Decompositional, Model-based Learning and its Analogy to Diagnosis

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http://www.ic.arc.nasa.gov/ic/projects/mba/index.html

Large-Scale Exploratory Modeling

How do communities of modelers:

- *Decompose models?*
- Simplify models?
- Select applicable data?
- *Coordinate analyses?*
- Combine estimates?
- Exploit qualitative knowledge?
- ...

Outline

- Smart buildings that model themselves
- Decompositional learning:
  - problem decomposition, recomposition and coordination
  - decomposition by analogy to model-based diagnosis
- Thermal problem revisited
- Wrapup

Terrestrial Analogues
Smart Buildings at CMU & Xerox PARC

Brian Williams - AAAI98

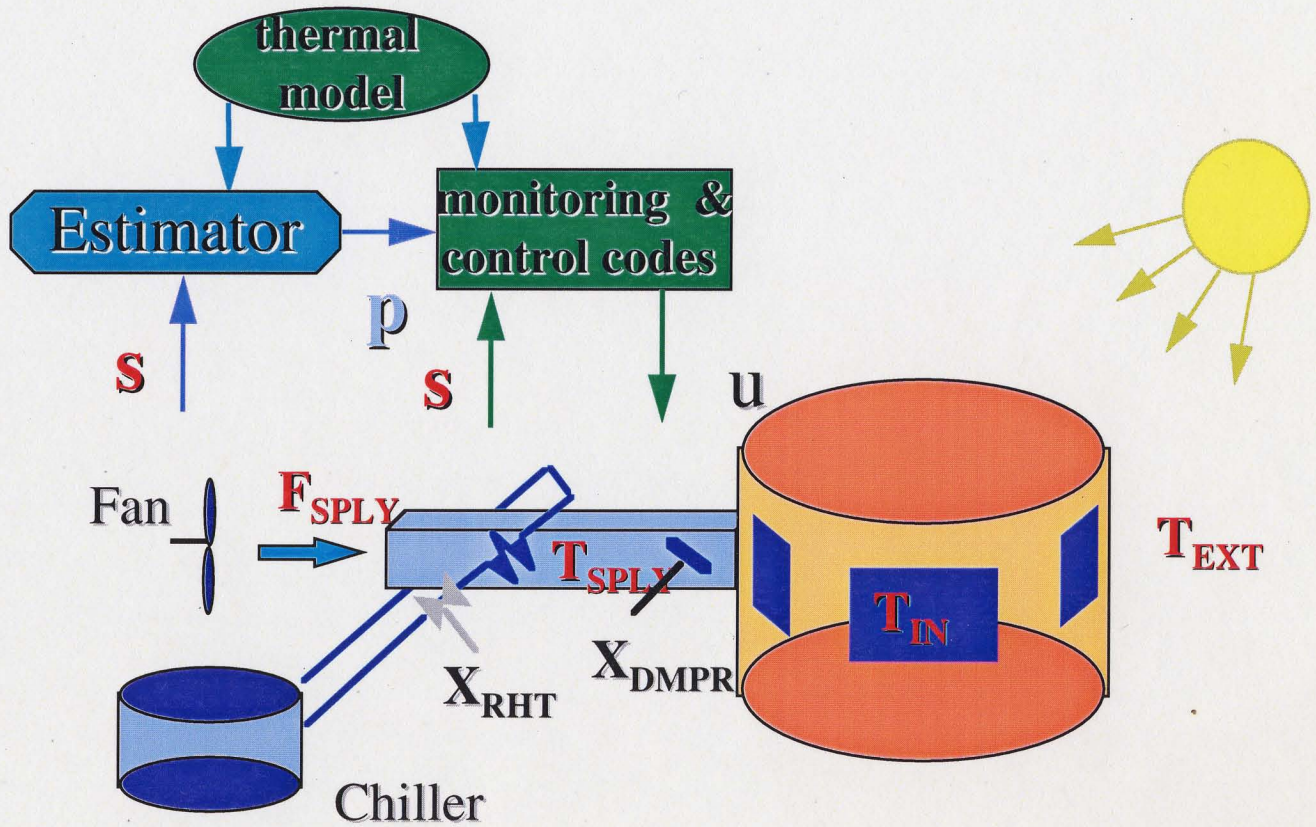
Controlling Complex Embedded Systems

Issues:

- overwhelming number of control parameters
- slow response time

globally optimal, model-based control

$$\mathbf{p}^* = \arg\min_{\mathbf{p}} \sum_{\langle y_i \ \mathbf{x}_i \rangle \in \mathbf{D}} \left[y_i - \hat{y}(\mathbf{x}_i, \mathbf{p}) \right]^2$$

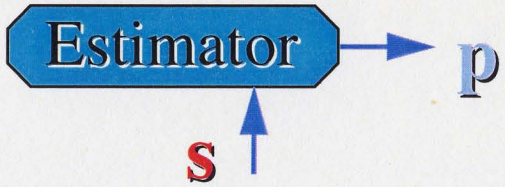


Improvement:

energy: ~ 45%

accuracy: ~ 65%

$$\mathbf{p}^* = \arg\min_{\mathbf{p}} \sum_{\langle y_i \quad \mathbf{x}_i \rangle \in \mathbf{D}} \left[y_i - \hat{y}(\mathbf{x}_i, \mathbf{p}) \right]^2$$



1) $F_{ext} = F_{sply}$

2) $F_{sply} = F_{rtrn}$

3) $Q_{ext} = C_o F_{ext} T_{ext}$

4) $Q_{sply} = C_o F_{sply} T_{sply}$

5) $Q_{rtrn} = C_o F_{rtrn} T_{rtrn}$

6) $Q_{rhtcap} = Q_{ext} - Q_{sply} + Q_{rht}$

7) $Q_{rhtcap} = C_{rht}\, dT_{sply}/dt$

8) $Q_{rht} = \left(\dfrac{Q_{rht\max}}{X_{rht\max}} \right) X_{rht}$

9) $F_{ext} = F_{lkg} + F_{dmpr}$

10) $F_{lkg} = \left(\dfrac{\rho_{lkg}}{R_{dct}} \right) \sqrt{P_{dct}}$

11) $F_{dmpr} = \left(\dfrac{\rho_{dmpr}(X_{dmpr})}{R_{dct}} \right) \sqrt{P_{dct}}$

