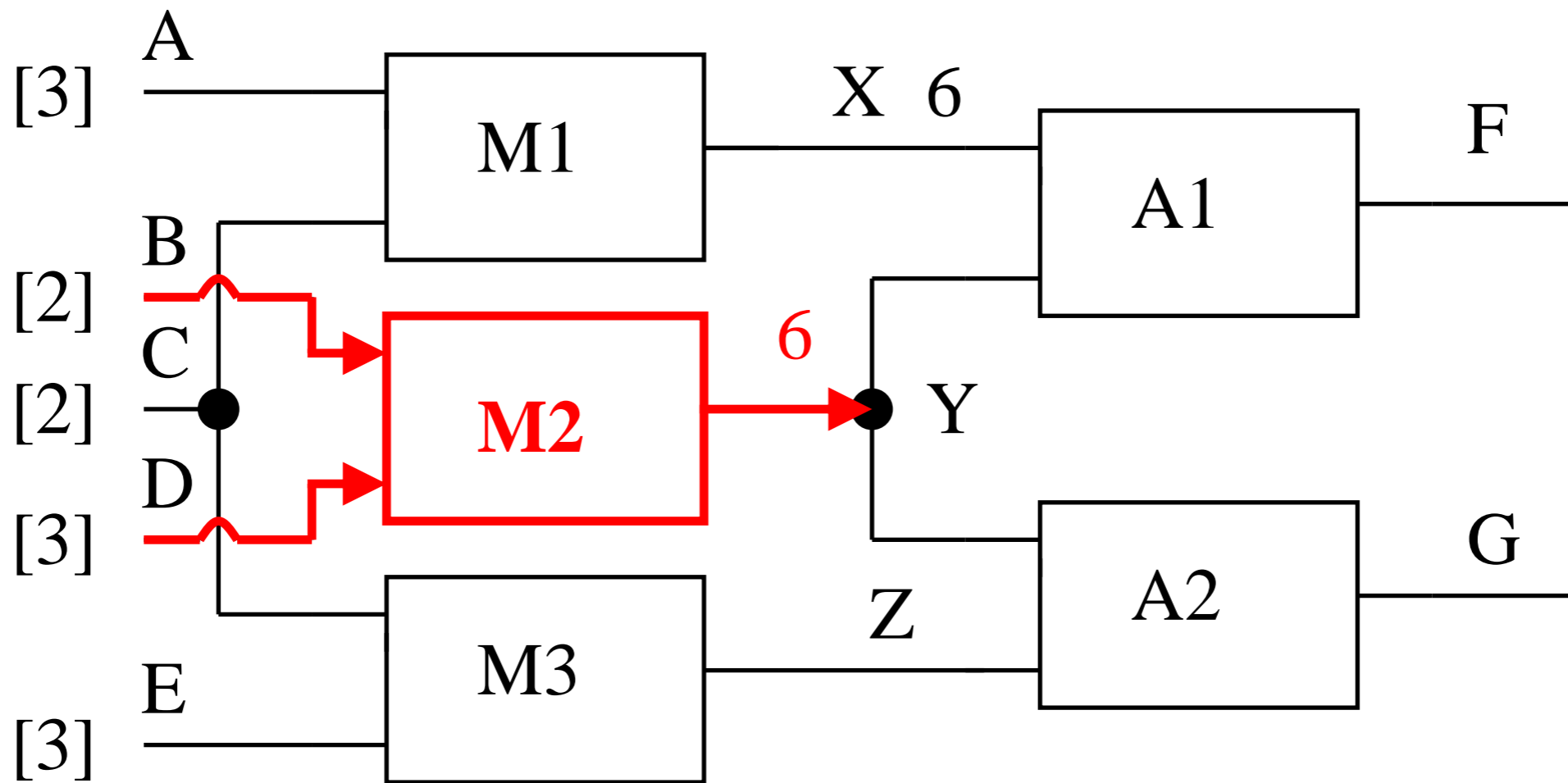
MODEL-BASED APPROACH TO DIAGNOSIS



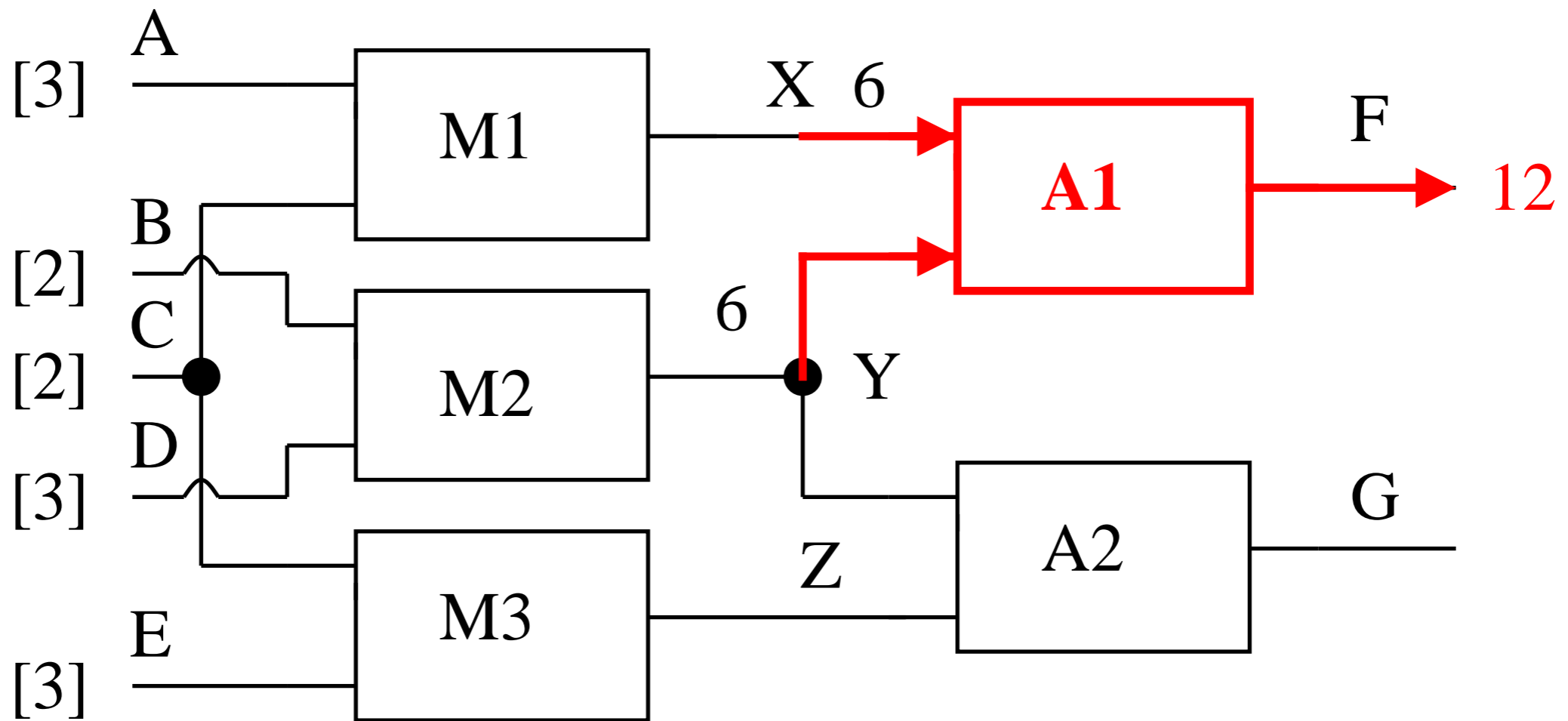
LOCAL PROPAGATION (I)



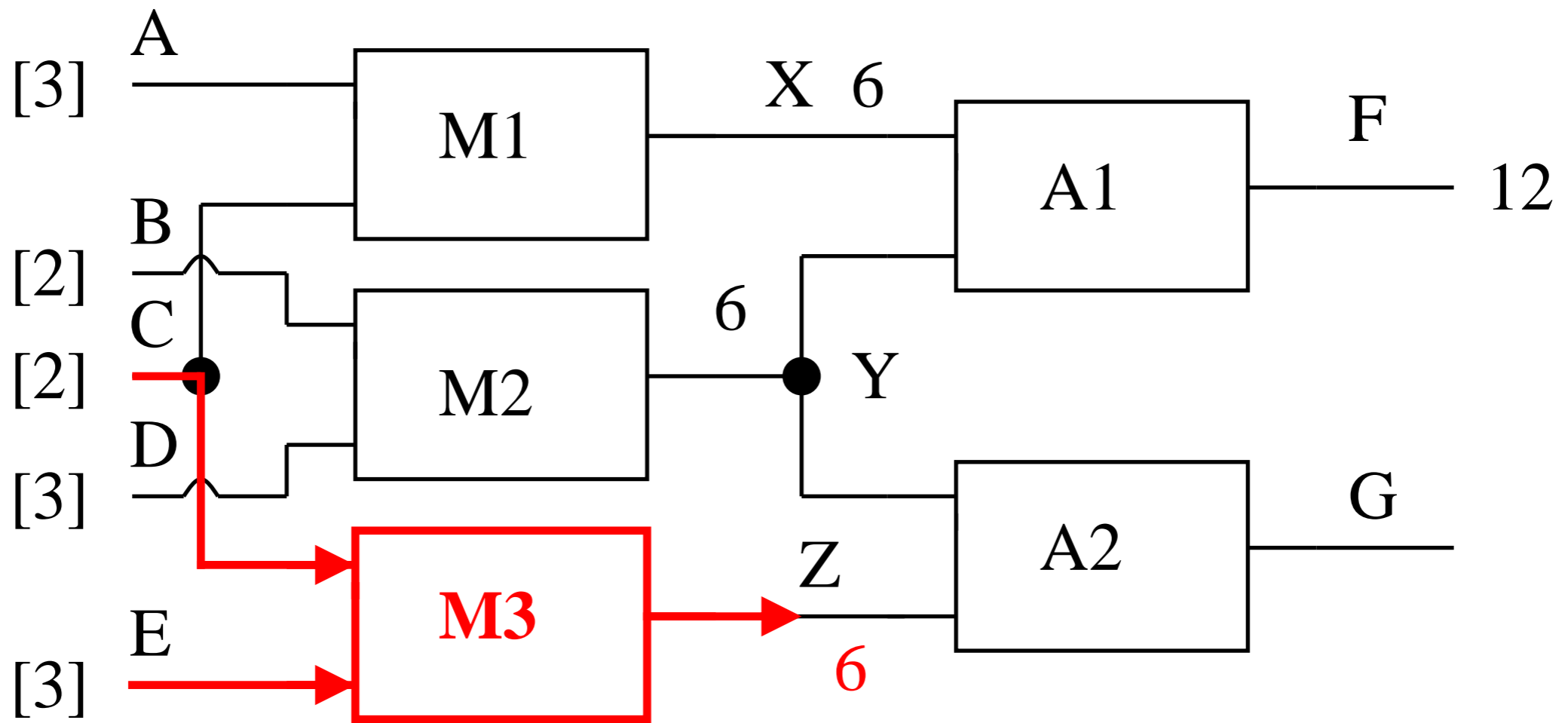
LOCAL PROPAGATION (II)



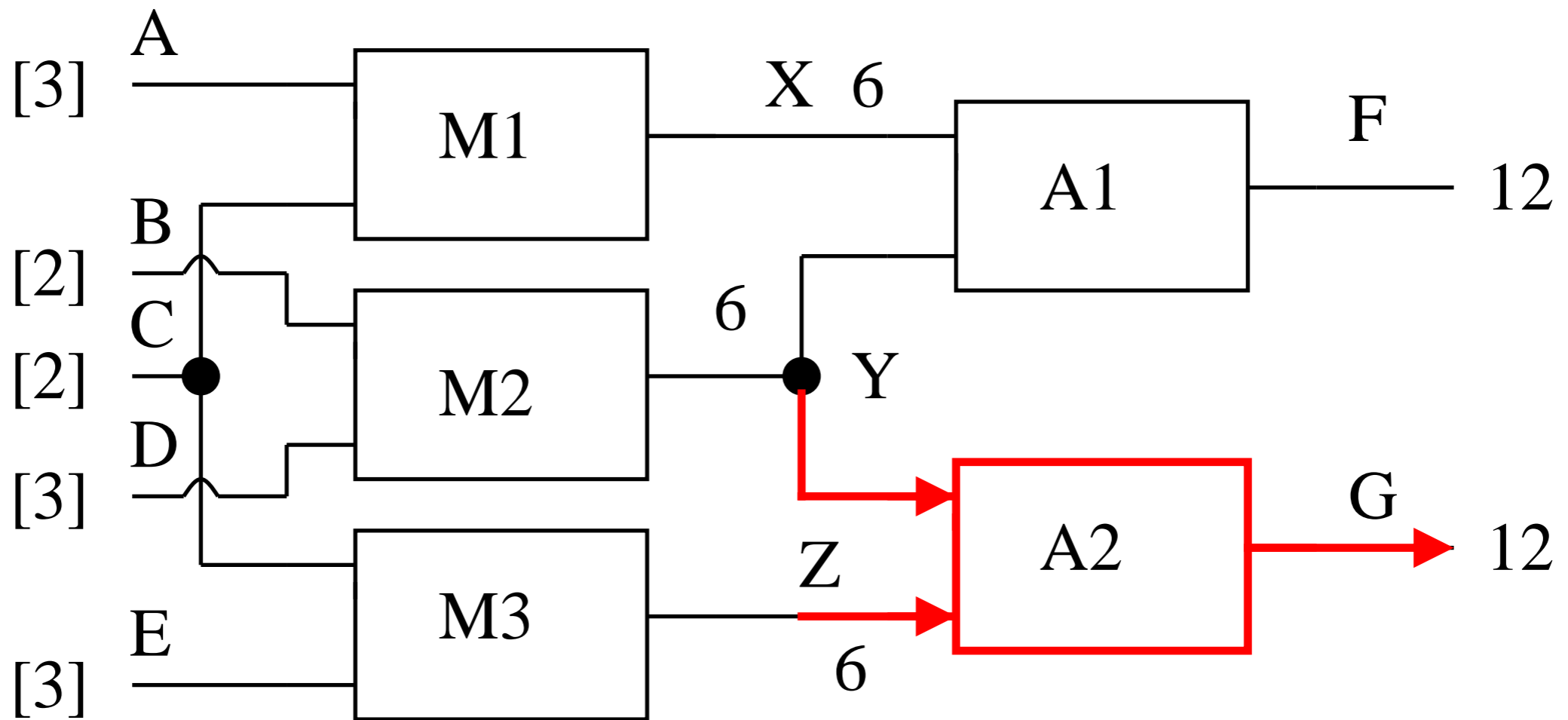
LOCAL PROPAGATION (III)



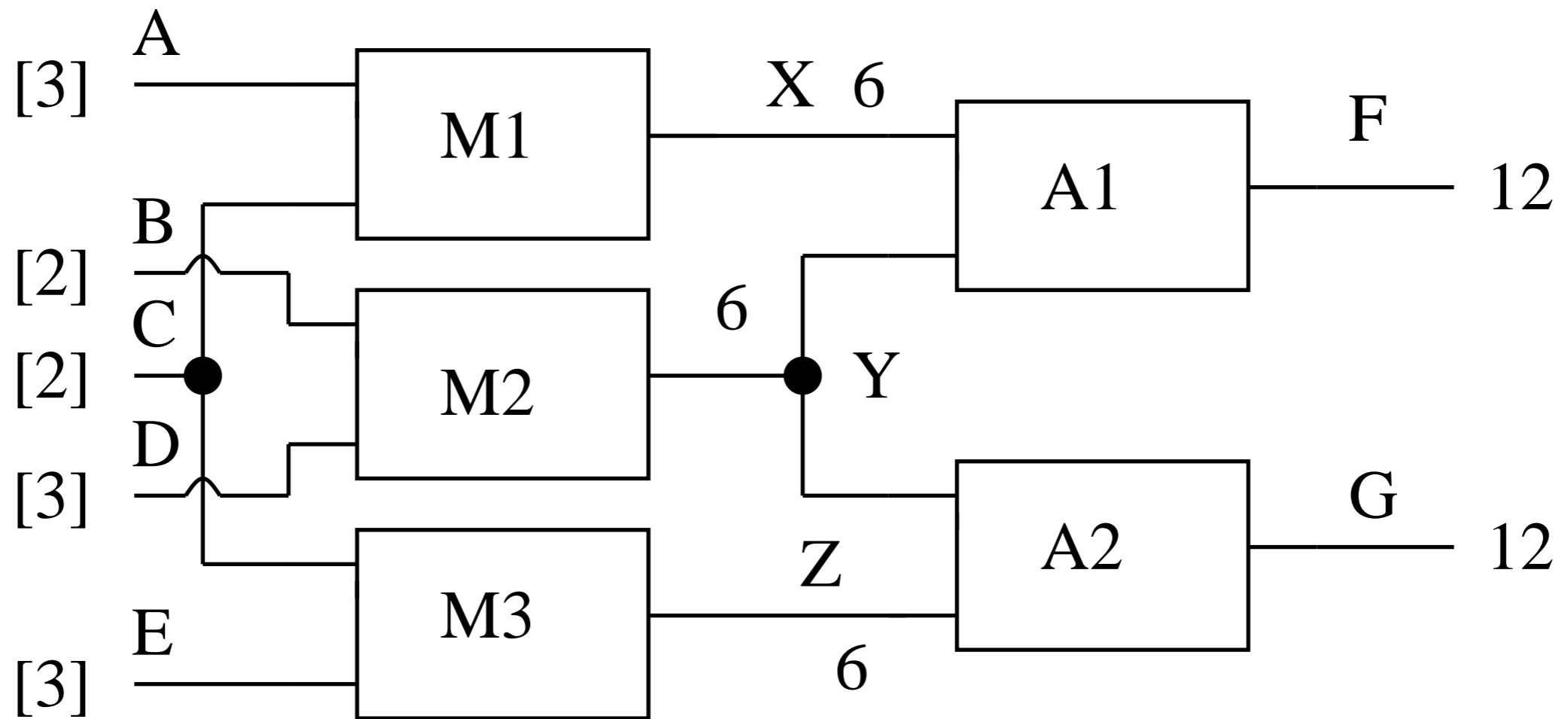
LOCAL PROPAGATION (IV)



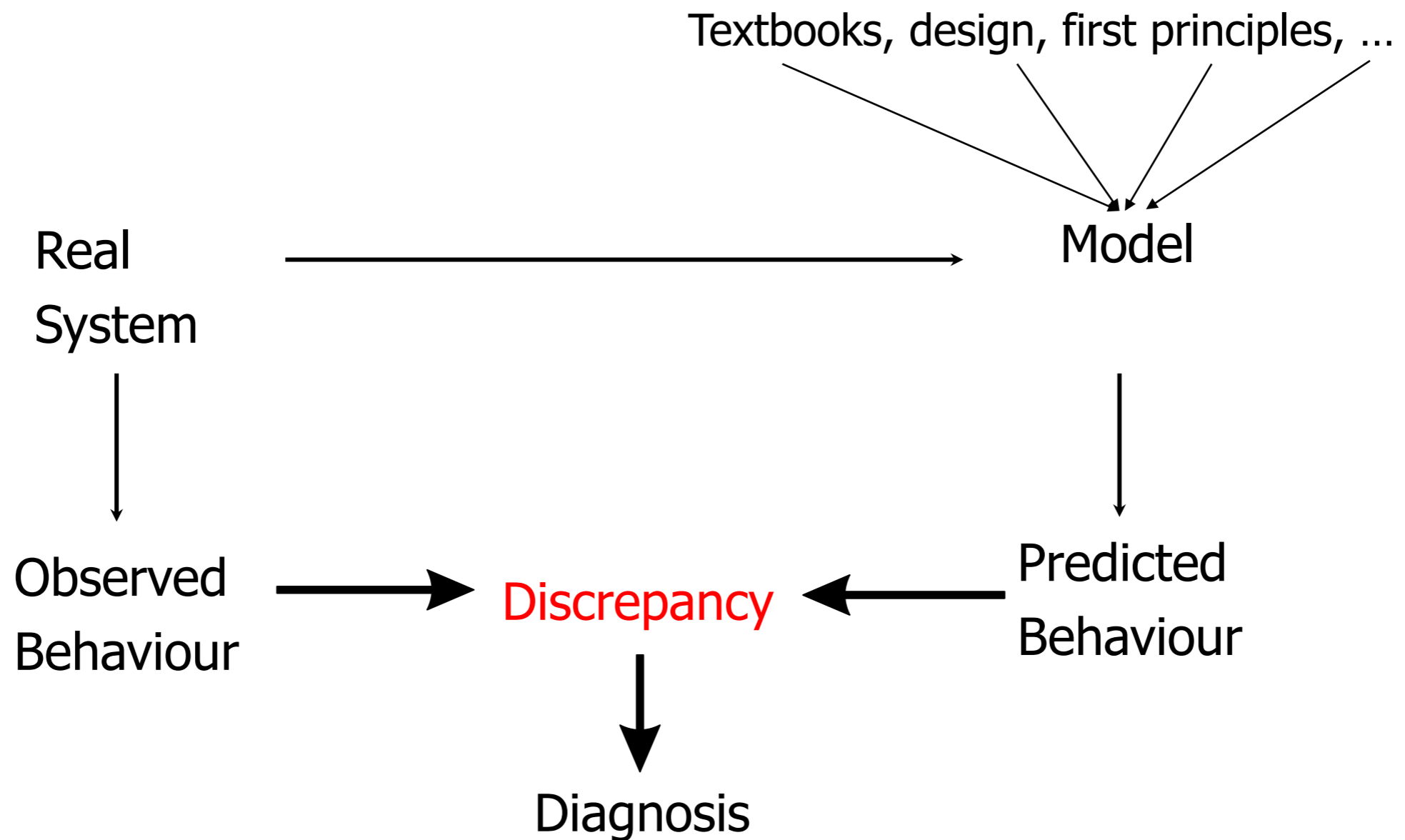
LOCAL PROPAGATION (V)



