Information Trust
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Automatic Recovery from Failures and Attacks using Partially Observable Markov Decision Processes

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Outline

- Motivation
- Driving Application
  - A problem looking for a (better) solution
  - Other infrastructures with similar problems
- Model-based solution
  - Probabilistic diagnosis
  - POMDP-based recovery
  - Stability and performance properties
  - Results
- Future work
- Conclusions

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Motivation

- System management must be automated:
  - Driving factors speed of response, cost, and amount of data
  - Needed for true intrusion tolerance
- Drivers of change
  - Failures and attacks
  - Changing workloads and requirements
  - Changing resources
- Dealing with change
  - Recovery – rapid response crucial
  - Rejuvenation - preventive maintenance and reconfiguration
  - Only different in the types of indicators used

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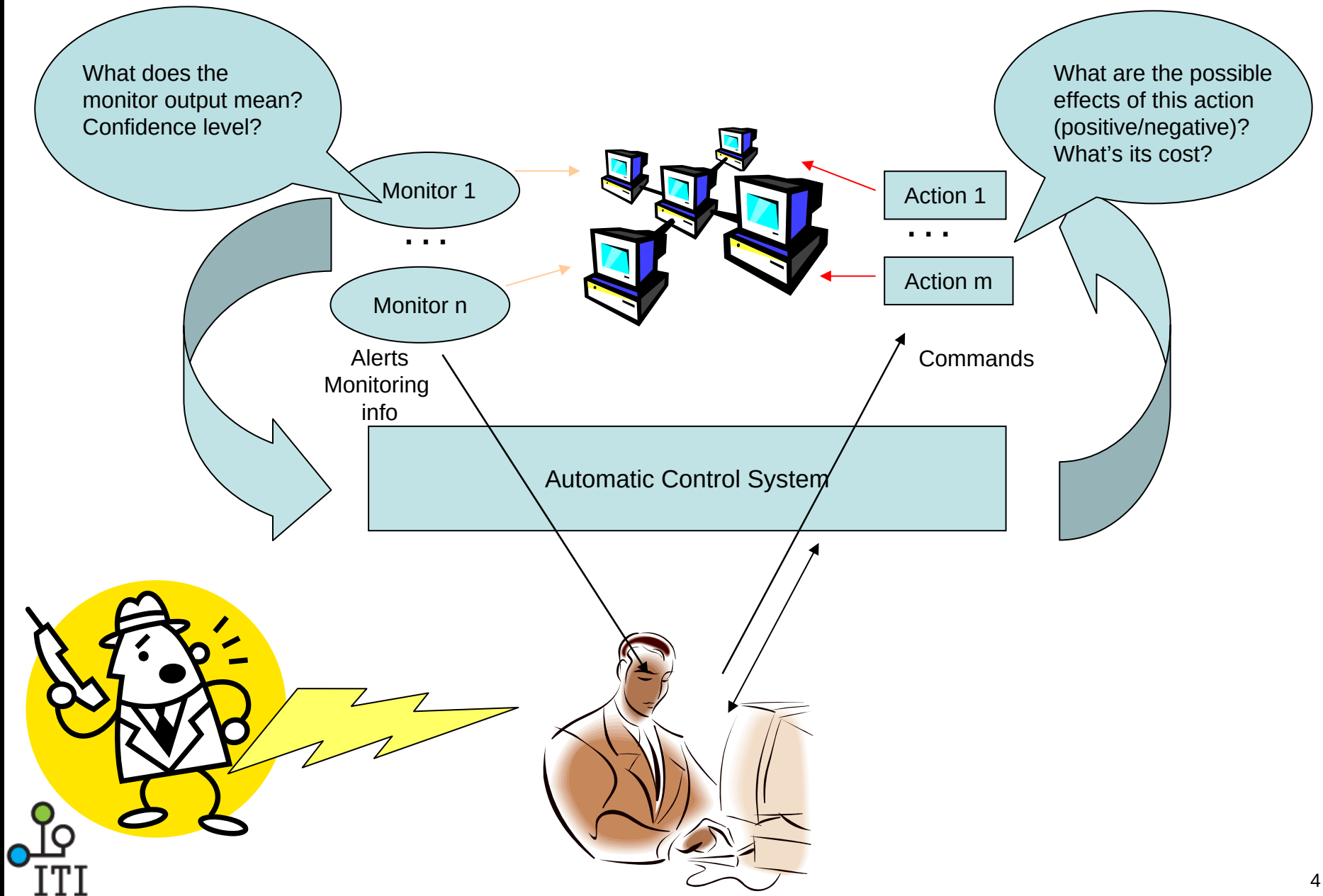
Motivation, cont.