12) $Q_{rm} = Q_{sply} + Q_{eqp} + Q_{slr} + Q_{wll} + Q_{rtrn}$

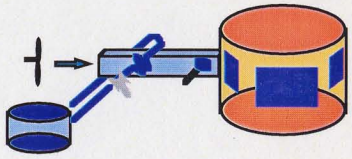
13) $Q_{rm} = C_{rm}\, dT_{rm}/dt$

14) $Q_{wll} = \sigma_{wll}(T_{rm} - T_{ext})$

- $\mathbf{s} = \langle T_{ext} \quad T_{sply} \quad T_{rm} \quad dT_{sply}/dt \quad dT_{rm}/dt \quad X_{rht} \quad X_{dmpr} \quad F_{sply} \quad P_{dct} \rangle^T$

$\mathbf{p} = \langle R_{dct} \quad C_{rht} \quad Q_{rht\max} \quad C_{rm} \quad \sigma_{wll} \quad Q_{eqp} \quad Q_{slr} \rangle^T$

Model Decomposition



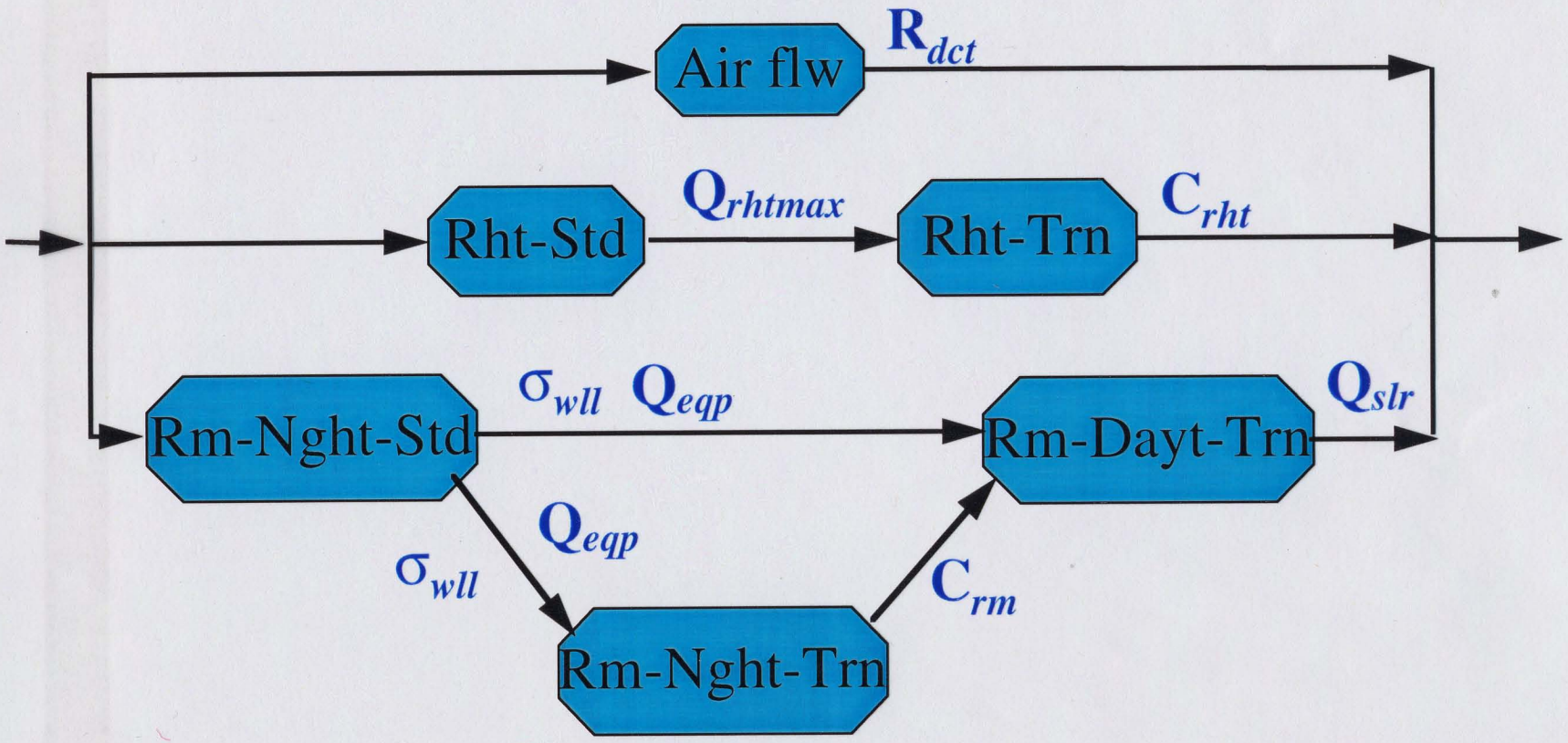
Estimator → **Parameters**

- **air flow** — R_{dct}
- **heat flow through reheat**
  - transient T — Q_{rhtmax}, C_{rht}
  - steady T — Q_{rhtmax}
- **heat flow through room**
  - day time, transient T — σ_{dct} , Q_{eqp}, C_{rm}, Q_{slr}
  - night time, transient T — σ_{dct} , Q_{eqp}, C_{rm}
  - night time, steady T — σ_{dct} , Q_{eqp}

How do we generate smallest decompositions?

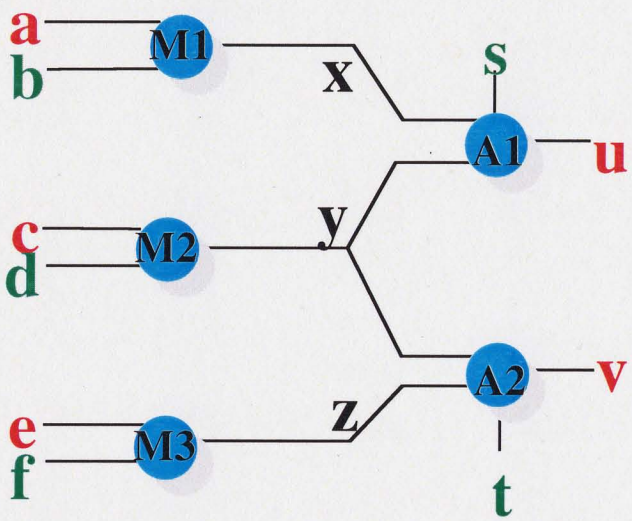
How do we simplify these decompositions? Not Addressed

Decomposing and Coordinating Estimates



How do we generate these estimation plans?