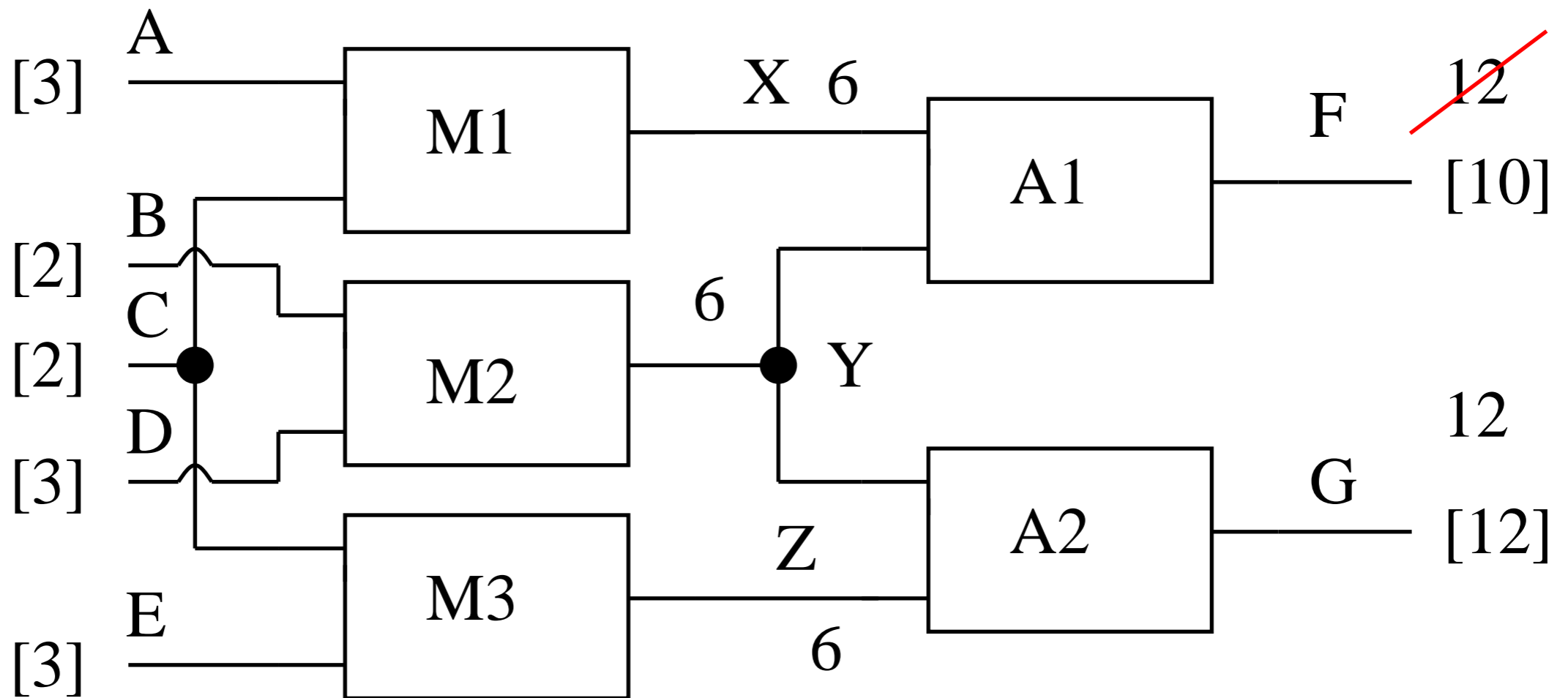
PREDICTED BEHAVIOUR



MODEL-BASED APPROACH TO DIAGNOSIS

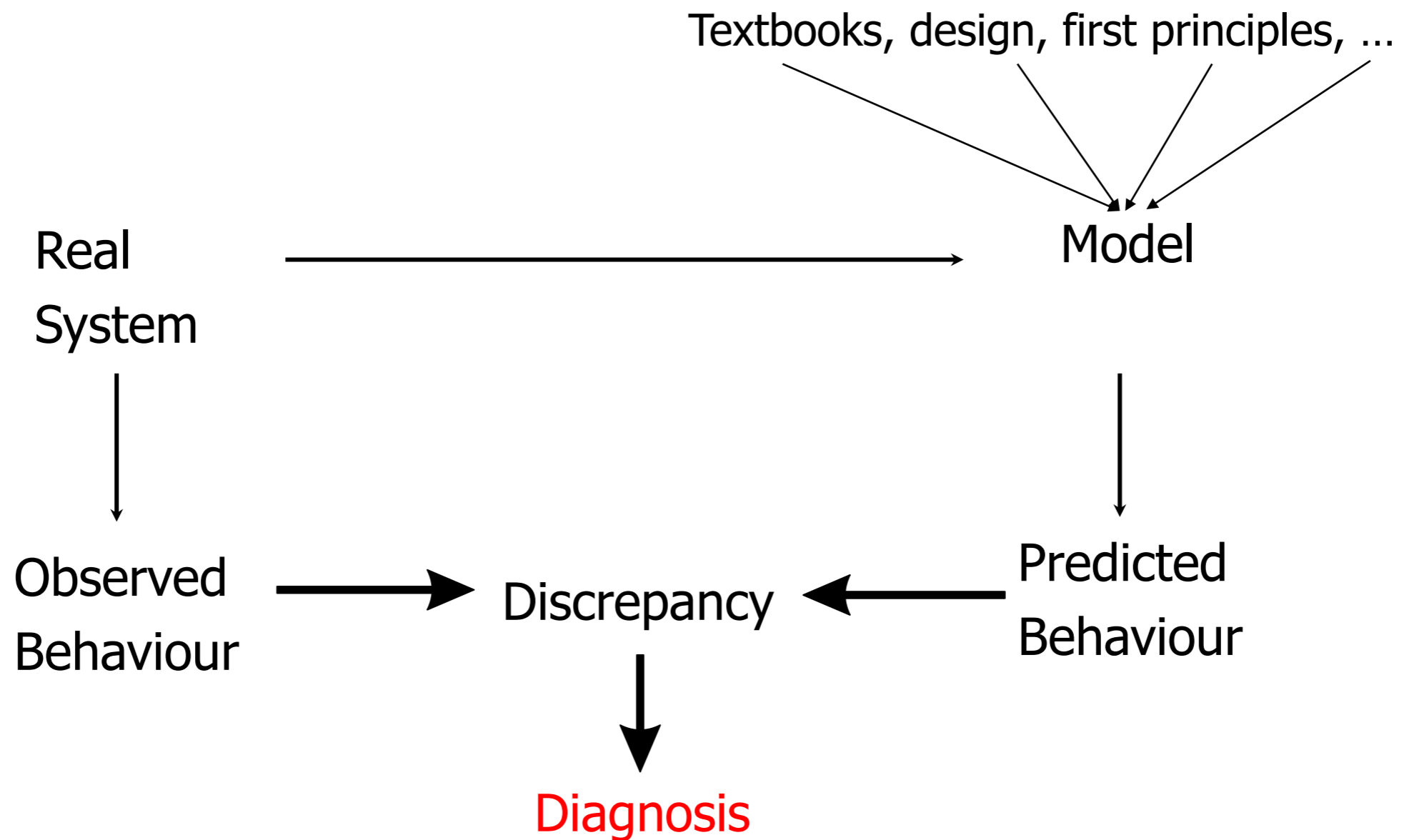


DISCREPANCY FOUND

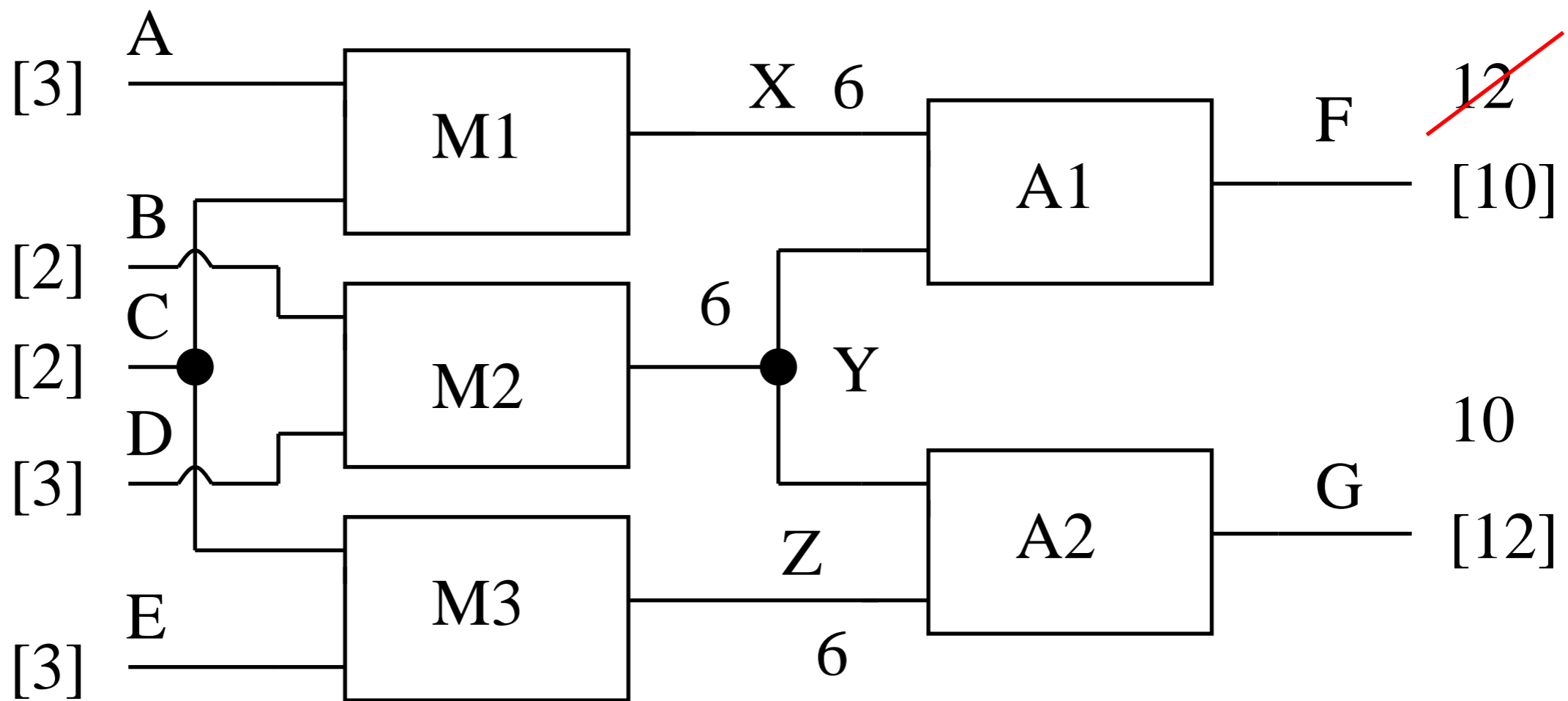


- Detect Symptoms: $F=12$ and $F=10$

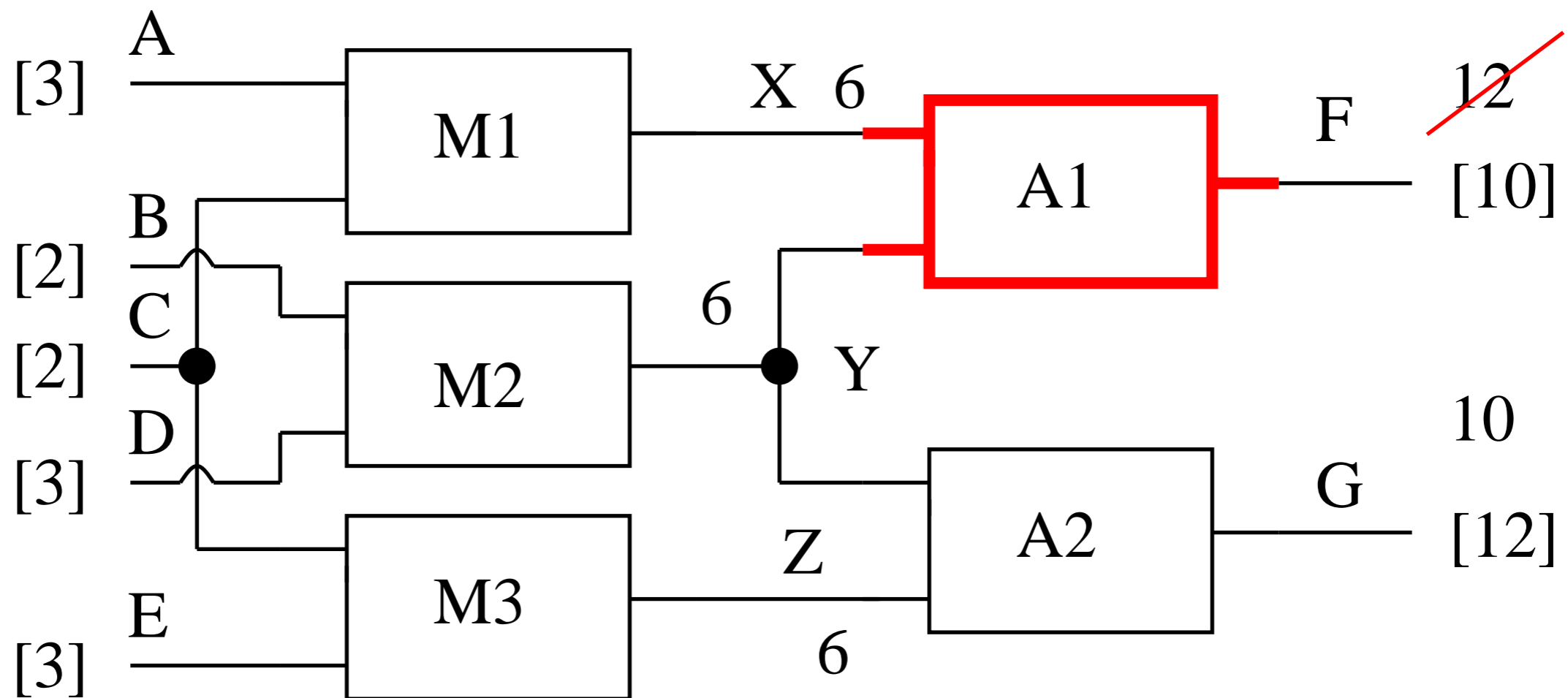
MODEL-BASED APPROACH TO DIAGNOSIS



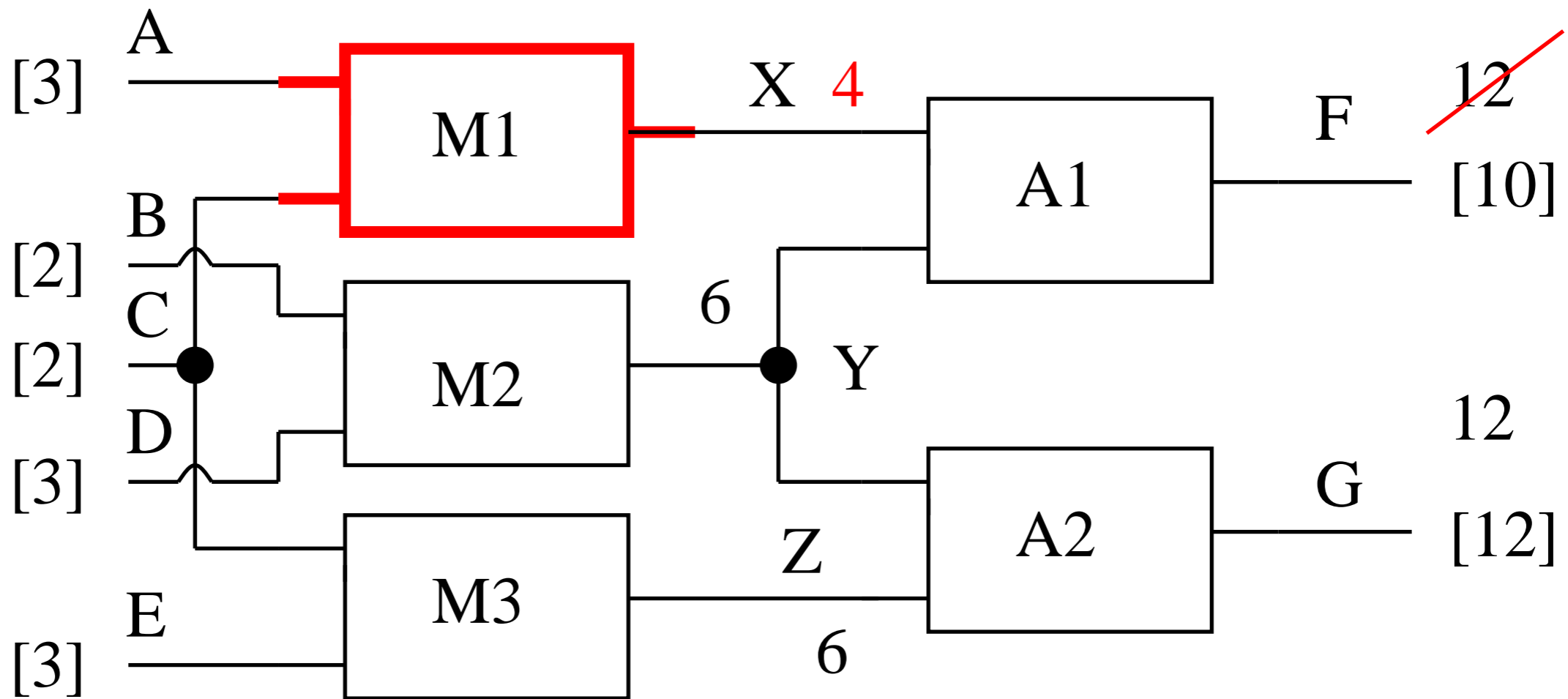
DIAGNOSIS FOR THE POLYBOX



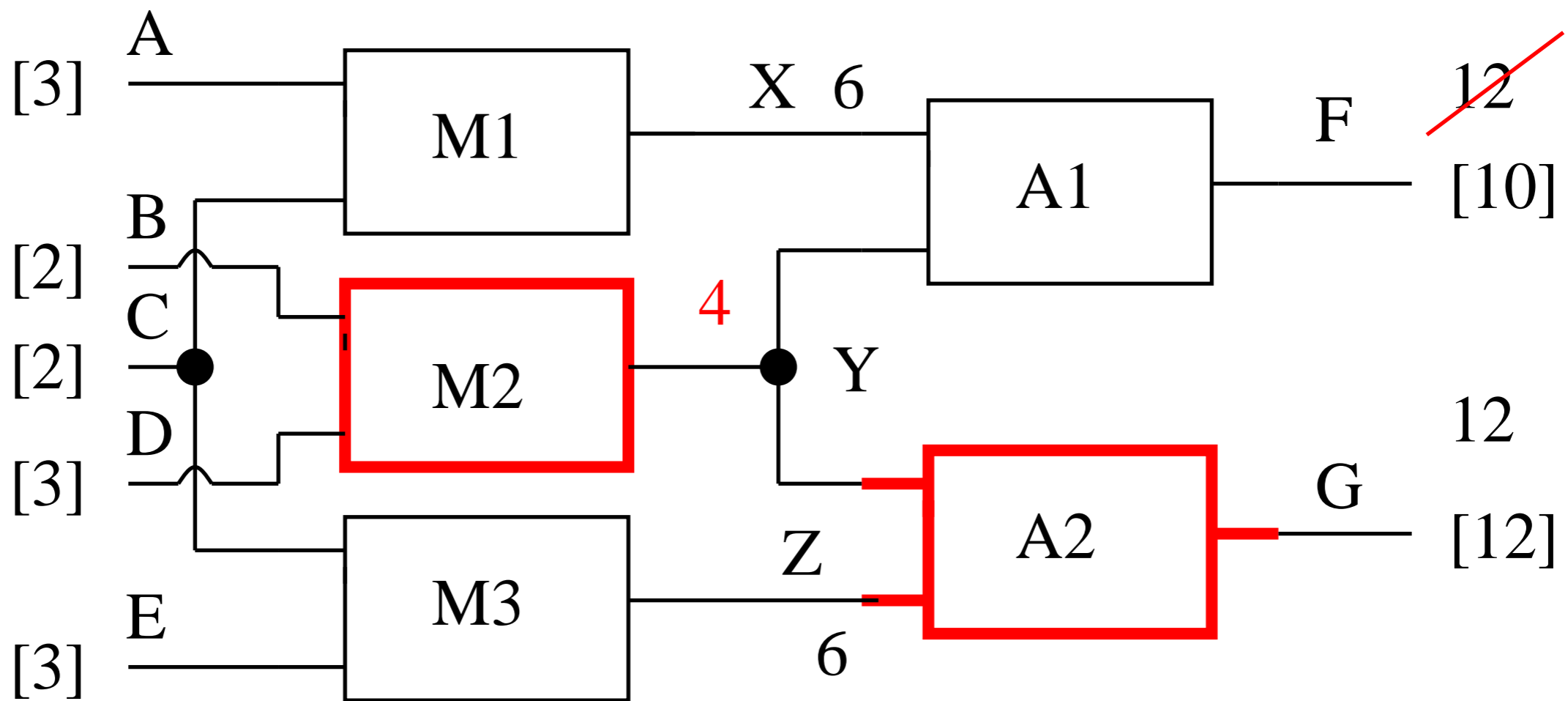
DIAGNOSIS FOR THE POLYBOX



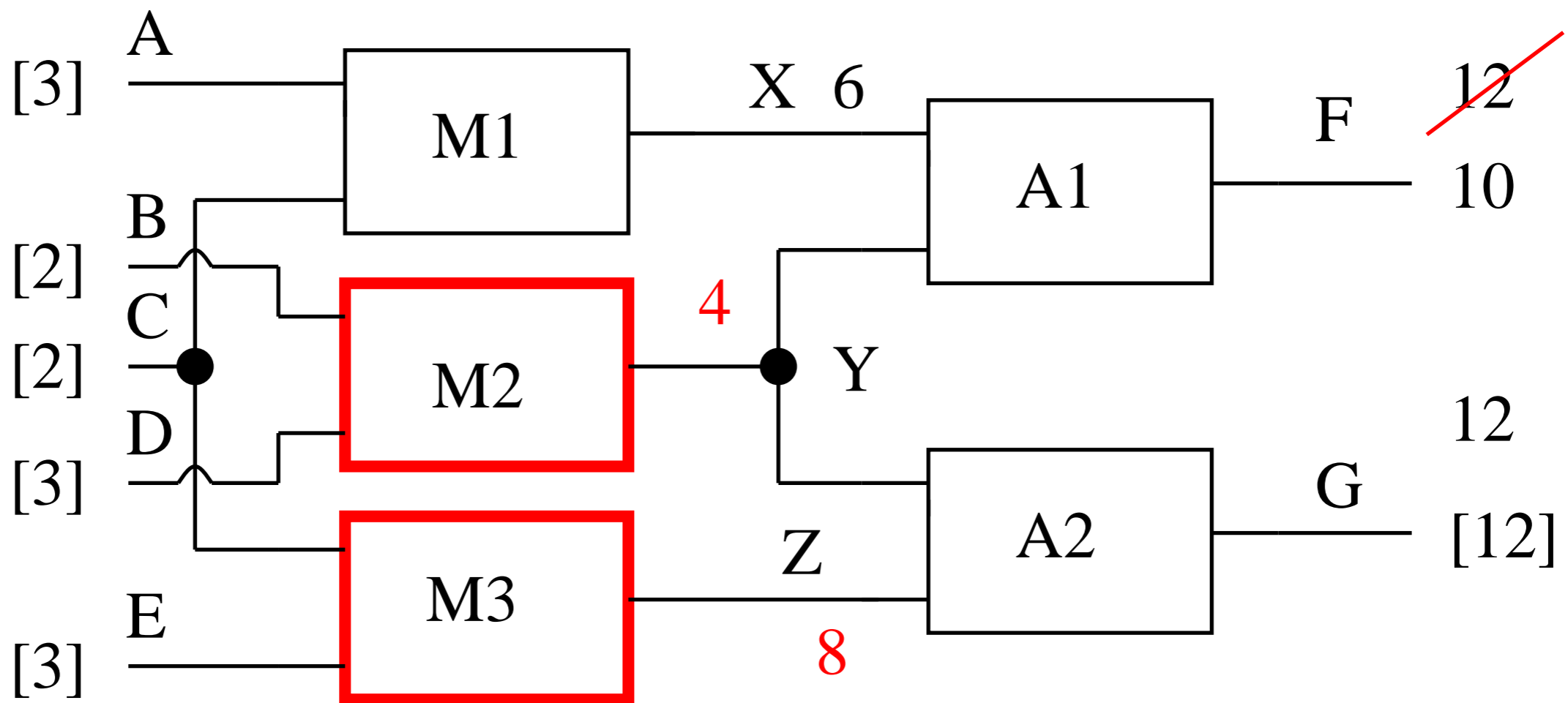
DIAGNOSIS FOR THE POLYBOX



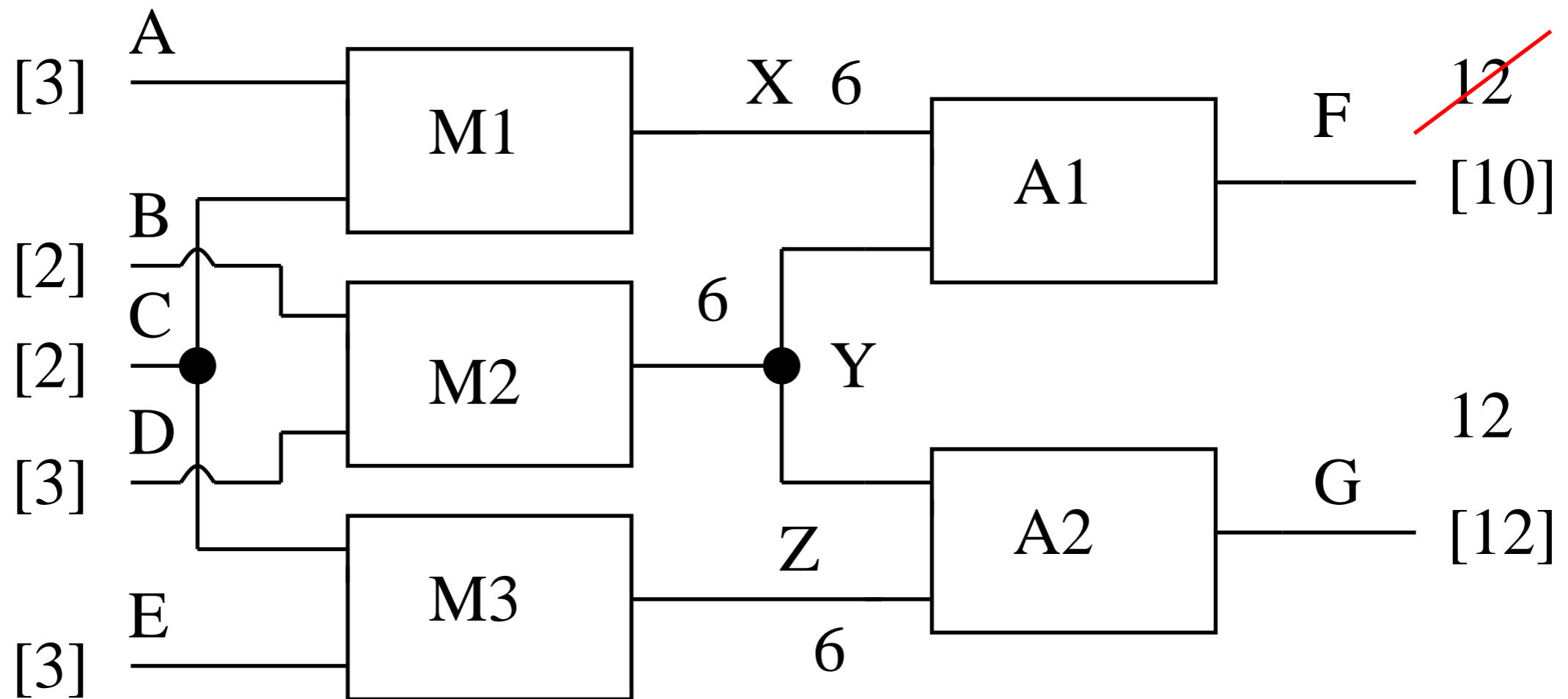
DIAGNOSIS FOR THE POLYBOX



DIAGNOSIS FOR THE POLYBOX



CANDIDATES



- Detect Symptoms: $F=12$ and $F=10$
- Generate Candidates: $\{M1\}$, $\{A1\}$, $\{M2, A2\}$, $\{M2, M3\}$



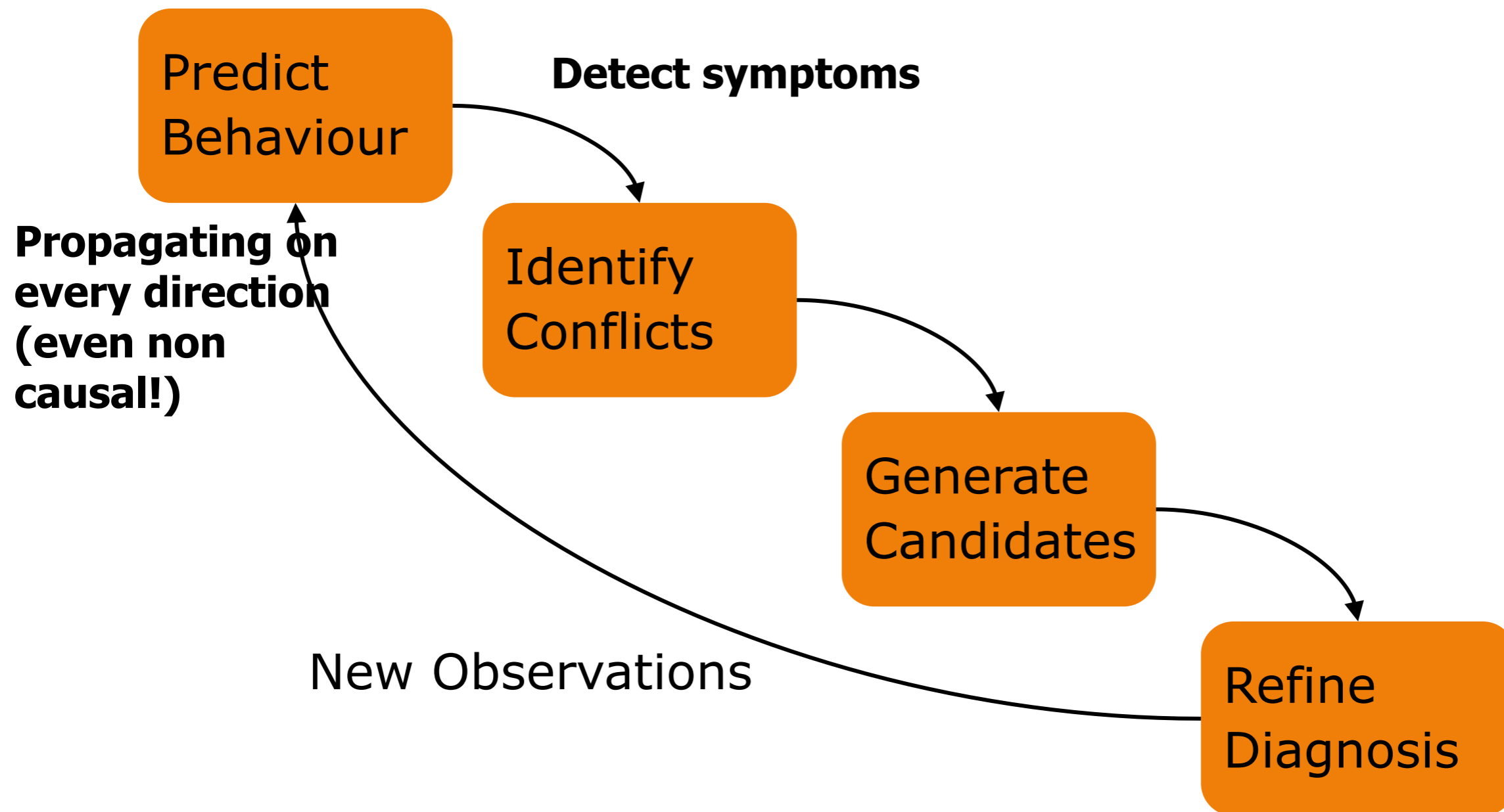
CONSISTENCY-BASED
DIAGNOSIS USING GDE



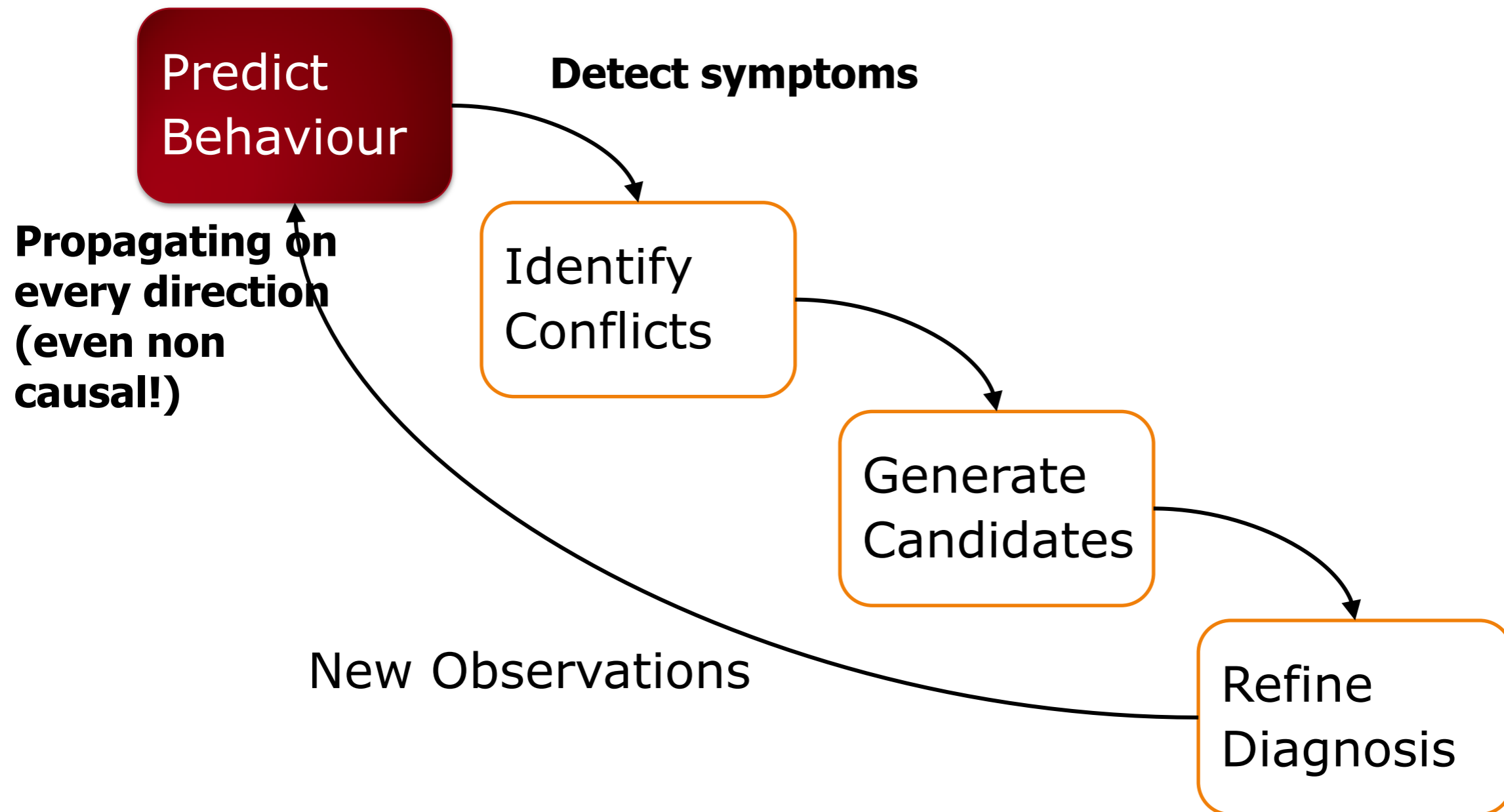
CONSISTENCY-BASED DIAGNOSIS GENERAL DIAGNOSTIC ENGINE

- GDE, de Kleer and Williams, 87
- First model-based computational system for multiple faults
- Main computational paradigm
- Still a reference to compare any model-based proposal on DX community

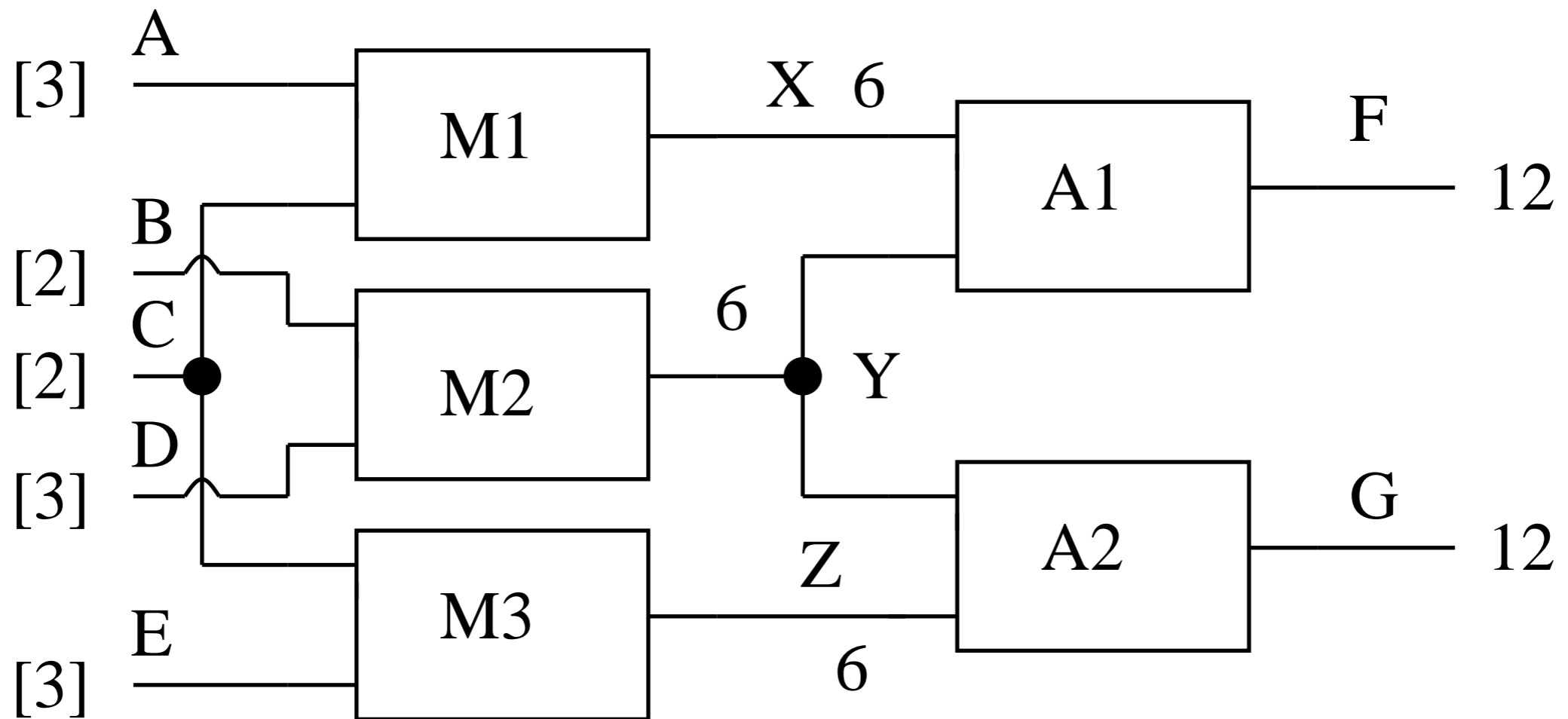
GDE: THE COMPUTATIONAL PARADIGM FOR CONSISTENCY-BASED DIAGNOSIS



GDE: THE COMPUTATIONAL PARADIGM FOR CONSISTENCY-BASED DIAGNOSIS



PREDICTION - REQUIREMENTS



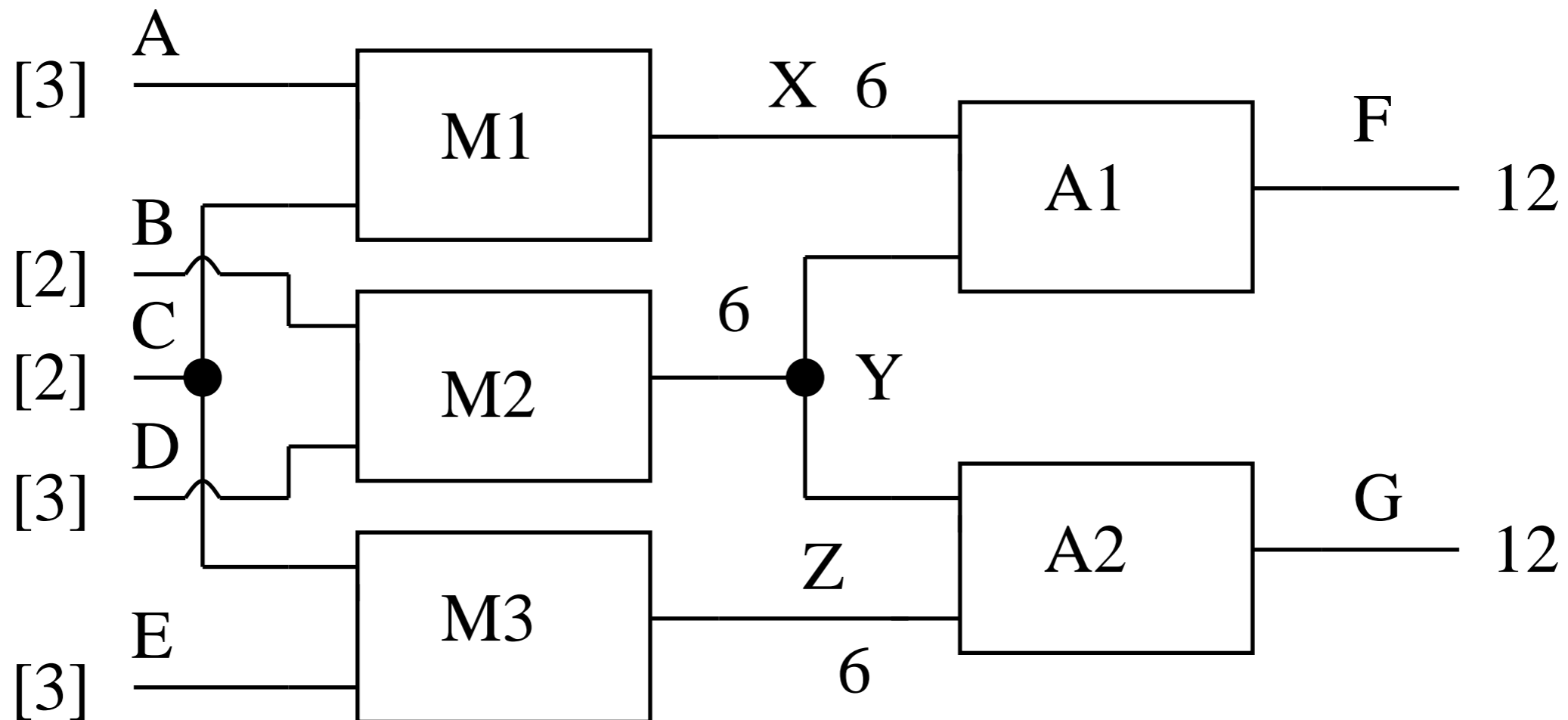
- Modeling **structure**
- Modeling **component behaviour**
- Predict overall behaviour



COMPONENT-ORIENTED MODELLING: COMPONENTS AND CONNECTIONS

- **Systems: components linked by connections via terminals**
 - **Components:** Normally physical objects
 - Resistors, diodes, voltage sources, tanks, valves
 - **Terminals:** unique communication link
 - **Connections:** ideal connections (but may be modelled as components)
 - No resistance wires, loadless pipes...
- **Possible faults:** defective components, broken connection

MODELING STRUCTURE



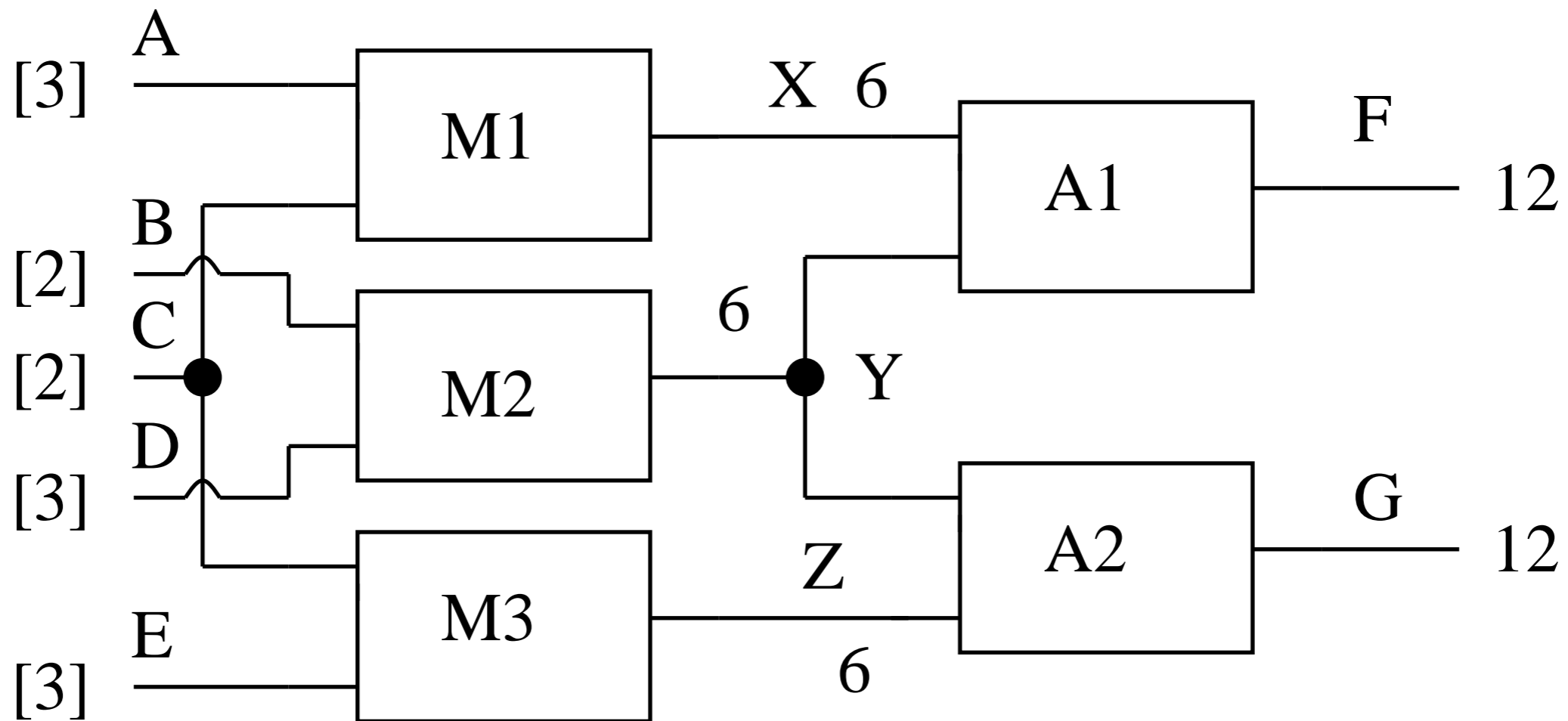
- $MULT(M1)$, $MULT(M2)$, $MULT(M3)$, $ADD(A1)$, $ADD(A2)$,
 $in2(M1)=in1(M3)$, $out(M1)=in1(A1)$, $out(M2)=in2(A1)$,
 $out(M2)=in1(A2)$, $out(M3)=in2(A2)$



MODELING BEHAVIOR

- Constrains / relations among
 - Input/Output variables
 - Internal parameters
- Various directions
- No implicit reference to or implicit assumptions about context (existence or state of other components) : no function-in-structure principle

MODELING BEHAVIOR

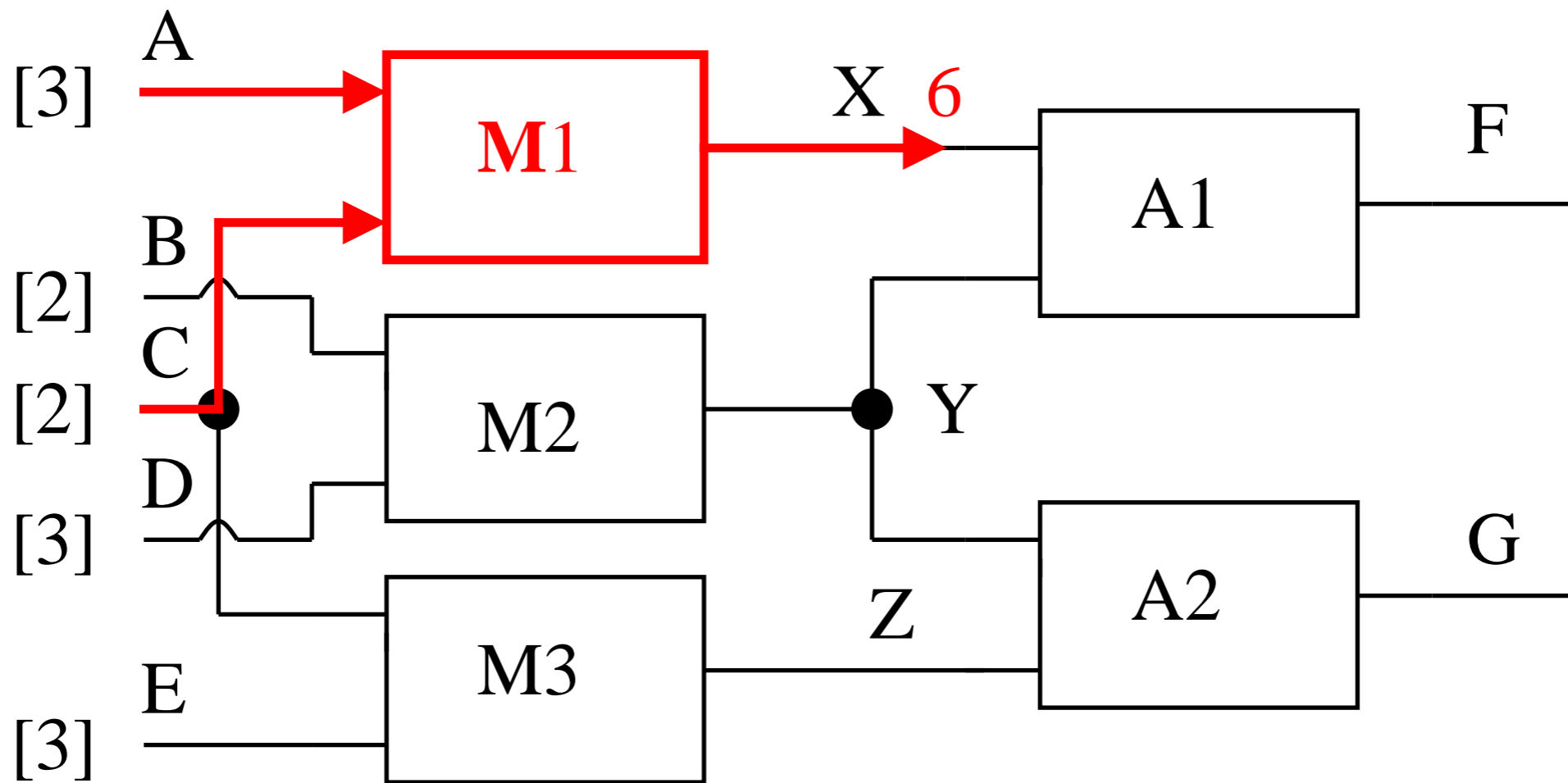


- $MULT(x) \rightarrow OK(x) \rightarrow out(x) = in1(x) * in2(x)$
 $ADD(x) \rightarrow OK(x) \rightarrow out(x) = in1(x) + in2(x)$

PREDICTION - PRINCIPLES

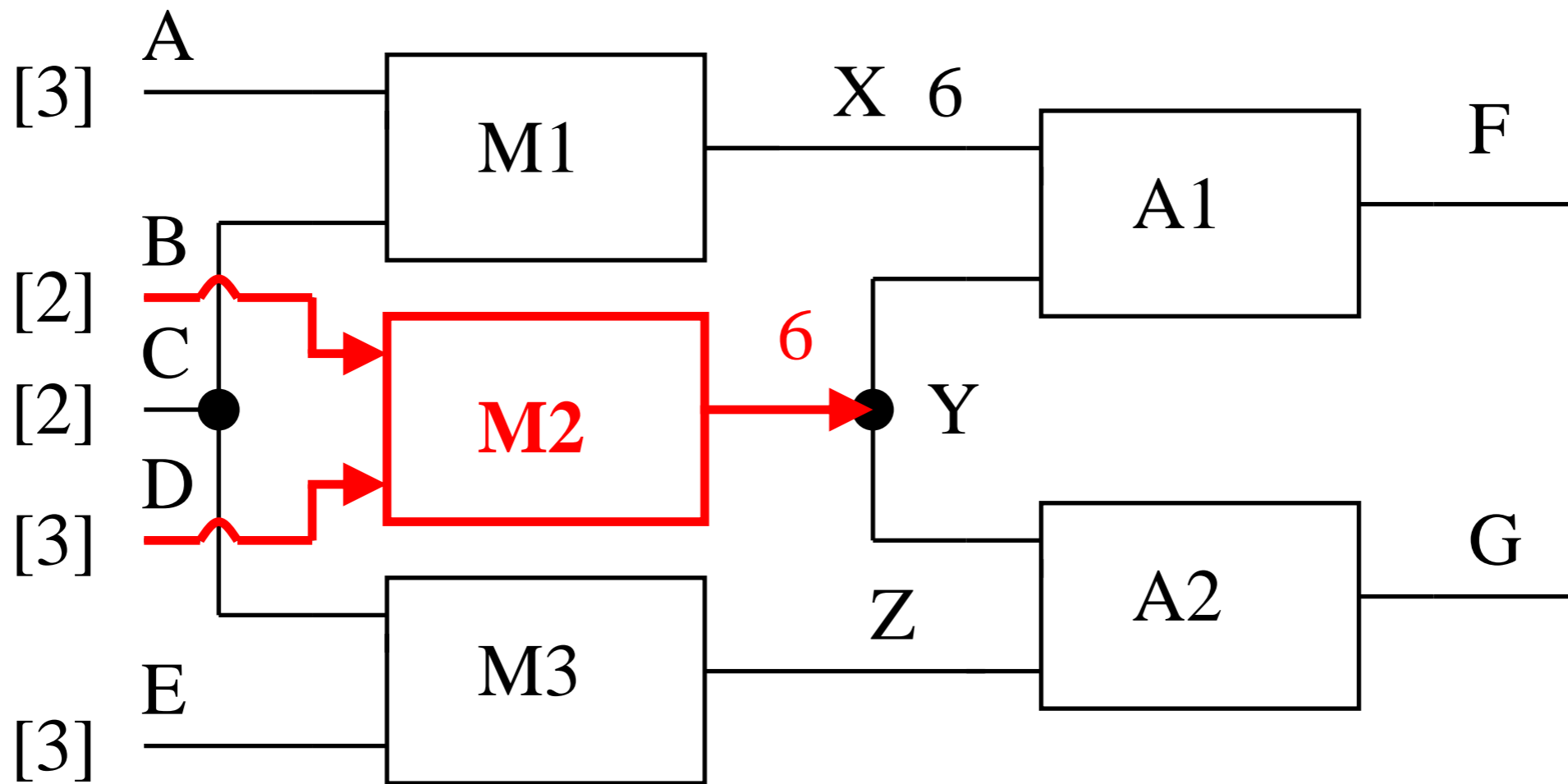
- Infer the behaviour of the entire device from
 - Structural description
 - Component models
 - Observations (inputs/measurements)
- Preserve dependencies on component models – OK(M1)
- Propagate the effects of local models along the interaction paths (connections)
- Propagate **not only in the causal direction**

PROPAGATION CAUSAL DIRECTION (I)



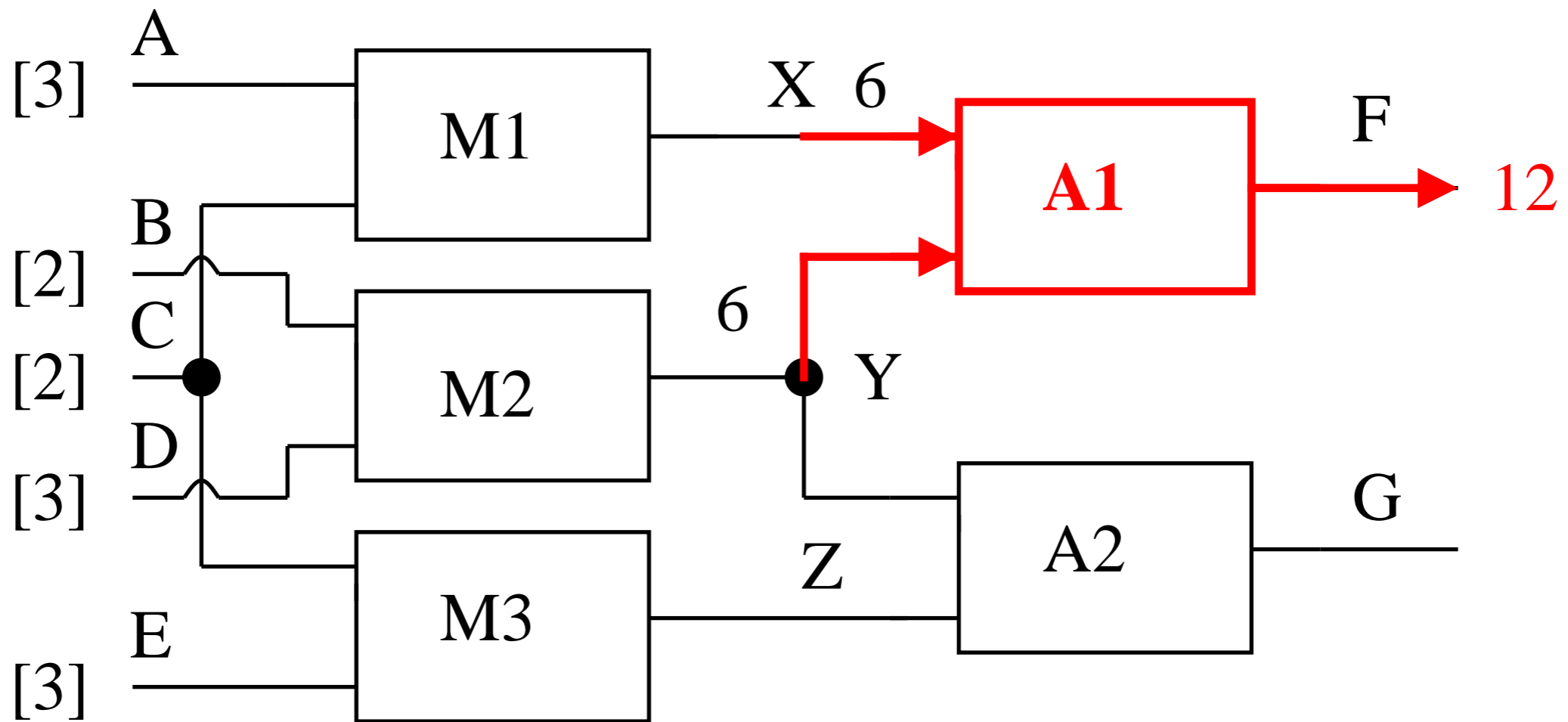
- $[A]=3 \wedge [C]=2 \supset X=6$ (M1)

PROPAGATION CAUSAL DIRECTION (II)



- $[B]=2 \wedge [D]=3 \supset Y=6$ (M2)

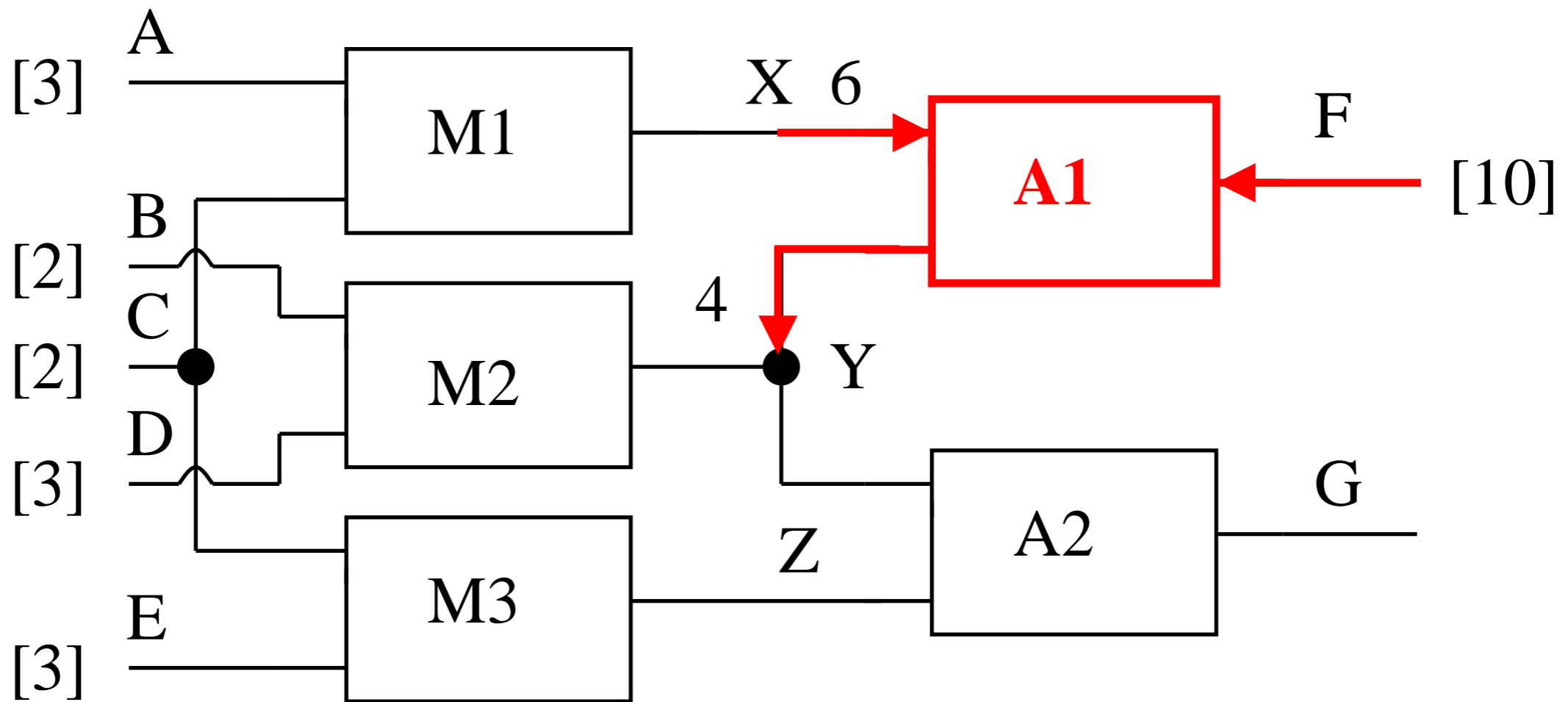
PROPAGATION CAUSAL DIRECTION (III)



○ $X=6 \wedge Y=6 \supset F=12$ (A1)

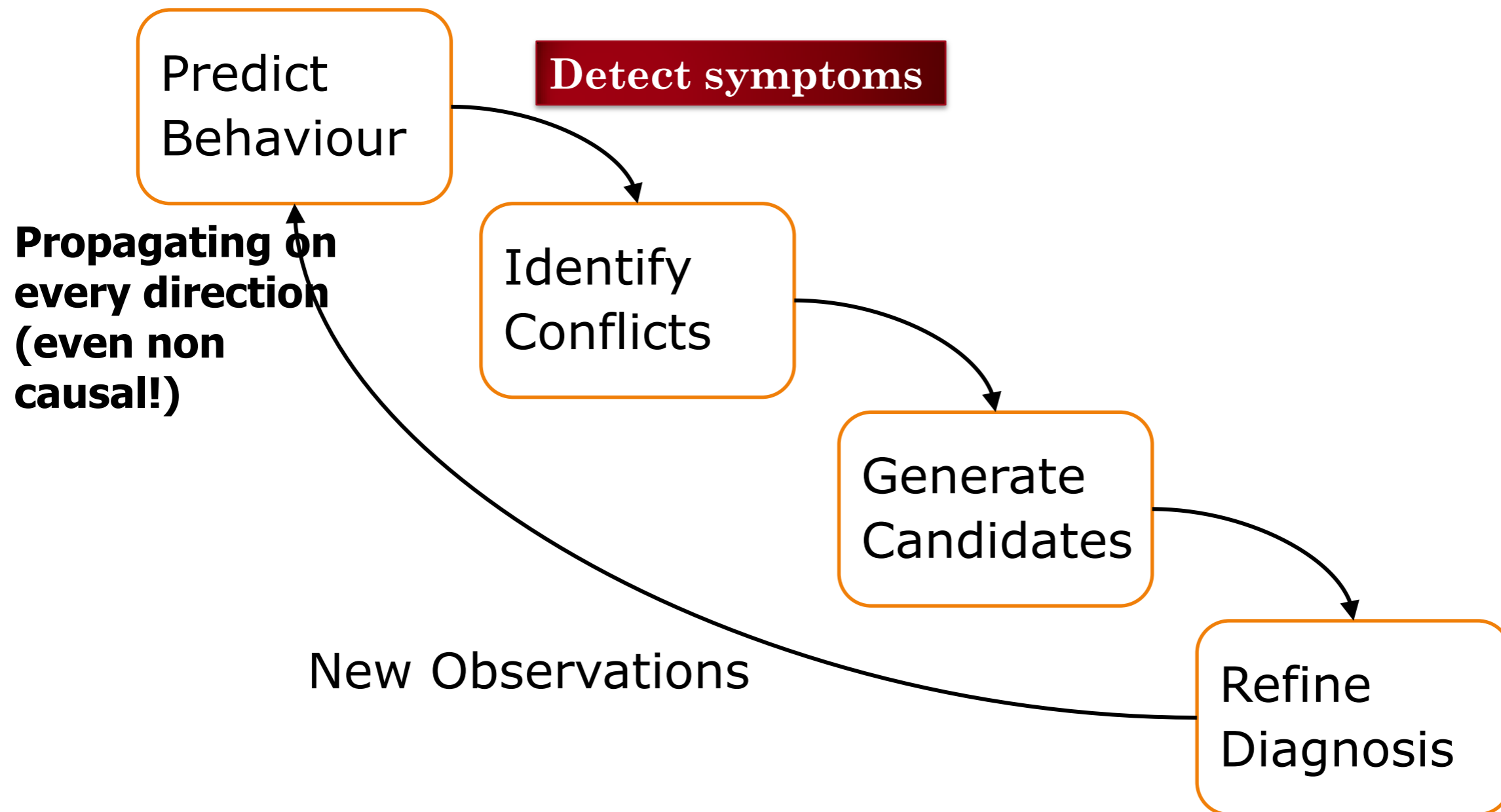
PROPAGATION

“BACKWARD” DIRECTION (II)

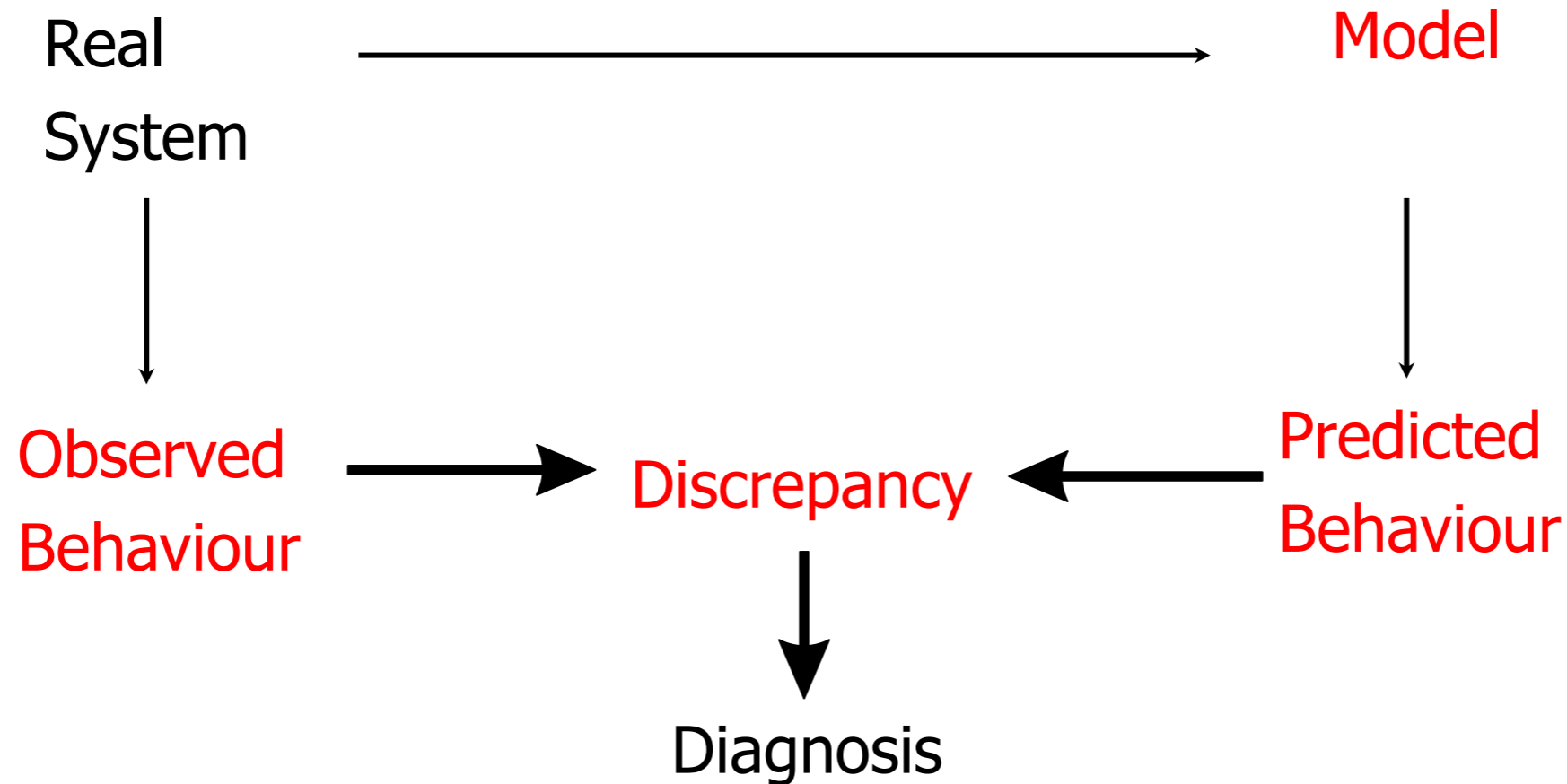


- $[F]=10 \wedge X=6 \supset Y=4$ (A1)

GDE: THE COMPUTATIONAL PARADIGM FOR CONSISTENCY-BASED DIAGNOSIS



SYMPTOMS



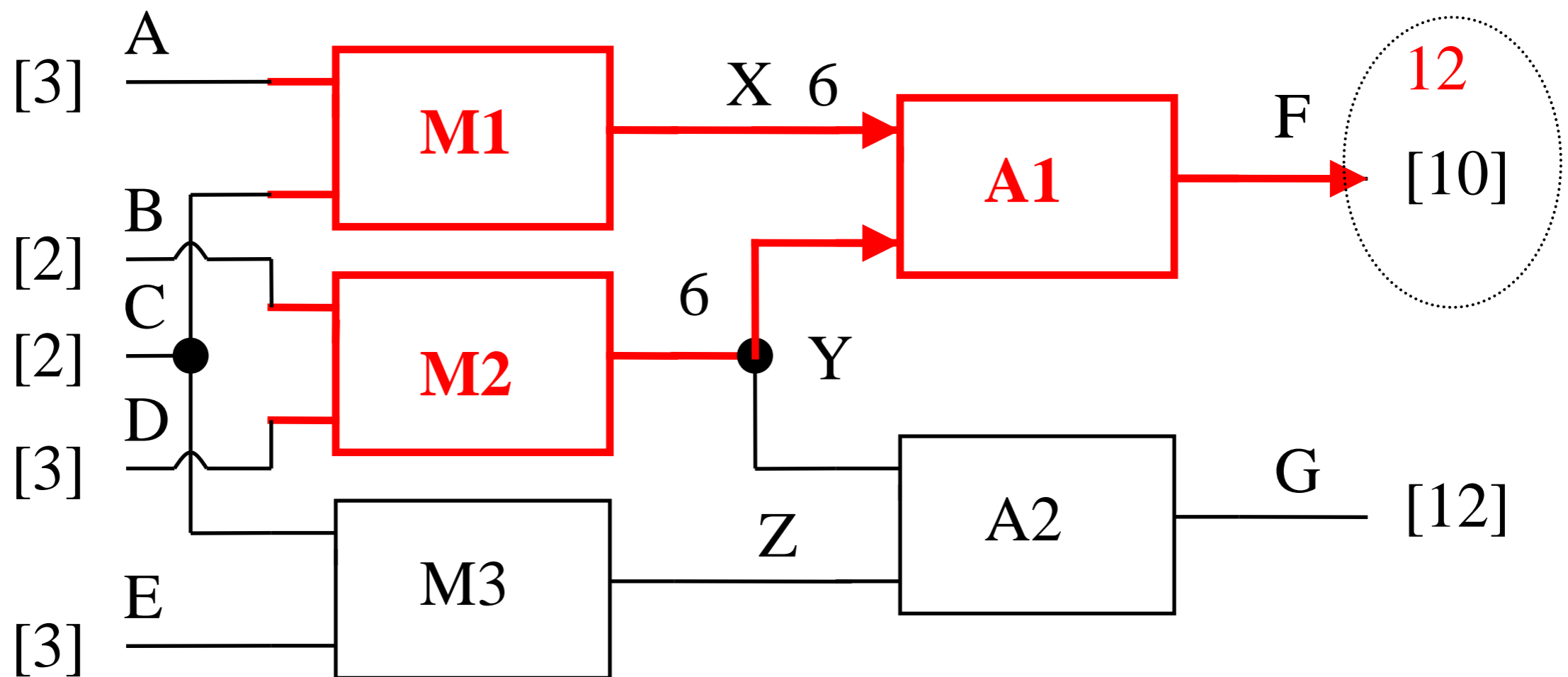
- Symptoms are **contradictions that indicate an inconsistency between observations and correct behaviour**
 - But other potential sources of contradictions
 - Imprecise measurements
 - Bugs in the model
 - Bugs in propagation



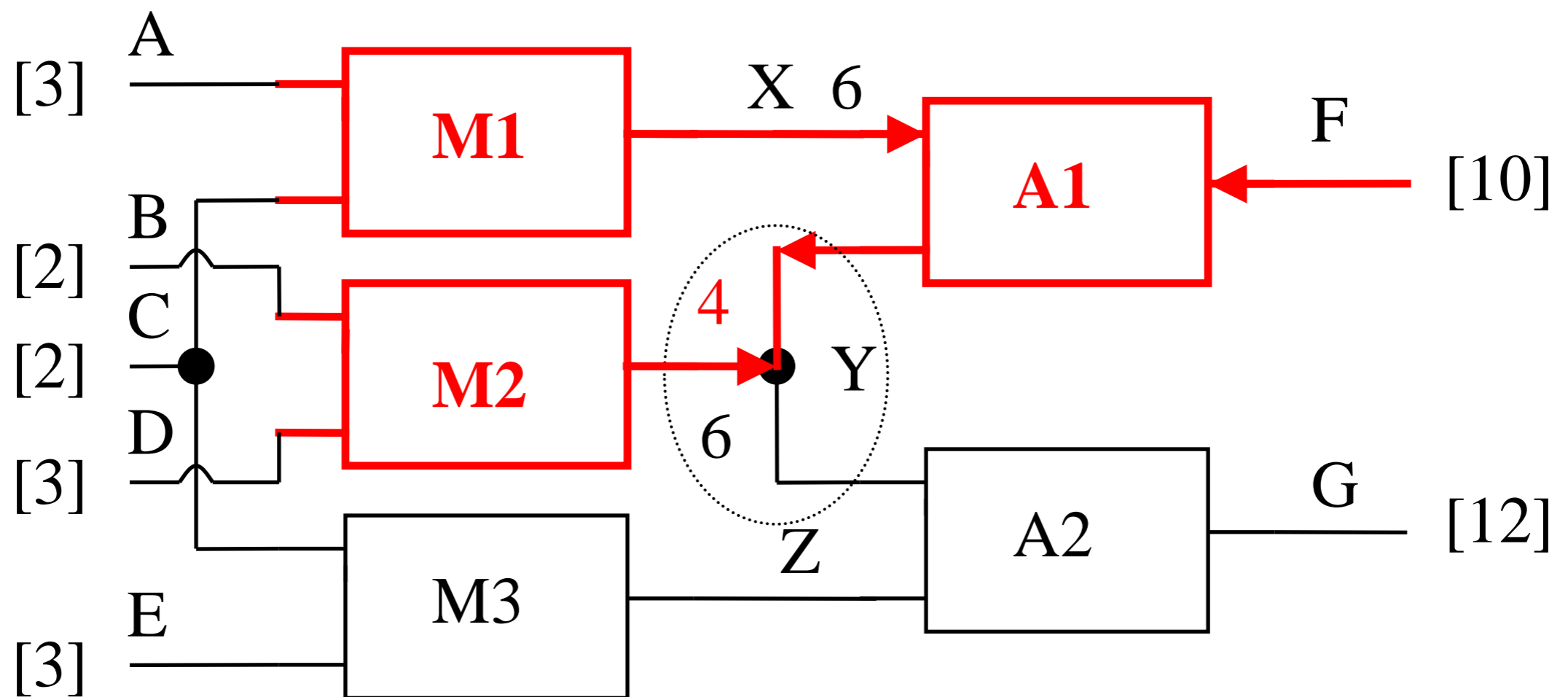
SYMPTOMS DETECTION

- Symptoms occur as contradictory values for one variable
 - Predicted plus observed
 - Predicted following two different paths
- Dissimilarity measure: determine the level of “contradictoriness” between the values

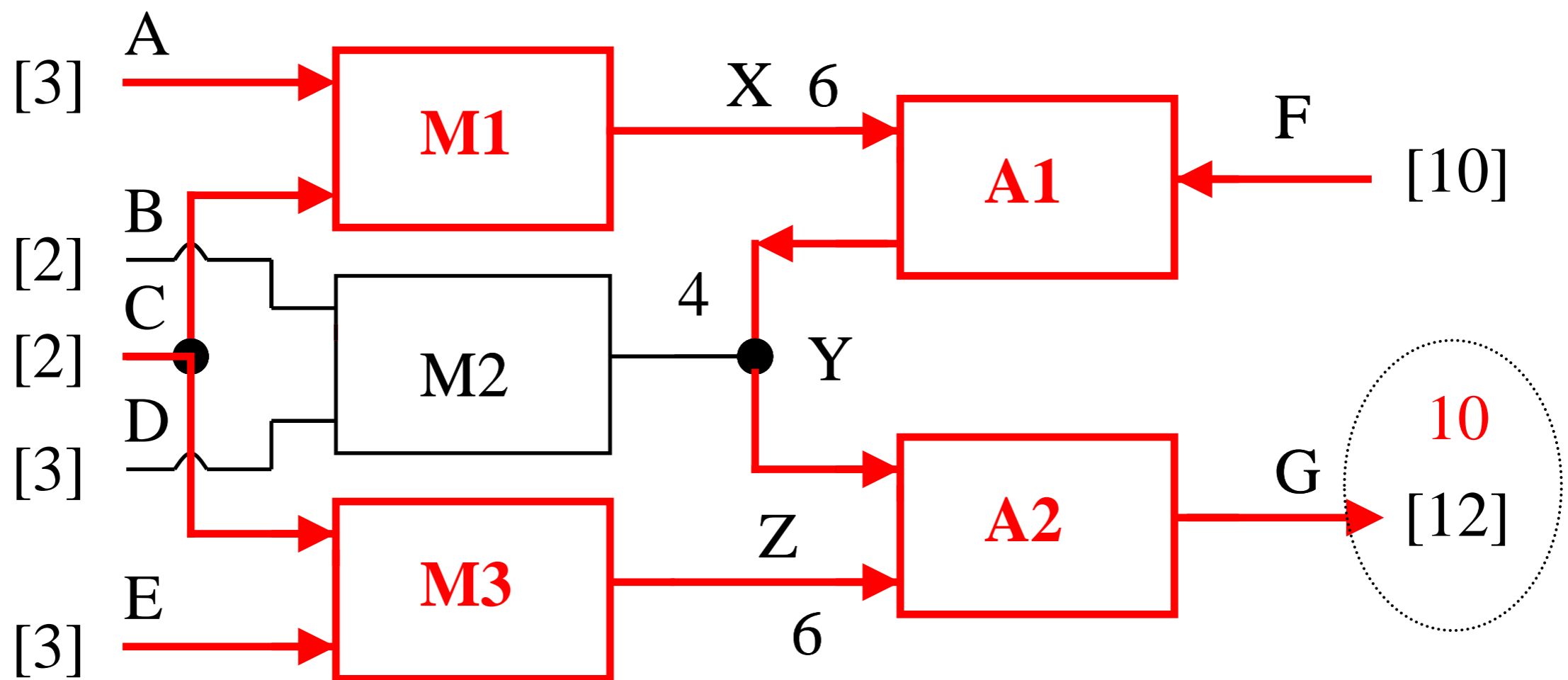
SOME SYMPTOMS FOR THE POLYBOX (I)



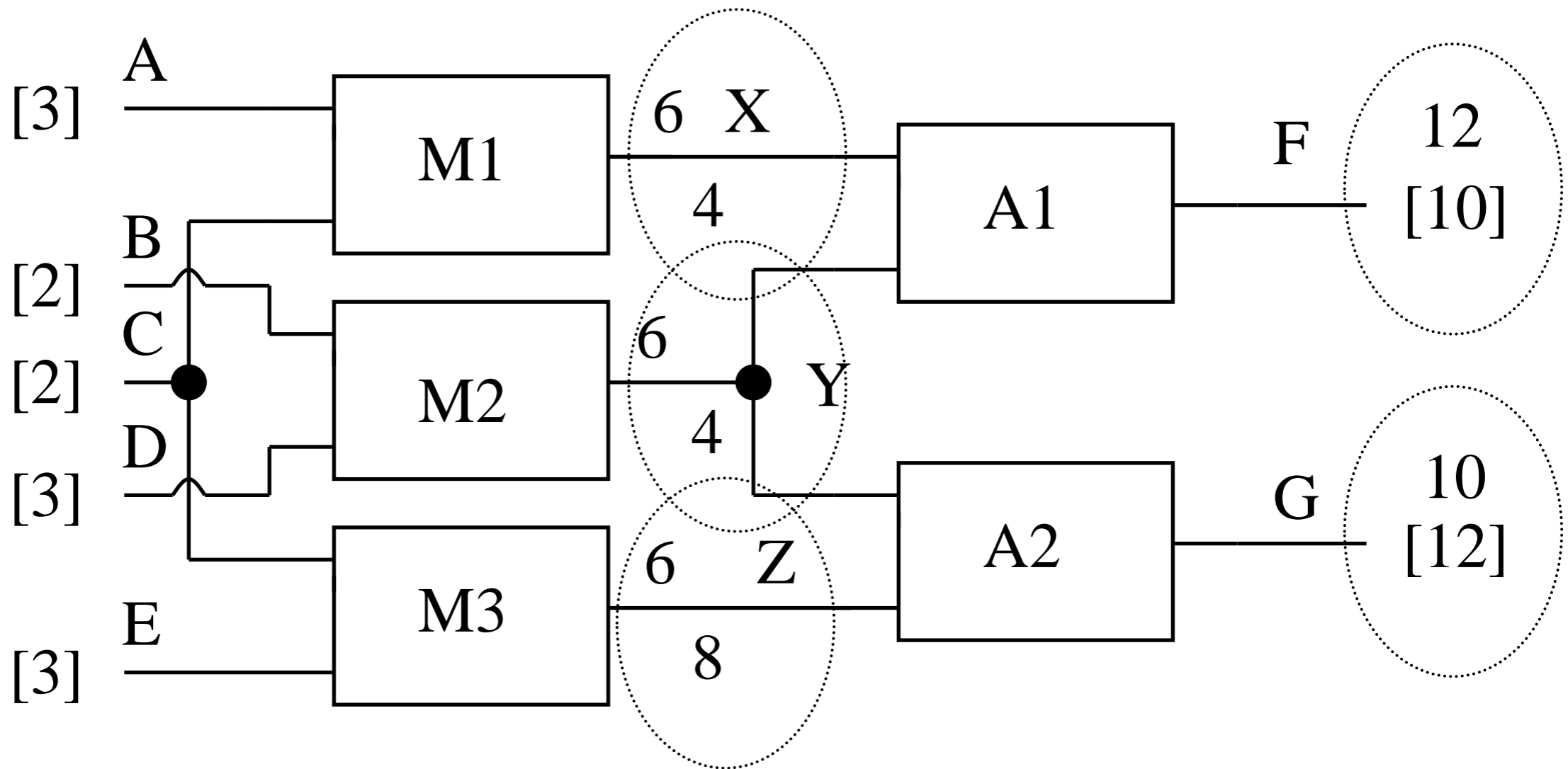
SOME SYMPTOMS FOR THE POLYBOX (II)



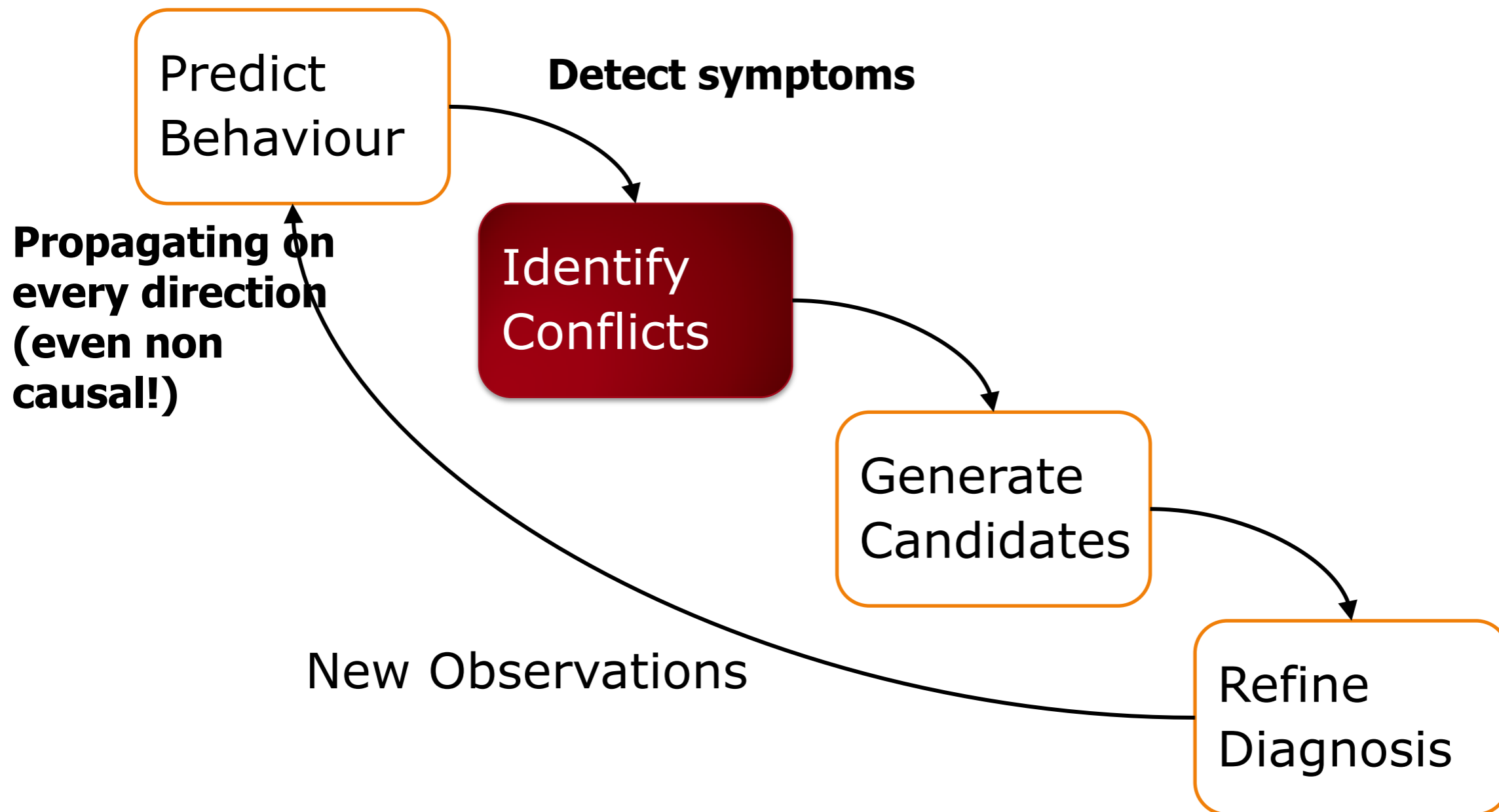
SOME SYMPTOMS FOR THE POLYBOX (III)



SOME SYMPTOMS FOR THE POLYBOX (IV)

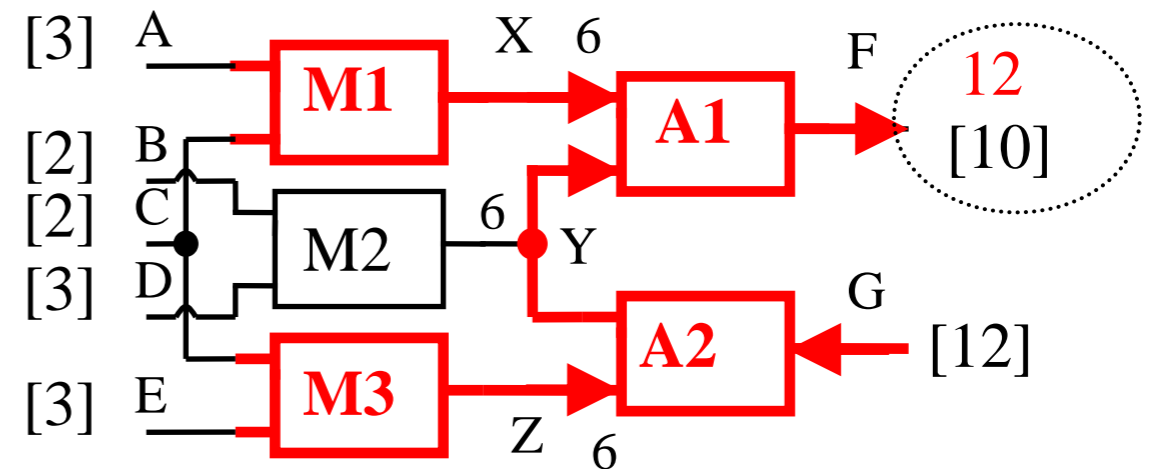
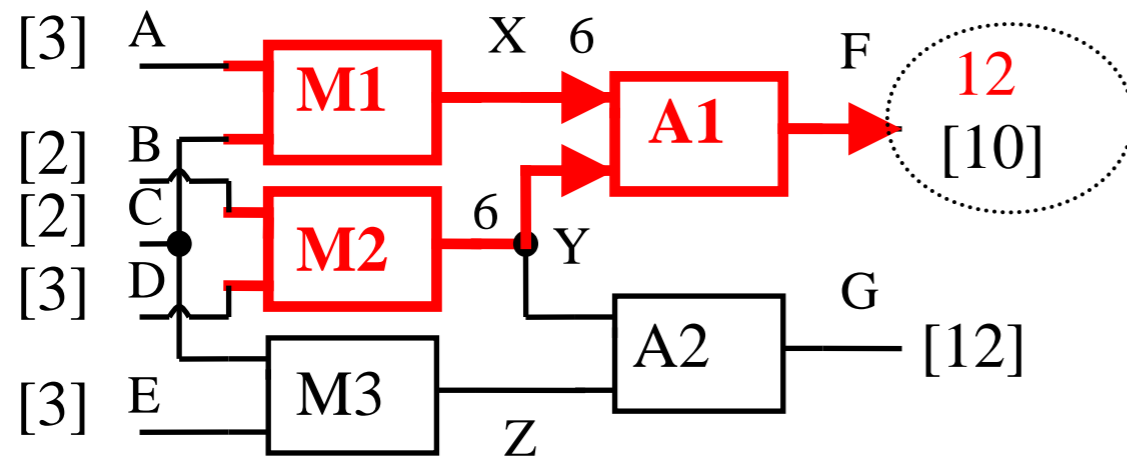


GDE: THE COMPUTATIONAL PARADIGM FOR CONSISTENCY-BASED DIAGNOSIS



IDENTIFY CONFLICTS

- **Conflict (informal):** set components involved in the discrepancy; they cannot be all working properly
- Polybox (minimal) conflicts
 - $F=[10] \wedge F=12$ $\{M1, M2, A1\}, \{M1, M3, A1, A2\}$



IDENTIFY CONFLICTS

- Polybox (minimal) conflicts
 - $F=[10] \wedge F=12$ $\{M1, M2, A1\}, \{M1, M3, A1, A2\}$
 - $X=6 \wedge X=4$ $\{M1, M2, A1\}, \{M1, M3, A1, A2\}$
 - $Y=6 \wedge Y=4$ $\{M1, M2, A1\}, \{M1, M3, A1, A2\}$
 - $Z=6 \wedge Z=8$ $\{M1, M3, A1, A2\}$
 - $G=[12] \wedge G=10$ $\{M1, M3, A1, A2\}$
- By definition, any superset of a conflict set is a conflict
 - $\{M1, M2, A1\} \subset \{M1, M2, A1, A2\} \subset \{M1, M2, M3, A1, A2\}$
- Minimal conflict: conflict no proper subset of which is a conflict
- It is essential to represent the conflicts through the set of minimal conflicts (to avoid combinatorial explosion)
- **At least one component in each conflict must be faulty!!!**

CONFLICTS GENERATION WITH ATMS

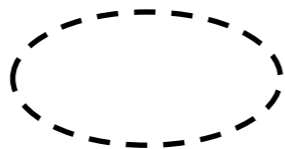
1. The problem solver performs inferences
2. The Assumption-based Truth Maintenance System (ATMS) records the dependencies between inferences
 - Introduce observations as facts
 - Support each local propagation with a correctness assumption for the component
 - Label of a node: (minimal) environments that entails the prediction
 - Records components that support prediction
 - Avoids recomputation
 - Symptoms: produce NOGOODS