Model Estimation



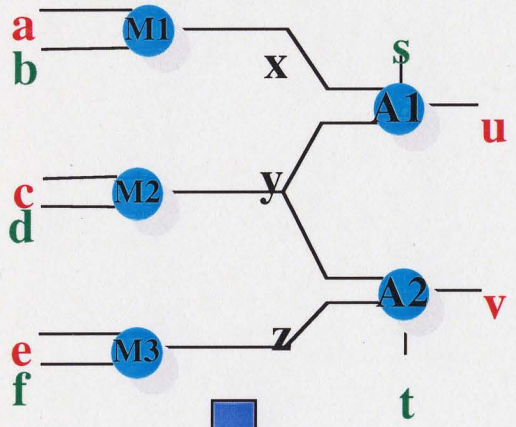
Legend

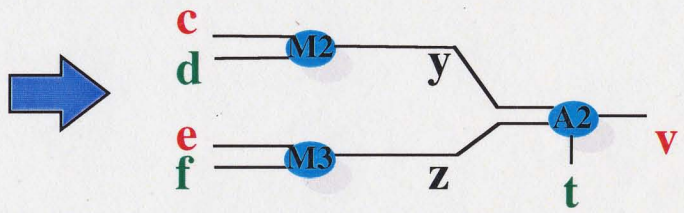
- s sensed variable
- p parameter
- h hidden variable

Problem:

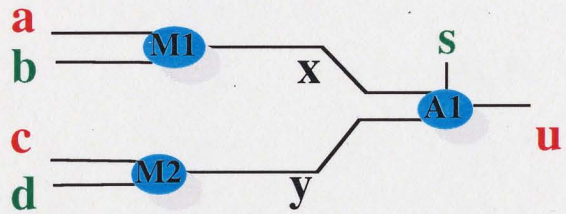
Identify parameter values that minimize disagreement between the model and the observables. ➡ System is overdetermined

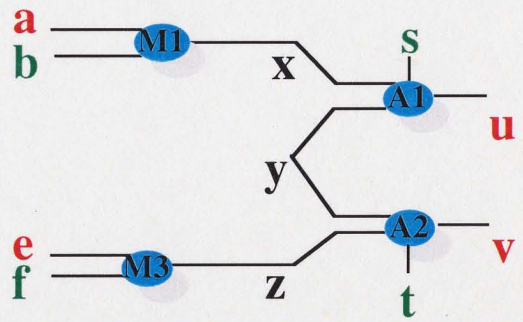
Step 1: Decomposition Involves Finding a Simplest Subproblem





D3) {M2, M3, A2, c, e, v} ⇨ d, f, t



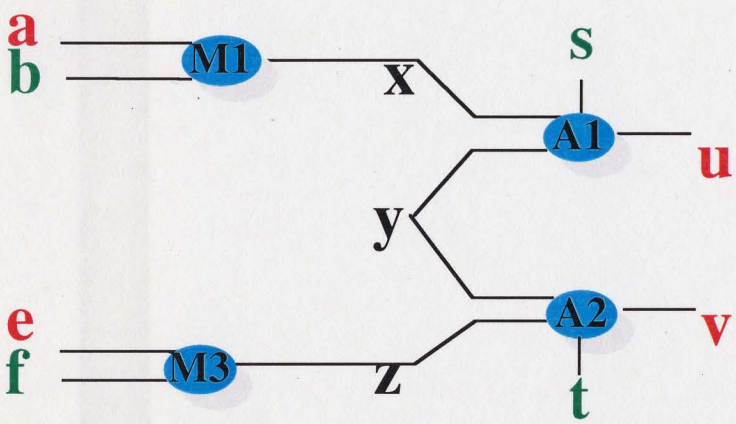


D2) {M1, M3, A1, A2, a, e, u, v} ⇨ b, f, s, t

Dissent: {M1, M2, A1, a, c, u} ⇨ b, d s

Minimal subset of the model and sensed variables that are overdetermined.

Step 2: Estimators are Generated from each Submodel



$$v_i = (u_i - ba_i - s) + fe_i + t$$

$$\underset{\langle b \;\; f \;\; s \;\; t\rangle^T \;\; \langle a_i \;\; e_i \;\; u_i \;\; v_i\rangle^T}{\arg\min} \sum [v_i - v]^2$$

Step 3: Estimates are Shared between Estimators to Reduce Dimensionality

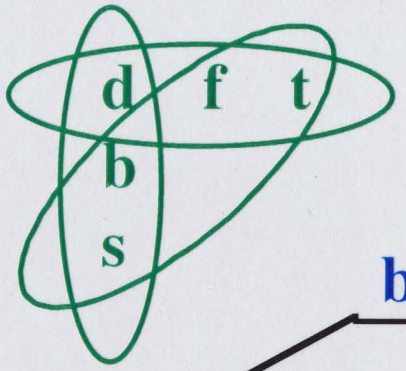
Idea: Use prior estimates as initial conditions to subsequent estimators.

Greedy Sequencing Approach:

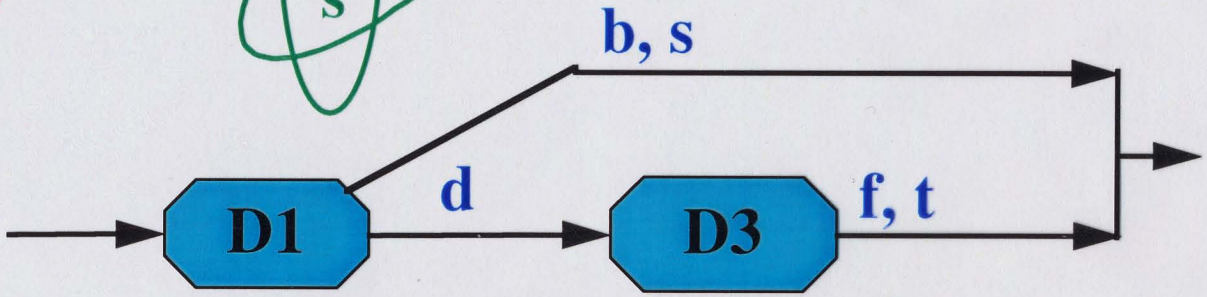
- Select estimator that minimizes number of unknown parameters.
- All else being equal, minimize sensor noise.

D1) a, c, u

D3) c, e, v

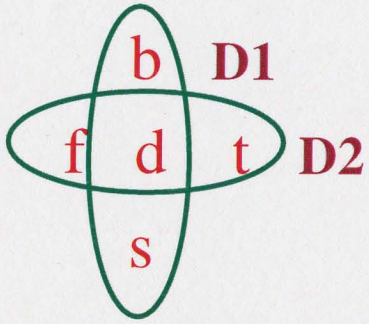


D2) a, e, u, v



$u = ba + dc + s$ $\quad$ $v = fe + dc + t$

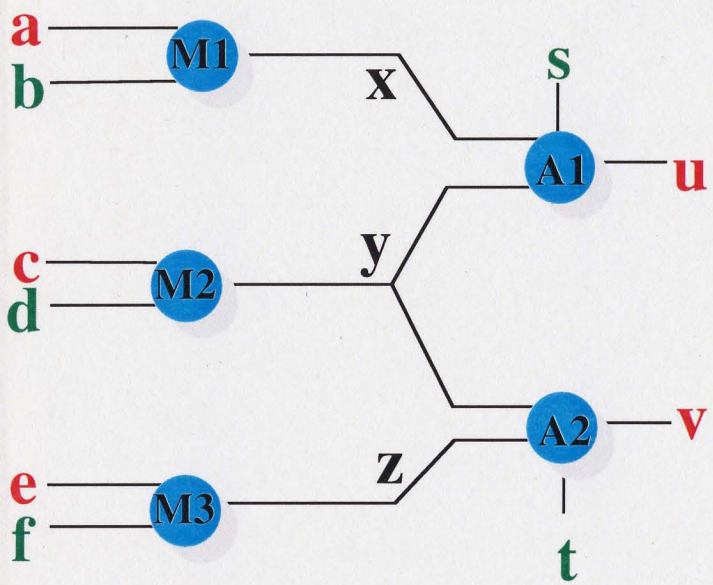
Step 4: Estimates are Shared between Estimators to Improve Accuracy

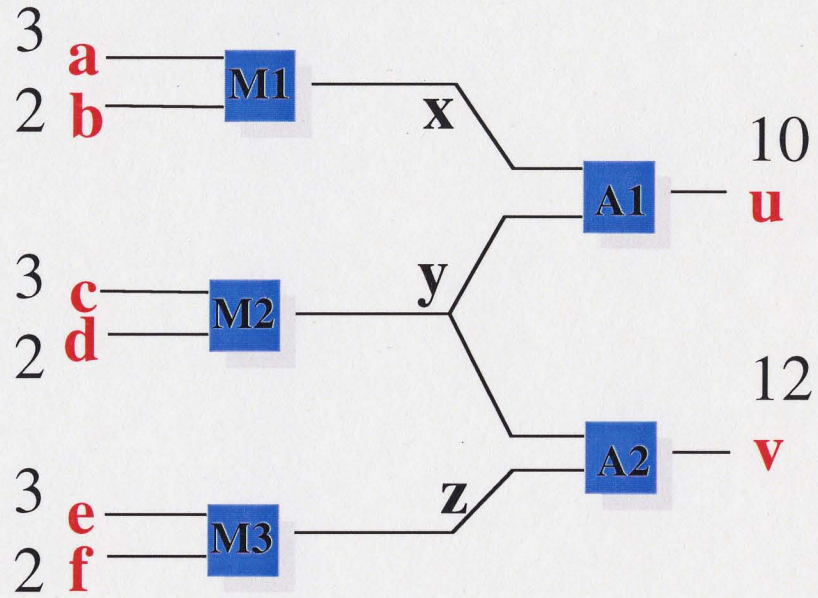


$$d_{comb} = \frac{d_1 \sigma_{d_2}^2 + d_2 \sigma_{d_1}^2}{\sigma_{d_1}^2 + \sigma_{d_2}^2}$$

$$\sigma_{d_{comb}} = \frac{\sigma_{d_1}^2 \sigma_{d_2}^2}{\sigma_{d_1}^2 + \sigma_{d_2}^2}$$

Analogy to Diagnosis





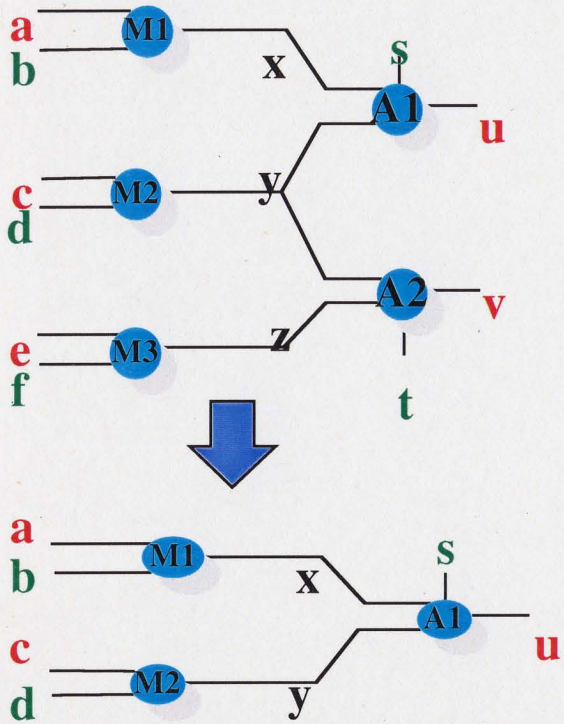
Model Estimation:

Identify parameter values that minimize disagreement between the model and the observables.

Model-based Diagnosis:

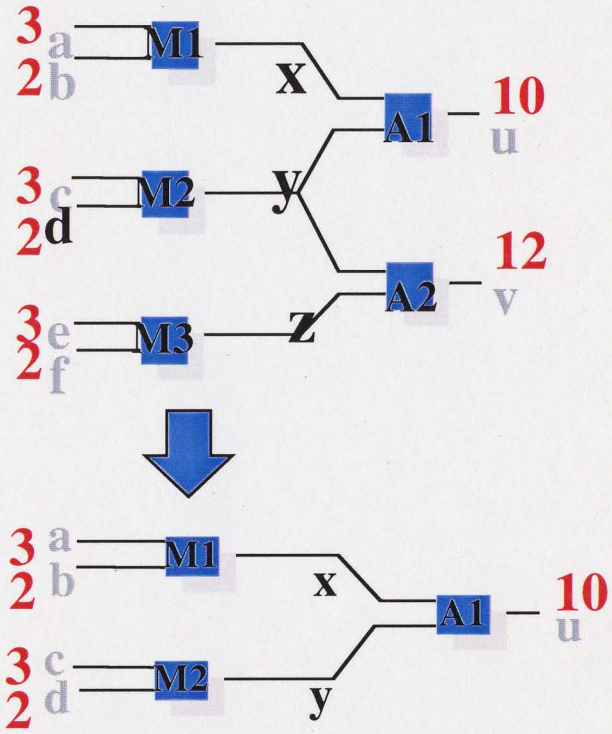
Identify failure modes that eliminate disagreement between the model and the observables.

Analogy between Dissents and Conflicts



Dissent: {M1, M2, A1, a, c, u}

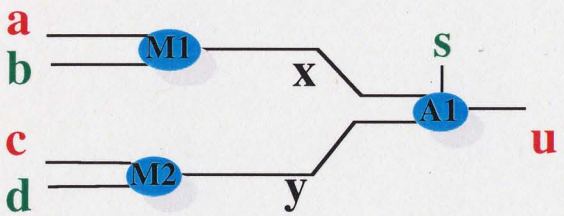
Minimal subset of the model and sensed variables that are overdetermined.