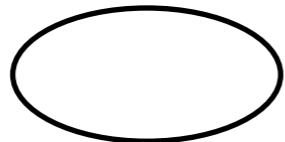
NOGOODS are the MINIMAL CONFLICTS

INFERENCE RECORDING VIA ATMS

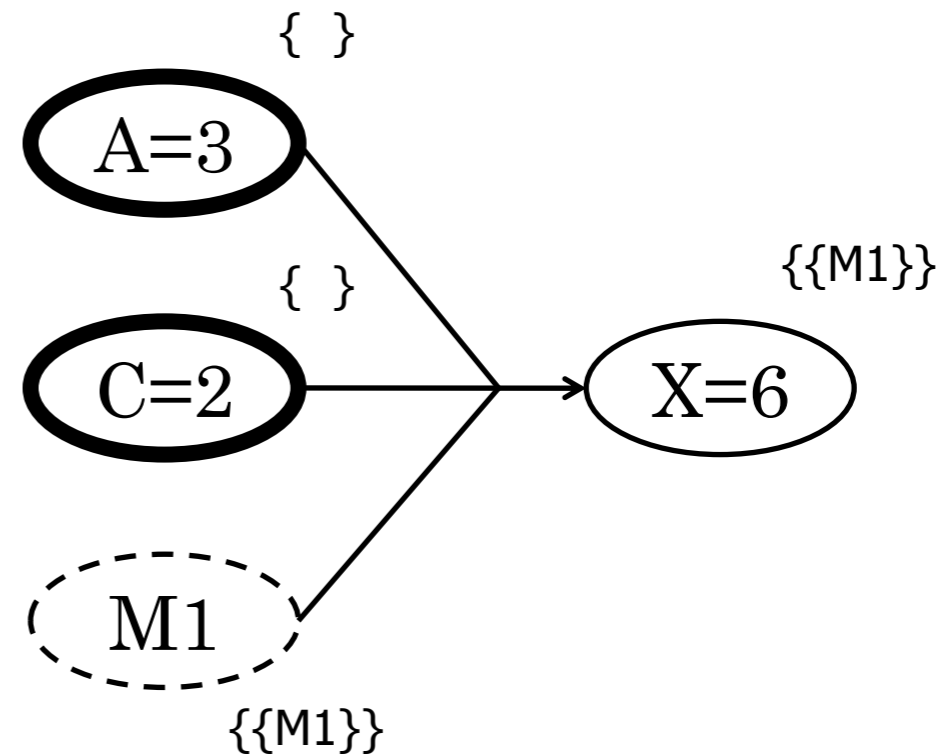
- Graphical representation ATMS nodes

- Facts 

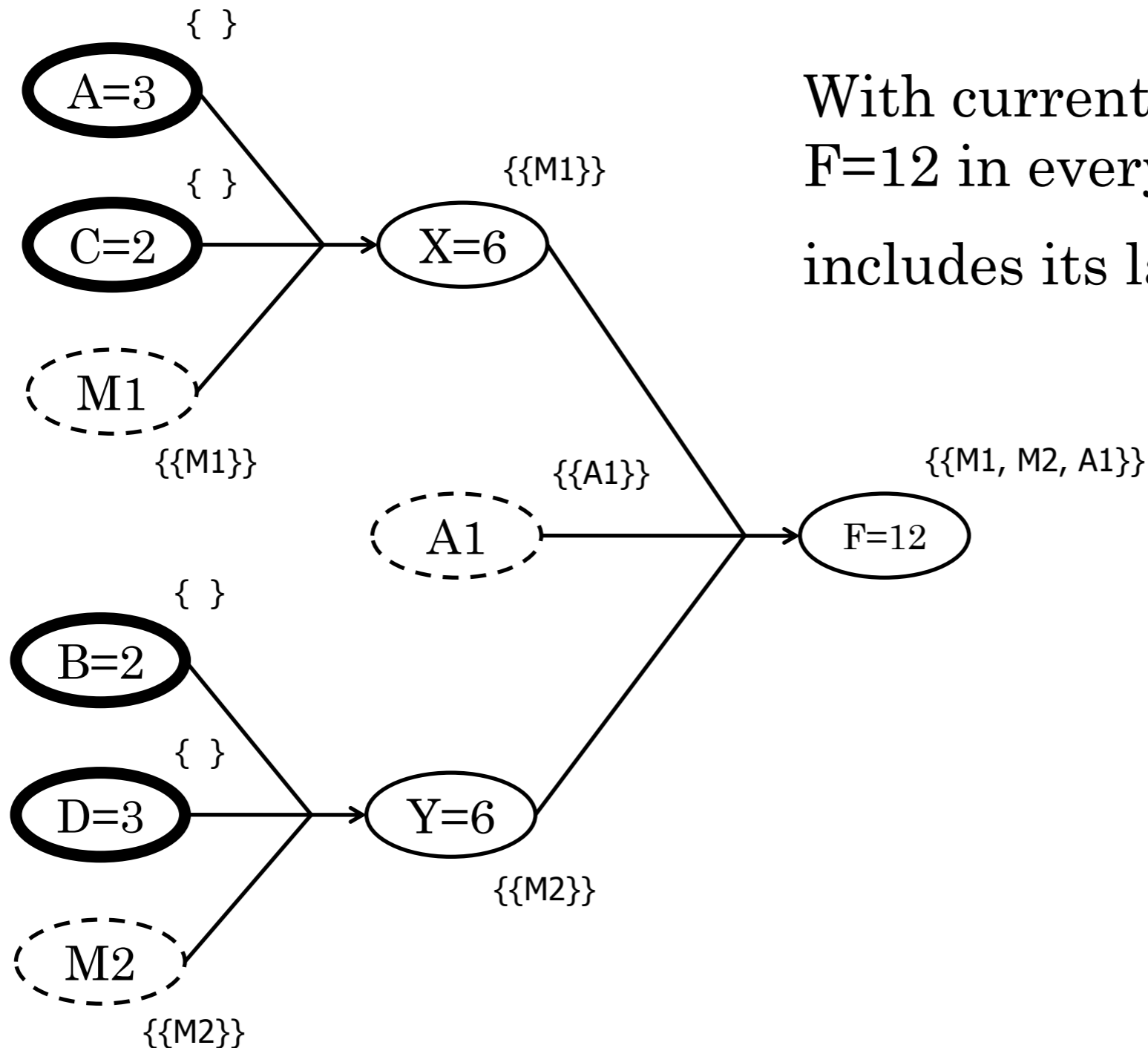
- Assumed node 

- Derived node 

- Inference recording if $A=3$, $C=2$ and $M1$ OK, $X=6$

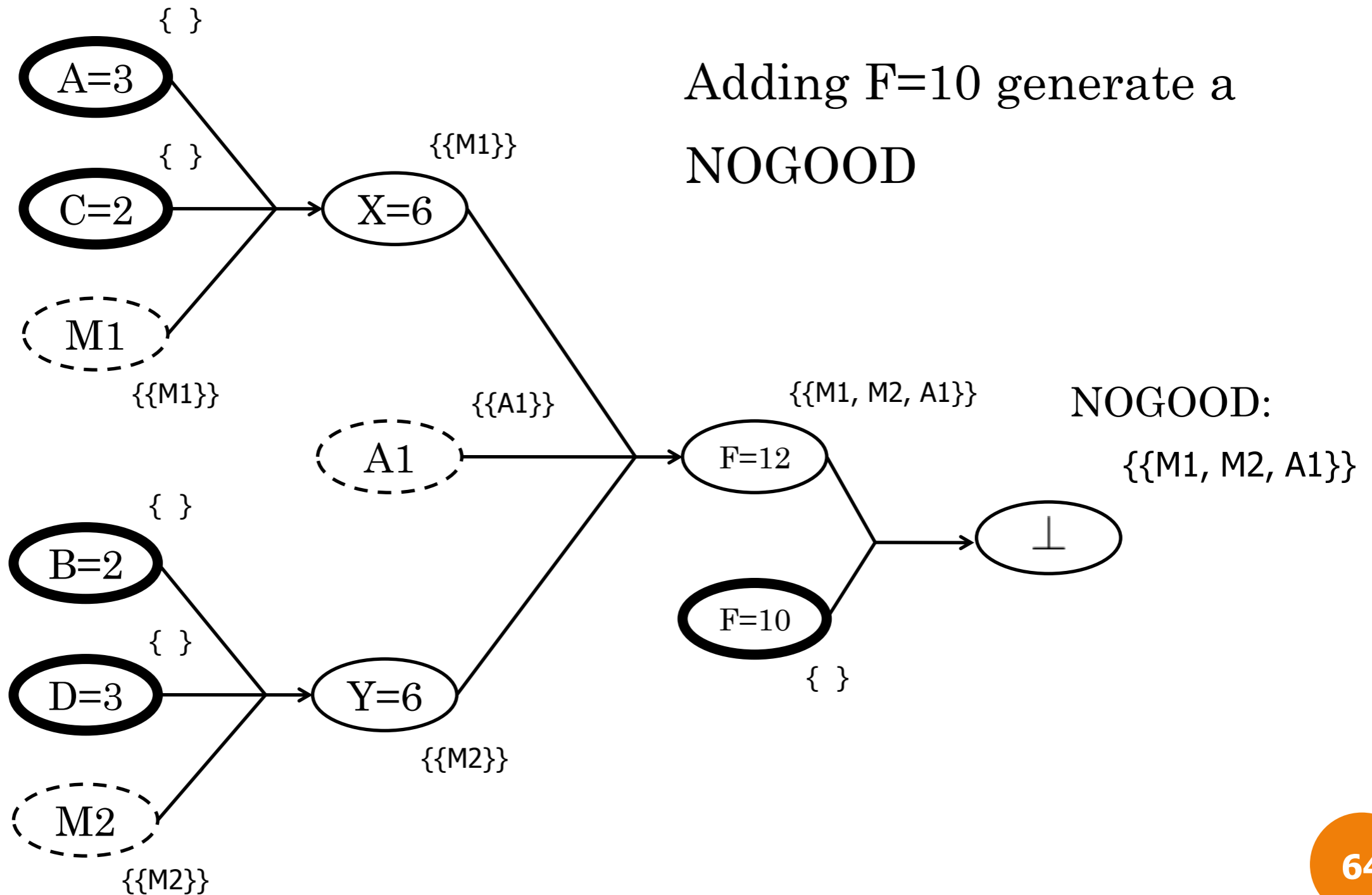


INFERENCE RECORDING VIA ATMS

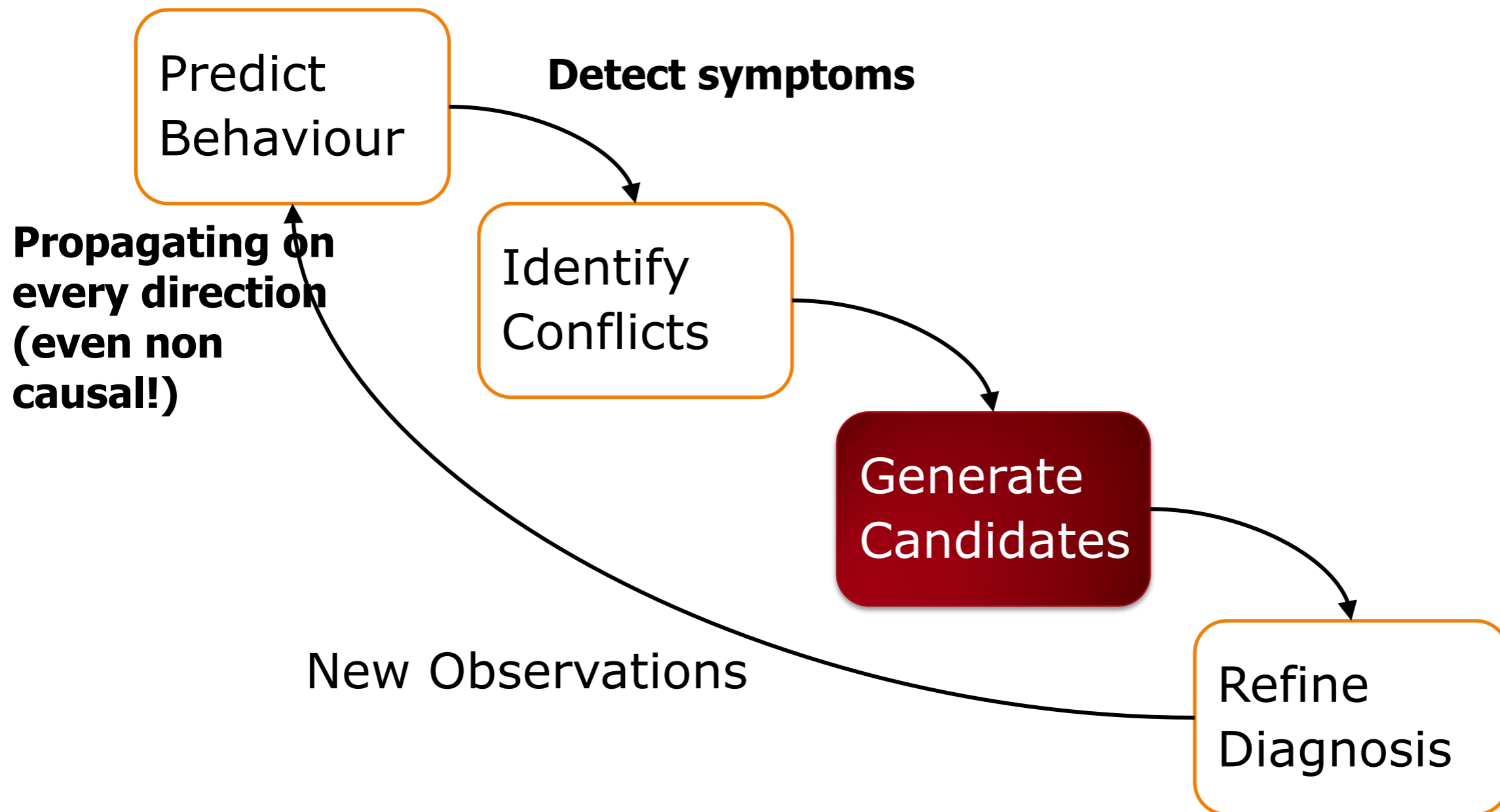


With current observations, $F=12$ in every context which includes its label: $\{M1, M2, A1\}$

INFERENCE RECORDING VIA ATMS



GDE: THE COMPUTATIONAL PARADIGM FOR CONSISTENCY-BASED DIAGNOSIS



CANDIDATES

- Candidate: hypothesis of how the device differs from model
 - Represented as a set of assumptions
 - Assumptions included: faulty
 - Assumptions not included: correct

Candidate example: {M2, A2}

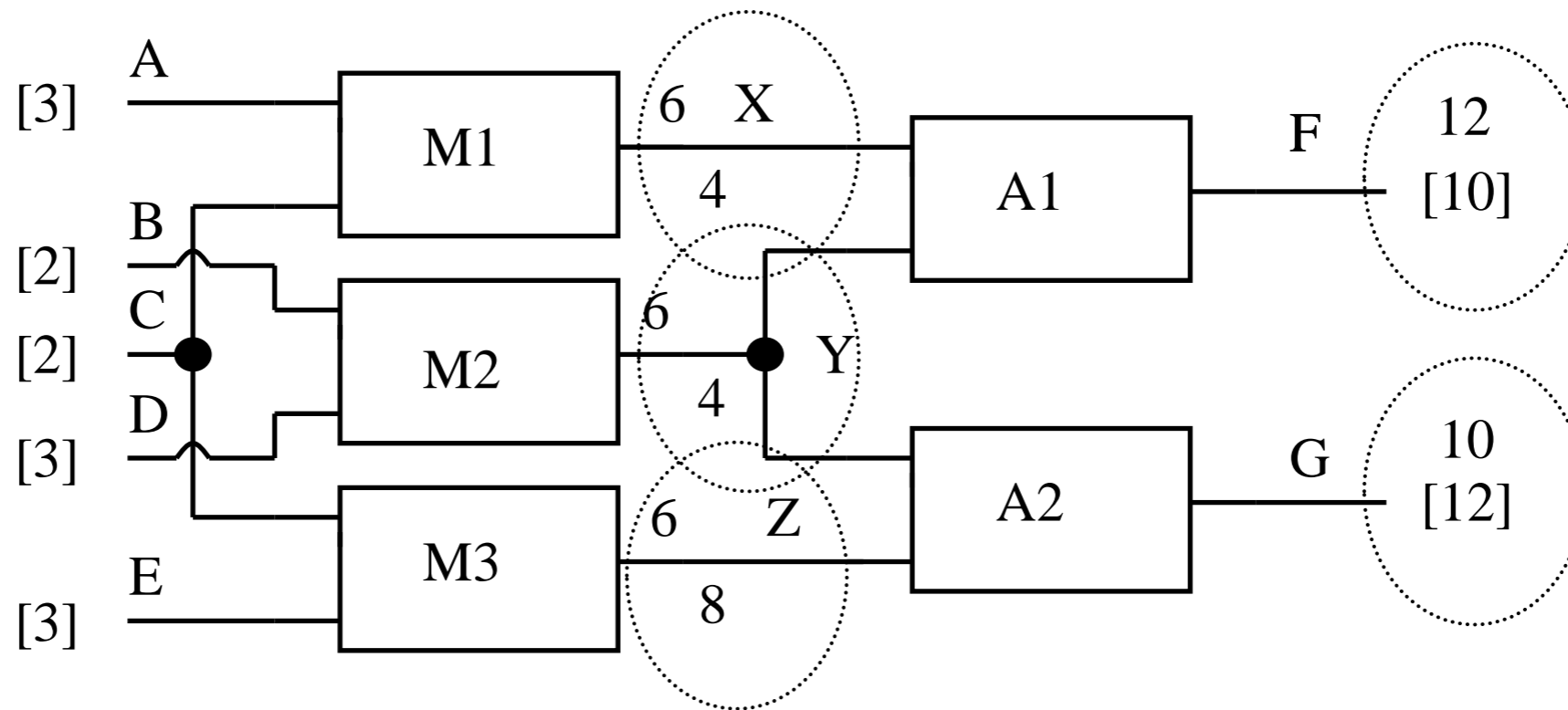
Meaning: M2, A2 are faulty
M1, M3, A1 are correct

- Diagnosis: identify every candidate consistent with observations

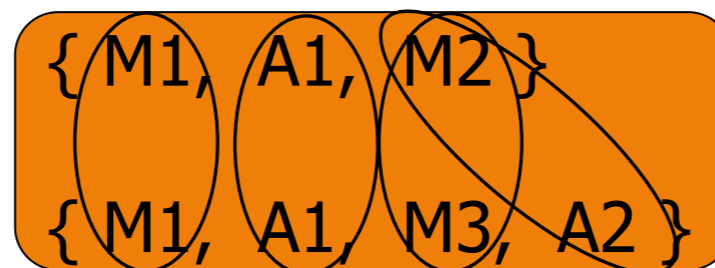
CANDIDATE GENERATION

- Since at least one component in each conflict must be faulty
- Each candidate has to account for all conflicts
- Each candidate has to retract at least one correctness assumption out of each conflict
- Construct candidates as Hitting Set of (minimal) conflicts
 - C_a candidate, C_i conflict, $C_a \cap C_i \neq \emptyset \forall C_i$
 - $\forall C_a, C_a \subset \cup_i C_i$
- Each superset of a candidate is also a candidate:
Minimal candidates: minimal hitting set of minimal conflicts

CANDIDATE GENERATION EXAMPLE



- Minimal conflicts



- Minimal candidates





CBD USING GDE

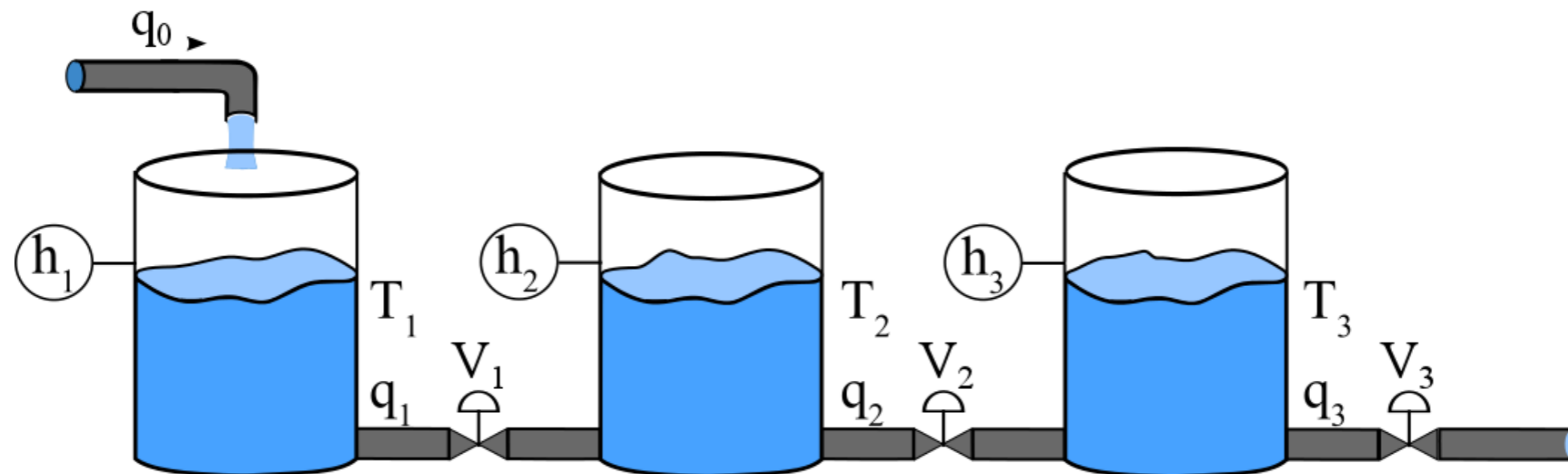
SUMMARY

- It is based just on correct behavior models
 - No fault models are needed for fault isolation
 - Fault isolation is straightforward
- Conflict calculation at run time, by means of a dependency recording engine (ATMS)
- Diagnosis candidates computed as the minimal hitting set of minimal conflicts
- Minimal conflicts and minimal diagnosis usually avoid exponential time and space
- **Defined for static systems, discrete-valued models, but is ready for real-life, complex systems?**

CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

- Let's consider a three-tank system



- It has a set of related components like the polybox
 - We are measuring the level in the tanks

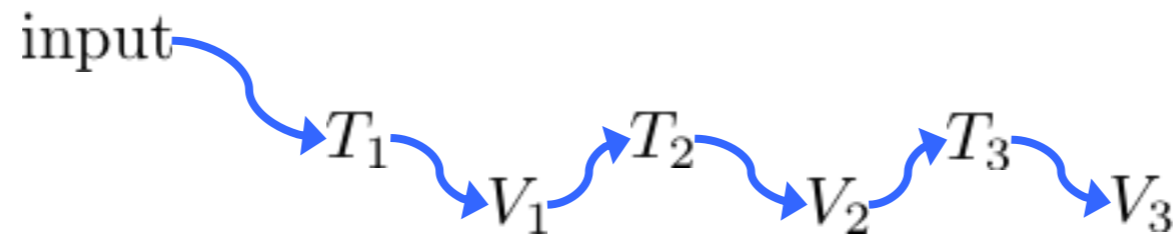
CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

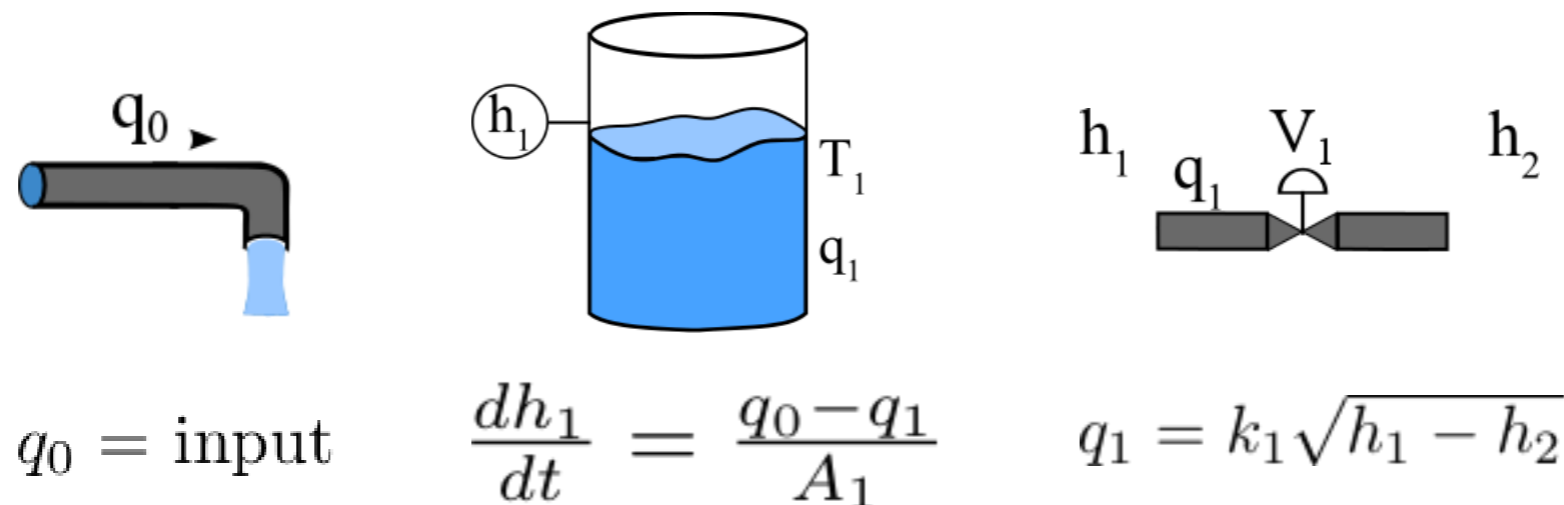
- Step 1: predict behavior

- Modeling structure

- Relations between tanks, pipes/valves, and sensors as seen in the previous slide



- Modeling component behaviour



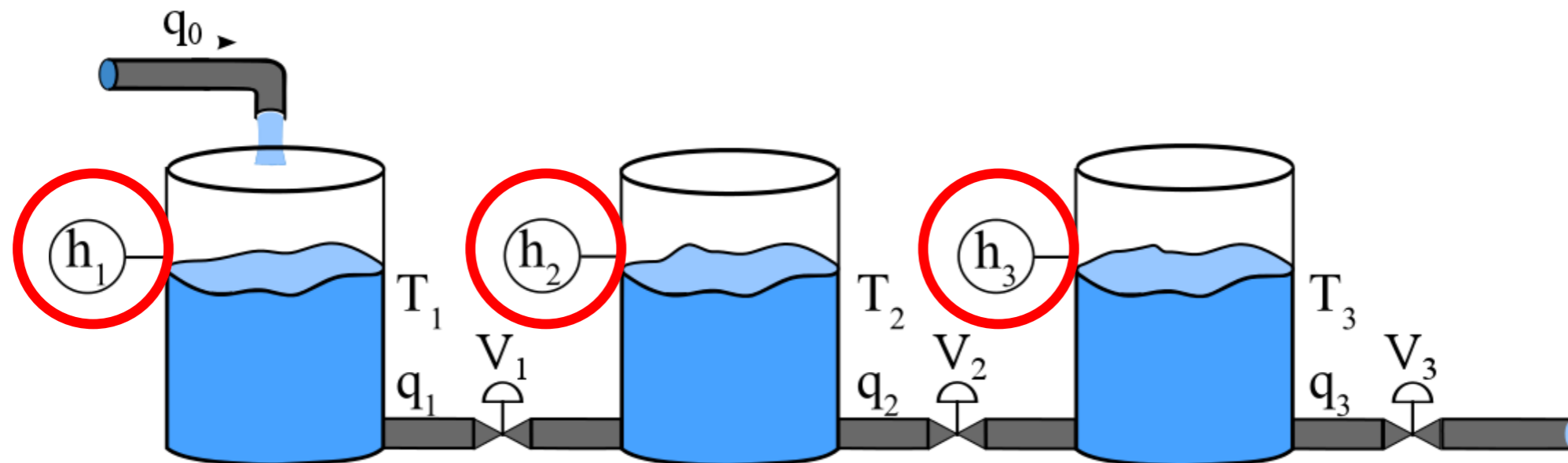
- Predict overall behavior

- Local propagation

CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

- Step 2: detect symptoms

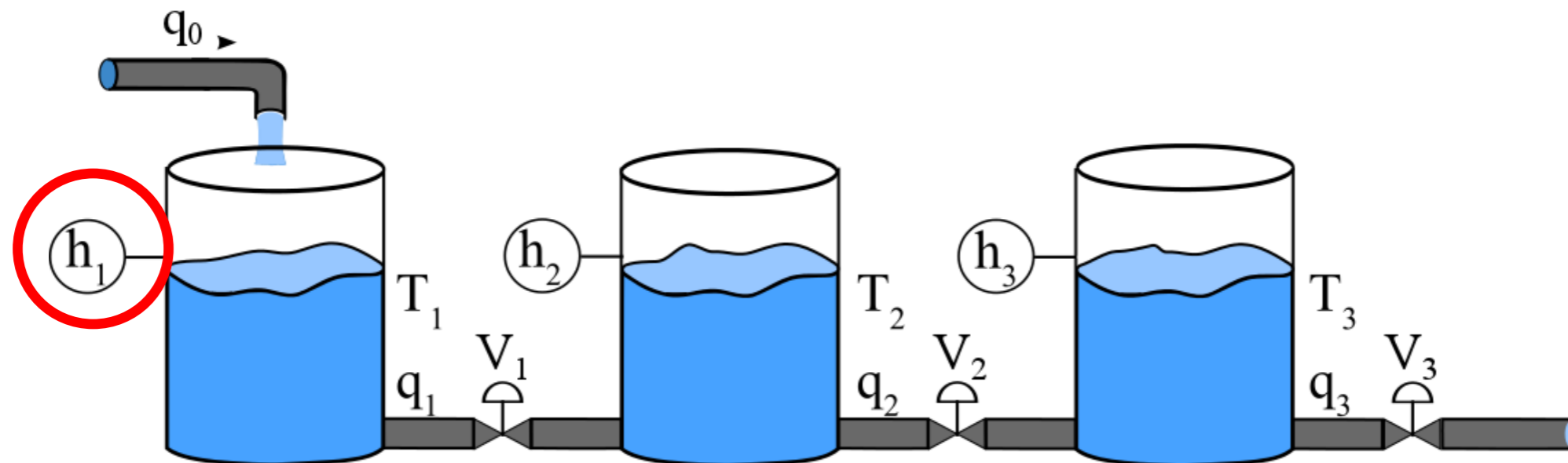


- Differences between sensor measurements and estimations

CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

- Step 3: identify conflicts

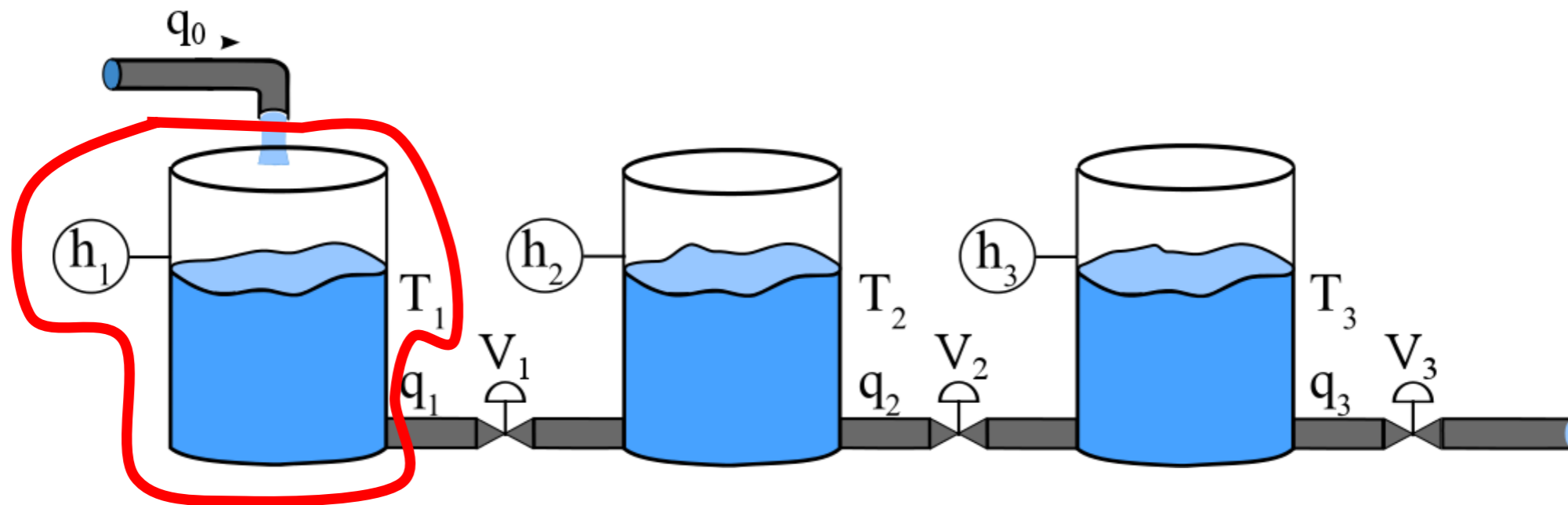


- Let's assume we see a discrepancy in the measurement h_1

CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

- Step 3: identify conflicts



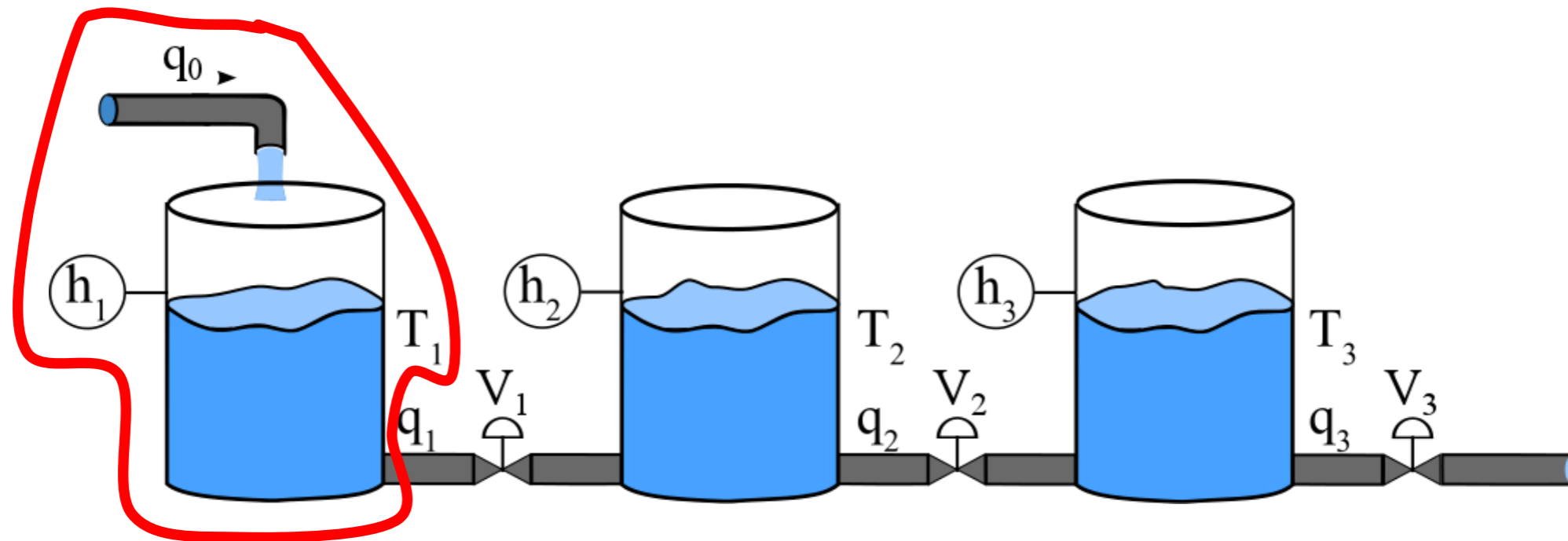
$$\frac{dh_1}{dt} = \frac{q_0 - q_1}{A_1}$$

{{T₁}}

CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

- Step 3: identify conflicts



$$\frac{dh_1}{dt} = \frac{q_0 - q_1}{A_1}$$

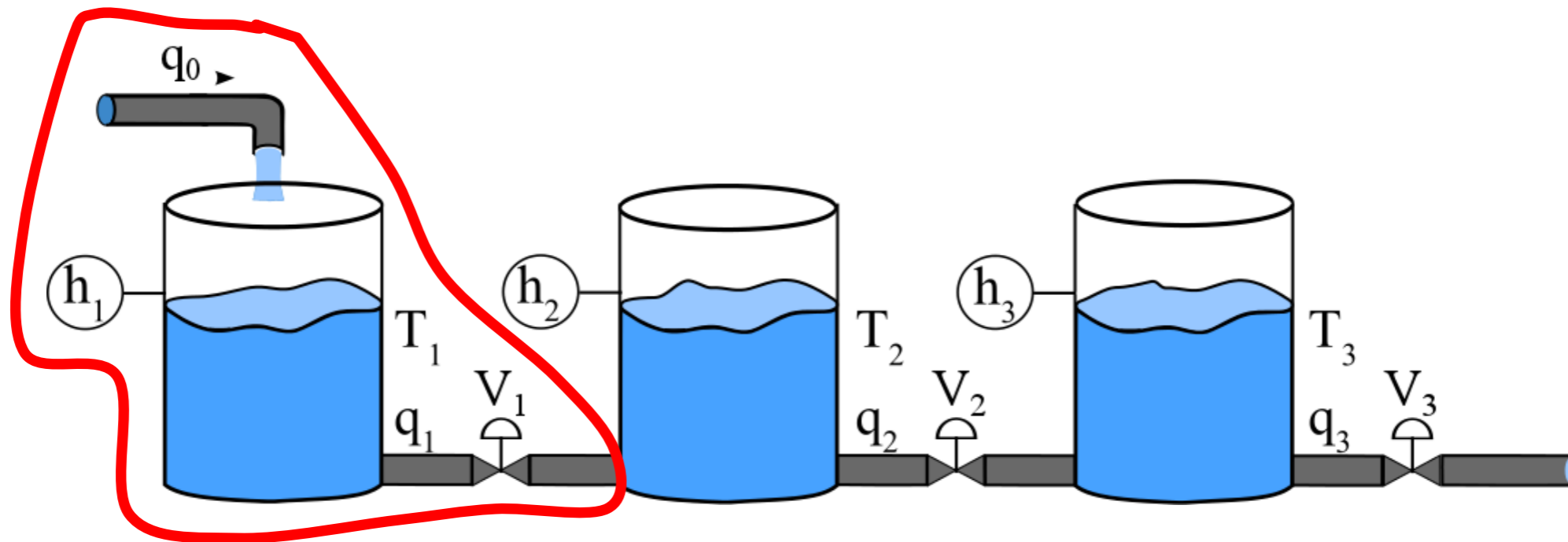
$q_0 = \text{input}$

{{T₁}}

CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

- Step 3: identify conflicts



$$\frac{dh_1}{dt} = \frac{q_0 - q_1}{A_1}$$

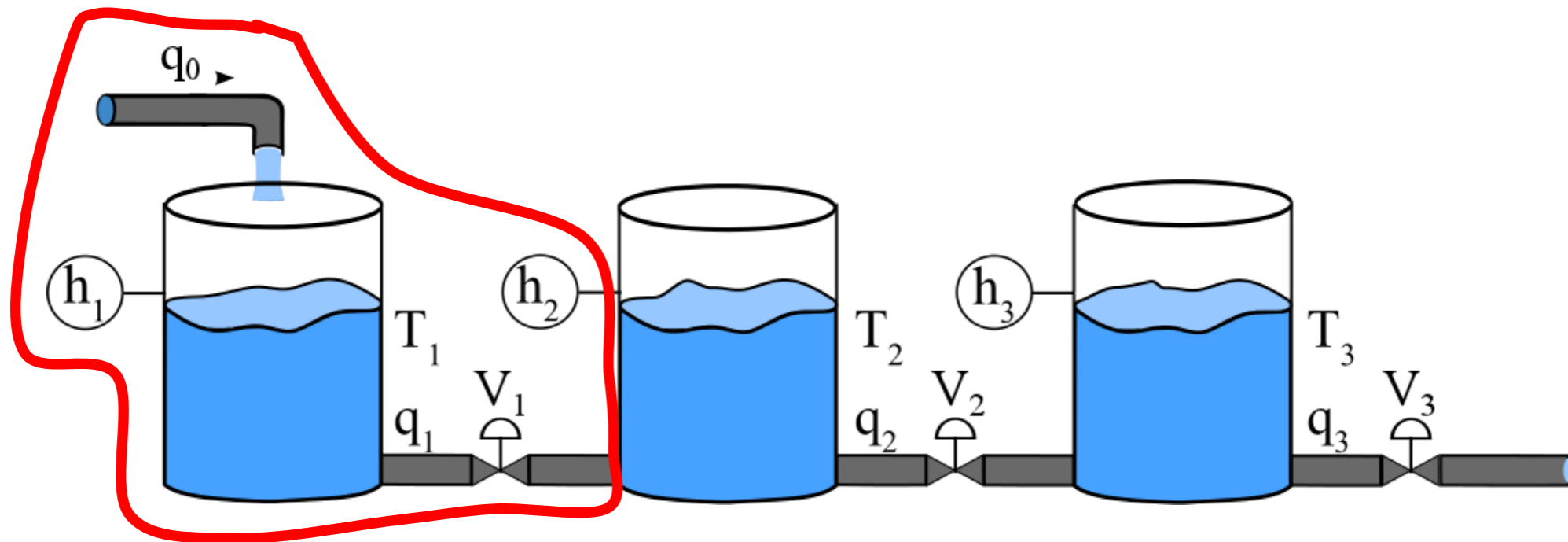
$q_0 = \text{input}$
 $q_1 = k_1 \sqrt{h_1 - h_2}$

{{T₁}}
{{T₁, V₁}}

CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

- Step 3: identify conflicts



$$\frac{dh_1}{dt} = \frac{q_0 - q_1}{A_1}$$

$q_0 = \text{input}$
 $q_1 = k_1 \sqrt{h_1 - h_2}$

{{T₁}}
{{T₁, V₁}}

h₂ is measured!!!

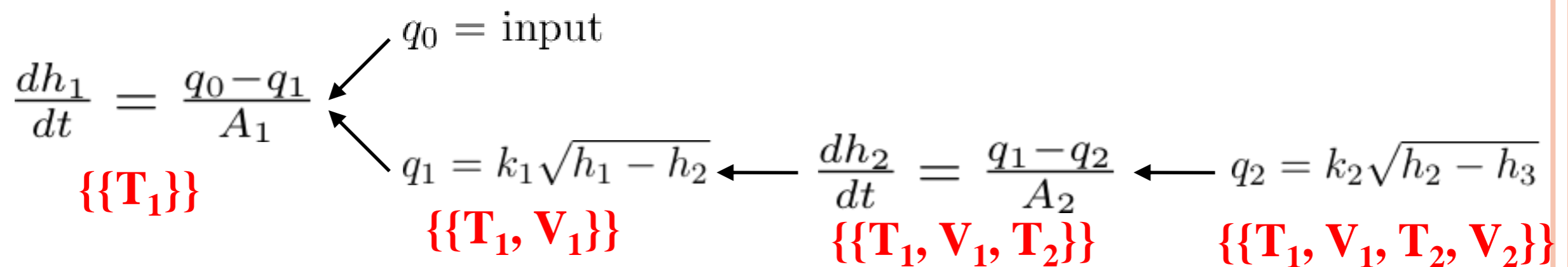
CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

- Step 3: identify conflicts

- $\{\{T_1, V_1\}\}$ is a conflict

- However, GDE has to consider all possible propagations, e.g., h_2 can also be computed from $\frac{dh_2}{dt} = \frac{q_1 - q_2}{A_2}$



$$\{\{T_1, V_1\}\} \subset \{\{T_1, V_1, T_2, V_2\}\}$$

- After doing all possible propagations: $\{\{T_1, V_1\}\}$ is the minimal conflict



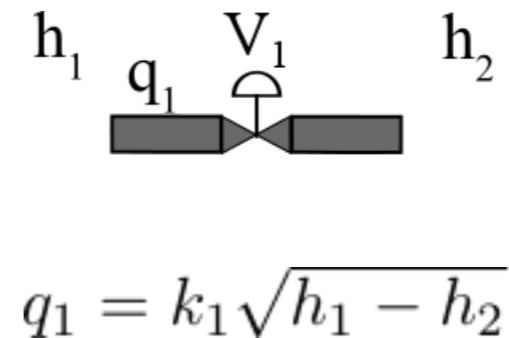
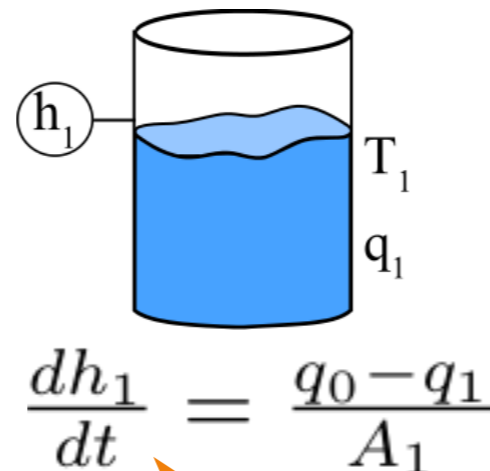
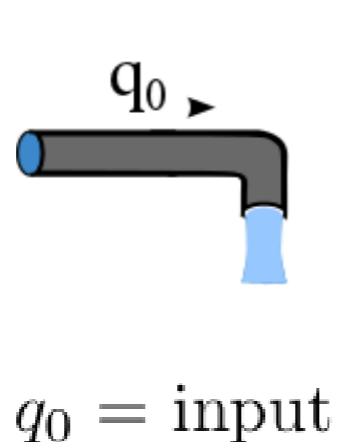
CBD USING GDE

A MORE COMPLEX REAL-LIFE SYSTEM

- Step 4: Candidate generation
 - Minimal candidates: $[T_1]$, $[V_1]$

MAIN DIFFICULTIES FOR CONTINUOUS DYNAMIC SYSTEMS

- Inclusion of time in the models
 - There is no general extension for dynamic systems and Reiter's theory
 - Not obvious how to model continuous systems in a component-based approach
 - Current estimations depend on current and past



$$h_1 = \int dh_1 \cdot dt$$

How is this computed???

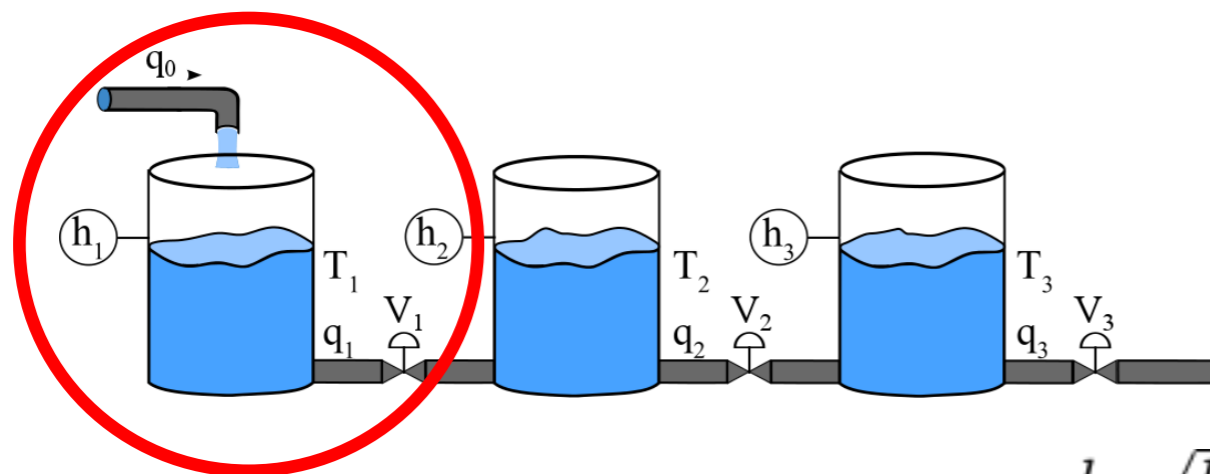
MAIN DIFFICULTIES FOR CONTINUOUS DYNAMIC SYSTEMS

On-line simulation

- Very demanding for continuous dynamic systems, especially if
 - Local models
 - Local propagation (which may easily stop!)