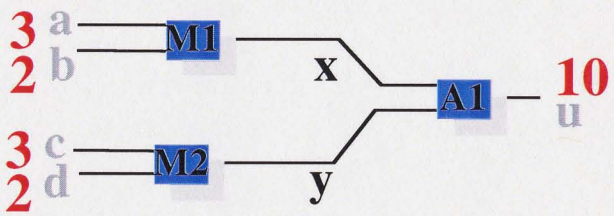


Conflict: {ok(M1),ok(M2),ok(A1)}

Minimal subset of the model and observables that are inconsistent.

Analogy between Support and Environments





Support:
{M1, M2, A1, a, c} ➡ **u**

Minimal subset of the model and sensed variables that determine a variable.

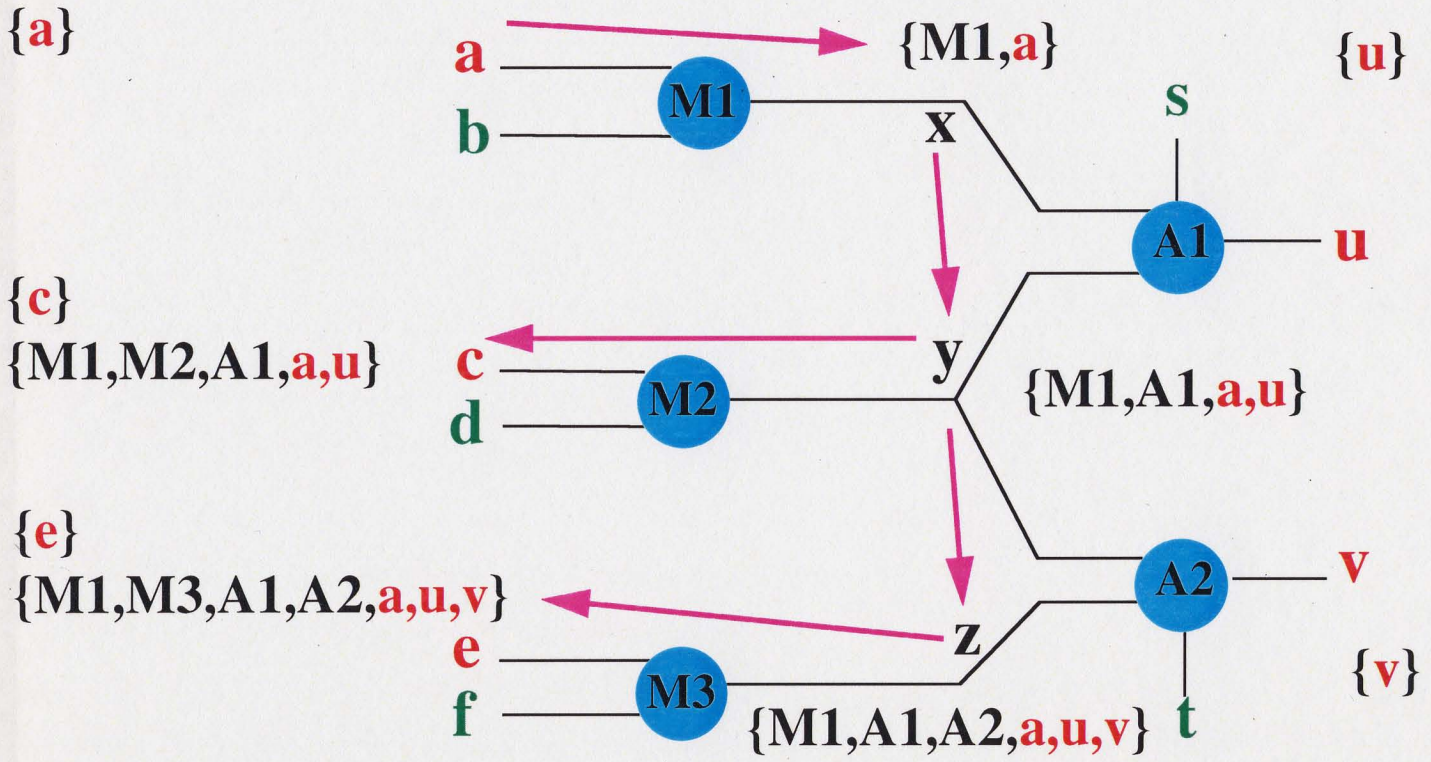
Two support for a variable form a dissent.

Environment:
{ok(M1),ok(M2),ok(A1)} ➡ **u=12**

Minimal subset of the model and observables that entail a variable/value assignment.

Two environments for an assignment form a conflict.

Support Maintenance System: Generating Dissents/Support by Propagation



Dissents		Parameters
D1) {M1, M2, A1, a, c, u}	→	b, d, s
D2) {M1, M3, A1, A2, a, e, u, v}		b, f, s, t