On-line dependency recording: difficulties

- Very demanding on memory terms



Label registered with real values + time

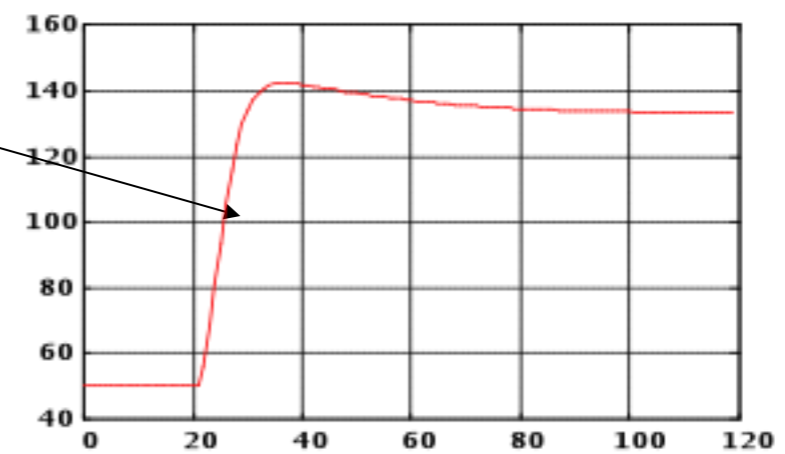
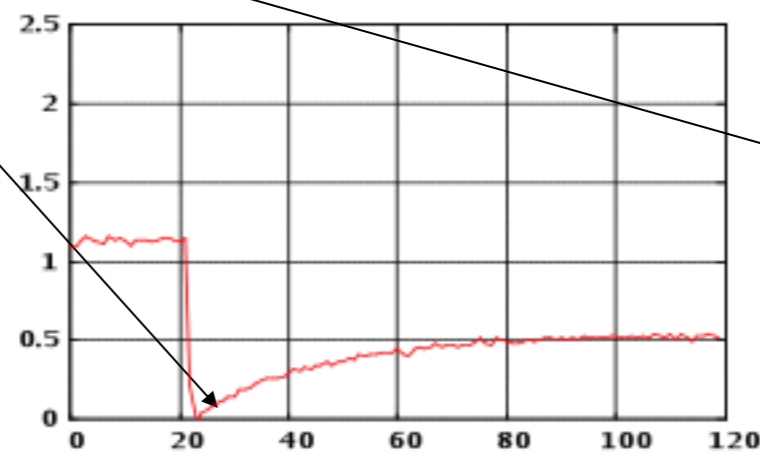
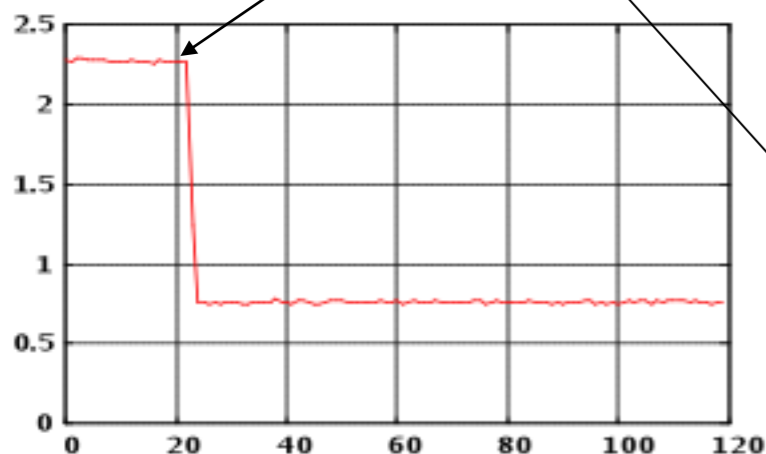
$$\frac{dh_1}{dt} = \frac{q_0 - q_1}{A_1}$$

$q_1 = k_1 \sqrt{h_1 - h_2}$
 $\{\{T_1, V_1\}\}$
 $q_0 = \text{input}$
 $\{\{T_1\}\}$

MAIN DIFFICULTIES FOR CONTINUOUS DYNAMIC SYSTEMS

- Conflict generation
 - Consistency-check is not trivial:
 - Dynamic systems may exhibit considerable delays
 - We need incremental diagnosis
 - How we can discriminate between faults?

Different symptom activation times





INCLUSION OF TEMPORAL
INFORMATION WITHIN CBD

INCLUSION OF TEMPORAL INFORMATION IN THE DX MODELS: EARLY APPROACHES (SURVEY)

- Several extensions proposed for GDE
 - DEDALE (Dague et al. 1987) → CATS (Dague et al. 1990) → DOGS (Taillibert & Loiez, 1997)
 - Inclusion of temporal indices for values
 - MIMIC (Dvorak & Kuipers, 1990)
 - Qualitative values with different time stamps
 - SIDIA (Guckenbiehl & Shaffer-Richter, 1990), MUDIA
 - Improves GDE with values over intervals
 - Magellan-MT (Dressler et al., 1994)
 - Avoid qualitative simulation

CONSISTENCY-BASED DIAGNOSIS

SOME SOLUTIONS

- Topological methods
 - On-line backward search through a causal or functional structure
 - estimation = propagation through causal/functional structure
 - consistency check (of qualitative values)
 - if a discrepancy is found: propagation backward: where is the source of inconsistency?
 - **Off-line dependency-recording (i.e. compilation) techniques**
 - System Description = Structural and Behavioural Information
 - Most of the times topology is fixed
 - Set of available observations is fixed and known beforehand
 - Is possible to propagate values/energy through every path?
 - No, if no structural faults are present

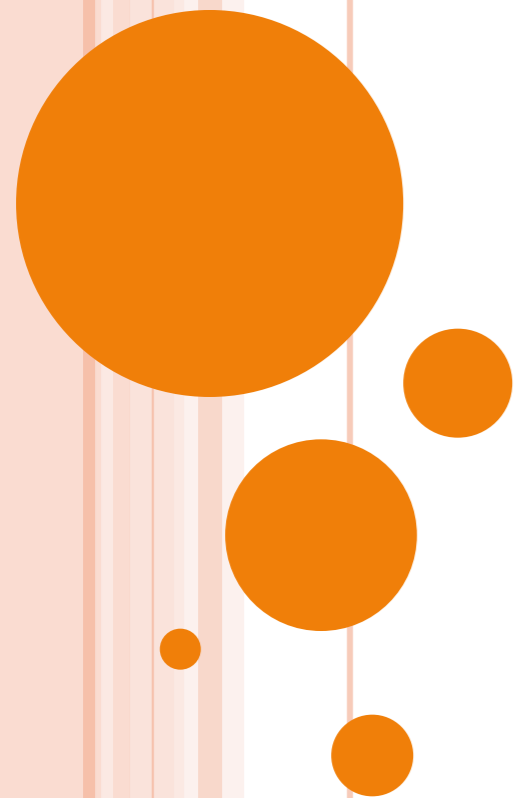
ON-LINE FORWARD PROPAGATION AND BACKWARD SEARCH (SURVEY)

- On-line backward search through a causal or functional structure:
 - CAEN (Bousson & Travé-Massuyès, 92),
 - causal graphs, influences,...
 - DYNAMIS (Chittaro et al., 1996),
 - Topological + behavioural + functional (and teleological) models
 - TRANSCEND (Mosterman & Biswas, 1997; 1999)
 - Fault detection using state-observers: provide qualitative signatures
 - Temporal causal graphs from bond-graphs (continuous & discrete behaviour → hybrid systems)



OFF-LINE DEPENDENCY-RECORDING (I.E. COMPILATION) TECHNIQUES (SURVEY)

- FDI community:
 - Staroswiecki and Declerk 1989, Staroswiecki et al., 1997
 - Lunze and Schiller, 1992
 - Nyberg, 2001, 2008
 - Ploix, 2001, 2003, 2005
 - Blanke, 2003, 2006
- AI / DX community:
 - DOGS (Loiez & Taillibert, 1997)
 - DRUM-II (Frölich & Nejd, 1997)
 - Washio et al., 1997
 - Ligeza and Gorny, 2000
 - **PCs (Pulido and Alonso, 1999, 2004 / Bregon et al. 2009, 2014)**
- BRIDGE (FDI & AI communities)
 - Cordier et al. 2000; 2004
 - BRIDGE task group within MONET2
 - IEEE TSMC Part B, Special Issue on Bridge, 2004



POSSIBLE CONFLICTS

A compilation technique for CBD



POSSIBLE CONFLICTS

Motivation:

- How Consistency-based Diagnosis can be applied to **continuous dynamic systems** without on-line dependency-recording
- Following GDE-like computational approach

POSSIBLE CONFLICTS

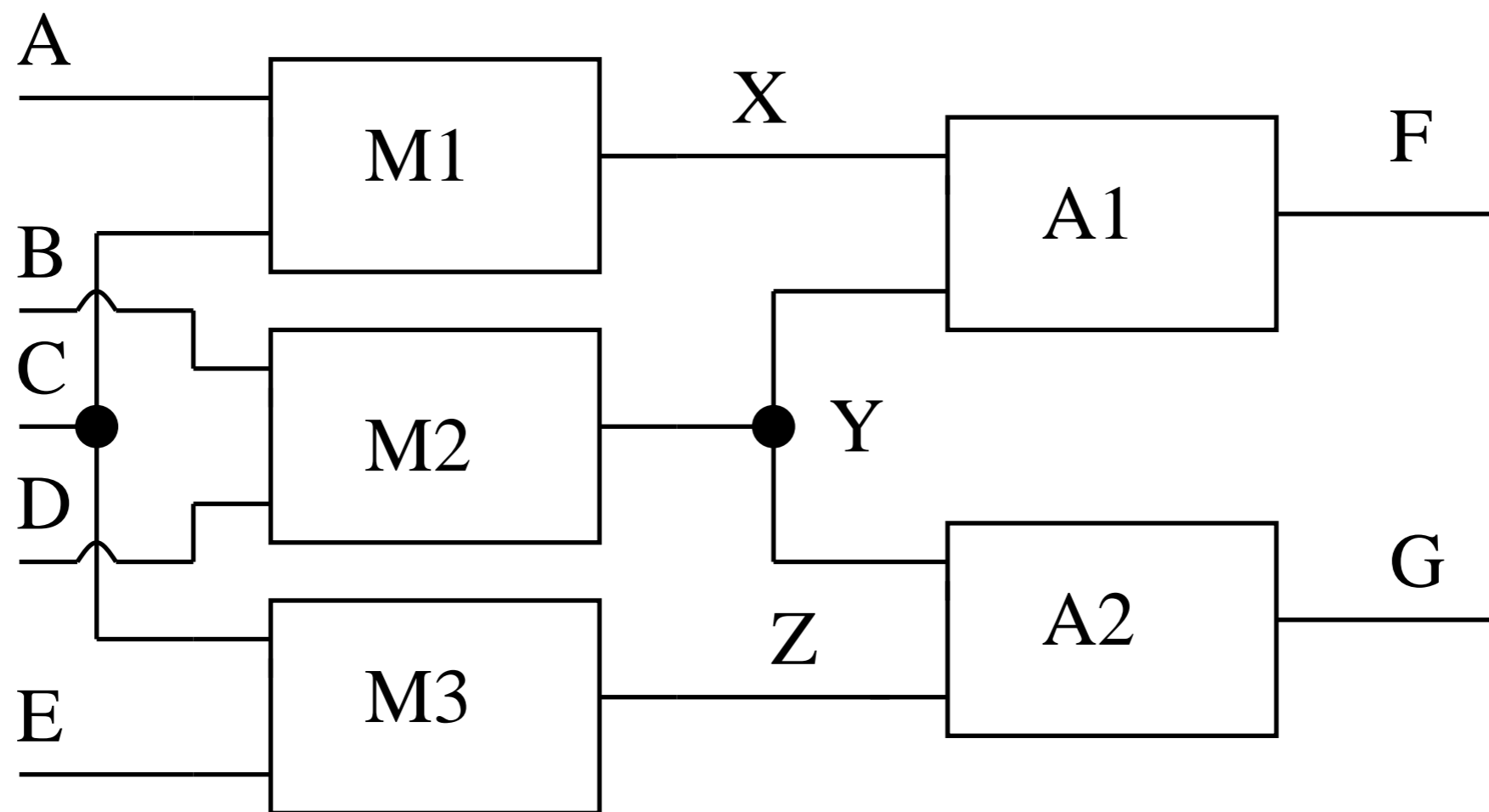
(PULIDO AND ALONSO, 1999; 2004)

- Dependency-Compilation technique
 - **In industrial environments the set of available measurements is known and fixed beforehand**
 - Main ideas
 - Not every sub-system in SD can be a conflict
 - A minimal conflict is a strictly over-determined set of constraints
 - It can be solved using local propagation
- we will compute the set of (minimal) over-determined systems **off-line!!!**

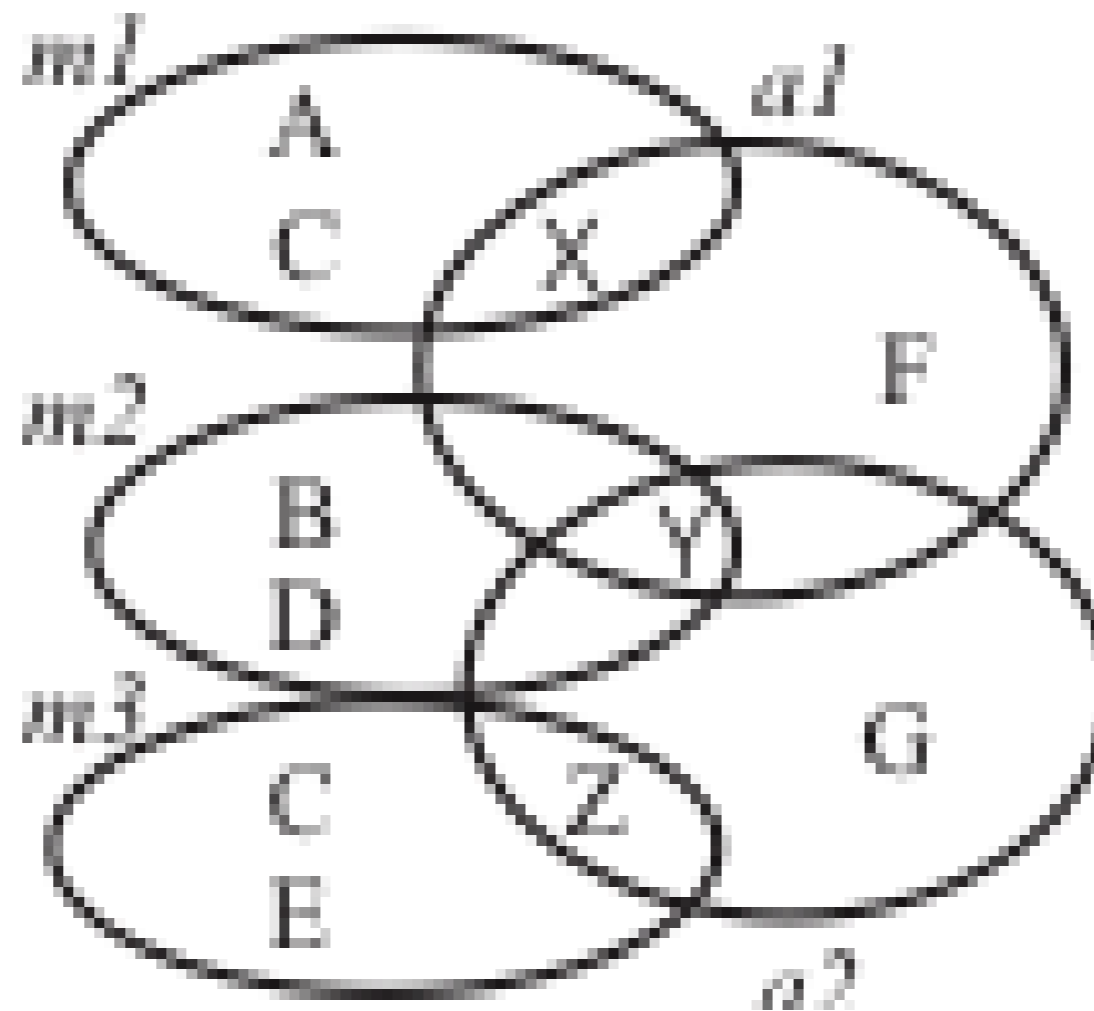
POSSIBLE CONFLICTS COMPUTATION

- Computing Possible Conflicts:
 - Generate an abstract representation of system as a hypergraph (some extensions to use causal graphs, temporal causal graphs, and bond graphs)
 - Derive the minimal set of overdetermined subsystems (Minimal Evaluation Chains, MECs).
 - Equivalent to all MSO sets and all minimal ARR_s)
 - Generate Minimal Evaluation Models (MEMs) that are generated from MECs by introducing causality in the structural model. Obtain for each MEC all globally consistent causal assignments.

A CLASSICAL EXAMPLE REVISITED

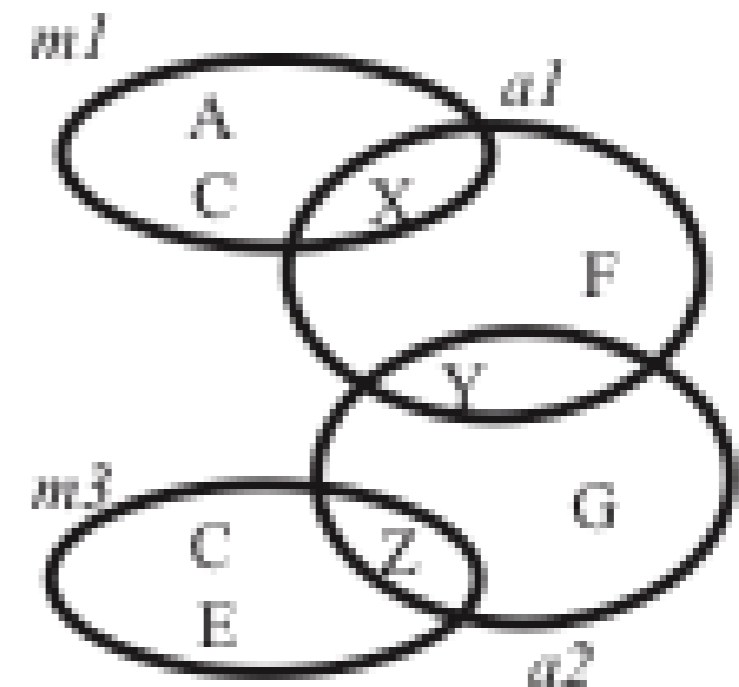
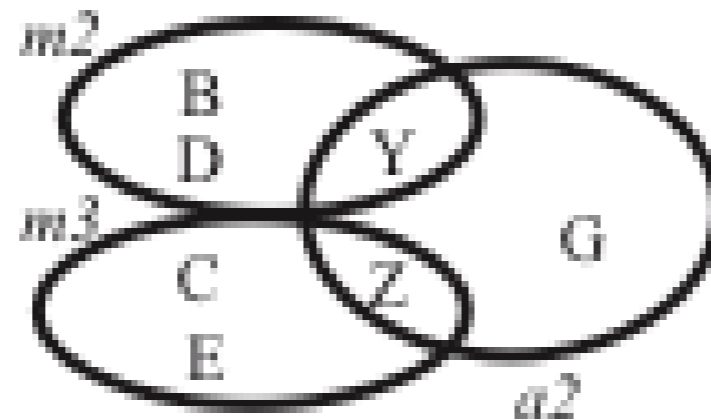
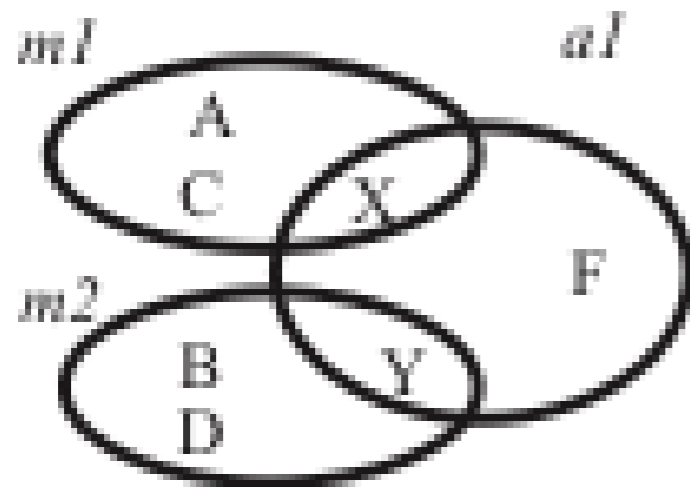


STEP 1: REPRESENTING SD AS AN HYPERGRAPH



STEP 2: SEARCHING FOR OVER-CONSTRAINED SUB-SYSTEMS

- Minimal evaluable chain, MEC:
 - Connected and strictly over-determined sub-systems
 - At least, one observation

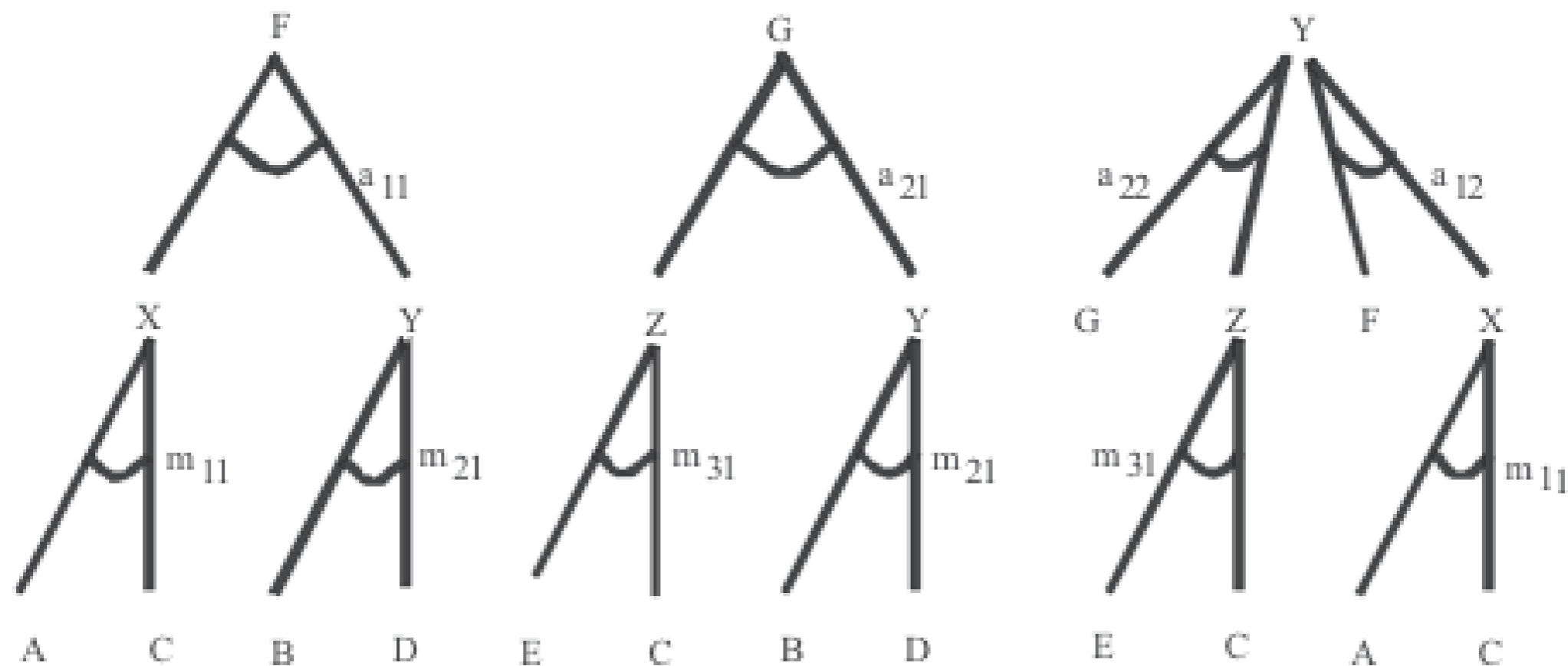


STEP 3: CAN THE MEC BE SOLVED USING LOCAL PROPAGATION?

- Each hyper-arc in a MEC can be solved in different ways
- Each MEC generates an and-or graph
- In the and-or graph zero, one or more Minimal Evaluation Models, MEM, can be found:
 - Predictions are done from observations
 - Only local propagation is used
 - A possible discrepancy is found:
 - If an observed variable is predicted once
 - If a non-observed variable is predicted twice

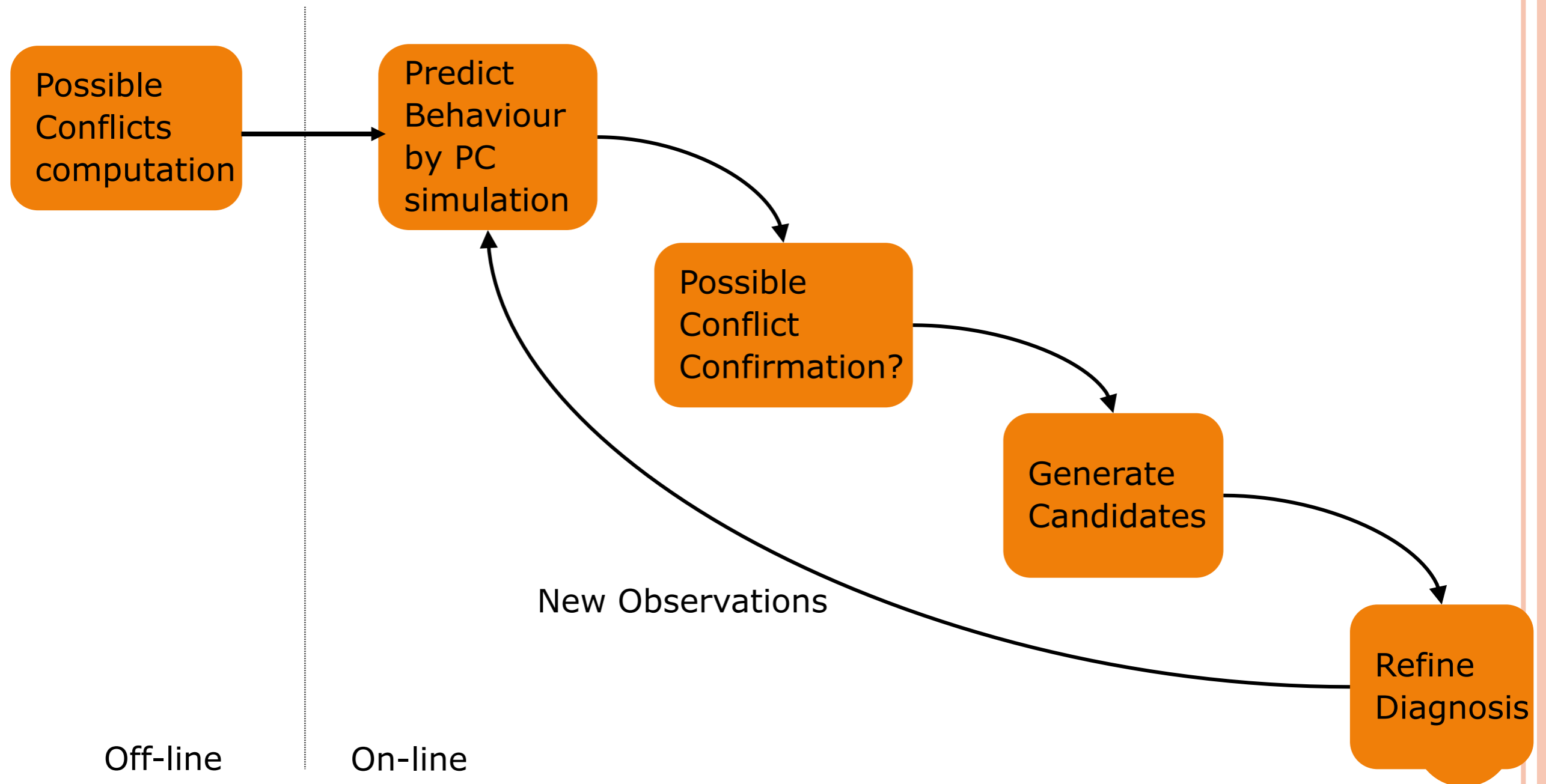
STEP 3: CAN THE MEC BE SOLVED USING LOCAL PROPAGATION?

- MEMs are not evaluated off-line \rightarrow provide a model for simulation \rightarrow fault detection is on-line
- What is a possible conflict? Set of relations in a MEC containing, at least, one MEM





CONSISTENCY-BASED DIAGNOSIS WITH POSSIBLE CONFLICTS



INCLUSION OF TEMPORAL INFORMATION

- Differential constraints (Dressler et al. 1996; Chantler et al., 1996)

$$(x_i, dx_i/dt)$$

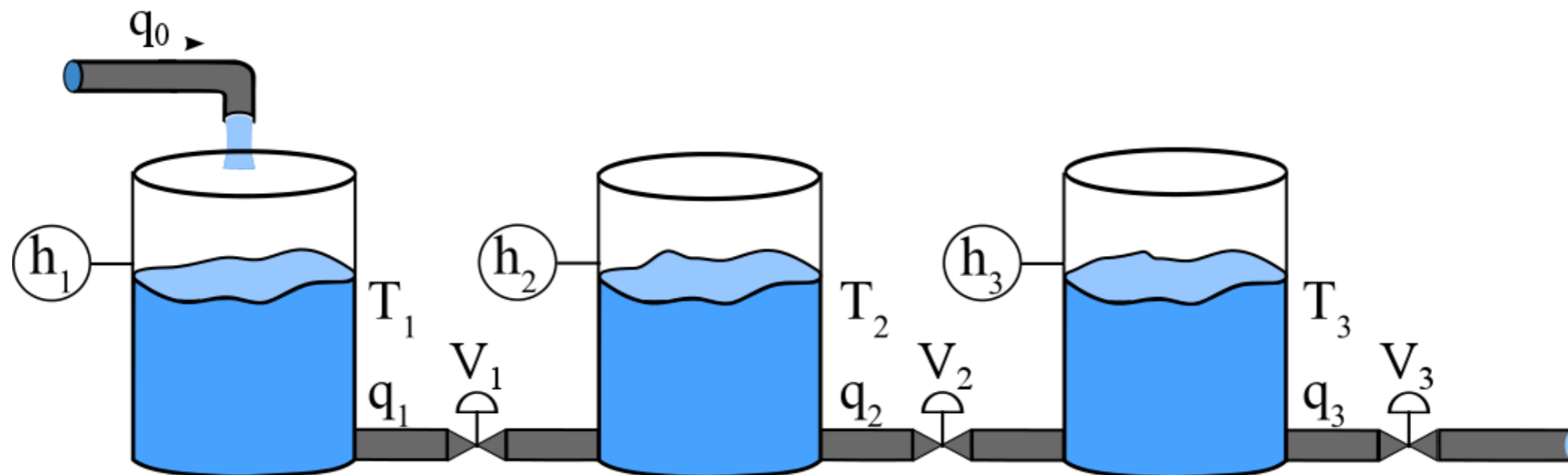
- Interpretations (propagations through differential constraints)
 - Integral $(x_i \leftarrow dx_i/dt)$
 - Derivative $(x_i \rightarrow dx_i/dt)$
- Extension of hypergraph and hyperarc definitions



- PCs can be computed with either integral or derivative causality

AN EXAMPLE: THREE-TANK SYSTEM

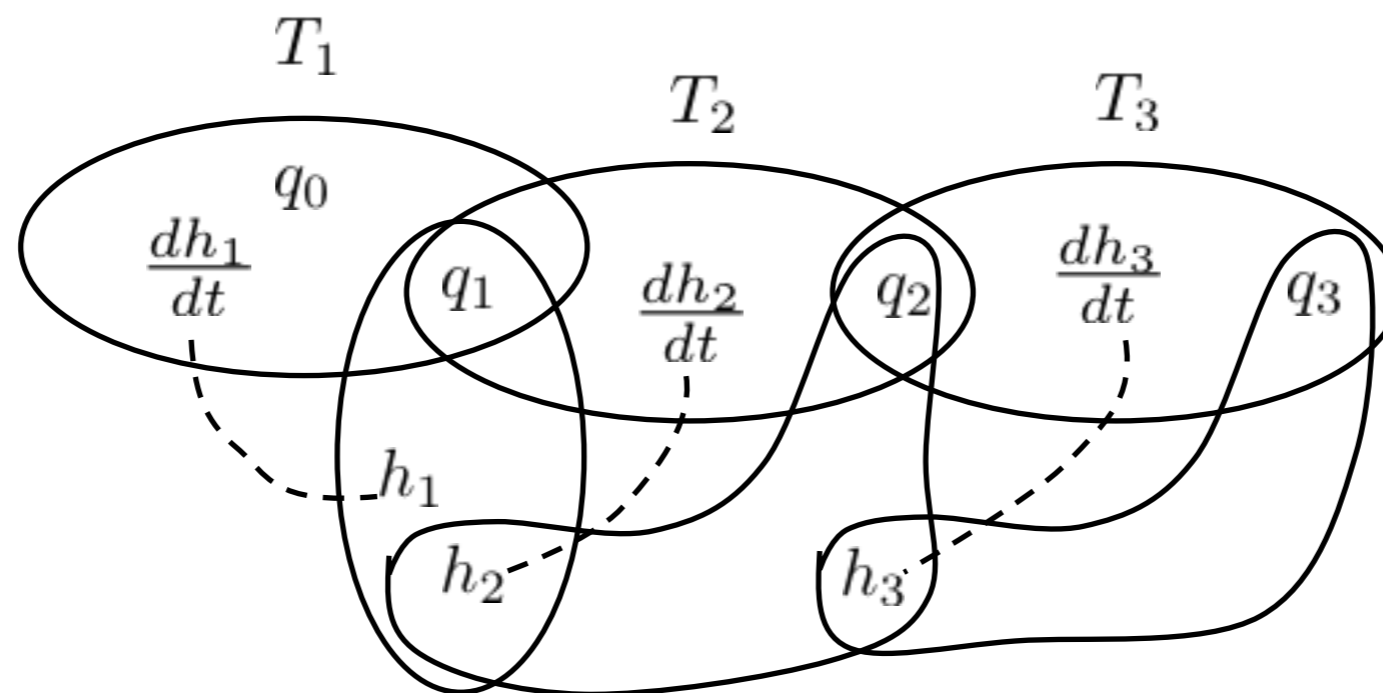
- Let's consider again the three-tank system



- Which are the Possible Conflicts for this system?

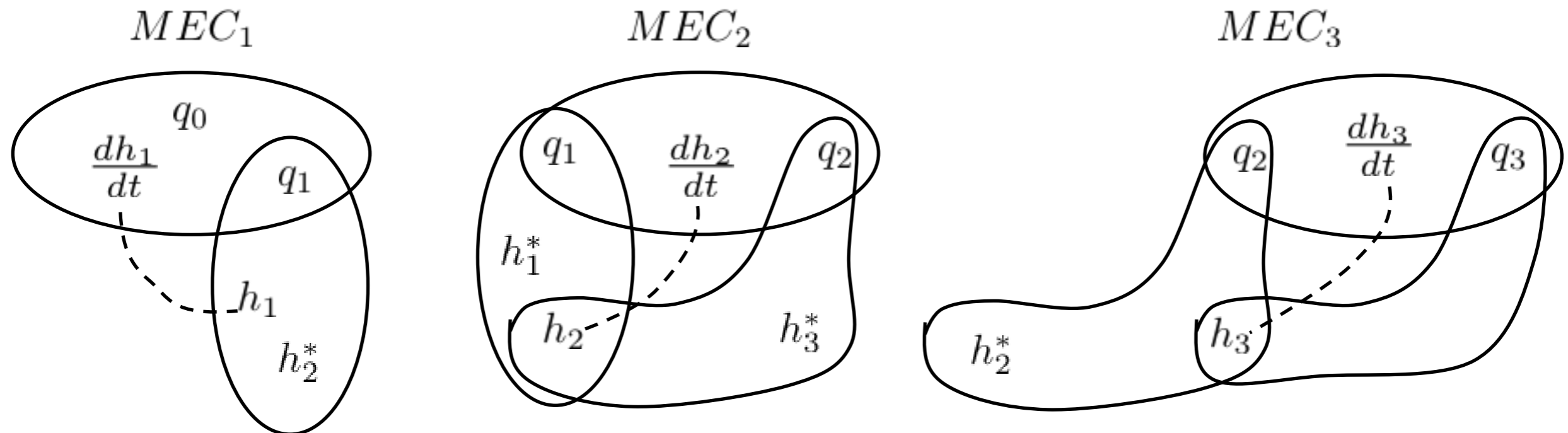
AN EXAMPLE: THREE-TANK SYSTEM

- Step 1 - System as a hypergraph



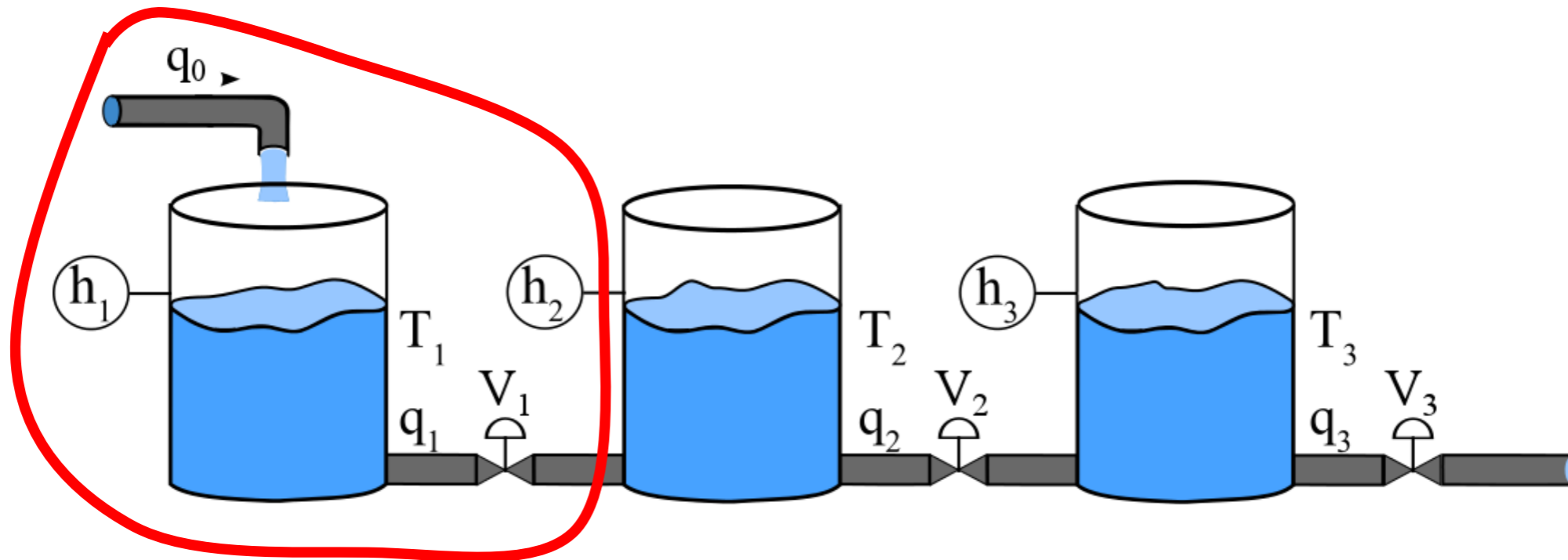
AN EXAMPLE: THREE-TANK SYSTEM

- Step 2 - Minimal Evaluation Chains - MECs



AN EXAMPLE: THREE-TANK SYSTEM

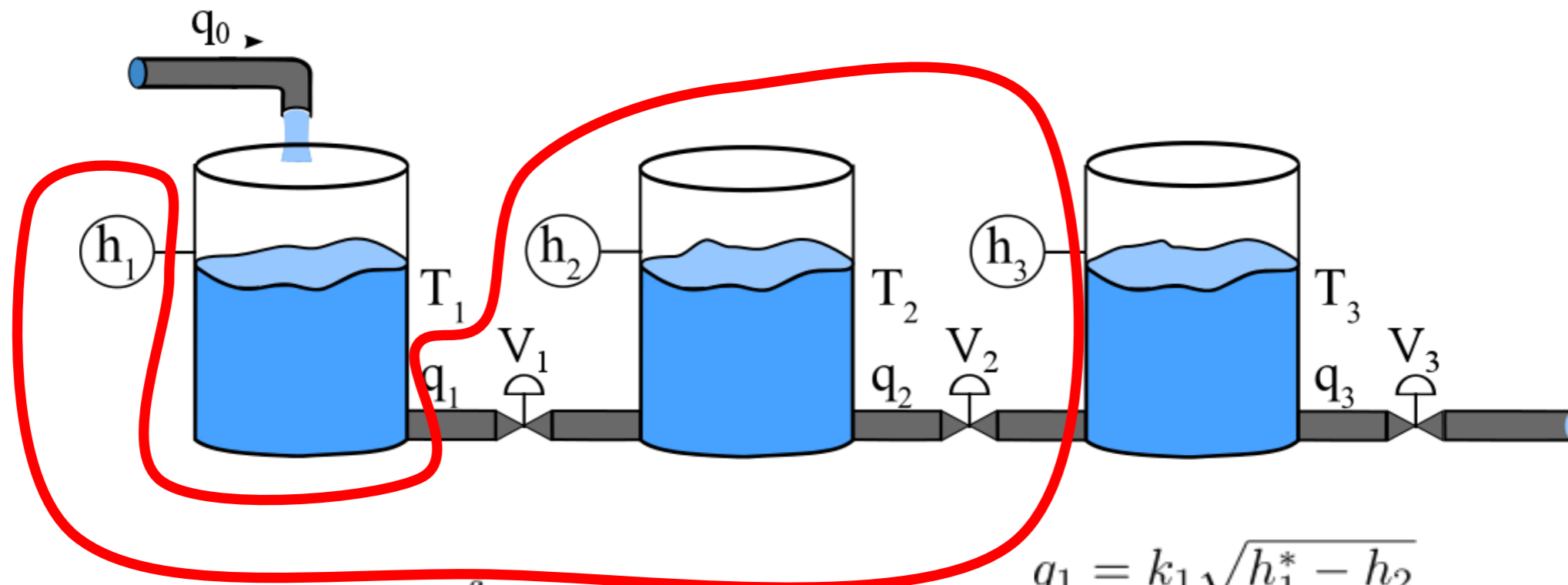
- Step 3 - Possible Conflict 1



$$\begin{aligned}
 & \int_{h_1^*}^{h_1} \frac{dh_1}{dt} = \frac{q_0 - q_1}{A_1} \\
 & \left. \begin{array}{l} =? \\ h_1^* \end{array} \right\} \begin{array}{l} \leftarrow q_1 = k_1 \sqrt{h_1 - h_2^*} \\ \leftarrow q_0 = \text{input} \end{array}
 \end{aligned}$$