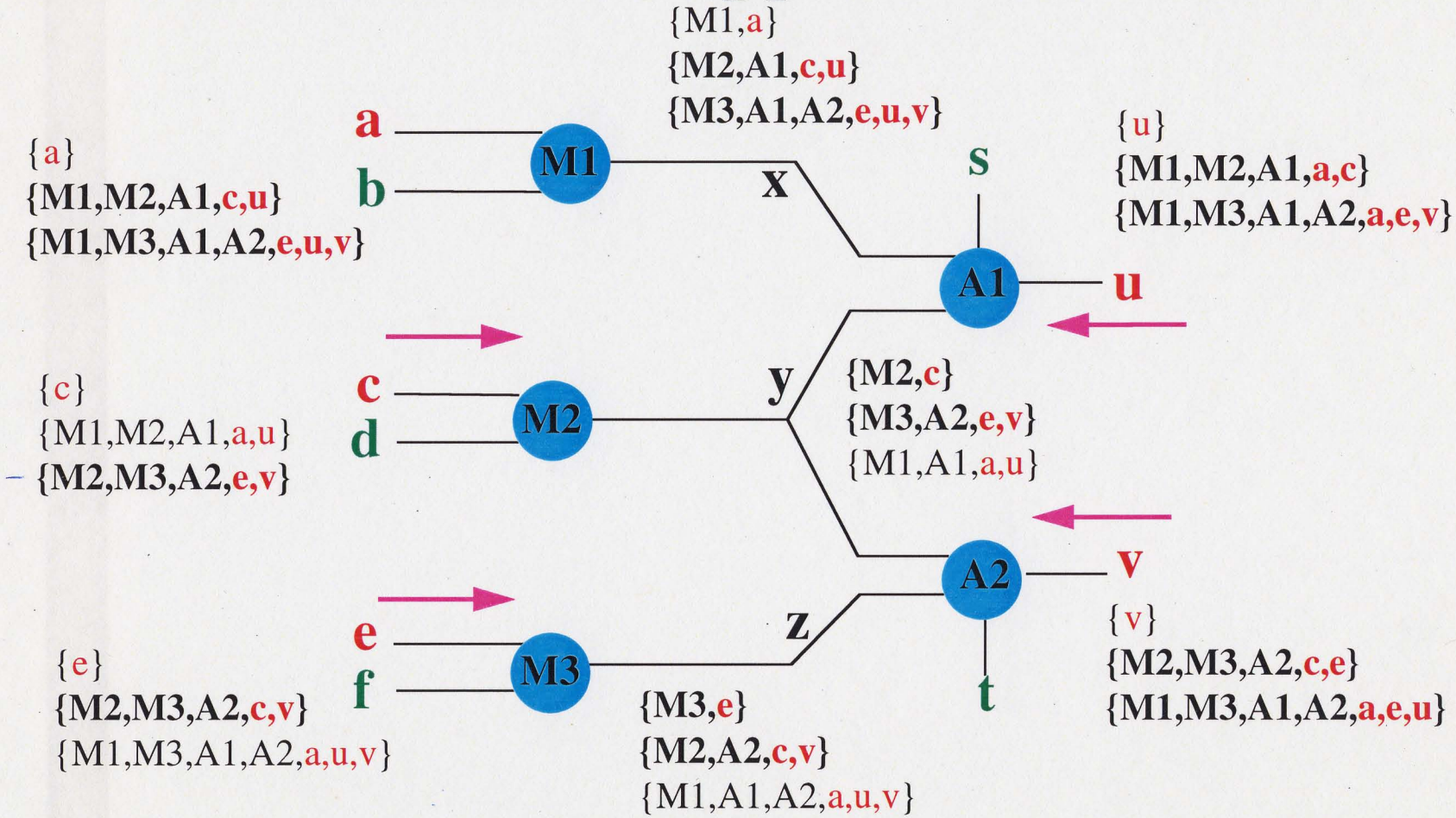
Support Maintenance: Propagation Step

Initially: support each sensed variable s by {s}

To compute a support S for vn from constraint C(v1,v2,...vn):

- Nondeterministically select one support for each of v1 .. v(n-1).
- S = union of these support plus C.
- Check determinacy of S:
  - n eqns with n dependent variables ➡ uniquely determined
  - n eqns with $\leq$ n dependent variables ➡ overdetermined

All Generated Support and Dissents



D1) {M1,M2,A1,a,c,u} b, d, s

D2) {M1,M3,A1,A2,a,e,u,v} → b, f, s, t

D3) **{M2,M3,A2,c,e,v}** **d, f, t**

Dissents for the Thermal Example

D1: dT_{sply}/dt , T_{sply} , F_{sply} , T_{ext} , X_{rht}

C_{rht} , Q_{rhtmax}

D2: F_{sply} , P_{dct} , X_{dmpr}

R_{dct}

D3: dT_{sply}/dt , F_{sply} , P_{dct} , T_{ext} , T_{rm} , X_{rht} , X_{dmpr}

C_{rht} , R_{dct} , Q_{rhtmax}

D4: dT_{rm}/dt , dT_{sply}/dt , F_{sply} , P_{dct} , T_{ext} , T_{rm} , X_{rht} , X_{dmpr}

C_{rht} , C_{rm} , R_{dct} , Q_{rhtmax} , Q_{eqp} , Q_{slr} , σ_{wll}

D5: dT_{rm}/dt , dT_{sply}/dt , F_{sply} , T_{ext} , T_{rm} , X_{rht}

C_{rht} , C_{rm} , Q_{rhtmax} , Q_{eqp} , Q_{slr} , σ_{wll}

D6: dT_{rm}/dt , T_{rm} , F_{sply} , T_{sply} , T_{ext}

C_{rm} , Q_{eqp} , Q_{slr} , σ_{wll}

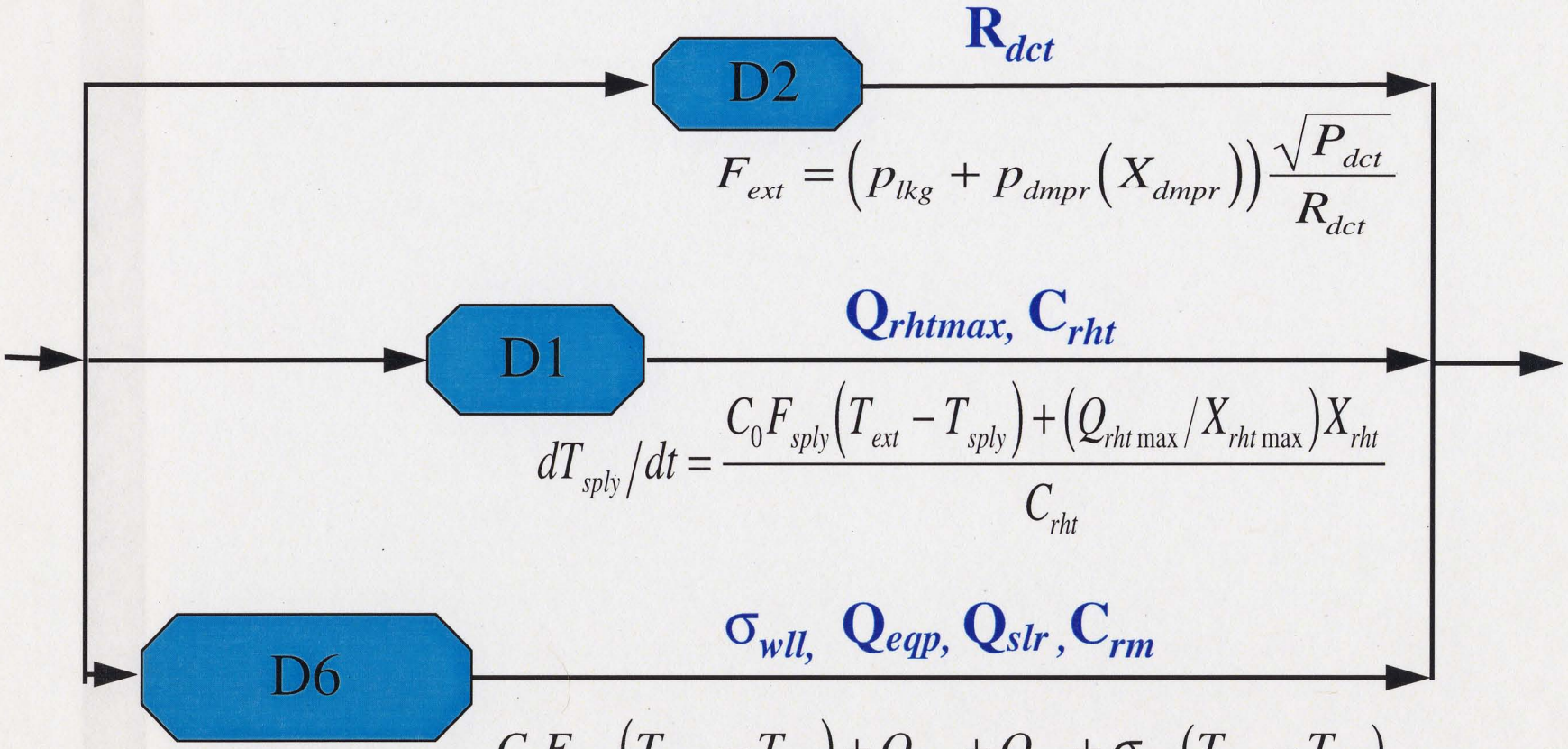
D7: dT_{rm}/dt , dT_{sply}/dt , F_{sply} , P_{dct} , T_{sply} , T_{rm} , X_{rht} , X_{dmpr}

C_{rht} , C_{rm} , R_{dct} , Q_{rhtmax} , Q_{eqp} , Q_{slr} , σ_{wll}

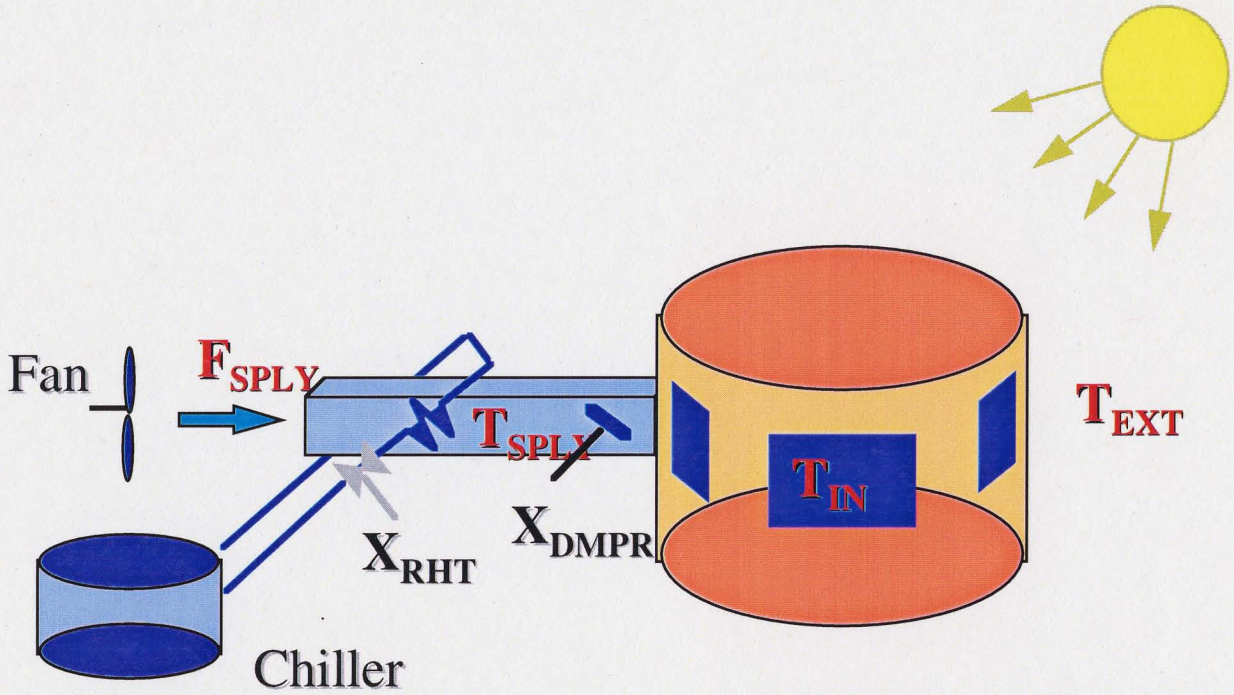
D8: dT_{rm}/dt , dT_{sply}/dt , F_{sply} , T_{rm} , T_{sply} , X_{rht}