AN EXAMPLE: THREE-TANK SYSTEM

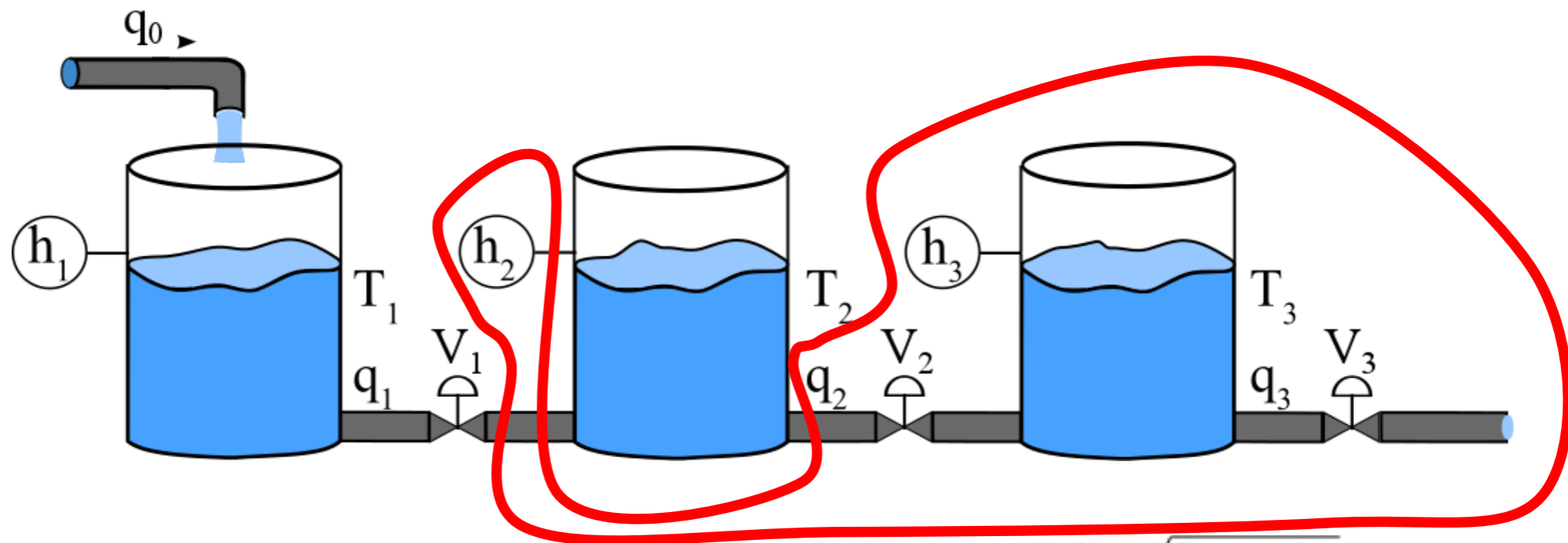
Step 3 - Possible Conflict 2



$$\begin{aligned}
 & \int_{h_2^*}^{h_2} \frac{dh_2}{dt} = \frac{q_1 - q_2}{A_2} \\
 & \left. \begin{aligned} q_1 &= k_1 \sqrt{h_1^* - h_2} \\ q_2 &= k_2 \sqrt{h_2 - h_3^*} \end{aligned} \right\}
 \end{aligned}$$

AN EXAMPLE: THREE-TANK SYSTEM

- Step 3 - Possible Conflict 3

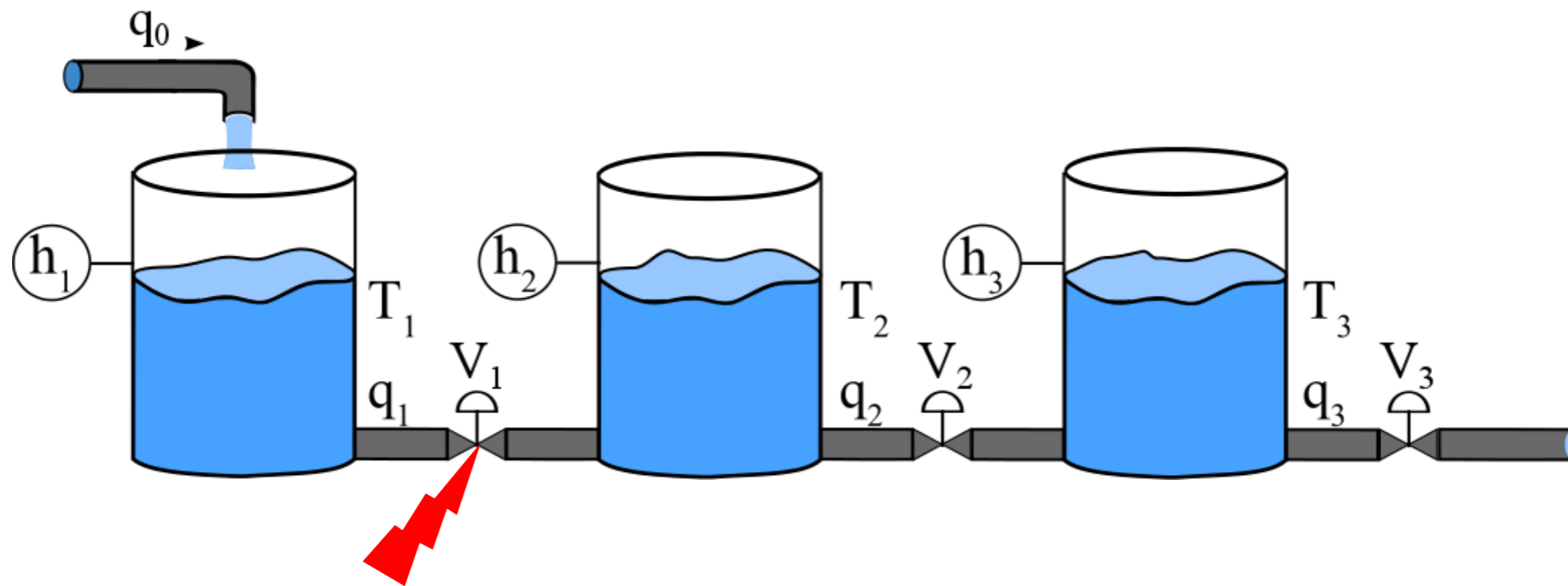


$$\begin{aligned}
 & \int \frac{dh_3}{dt} = \frac{q_2 - q_3}{A_3} \\
 & \begin{array}{l} h_3 \\ \left| \right. \\ =? \\ h_3^* \end{array} \quad \begin{array}{l} \swarrow \\ \searrow \end{array} \begin{array}{l} q_2 = k_2 \sqrt{h_2^* - h_3} \\ q_3 = k_3 \sqrt{h_3} \end{array}
 \end{aligned}$$

AN EXAMPLE: THREE-TANK SYSTEM

- PCs identified 3 minimal computational subsystems that decompose the complete system and that can be simulated independently.
- PCs are based on Reiter's theory of diagnosis from first principles
 - Are able to automatically generate fault isolation candidates from model of correct behavior
 - Components involved within each PC:
 - **For PC1:** T_1, V_1
 - **For PC2:** T_2, V_1, V_2
 - **For PC3:** T_3, V_2, V_3

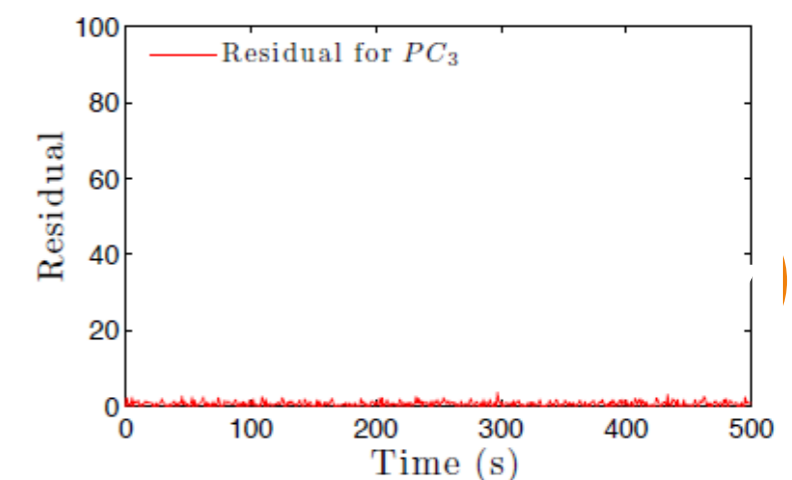
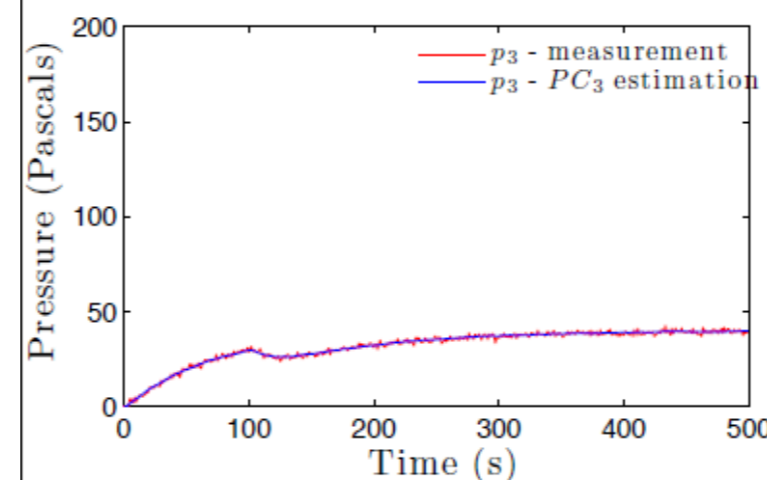
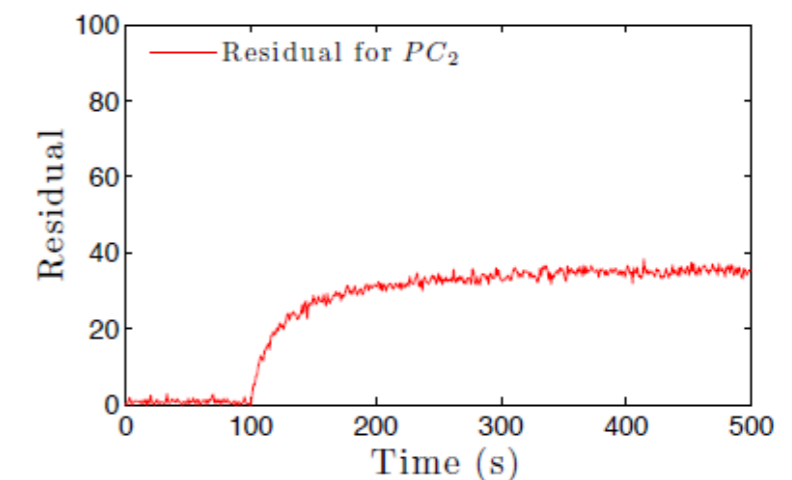
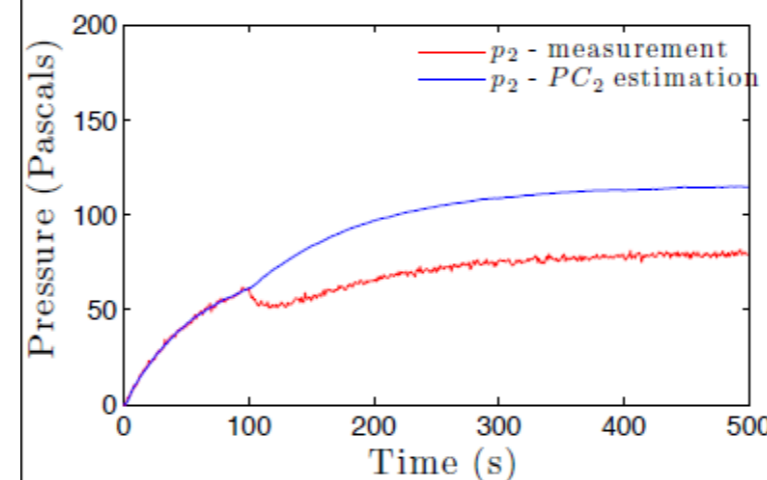
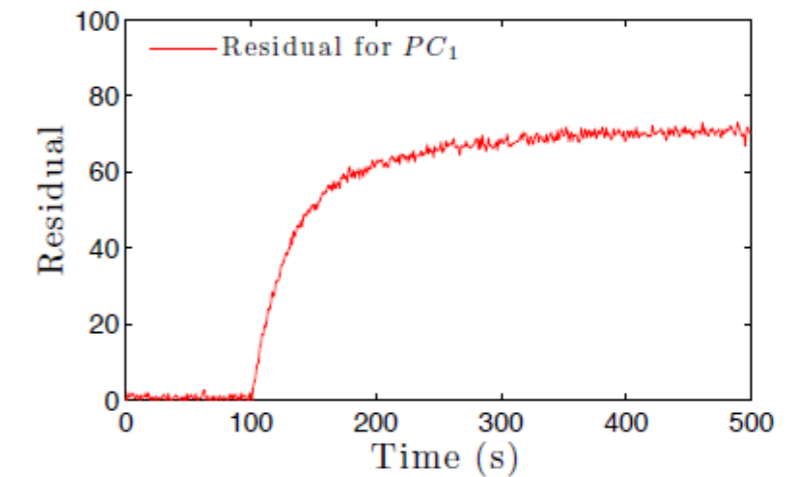
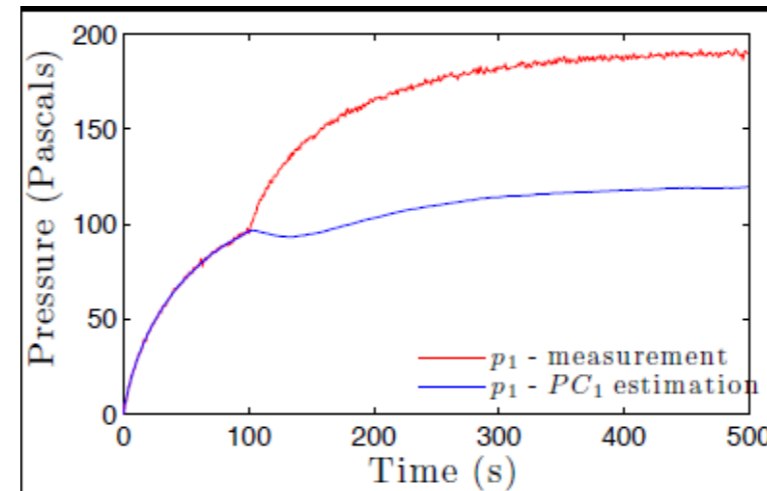
AN EXAMPLE: THREE-TANK SYSTEM



**Stuck fault in
valve position at $t=100$ sec.**

AN EXAMPLE: THREE-TANK SYSTEM

- Fault: Blockage in V_1
- 2 PCs trigger
- 2 of the residuals deviate, PC1 and PC2:
 - PC1: $\{V_1, T_1\}$
 - PC2: $\{V_1, V_2, T_2\}$
- Fault candidates:
 - $[[V_1], [T_1, V_2], [T_1, T_2]]$
- $[V_1]$ is the only single-fault candidate



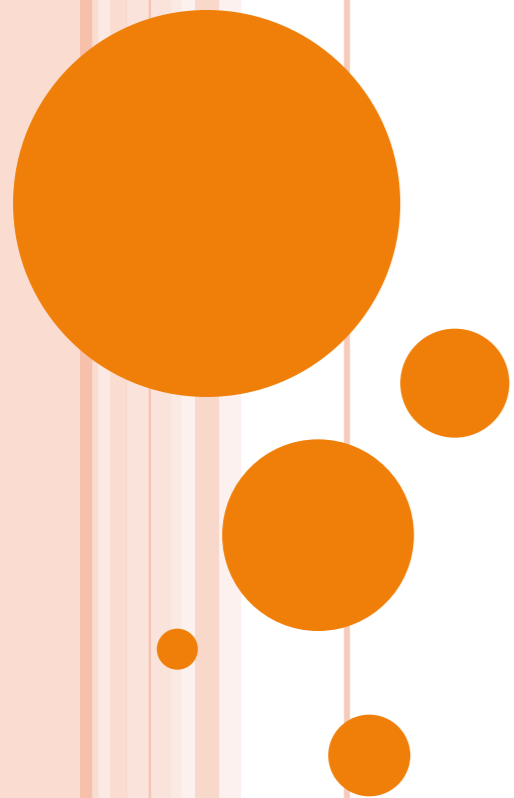
CBD WITH PCs

SUMMARY

- It is a quite simple but powerful approach to automatically perform fault detection and isolation (thanks to the AI and CBD background)
- By using PCs, we computed a subset of minimal submodels which:
 - Define the minimal conflicts that can appear in a system
 - Avoids online dependency recording
 - Allows incremental diagnosis
 - Provides simulation submodels to estimate the behavior of the system
 - Can be run in separate processors “allowing” distributed diagnosis
 - Provides automatic fault isolation
 - Allows multiple fault diagnosis
 - Facilitates the integration with distributed prognostics solutions

CBD WITH PCs EXTENSIONS

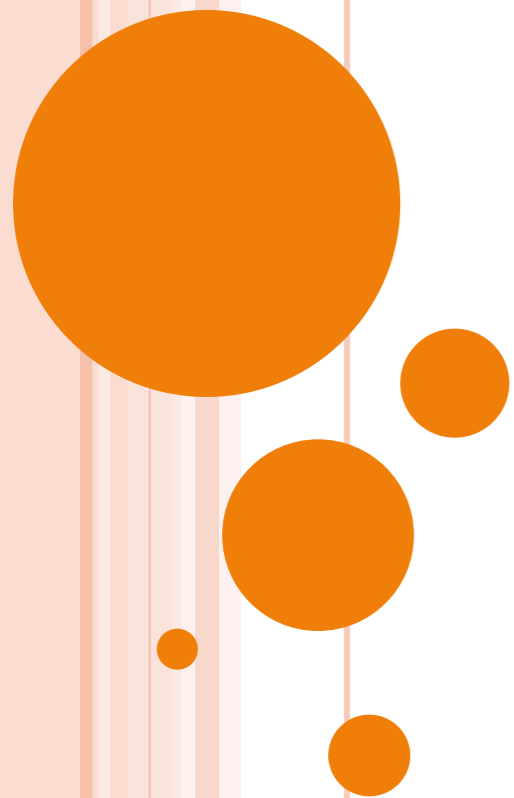
- The approach presented in this work is just the basic theory underlying CBD and PCs. Currently there are extensions for:
 - Integration of both simulation and state observers for fault detection
 - Integration of qualitative information for fault isolation
 - Efficient fault identification with minimal parameter estimators
 - Extension to hybrid systems fault diagnosis
 - Distributed diagnosis
 - Distributed and system-level prognosis
 - Multiple fault identification



SOME APPLICATION
EXAMPLES

PCs APPLICATION EXAMPLES

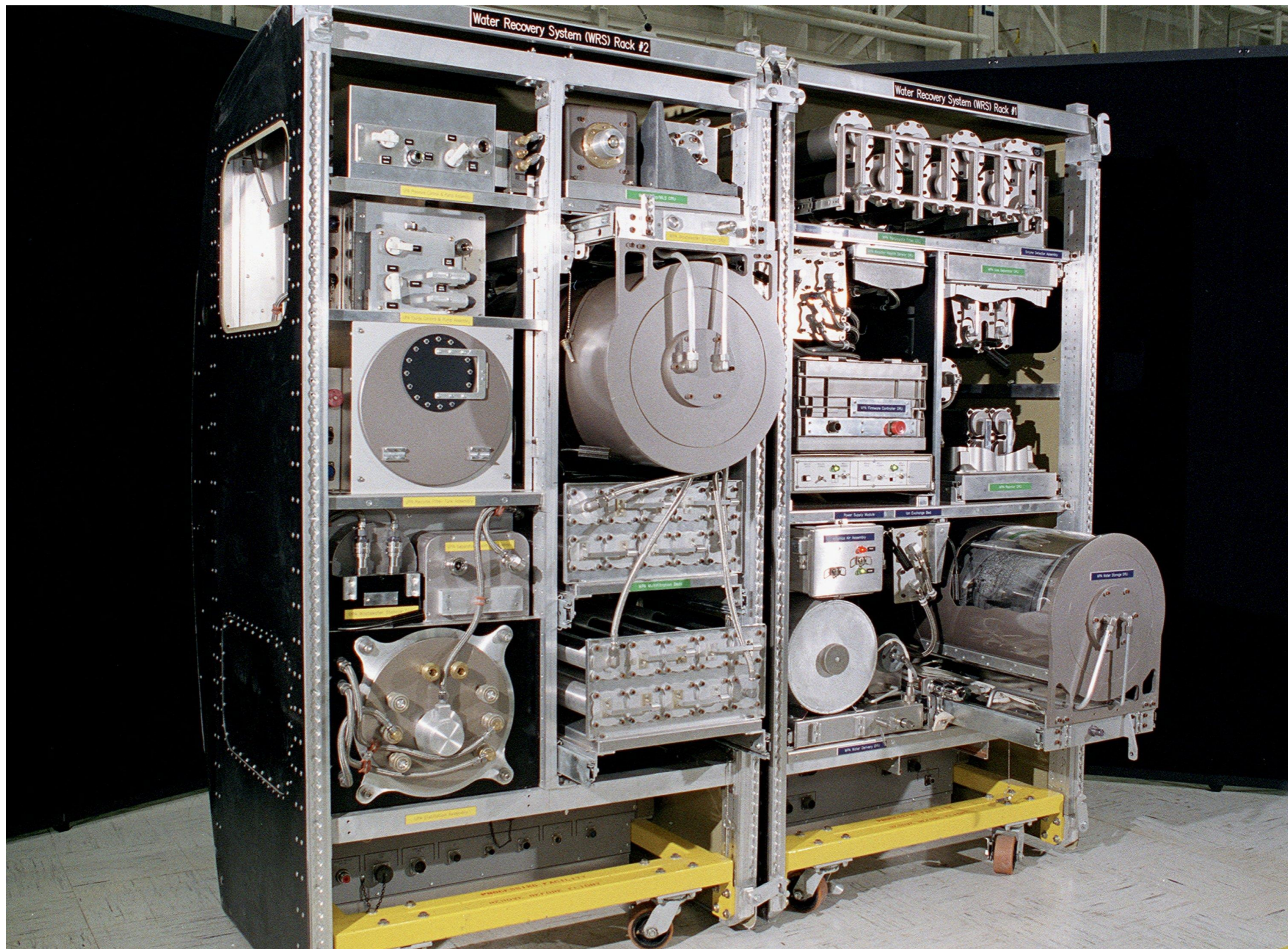
- **Efficient fault identification (advanced water recovery system)**
- **Distributed diagnosis (planetary rover)**
- **Distributed prognostics (centrifugal pump)**
- Efficient fault diagnosis when no first first principles model is available (beet sugar factory)
- Fault detection, isolation and identification (spacecraft power distribution system)
- Integrated system-level diagnosis and prognosis (electrical power system in a planetary rover)
- Integrated diagnosis/prognosis



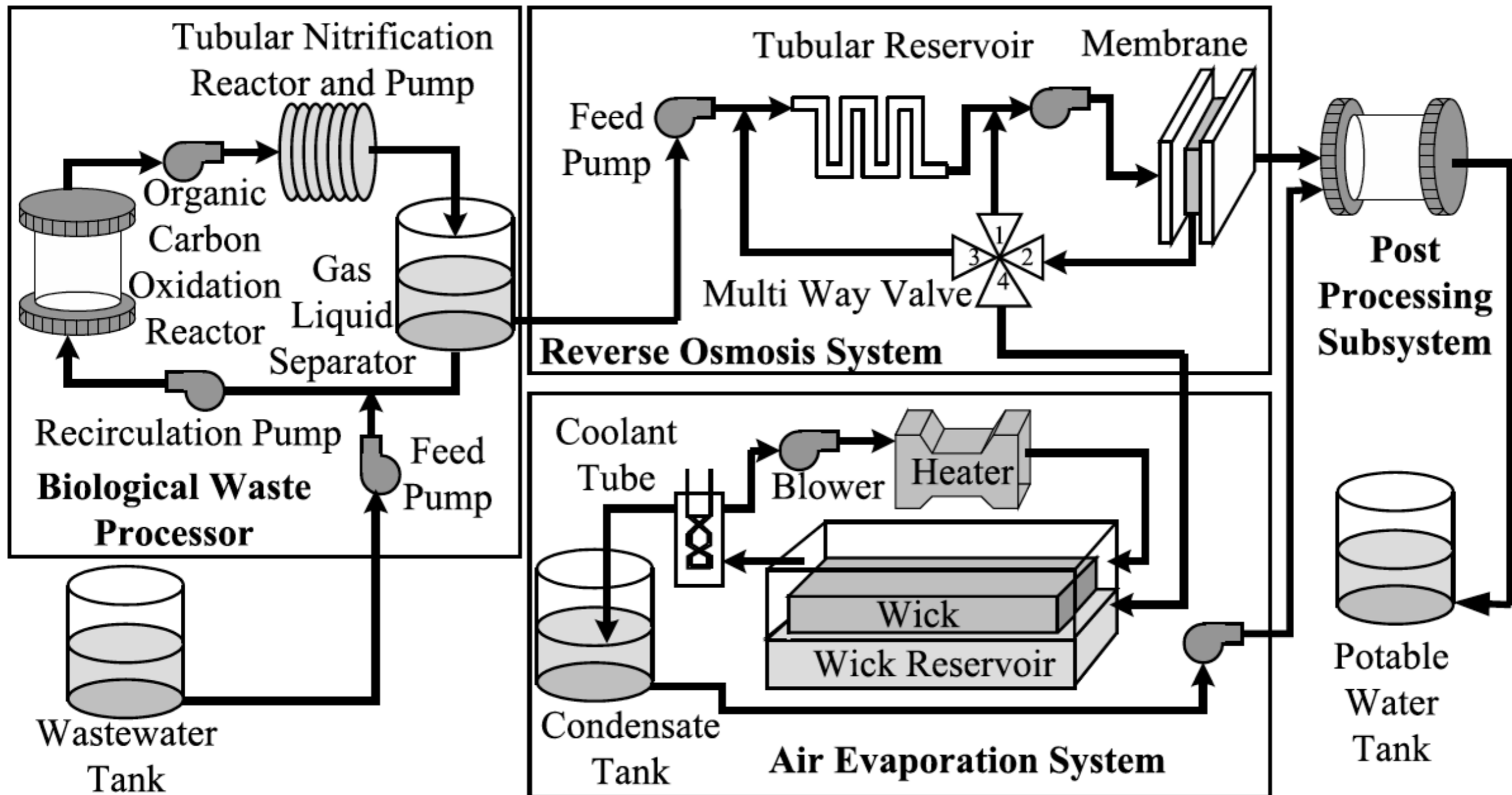
EFFICIENT FAULT
IDENTIFICATION

Advanced Water Recovery System

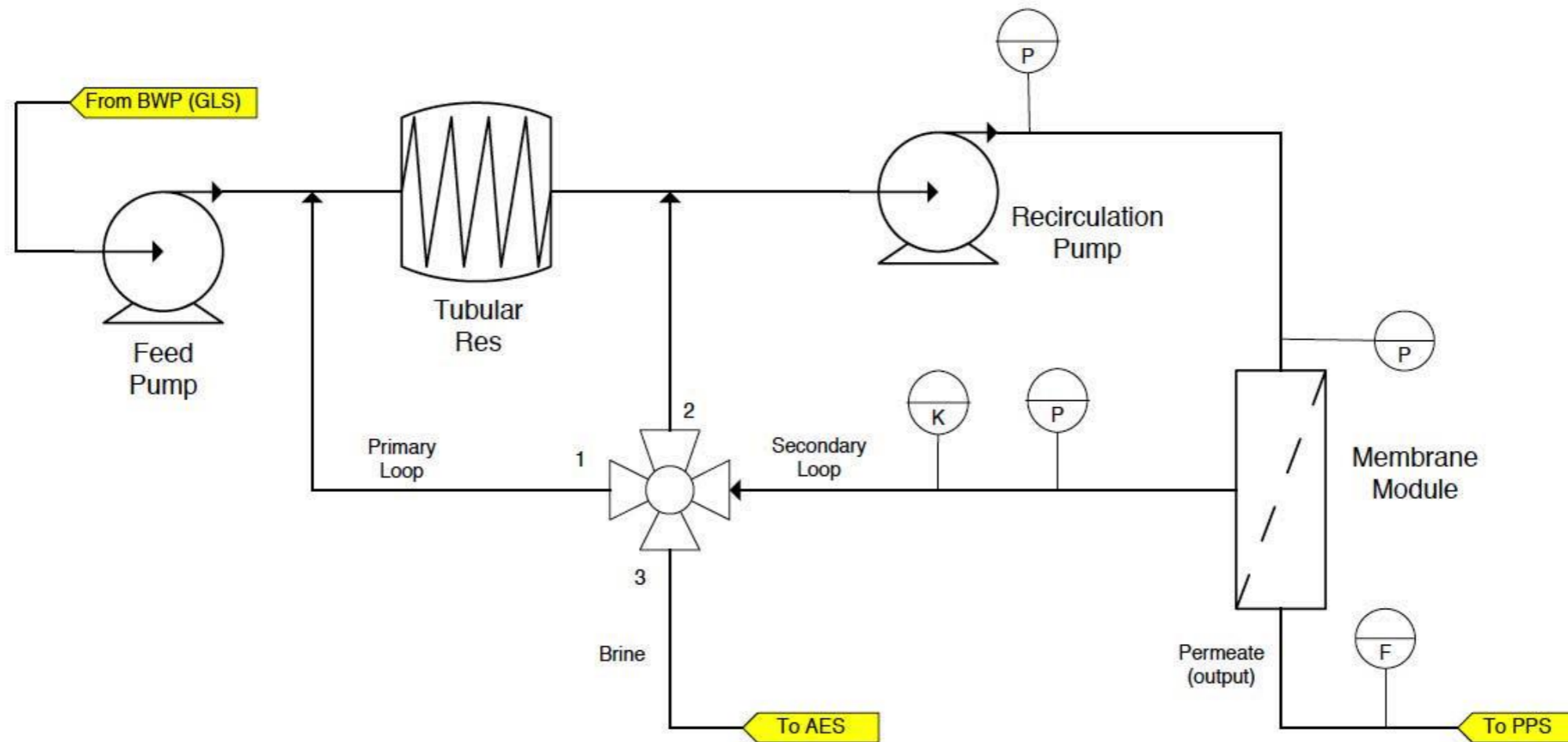
ADVANCED WATER RECOVERY SYSTEM



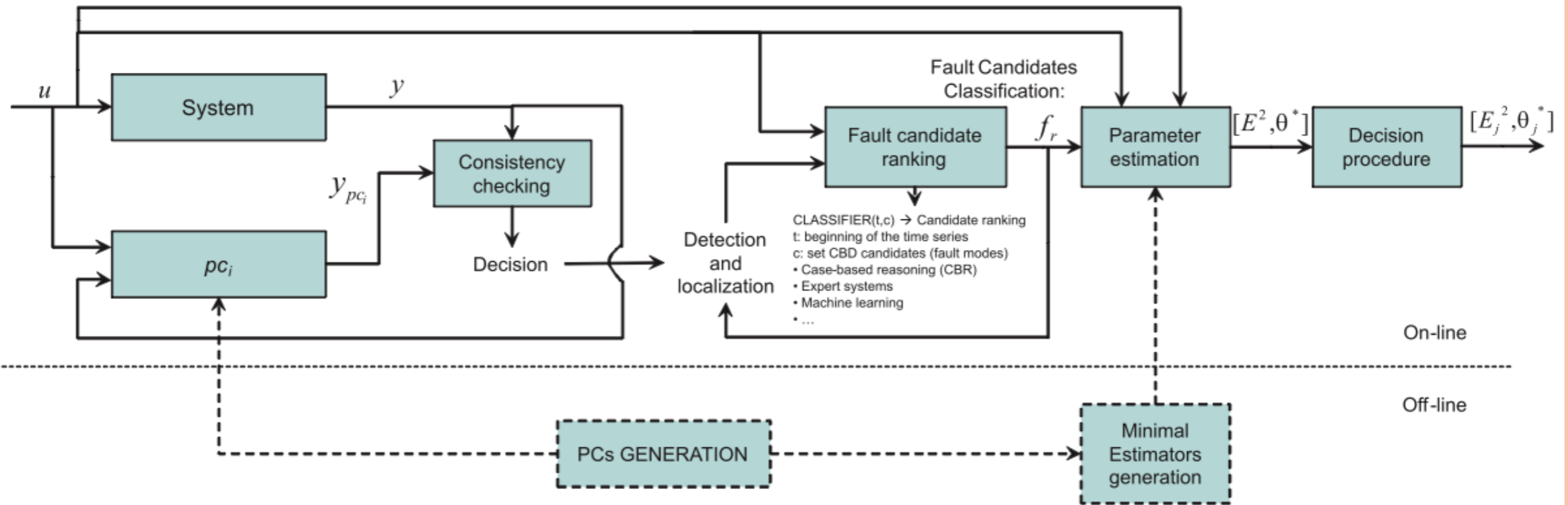
ADVANCED WATER RECOVERY SYSTEM



ADVANCED WATER RECOVERY SYSTEM



ADVANCED WATER RECOVERY SYSTEM



ADVANCED WATER RECOVERY SYSTEM

	Parameters (θ_j)	Components	Estimate (\hat{y}_{PC_j})
PC_1	I_{Fp}, R_{Fp}	Feed pump	F_{Fp}
PC_2	R_{Brine}, R_{Pipe}	Effluent, Pipe	P_K
PC_3	$C_{TubRes}, R_{Brine}, R_{Pipe}$	Tubular resistance, Effluent, Pipe	P_{Back}
PC_4	$C_{Memb}, R_{Brine}, R_{Memb}, R_{Pipe}$	Membrane, Effluent, Pipe	P_{Memb}
PC_5	$GY_{Rp}, I_{Rp}, R_{Pipe}, R_{Rp}$	Recirculation pump, Pipe	P_{Pump}

	PC_1	PC_2	PC_3	PC_4	PC_5	I
C_{Memb}^-	0	0	0	1	0	0
C_{TubRes}^-	0	0	1	0	0	1
GY_{Rp}^-	0	0	0	0	1	0
I_{Fp}^-	1	0	0	0	0	0
I_{Rp}^-	0	0	0	0	1	0
R_{Brine}^+	0	1	1	1	0	1
R_{Memb}^+	0	0	0	1	0	0
R_{Pipe}^+	0	1	1	1	1	1
R_{Rp}^+	0	0	0	0	1	0
R_{Fp}^+	1	0	0	0	0	0

	PC_1	PC_2	PC_3	PC_4	PC_5	I
C_{Memb}^-				--+		1
C_{TubRes}^-			--+			1
GY_{Rp}^-					--+	0
I_{Fp}^-	--+					1
I_{Rp}^-					--+	0
R_{Brine}^+		0-	0-	0+		1
R_{Memb}^+				0+		1
R_{Pipe}^+		0-	0+	0-	0+	1
R_{Rp}^+					0-	1
R_{Fp}^+	0-					1



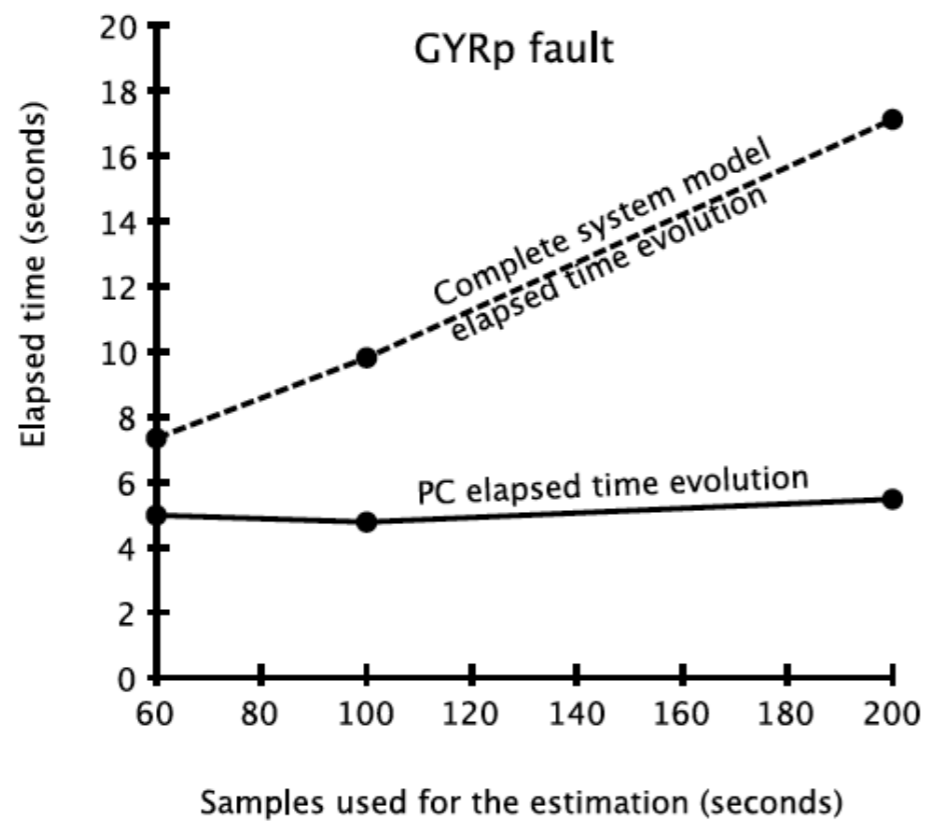
ADVANCED WATER RECOVERY SYSTEM

Faulty parameter :		GY_{Rp}	R_{Memb}	R_{Pipe}	I_{Fp}	R_{Brine}	R_{Fp}	R_{Rp}	C_{Memb}	C_{TubRes}	I_{Rp}
PC used :		PC_5	PC_4	PC_3	PC_2	PC_3	PC_1	PC_5	PC_4	PC_3	PC_5
5 % fault size											
60 sec.	PC convergence	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗
	PC squared error	0.04	2.25	0.99	0.09	0.17	0.36	5.50	1.59e+09	3.71e+09	9.75e+04
	CS convergence	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
	CS squared error	0.04	3.29	1.59	33.33	2.53	2.57	5.50	1.32e+09	3.81e+09	9.75e+04
100 sec.	PC convergence	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
	PC squared error	0.05	2.22	0.57	0.70	1.86	0	1.03	1.61e+11	1.12e+02	43.62
	CS convergence	✓	✓	✓	✗	✗	✗	✓	✗	✗	✗
	CS squared error	0.03	3.29	1.78	26.66	0.25	0.77	1.03	1.61e+11	1.89e+06	43.61
200 sec.	PC convergence	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
	PC squared error	0	0.47	0.27	1.57	0.72	0.02	0.33	8.74	6.72	0.25
	CS convergence	✓	✓	✓	✗	✗	✗	✓	✗	✗	✗
	CS squared error	0	0.46	0.04	1.21	2.61	1.01	0.33	8.13	21.19	0.15
10 % fault size											
60 sec.	PC convergence	✓	✓	✓	✗	✓	✓	✗	✗	✗	✗
	PC squared error	0	4.51	0.90	7.19	2.89	0.09	0.47	24.07	3.62e+03	65.37
	CS convergence	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗
	CS squared error	0	4.53	1.96	50	3.24	8.67	0.47	24.60	2.35e+06	65.40
100 sec.	PC convergence	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
	PC squared error	0.02	0.79	0.35	5.31	3.20	0.16	0.49	8.53	37.12	23.48
	CS convergence	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗
	CS squared error	0.02	0.78	0.38	12.08	5.10	1.37	0.49	8.19	52.03	23.45
200 sec.	PC convergence	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
	PC squared error	0	0.55	0.02	0.06	0.86	0.02	1.17	2.22	6.36	0.15
	CS convergence	✓	✓	✓	✗	✗	✗	✓	✗	✗	✗
	CS squared error	0	0.60	2.00	30.79	1.41	0.40	1.16	2.15	8.35	0.18