C_{rht} , C_{rm} , Q_{rhtmax} , Q_{eqp} , Q_{slr} , σ_{wll}

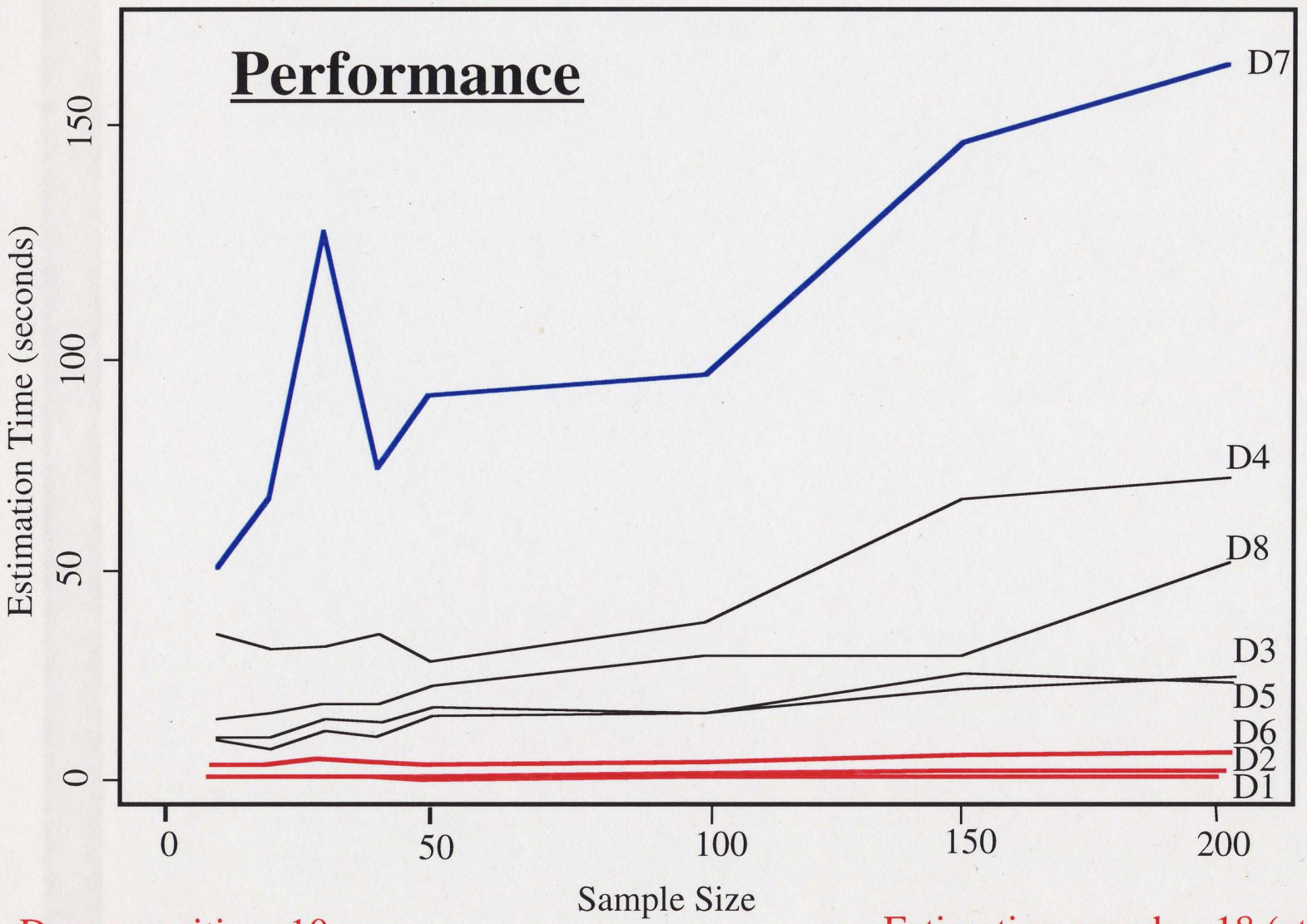
Estimation Plan for the Thermal Example



Thermal Example Revisited

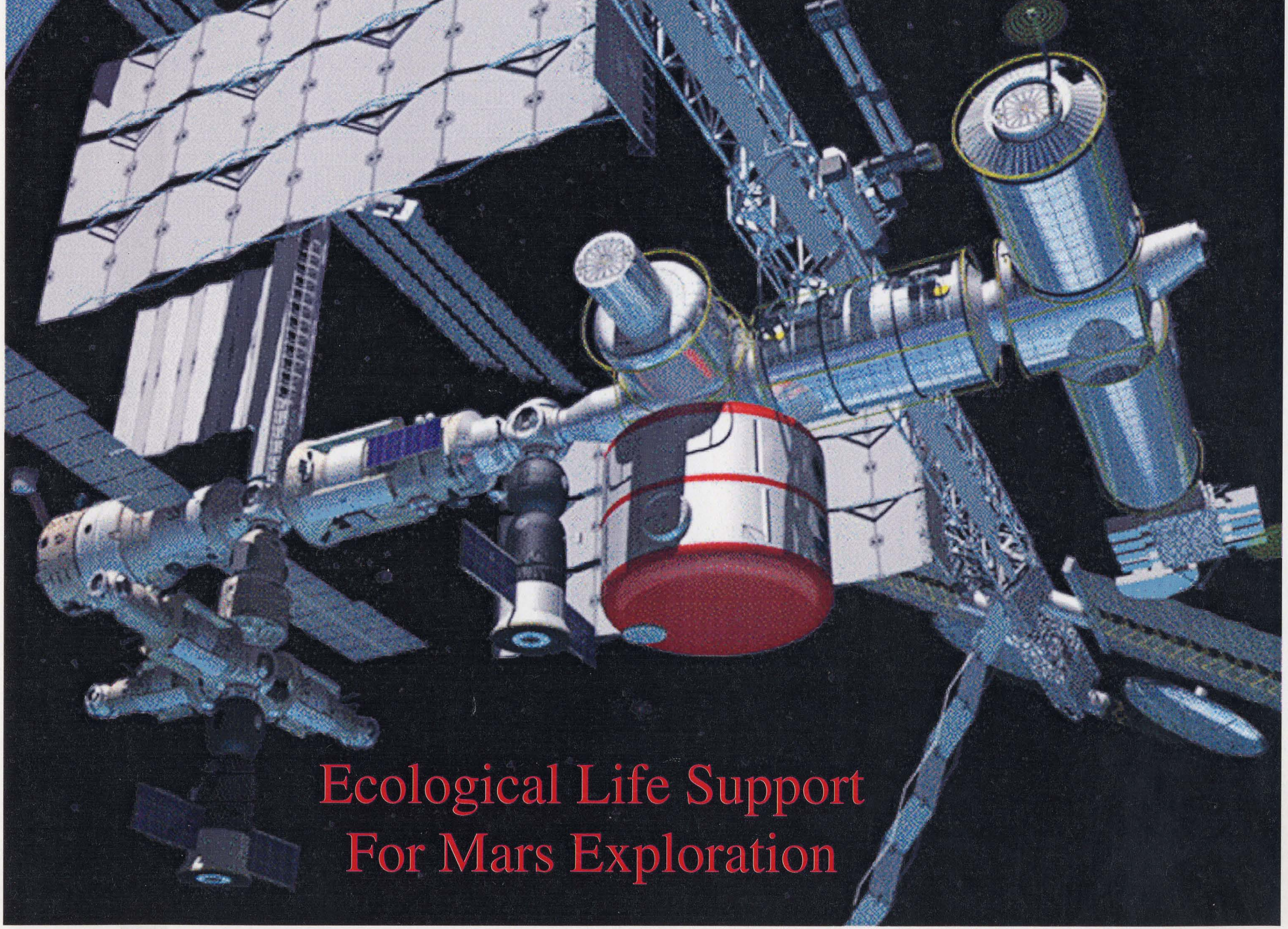


- air flow — R_{dct}
- heat flow through reheat — Q_{rhtmax}, C_{rht}
- heat flow through room — σ_{dct} , Q_{eqp}, C_{rm}, Q_{slr}



Decomposition: 10 secs.

Estimation speed: x 18 (at 200)



Ecological Life Support For Mars Exploration

Conclusions

- Model-based learning methods are essential to exploiting the power of networked embedded systems.
- Model-based learning on a large scale requires techniques for coordinating the learning process.
- DML automates three essential phases: decomposition, sequencing, and recomposition.
- DML demonstrates order of magnitude improvement.
- DML exploits a strong analogy to model-based diagnosis, helping to unify learning and diagnosis.