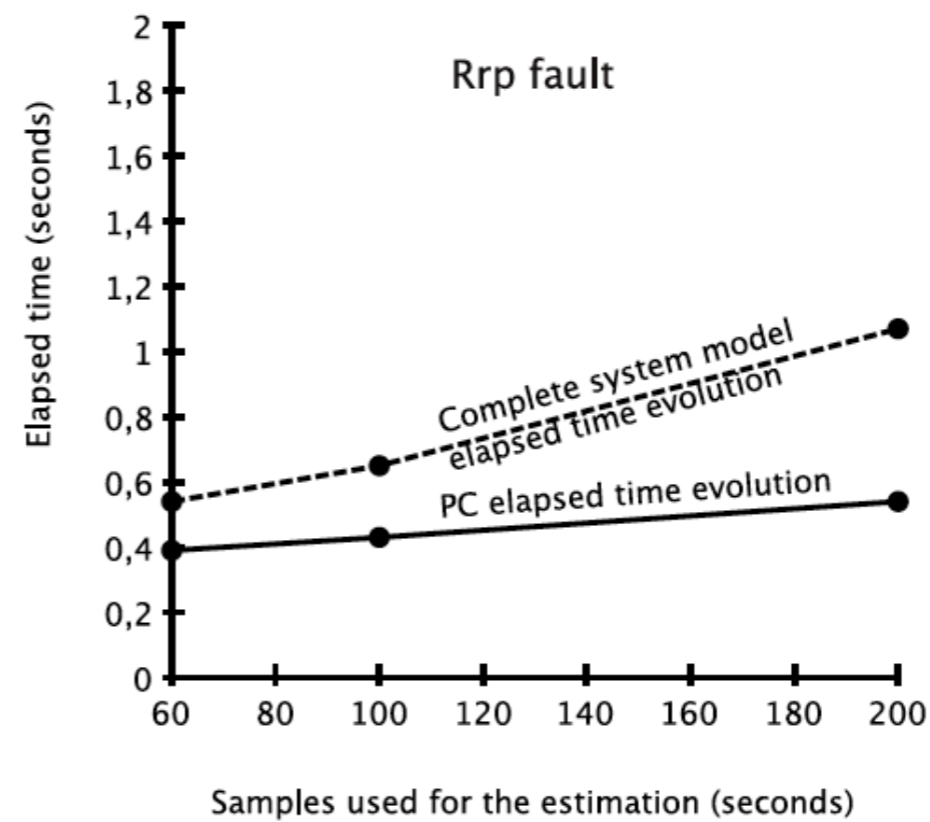
ADVANCED WATER RECOVERY SYSTEM

<i>Faulty parameter</i>	<i>Time improvement(%)</i>		
	<i>60 sec.</i>	<i>100 sec.</i>	<i>200 sec.</i>
<i>5 % fault magnitude</i>			
C_{Memb}	14.53	17.96	27.94
C_{TubRes}	15.70	36.89	49.34
GY_{Rp}	32.8	61.03	54.71
I_{Fp}	29.25	42.24	70.08
I_{Rp}	27.67	33.46	43.98
R_{Brine}	44.25	48.80	65.17
R_{Memb}	12.69	20.45	28.54
R_{Pipe}	52.82	53.11	65.81
R_{Rp}	29.00	32.11	45.46
R_{Fp}	61.13	64.08	69.53
<i>10 % fault magnitude</i>			
C_{Memb}	16.77	19.96	16.18
C_{TubRes}	29.61	38.30	41.57
GY_{Rp}	31.86	50.32	66.81
I_{Fp}	31.84	61.75	65.71
I_{Rp}	27.75	37.76	46.64
R_{Brine}	31.25	42.15	56.57
R_{Memb}	13.75	19.28	24.47
R_{Pipe}	35.68	44.54	57.90
R_{Rp}	26.32	33.14	48.61
R_{Fp}	57.05	57.83	73.03

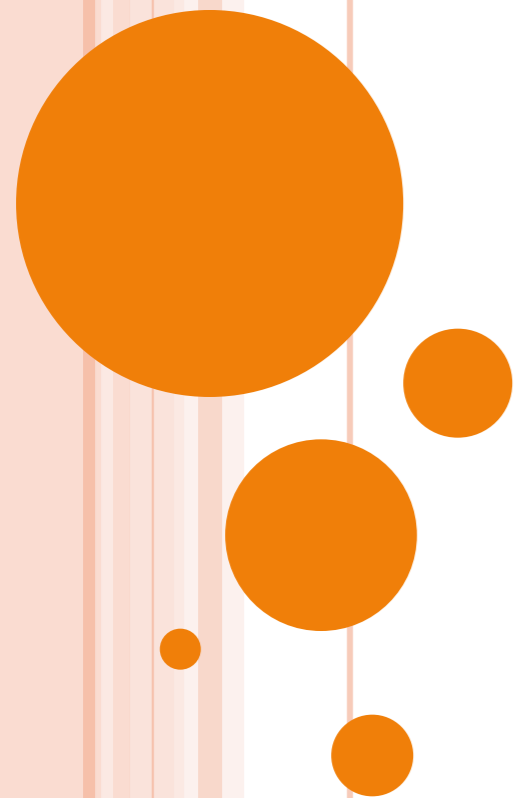
ADVANCED WATER RECOVERY SYSTEM



(a) GY_{Rp} fault



(b) R_{Rp} fault



DISTRIBUTED

DIAGNOSIS

Planetary rover

MOTIVATION

- Autonomous vehicles like UAVs and rovers receive command sequences from humans
 - E.g., as a set of waypoints with scientific objectives to achieve at each
- Unexpected situations can cause the vehicle to go into a **safe mode** while engineers diagnose the problem, which might take a long time
- An autonomous decision-making system that includes automated diagnosis and prognosis in making optimal decisions can **save time, money, and increase mission value**

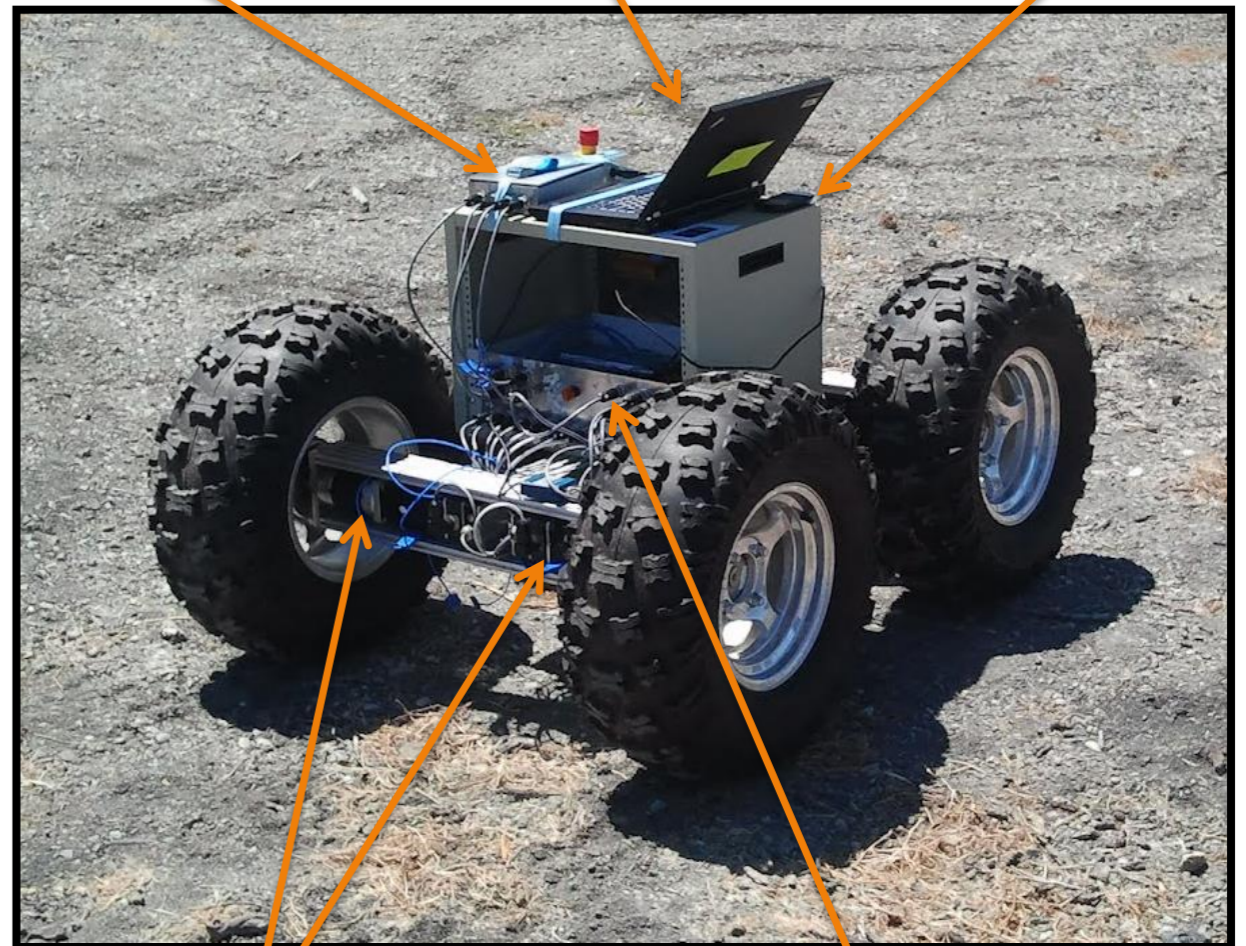


* E. Balaban, S. Narasimhan, M. Daigle, I. Roychoudhury, A. Sweet, C. Bond, G. Gorospe . "Development of a mobile robot test platform and methods for validation of prognostics-enabled decision making algorithms", Int. J. Prognost. Health Manag. 4 (1) (2013).

ROVER TESTBED

- Developed rover testbed for hardware-in-the-loop testing and validation of **control, diagnosis, prognosis, and decision-making algorithms**
- Skid-steered rover (1.4x1.1x0.63 m) with each wheel independently driven by a DC motor
- Four lithium-ion battery packs provide power to the wheels
- Separate battery pack powers the data acquisition system
- Onboard laptop implements control software
- Flexible publish/subscribe network architecture allows diagnosis, prognosis, decision-making to be implemented in a distributed fashion

Batteries Controlling Laptop Phone



Motors

Data Acquisition
and Power
Distribution

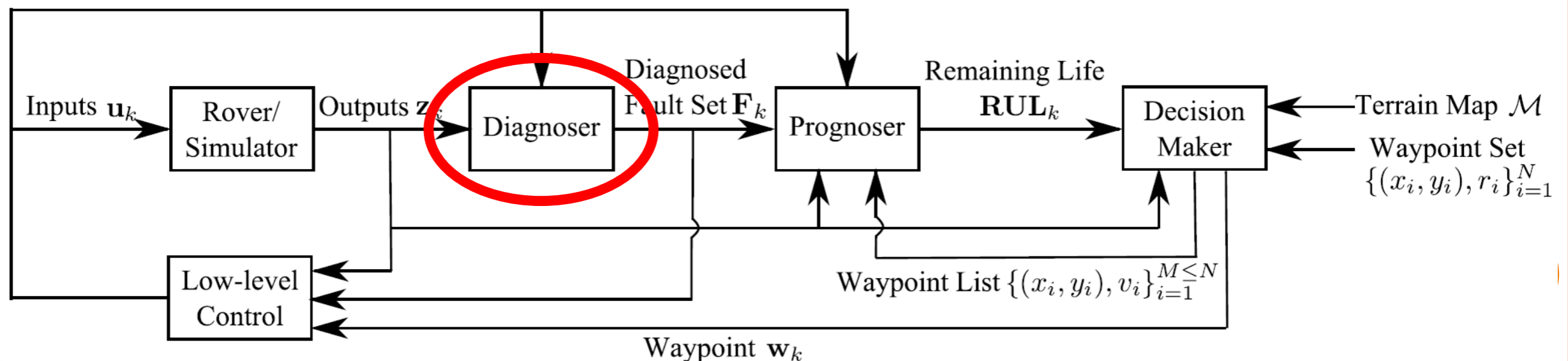


ROVER TESTBED SENSOR SUITE

Measurement Type	Manufacturer	Location/comments	Measurement Type
GPS (longitude and latitude)	Motorola	On the smartphone	GPS (longitude and latitude)
Gyroscope (roll, pitch, yaw)	Motorola	On the smartphone	Gyroscope (roll, pitch, yaw)
Motor temperature	Omega	On each motor (to be implemented)	Motor temperature
Battery temperature	Omega	On each battery pack (to be implemented)	Battery temperature
Position encoder	Maxon	On each drive motor	Position encoder
Battery voltage	Custom	On a custom PCB board measuring individual battery pack voltages	Battery voltage
Total current	Custom	On a custom PCB board measuring individual battery pack voltages	Total current
Individual motor current	Custom	On a custom PCB board measuring individual motor currents (on the battery side of the motor controllers)	Individual motor current

INTEGRATED DECISION MAKING ARCHITECTURE (BALABAN ET AL., 2013)

1. **Rover receives control inputs** (individual wheel speeds) and **sensors produce outputs**
2. **Low-level control** modifies wheel speed commands to move towards a given waypoint in the presence of diagnosed faults
3. **Diagnoser** receives rover inputs and outputs and **produces fault candidates**
4. **Prognoser** receives rover inputs and outputs and **predicts remaining useful life (RUL)** or rover and/or its components (eg, batteries, motors)
5. **Decision maker plans the order to visit the waypoints** (science objectives) given diagnostic and prognostic information. It **can also selectively eliminate some of the waypoints** if all of them are not achievable due to vehicle health or energy constraints.

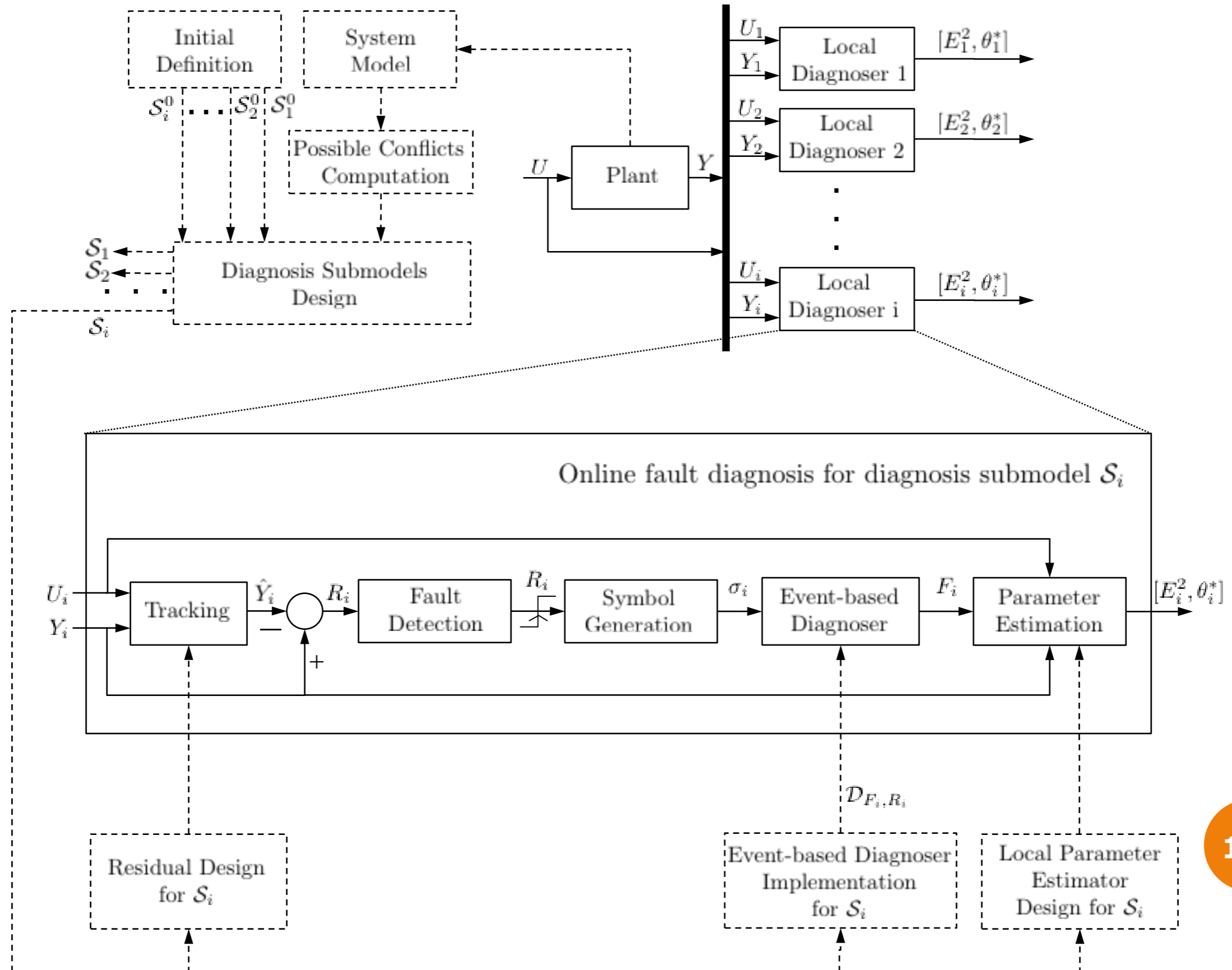


INTEGRATED AND DISTRIBUTED APPROACH

- **Distributed approach** needed to solve the problem efficiently
 - Common modeling framework for modeling both nominal and faulty system behavior and handling both the diagnosis and prognosis tasks
 - Use structural model decomposition to distribute the problem



DISTRIBUTED DIAGNOSIS ARCHITECTURE



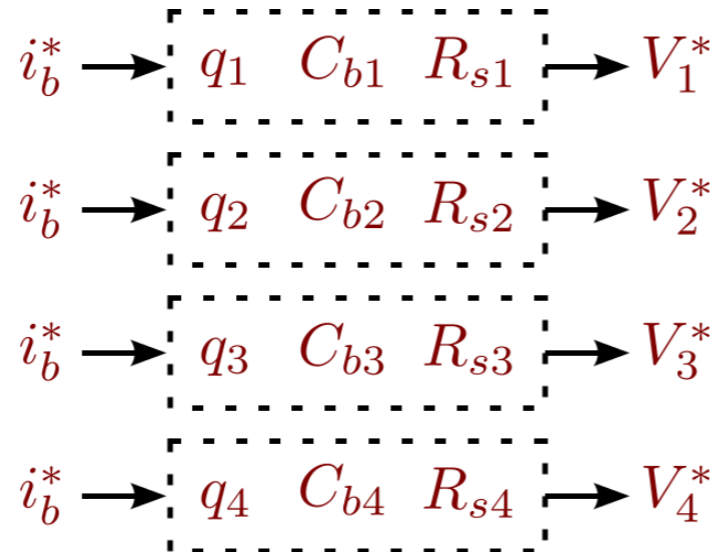
LOCAL DIAGNOSER DESIGN

- Diagnosers designed to be globally diagnosable, i.e., they have enough local diagnostic information to independently generate globally correct diagnoses
 - Design process is a search process
 - Start with minimal submodels and expand/merge until submodel is globally diagnosable (enough measurements from other parts of the system are added)
- Each local diagnoser operates fully independently from other local diagnosers
 - Has its own model for residual generation
 - Does its own fault detection
 - Does its own fault isolation
 - Does its own fault identification
- **No communication and no central diagnosis coordinator**

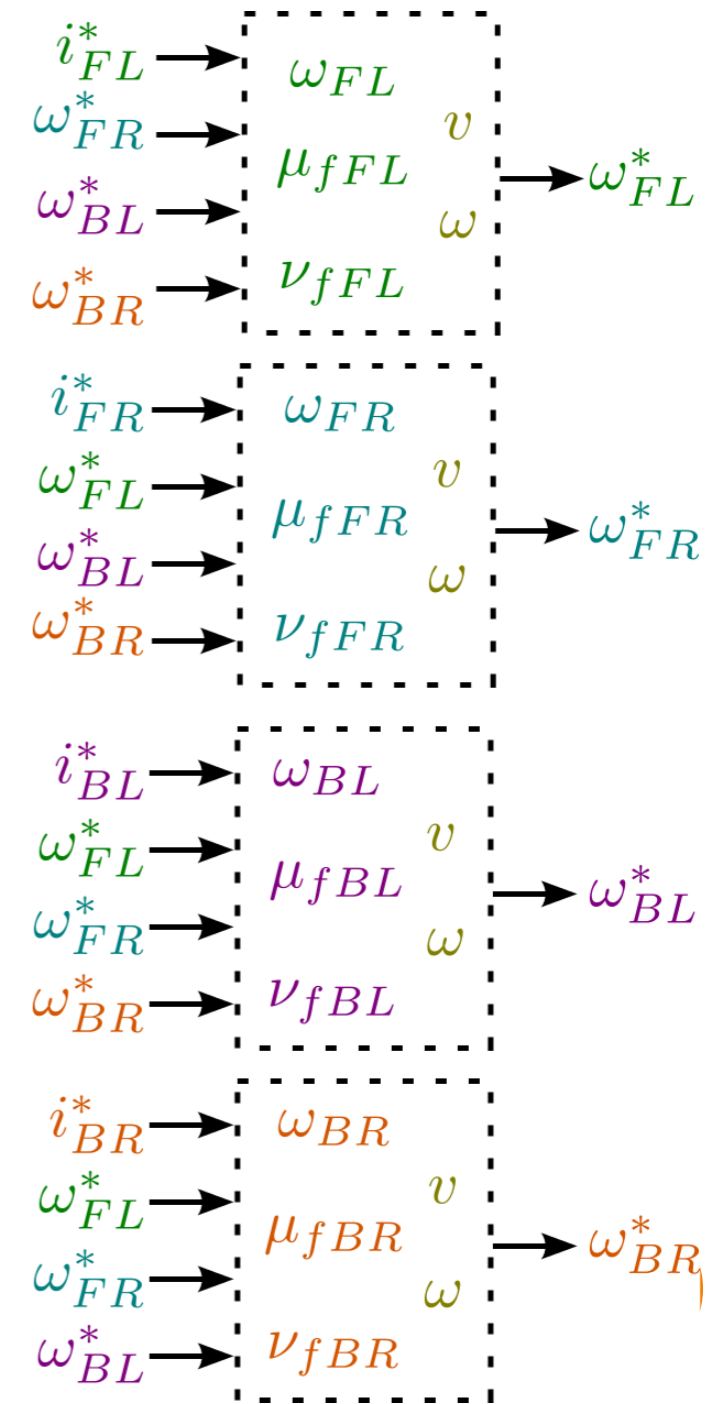


CASE STUDY: MINIMAL SUBMODELS (PCs)

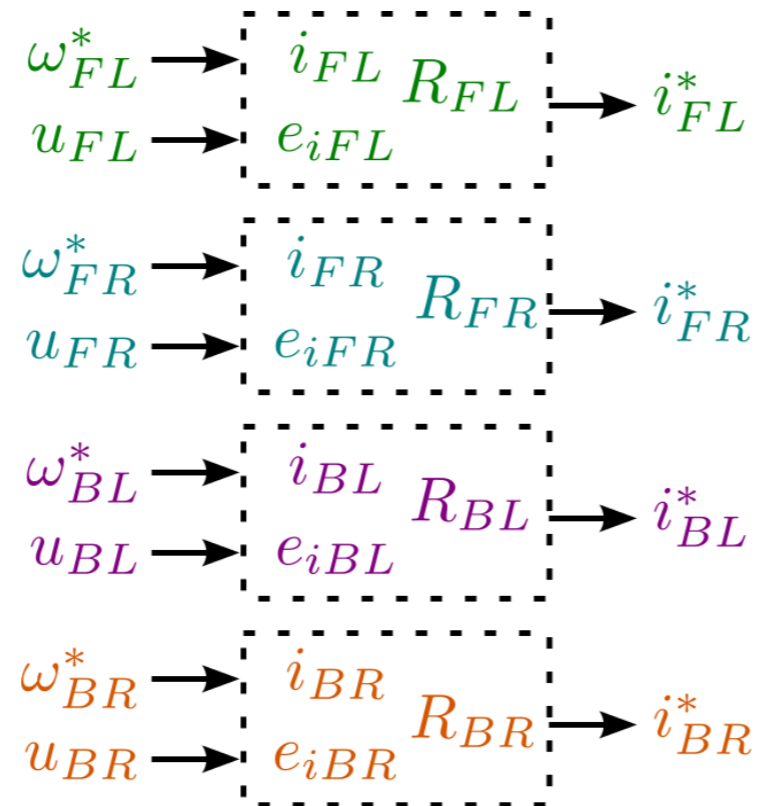
Battery Submodels



Wheel Submodels

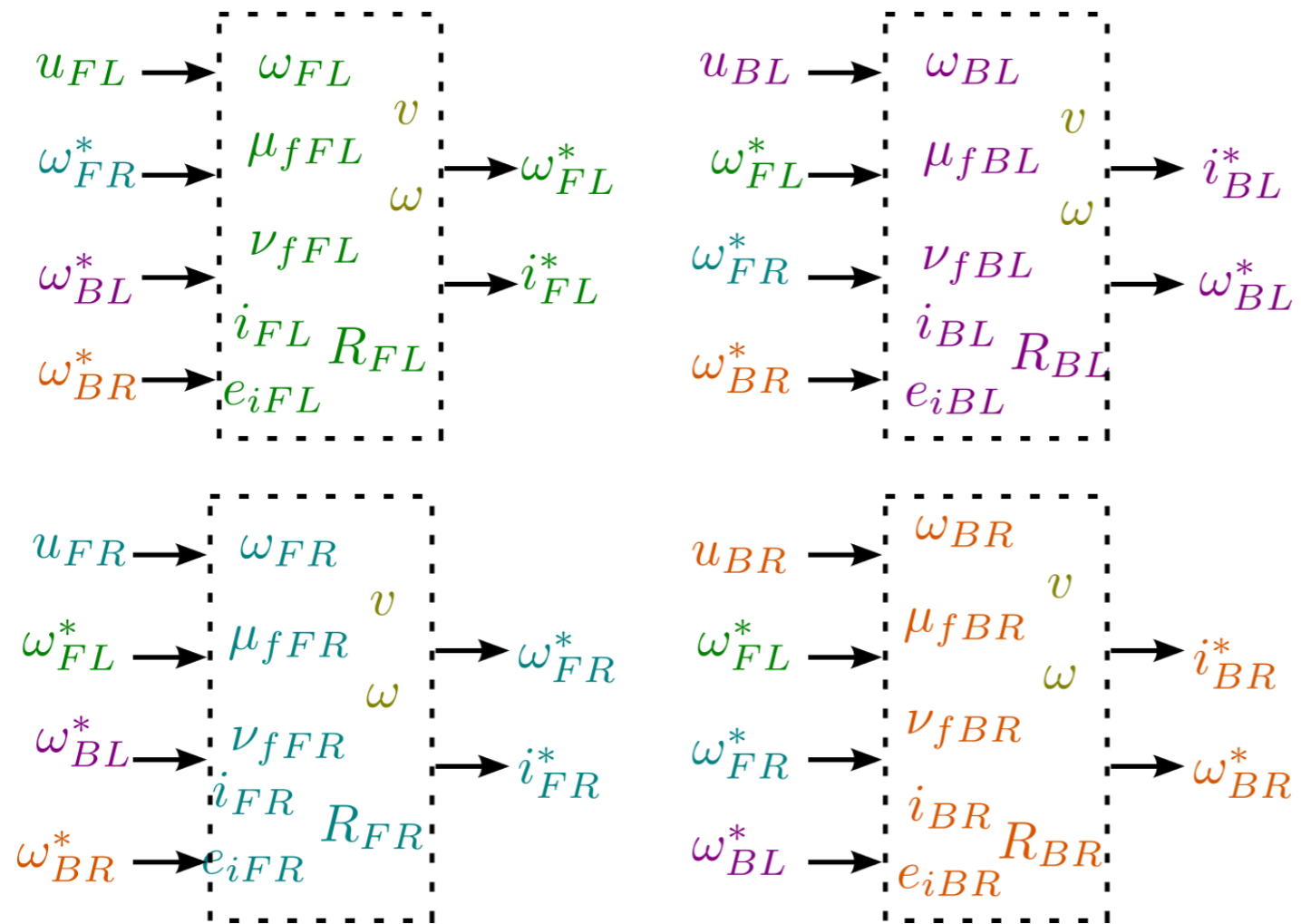


Motor Electrical Submodels

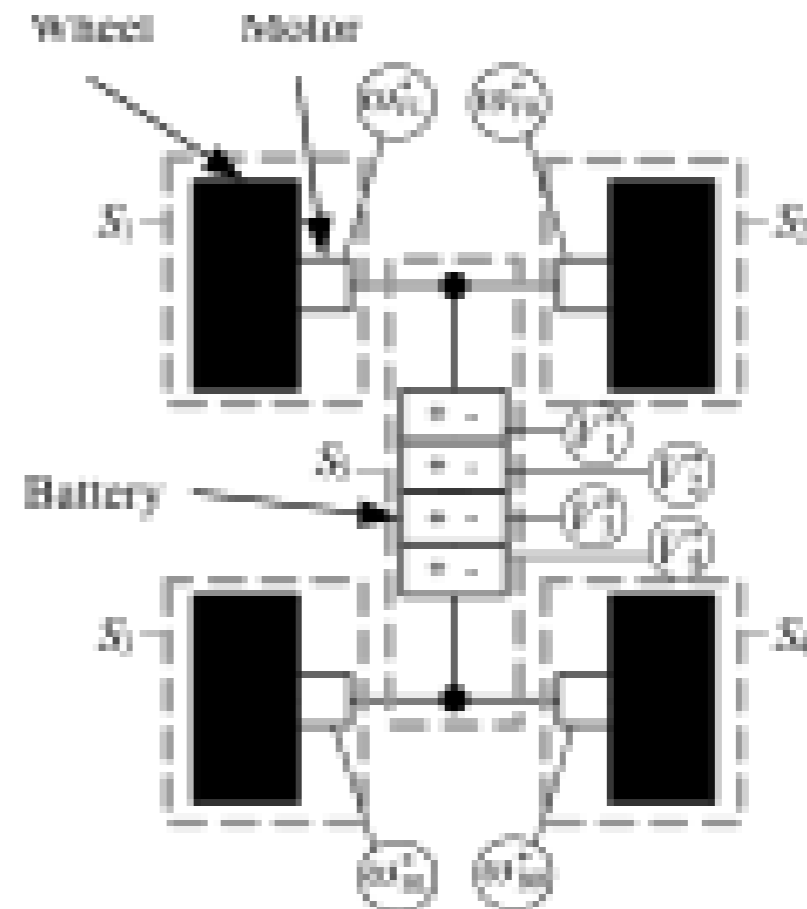
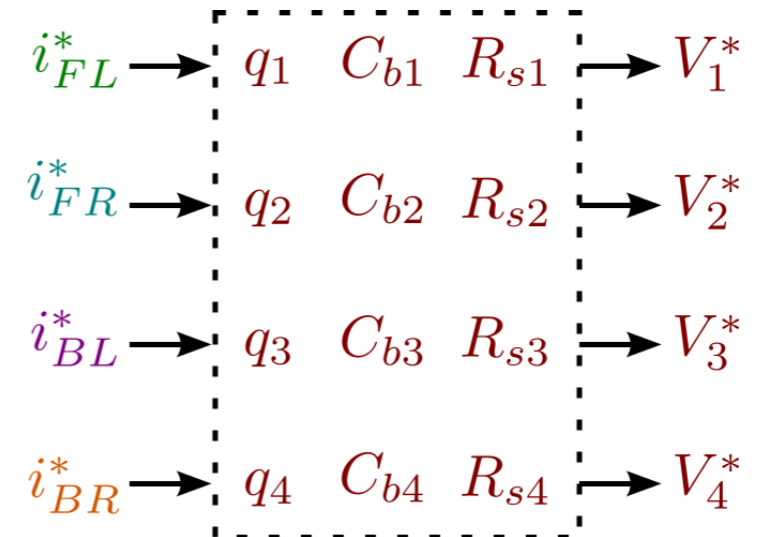


CASE STUDY: DIAGNOSER SUBMODELS

Wheel/Motor Submodels



Batteries Submodel



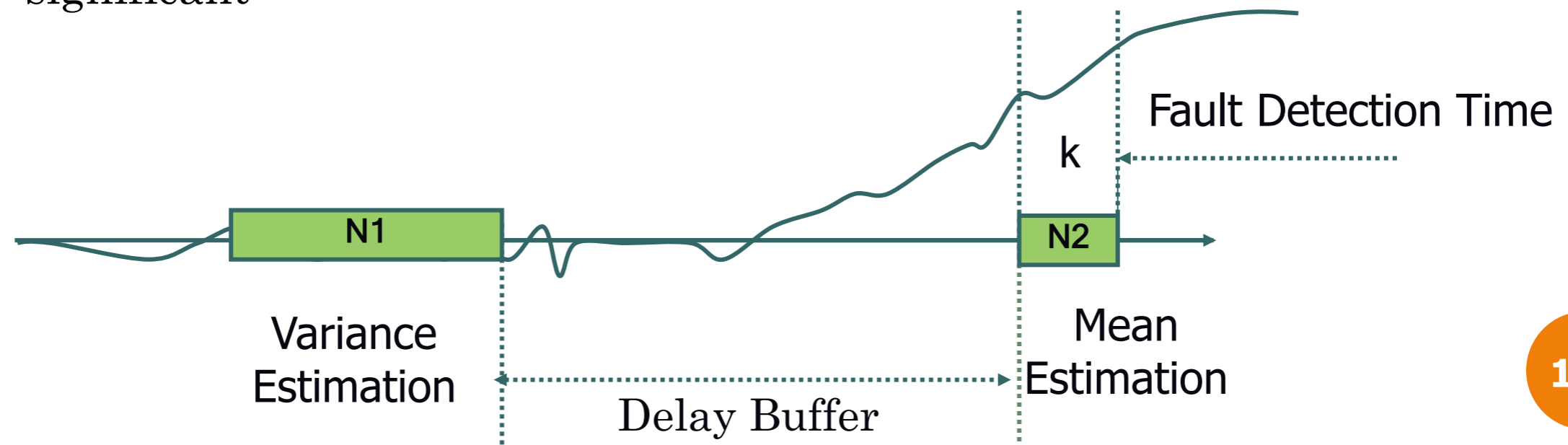
DISTRIBUTED DIAGNOSIS

○ Residual Generation

- Local observer (eg, Kalman filter, unscented Kalman filter, particle filter) based on nominal local submodel computes nominal behavior as a reference
- Residual computed as measured value minus reference value

○ Fault Detection

- Nominally residual is approximately zero
- Fault detected when residual deviation from zero is statistically significant



DISTRIBUTED DIAGNOSIS

○ Fault Isolation

- Initiated upon fault detection
- Residual deviations abstracted to qualitative 0, +, and - values for changes in magnitude and slope (termed qualitative fault signatures)
- Derived symbolic form of deviations compared to model-predicted deviations to isolate faults
- Each new residual deviation provides more information for reducing the candidate set
- Also use temporal order of residual deviations within a submodel (termed relative measurement orderings)

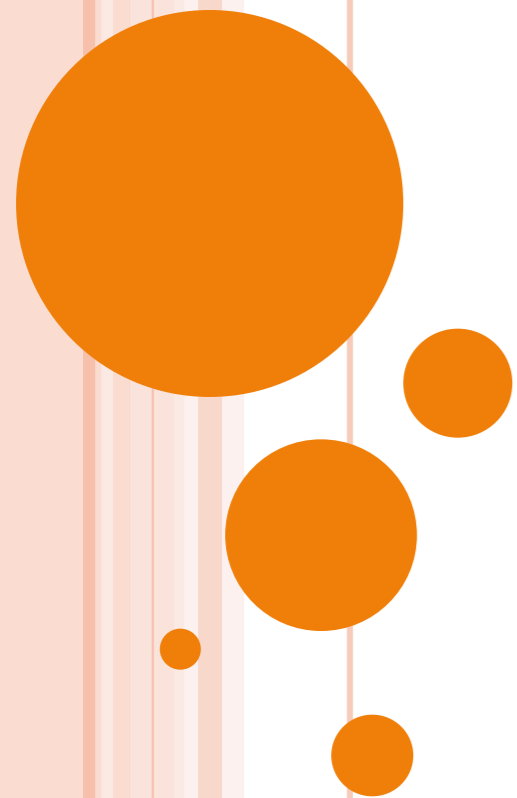
○ Fault Identification

- For each fault hypothesis, use (minimal) local observer based on faulty system model to estimate fault parameters (and system state)
- Fault hypotheses that cannot match measurements are eliminated

SOME RESULTS

INCREASES IN MOTOR FRICTION AND ELECTRICAL RESISTANCE

Fault	Magnitude	Centralized				Distributed			
		M_{td} (s)	M_{ti} (s)	M_{da} (%)	M_{std}	M_{td} (s)	M_{ti} (s)	M_{da} (%)	M_{std}
$\mu_{f,FL}^+$	5%	0.15	0.22	98.04	0.06	0.15	0.32	98.91	0.13
	10%	0.10	0.15	97.50	0.09	0.10	0.25	99.65	0.18
	20%	0.05	0.12	96.82	0.14	0.05	0.20	99.36	0.27
$\mu_{f,FR}^+$	5%	0.15	0.21	98.15	0.06	0.15	0.31	98.92	0.13
	10%	0.10	0.17	97.51	0.09	0.10	0.24	99.24	0.19
	20%	0.05	0.13	97.00	0.14	0.05	0.20	99.23	0.27
$\mu_{f,BL}^+$	5%	0.15	0.20	97.96	0.06	0.15	0.31	98.94	0.12
	10%	0.10	0.16	97.41	0.09	0.10	0.25	99.43	0.18
	20%	0.05	0.15	96.95	0.14	0.05	0.20	98.86	0.28
$\mu_{f,BR}^+$	5%	0.15	0.20	97.97	0.06	0.15	0.29	98.82	0.13
	10%	0.10	0.15	97.49	0.09	0.10	0.24	99.25	0.18
	20%	0.05	0.15	96.96	0.14	0.05	0.20	99.45	0.29
Re_{FL}^+	5%	0.19	0.67	92.80	0.29	0.36	0.66	98.62	0.28
	10%	0.14	0.51	94.54	0.49	0.23	0.55	96.70	0.54
	20%	0.10	0.45	92.82	0.99	0.16	0.46	95.92	1.30
Re_{FR}^+	5%	0.17	0.67	94.88	0.28	0.28	0.59	95.38	0.27
	10%	0.14	0.53	95.96	0.50	0.22	0.53	97.04	0.54
	20%	0.08	0.45	94.66	0.94	0.16	0.47	96.01	1.32
Re_{BL}^+	5%	0.19	0.67	94.06	0.29	0.29	0.59	96.41	0.27
	10%	0.14	0.54	94.92	0.49	0.23	0.53	97.56	0.52
	20%	0.10	0.45	95.63	0.96	0.18	0.51	97.07	1.39
Re_{BR}^+	5%	0.19	0.65	91.16	0.28	0.33	0.63	97.24	0.27
	10%	0.14	0.54	95.33	0.49	0.22	0.53	96.12	0.58
	20%	0.09	0.45	95.36	1.00	0.18	0.49	98.09	1.32

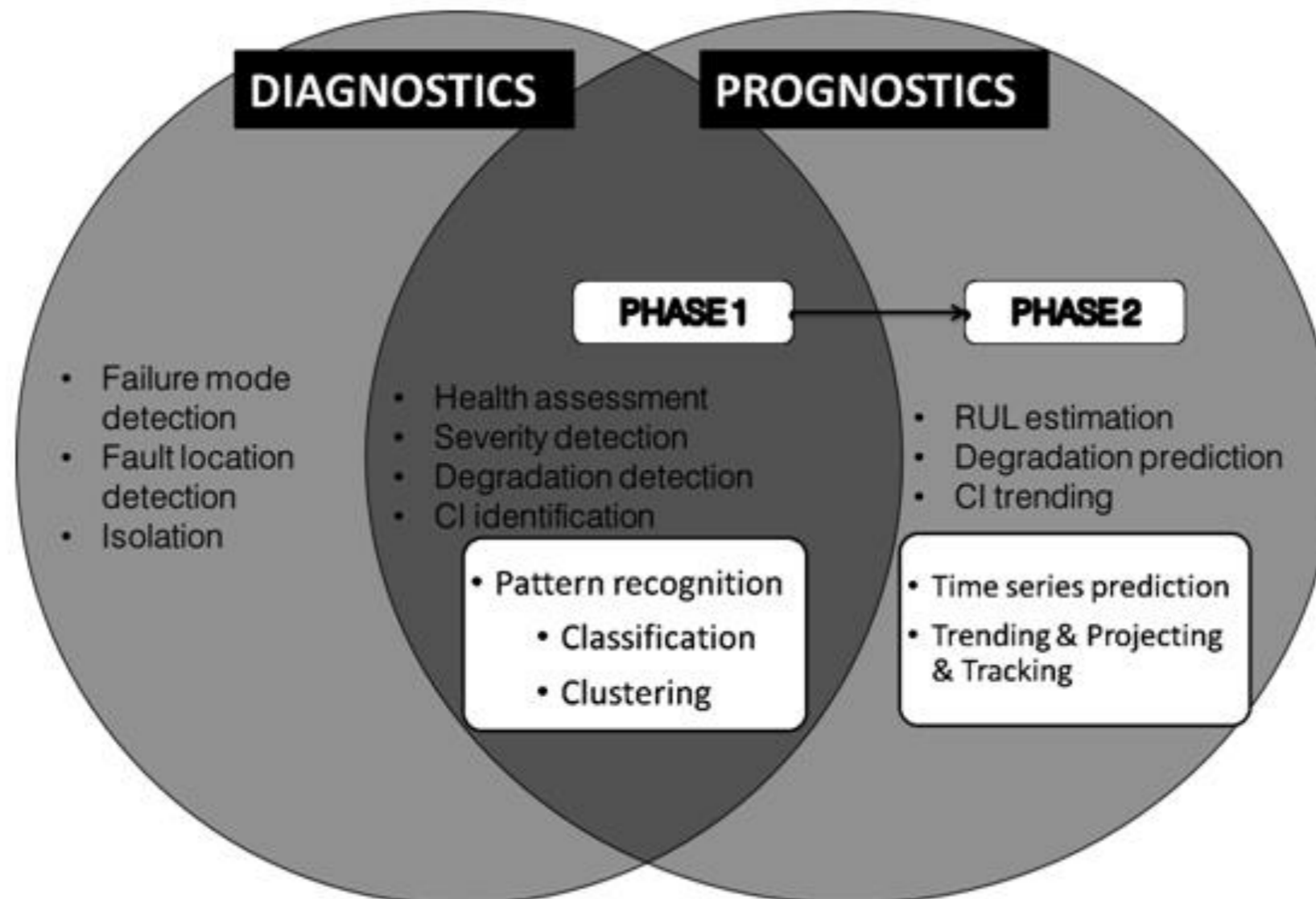


DISTRIBUTED

PROGNOSIS

**Centrifugal pump
(rapid propellant system)**

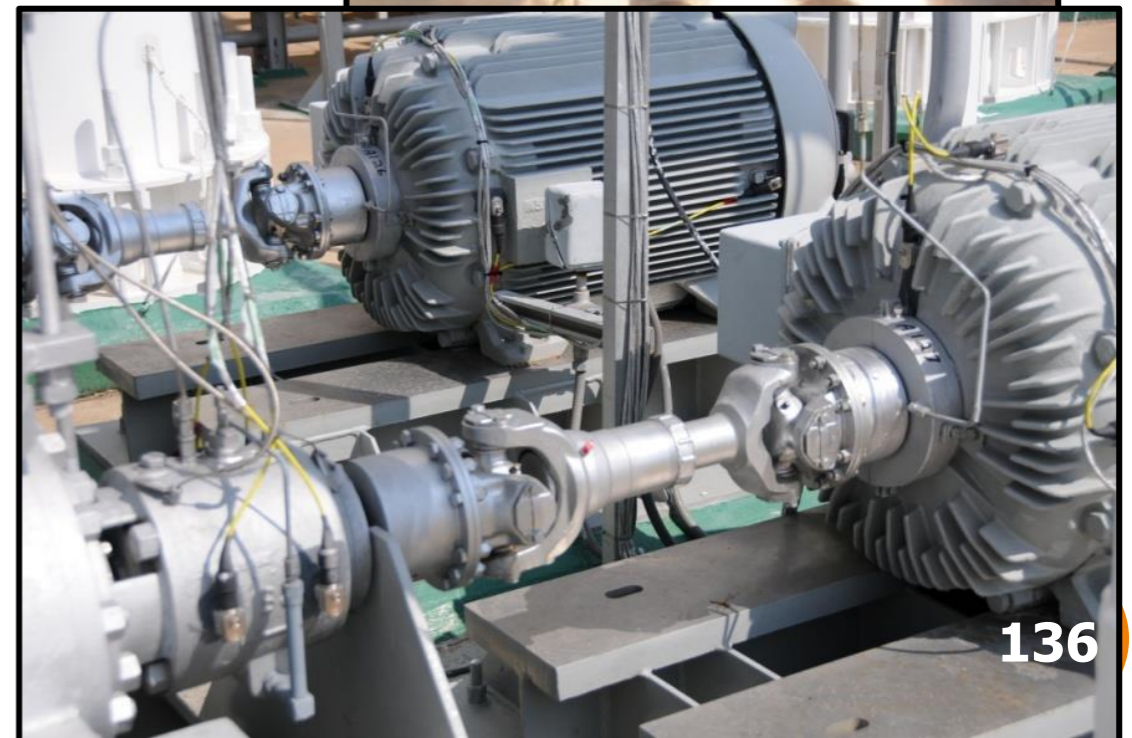
THE LINK BETWEEN DIAGNOSIS AND PROGNOSIS



- **Diagnosis – identification** (parameter estimation) – “*Process of determining the state of a component to perform its function(s)*”
- **Prognosis** – “*Estimation of remaining life of a component or subsystem*”

MOTIVATION

- Fast propellant
- Secure system
- We need fault diagnosis and prognosis
- Prognosis is computationally expensive
 - Propose **model decomposition** approach to define local state-parameter estimation problems from the global problem
 - **Allows estimation to be performed more efficiently**
 - **Allows damage estimation to be naturally distributed**

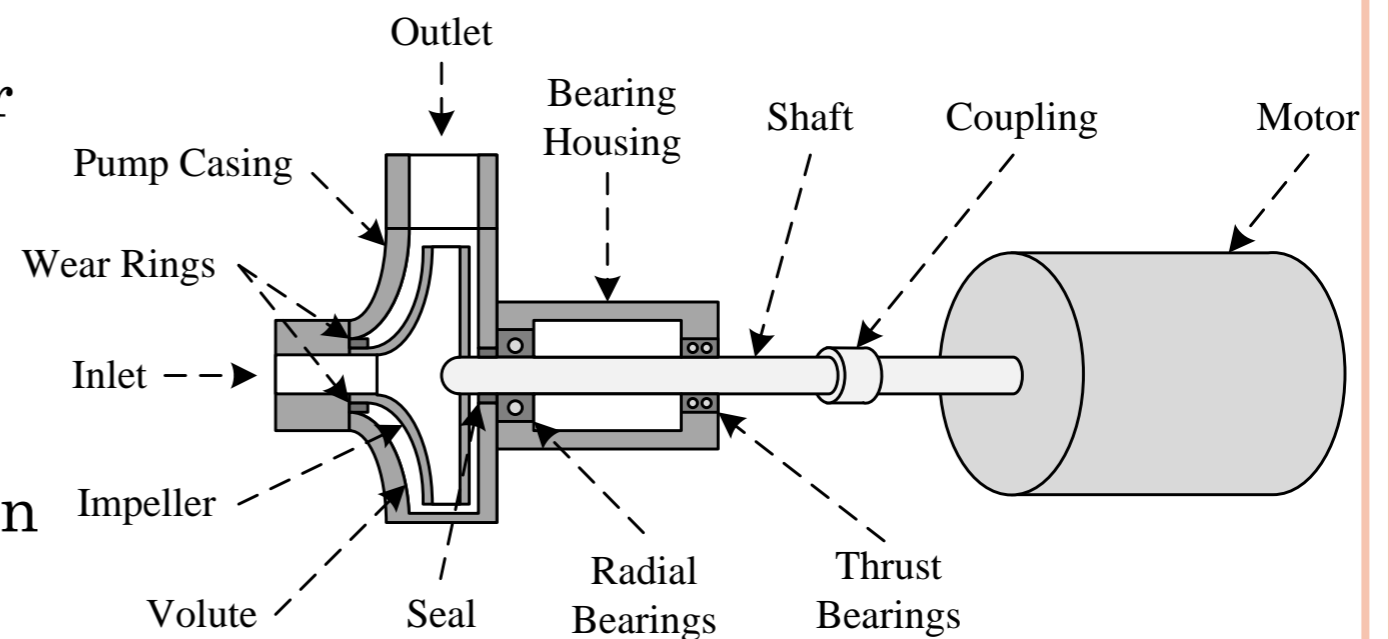


CASE STUDY

- Apply framework to centrifugal pump
 - Complex electro-mechanical devices used for fluid delivery in water systems, spacecraft fueling, etc.
 - Often undergo continuous usage, so require regular maintenance
 - Provide a critical function, so failures can cause loss of mission

- Centrifugal pump operation

- Fluid enters the inlet, impeller rotation forces fluid through the outlet
- Impeller rotation driven by electric motor
- Bearings help minimize friction
- Bearing housing contains lubricating oil
- Wear rings prevent excessive internal leakage

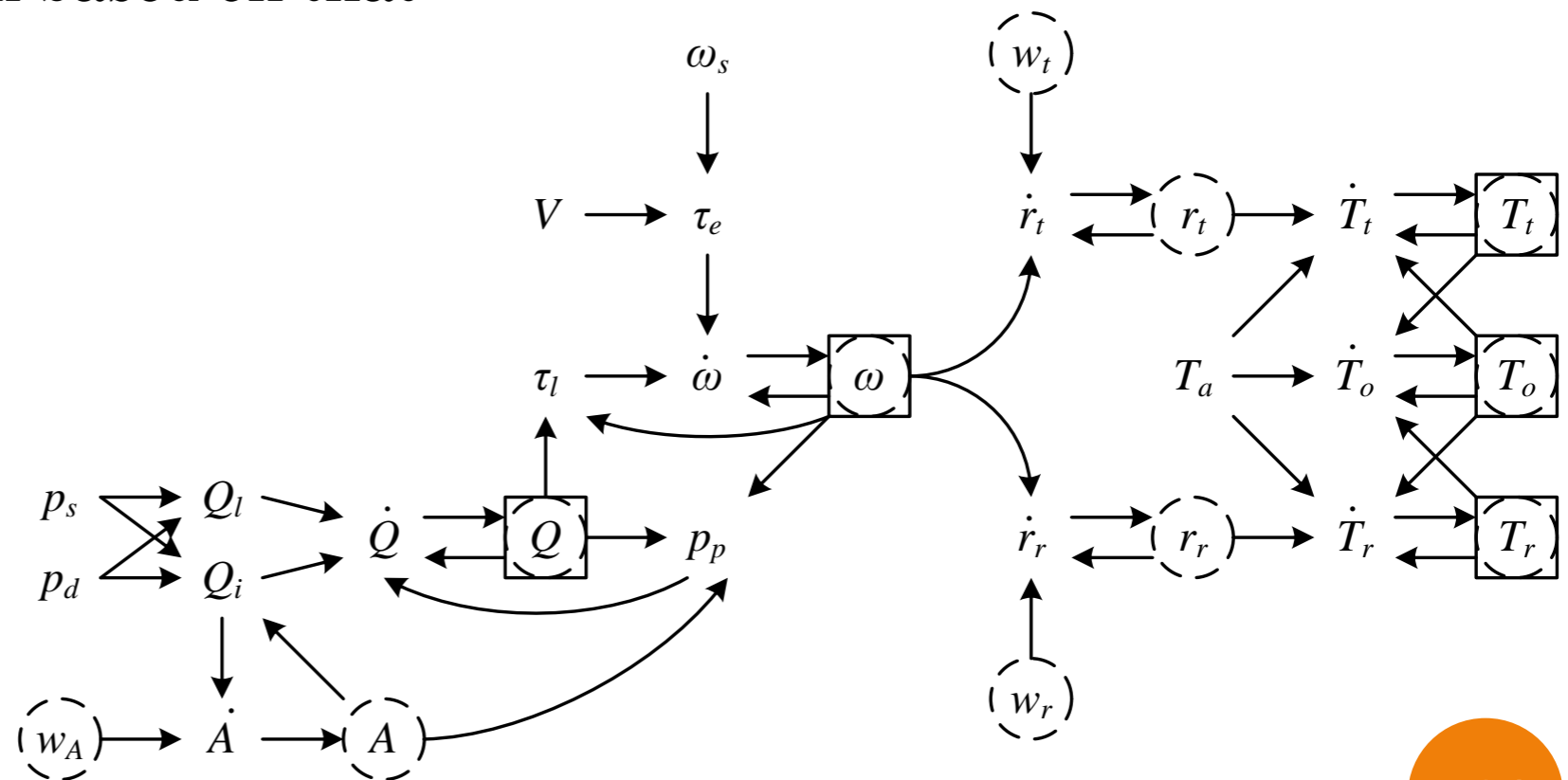


Centrifugal Pump

MODEL REPRESENTATION

- PCs may be derived from system equations or graphical representations
 - Graphical representations that include causality are preferred because they are more efficient and result in a simpler decomposition algorithm
- Use hypergraph structure to represent model and define a decomposition algorithm based on that
 - Variables are vertices
 - Hyperedges are causal relationships
 - Derived directly from system equations

Hypergraph for pump model. States and unknown parameters are contained in circles, measured variables in squares.



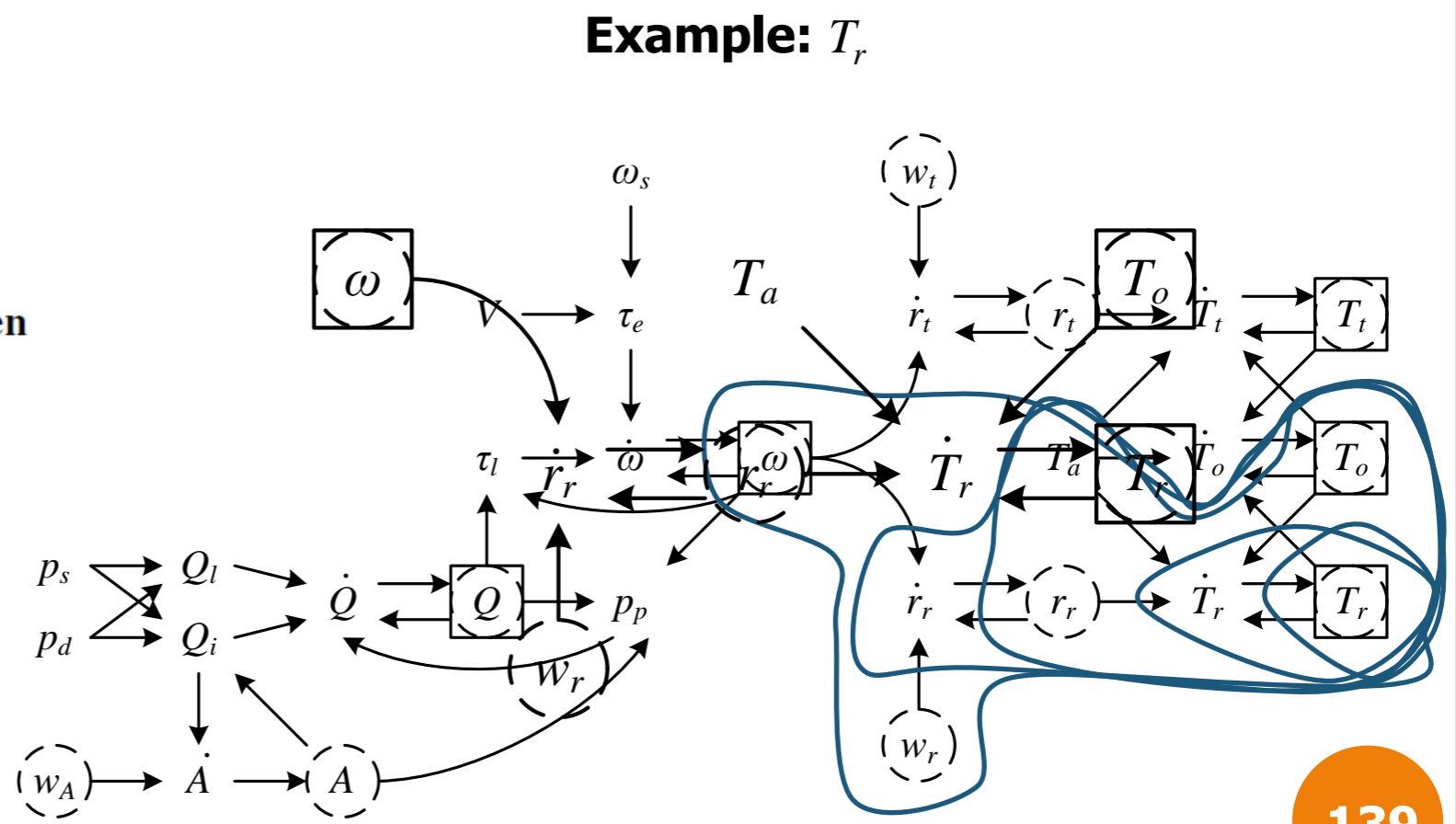
DECOMPOSITION ALGORITHM

Algorithm 1 $\{\mathcal{G}_i\}_{i=1}^{n_y} = \text{Decompose}(\mathcal{G})$

```

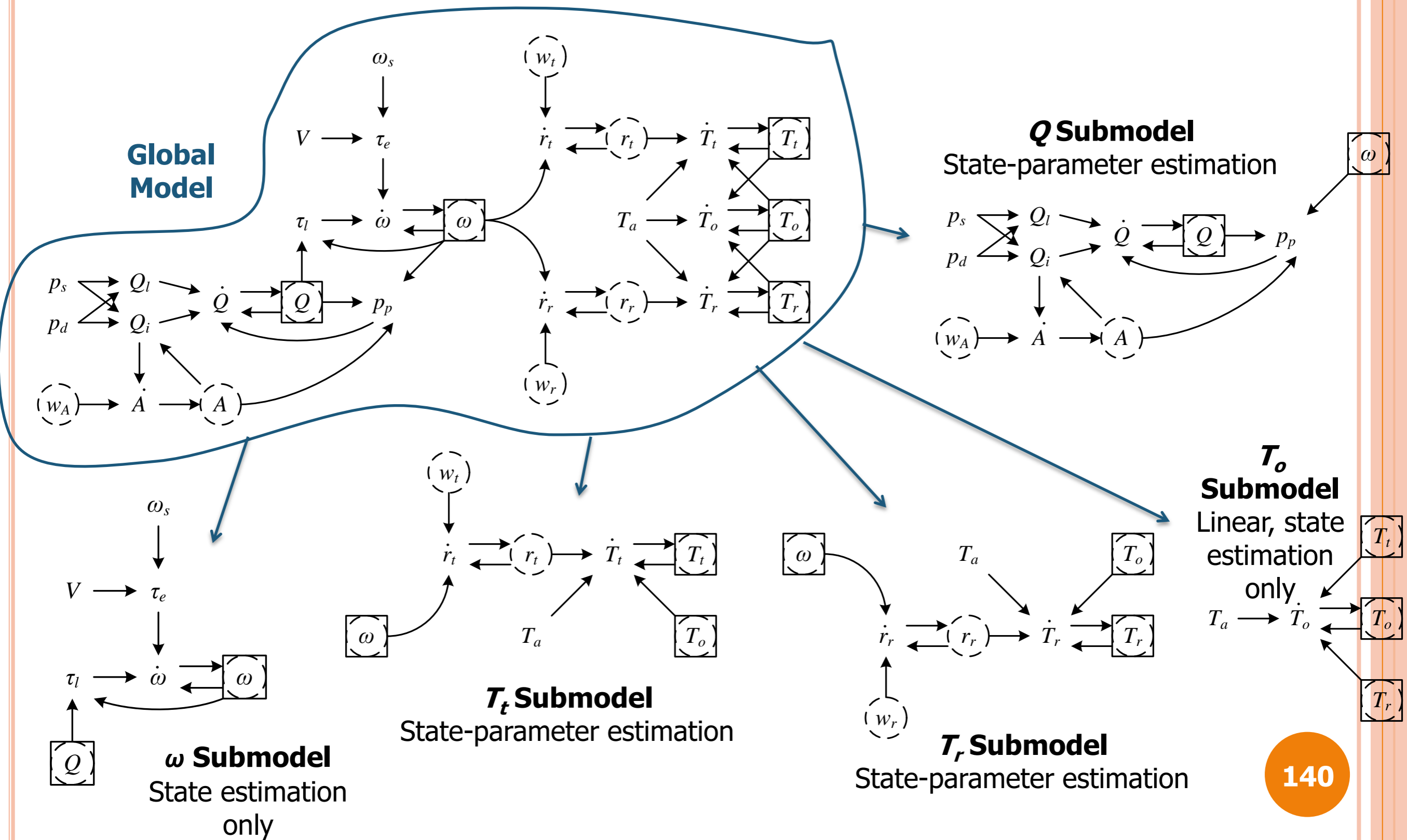
for  $i = 1$  to  $n_y$  do
   $V_i \leftarrow \{y_i\}$ 
   $E_i \leftarrow \emptyset$ 
   $vertices \leftarrow \{y_i\}$ 
  while  $vertices \neq \emptyset$  do
     $v \leftarrow vertices\{1\}$ 
     $vertices \leftarrow vertices \setminus \{v\}$ 
     $edges \leftarrow \{(V', v) \in E : V' \subseteq V\}$ 
    for all  $(V', v) \in edges$  do
      for all  $v' \in V'$  do
        if  $v' \notin U$  and  $v' \notin Y$  and  $v' \notin V_i$  then
           $vertices \leftarrow vertices \cup \{v'\}$ 
        end if
      end for
    end for
     $V_i \leftarrow V_i \cup V'$ 
     $E_i \leftarrow E_i \cup \{(V', v)\}$ 
     $F_i(V', v) \leftarrow F(V', v)$ 
  end for
end while
 $\mathcal{G}_i \leftarrow (V_i, E_i, F_i)$ 
end for
  
```

- Start at a measurement variable
- Propagate back to predecessor variables
- Stop propagation at measured variables and input variables, continue propagation on other variables until measured or input variables are reached

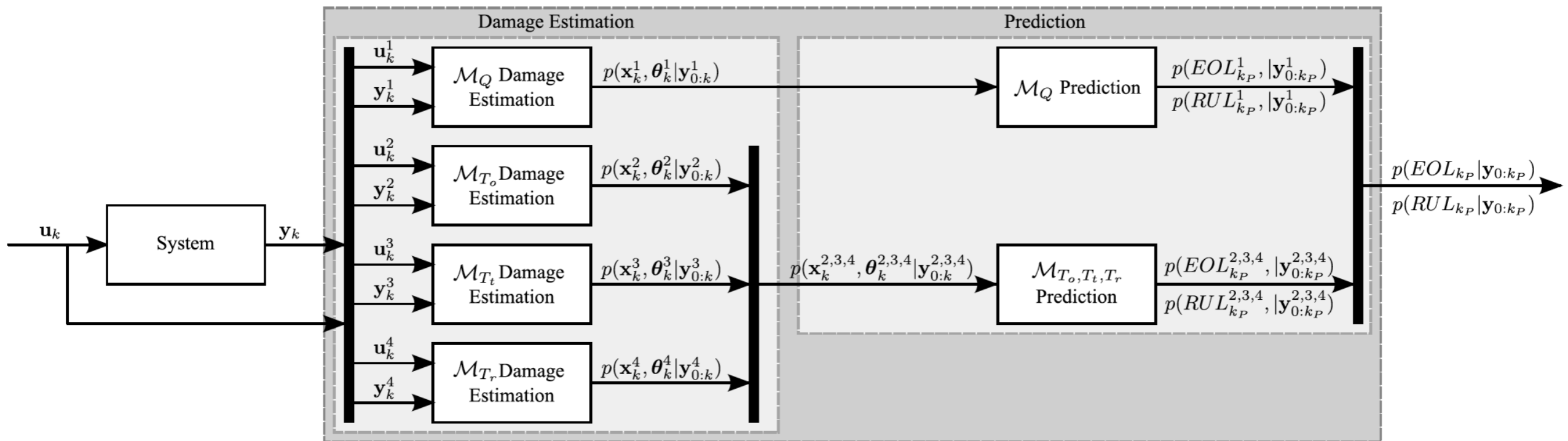




MODEL DECOMPOSITION RESULTS



DISTRIBUTED FAULT PROGNOSIS ARCHITECTURE



RESULTS

ESTIMATION AND PREDICTION PERFORMANCE

TABLE II
CENTRALIZED ESTIMATION AND PREDICTION PERFORMANCE

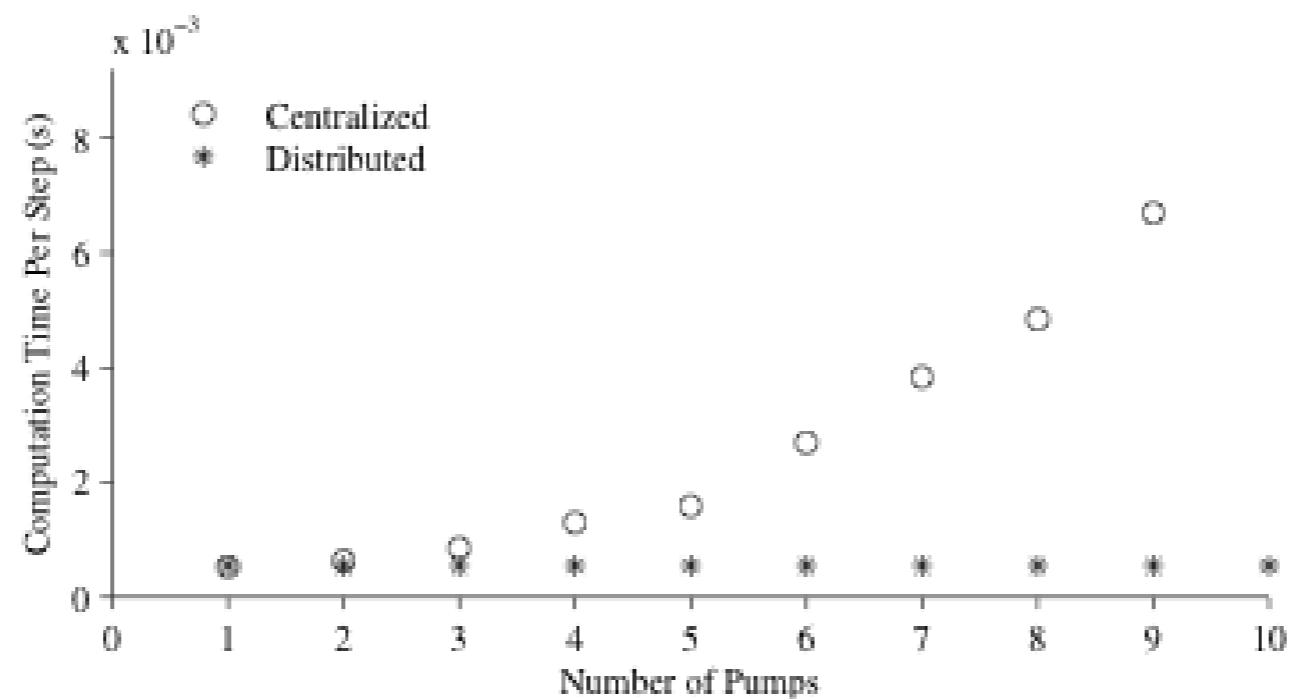
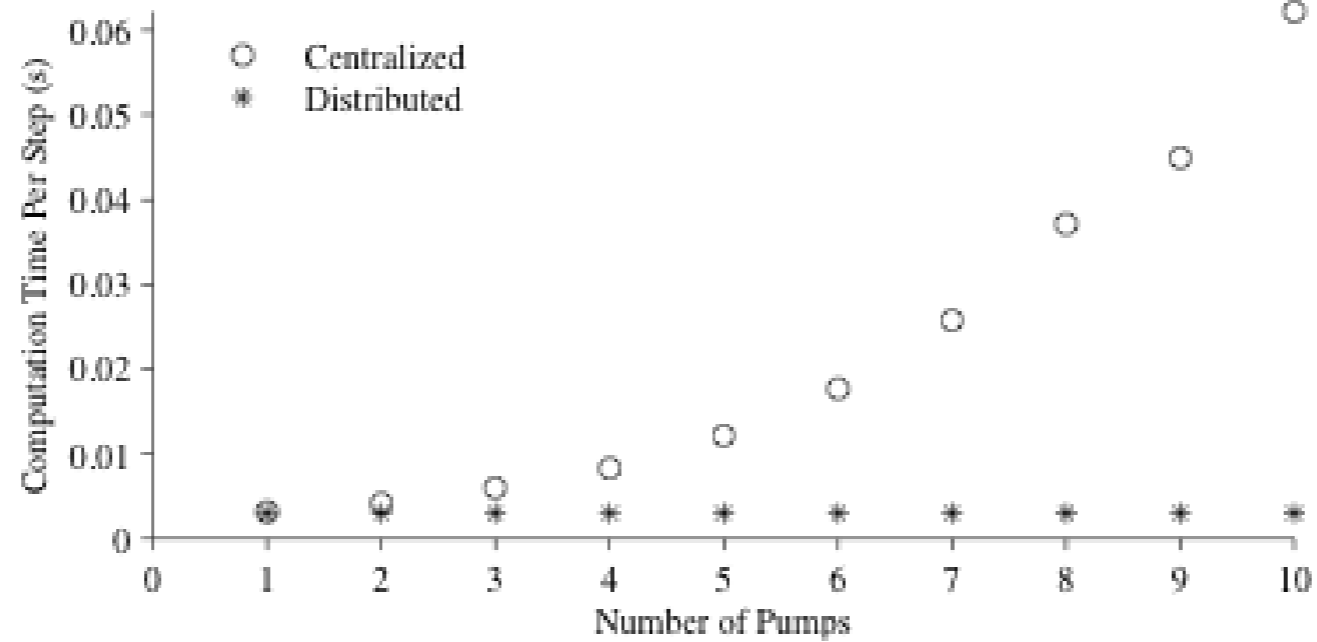
n	$PRMSE_{w_{b_0}}$	$PRMSE_{w_t}$	$PRMSE_{w_r}$	$\overline{RSD}_{w_{b_0}}$	\overline{RSD}_{w_t}	\overline{RSD}_{w_r}	\overline{RA}	\overline{RSD}_{RUL}
1	3.04	1.90	3.36	9.44	9.55	9.37	96.32	6.95
10	3.79	2.28	3.97	9.84	9.49	9.56	96.07	7.16
100	4.15	2.83	4.15	11.11	9.21	10.15	95.26	7.27
1000	3.59	3.21	4.50	11.78	9.37	10.78	94.98	7.49

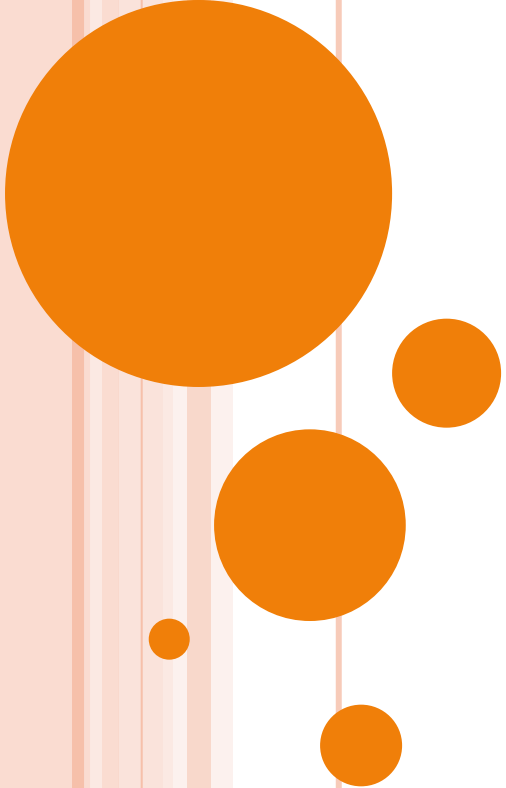
TABLE III
DISTRIBUTED ESTIMATION AND PREDICTION PERFORMANCE

n	$PRMSE_{w_{b_0}}$	$PRMSE_{w_t}$	$PRMSE_{w_r}$	$\overline{RSD}_{w_{b_0}}$	\overline{RSD}_{w_t}	\overline{RSD}_{w_r}	\overline{RA}	\overline{RSD}_{RUL}
1	2.98	1.85	4.10	10.39	10.49	10.30	96.21	8.12
10	3.77	2.35	5.28	10.79	10.42	10.55	95.78	7.99
100	4.28	2.88	5.69	11.81	10.14	11.02	95.32	7.75
1000	3.76	3.55	5.39	13.09	10.23	12.11	94.25	7.99

RESULTS

SCALABILITY





CURRENT CHALLENGES
AND OPEN PROBLEMS
(In Model-based Diagnosis)



CURRENT CHALLENGES AND OPEN PROBLEMS

- Modelling!!!
- On line simulation
 - Problems with dynamic systems: initial conditions or derivatives estimation
- What is the source of complexity?
 - Complex systems or large systems (# components)
- Multiple modelling:
 - At what level of abstraction are we modelling?
 - How we can combine results from different levels of abstraction?



CURRENT CHALLENGES AND OPEN PROBLEMS

- Real time model-based diagnosis
- Distributed diagnosis
- Diagnosis of Hybrid Systems
- Autonomous Systems
- Integration of Model-based diagnosis:
 - with other diagnosis techniques
 - with other tasks: prognostics, re-configuration, repair, monitoring, supervision/FTC,...
 - model-based diagnosis in the product life-cycle
 - (re-usable) model libraries



BIBLIOGRAPHY

CBD - MAIN REFERENCES

- R. Reiter. *A theory of diagnosis from first principles*. Artificial Intelligence, 32(1), 1987.
- W. Hamscher, J. de Kleer, and L. Console, editors. *Readings in Model-based Diagnosis: Diagnosis of Designed Artifacts Based on Descriptions of their Structure and Function*. Morgan Kaufmann, 1992.
- J.D. de Kleer and B.C. Williams. *Diagnosing multiple faults*. Artificial Intelligence, 31(1), 1987.
- J. de Kleer and J. Kurien. *Fundamentals of model-based diagnosis*. In Proceedings of SafeProcess03, 2003.
- J. de Kleer, A. Mackworth, and R. Reiter. *Characterizing diagnoses and systems*. Artificial Intelligence, 56, 1992.
- P. Struss and O. Dressler. *Physical negation: Introducing fault models into the General Diagnostic Engine*. In Proceedings of the 11th International Joint Conference on Artificial Intelligence, IJCAI89, pages 1318–1323, Detroit, Michigan, USA. 1989
- O. Dressler and P. Struss. *The Consistency-based approach to automated diagnosis of devices*. In Brewka, G., editor, Principles of Knowledge Representation, pages 269–314. CSLI Publications, Stanford, 1996
- D. Dvorak and B.J. Kuipers. *Model-based monitoring of dynamic systems*. In International Joint Conference on Artificial Intelligence, 1989.



BIBLIOGRAPHY

POSSIBLE CONFLICTS

- Belarmino Pulido, Carlos Alonso. “*Possible conflicts: a compilation technique for consistency-based diagnosis*”. IEEE Trans. on Systems Man and Cybernetics, Part B. Special Issue on “Diagnosis of Complex Systems: Bridging the methodologies of the FDI and DX communities. Volume 34 (5), pages 2192-2206, 2004.
- Anibal Bregon, Gautam Biswas, Belarmino Pulido. “*A Decomposition Method for Nonlinear Parameter Estimation in TRANSCEND*”. IEEE Transactions on Systems Man and Cybernetics, Part A: Systems and Humans. Volume 42 (3), pages 751-763, 2012.
- Anibal Bregon, Matthew Daigle, Indranil Roychoudhury, Gautam Biswas, Xenofon Koutsoukos, Belarmino Pulido. “*An Event-based Distributed Diagnosis Framework using Structural Model Decomposition*”. Artificial Intelligence. Volume 210, pages 1-35, 2014.
- Matthew Daigle, Anibal Bregon, Indranil Roychoudhury. “*Distributed Prognostics based on Structural Model Decomposition*”. IEEE Transactions on Reliability. Volume 63 (2), pages 495-510, 2014.
- Anibal Bregon, Gautam Biswas, Belarmino Pulido, Carlos Alonso-Gonzalez, Hamed Khorasgani. “*A Common Framework for Compilation Techniques Applied to Diagnosis of Linear Dynamic Systems*”. IEEE Transactions on Systems Man and Cybernetics: Systems. Volumen 44 (7), pages 863-876, 2014.

ADDITIONAL BIBLIOGRAPHY

- Armengol, J., Bregon, A., Escobet, T., Gelso, E., Krysander, M., Nyberg, M., Olive, X., Pulido, B., and Travé-Massuyès, L. *Minimal Structurally Overdetermined sets for residual generation: A comparison of alternative approaches*. In Proceedings of the 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, SAFEPROCESS09, pages 1480–1485, Barcelona, Spain, 2009.
- Blanke, M., Kinnaert, M., Lunze, J., and Staroswiecki, M. *Diagnosis and Fault-Tolerant Control*. Springer, 2006.
- Biswas, G., Cordier, M., Lunze, J., Travé-Massuyès, L., and Staroswiecki, M. *Diagnosis of complex systems: bridging the methodologies of the FDI and DX communities*. IEEE Trans. on Systems, Man, and Cybernetics. Part B: Cybernetics, 34(5):2159–2162, 2004.
- Cordier, M., Dague, P., Lévy, F., Montmain, J., Staroswiecki, M., and Travé-Massuyès, L. *Conflicts versus Analytical Redundancy Relations: a comparative analysis of the Model-based Diagnosis approach from the Artificial Intelligence and Automatic Control perspectives*. IEEE Trans. on Systems, Man, and Cybernetics. Part B: Cybernetics, 34(5):2163–2177, 2004.
- Guckenbiehl, T. and Schaefer-Richter, G. *SIDIA: Extending prediction based diagnosis to dynamic models*. In Proceedings of the 1st International Workshop on Principles of Diagnosis, DX90, pages 74–82, Stanford, California, USA, 1990.



ADDITIONAL BIBLIOGRAPHY

- Krysanter, M., Aslund, J., and Nyberg, M. *An Efficient Algorithm for Finding Minimal Over-constrained Sub-systems for Model-based Diagnosis*. IEEE Trans. on Systems, Man, and Cybernetics. Part A: Systems and Humans, 38(1):197–206, 2008.
- Loiez, E. and Taillibert, P. *Polynomial temporal band sequences for analog diagnosis*. In Proceedings of the 15th International Joint Conference on Artificial Intelligence, IJCAI97, pages 474–479, Nagoya, Japan, 1997.
- Mosterman, P. and Biswas, G. *Diagnosis of continuous valued systems in transient operating regions*. IEEE Transactions on Systems, Man, and Cybernetics, 29(6):554–565, 1999.
- Staroswiecki, M. *Fault Diagnosis and Fault Tolerant Control, chapter Structural Analysis for Fault Detection and Isolation and for Fault Tolerant Control*. Encyclopedia of Life Support Systems. Eolss Publishers, Oxford, UK, 2002.
- Struss, P. *Model-based diagnosis for industrial applications*. In Colloquium-Applications of Model-based Reasoning, Savoy Place, London, United Kingdom. Institute of Electrical Engineers (IEE), 1997.
- Travé-Massuyès, L. and Milne, R. *Gas-Turbine Condition Monitoring Using Qualitative Model-Based Diagnosis*. IEEE Expert, 12(3):22–31, 1997.



ADDITIONAL BIBLIOGRAPHY

- Travé-Massuyés, L., Escobet, T., and Olive, X. *Diagnosability analysis based on component supported analytical redundancy relations*. IEEE Trans. Syst. Man Cy. A., 36(6), 2006.
- Washio, T., Sakuma, M., and Kitamura, M. *A new approach to quantitative and credible diagnosis for multiple faults of components and sensors*. Artificial Intelligence, 91(1):103–130, 1997.
- Williams, B. and Millar, B. *Automated decomposition of Model-based Learning Problems*. In Proceedings of the 7th International Workshop on Principles of Diagnosis, DX96, pages 258–266, Val Morin, Quebec, Canada, 1996.
- Williams, B. and Millar, B. *Decompositional Model-based Learning and its analogy to diagnosis*. In Proceedings of the 15th National Conference on Artificial Intelligence, AAAI98, Madison, Wisconsin, USA, 1998.

WHERE TO FIND MORE INFORMATION...

○ Conferences

- PHM: <http://www.phmsociety.org/>
- DX: <http://dx-2014.ist.tugraz.at/>
- IJCAI: <http://ijcai.org/>
- Safeprocess: <http://safeprocess15.sciencesconf.org/> part of IFAC organization,
- IFAC world conference: <http://www.ifac2014.org/>

○ Journals

- Artificial Intelligence Journal
- International Journal of the PHM Society (IJPHM)
- Journal of AI Research
- IEEE Transactions On Systems, Man and Cybernetics
- AI Communications
- Control Engineering Practice
- Engineering Application on Artificial Intelligence



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