Automatic Intrusion Tolerance

- Triggers, actions, and metrics
- Fundamental cost/benefit tradeoff
  - When is change needed, what benefits does it bring?
  - Simplest example – does adaptation take system to a "good" state?
  - Need a way to encode some operator knowledge (e.g., which actions may correct a problem)
  - Need metrics (cost/rewards) to perform this automatically

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Driving Application

- *Problem*: Monitoring and operator alerting for a complex internet-based system
- Home grown + COTS components:
  - Firewalls, load balancers, web servers, JMS servers, databases, Voice Genie, SMTP/IMAP servers,..
  - Network elements: routers, switches, links
  - External services
- Different independent monitors for some individual components and for end to end service functionality
- Problems:
  - Lots of operator alarms (one problem, multiple alarms)
  - False positives
  - Poor localization (i.e., what is the real problem)
  - Not great fault coverage
- Goal: Make things better

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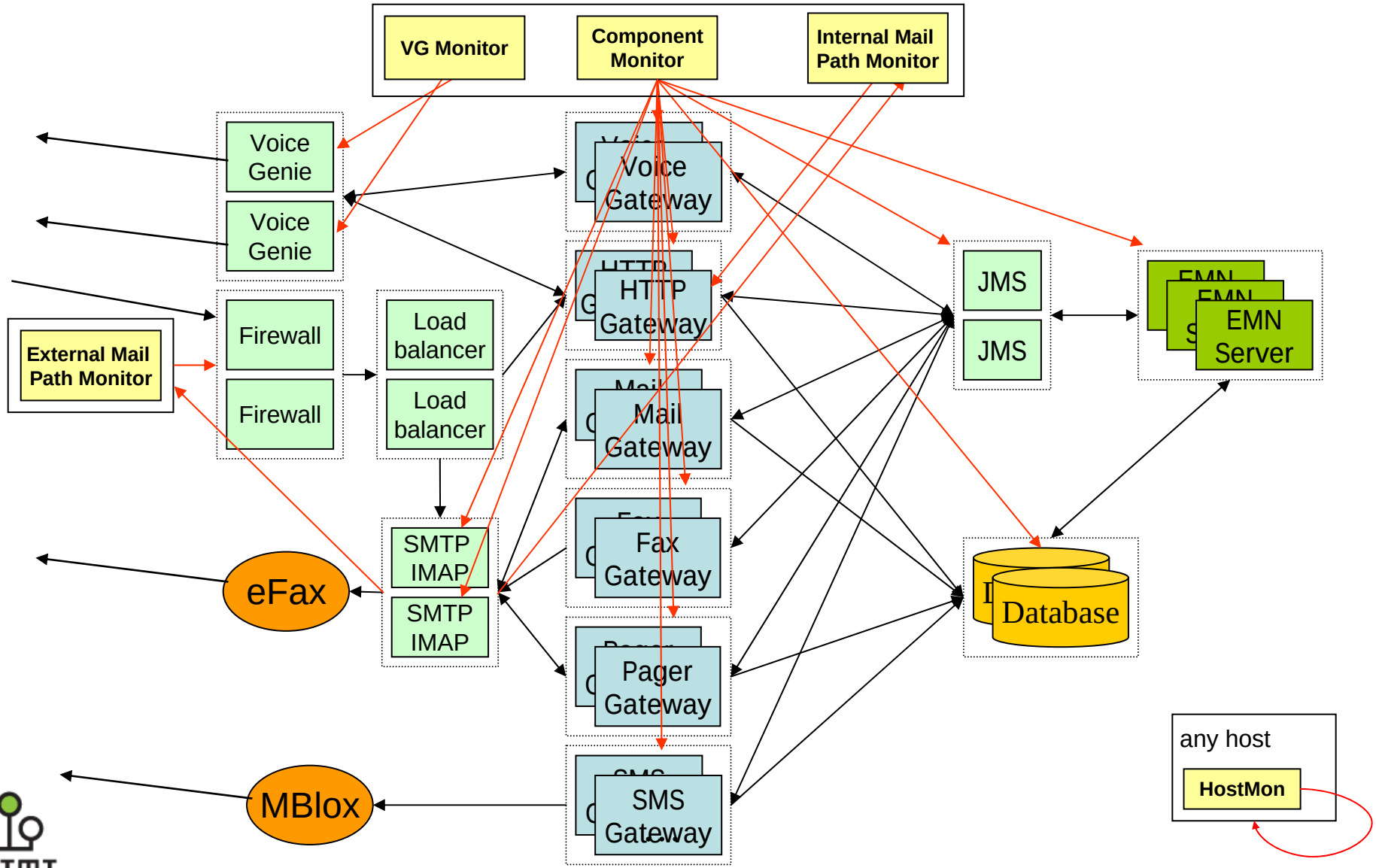
Driving Application: AT&T's Enterprise Messaging Network (EMN)



Previous Solution

- Collect the outputs of all the monitors into a centralized syslog
  - Disable direct operator alerting from the individual monitors
- A *MasterMonitor* program continuously reads the log, forms an estimate of the system state, and alerts operators when necessary
  - Various heuristics used to combine information
  - Use passage of time to deal with false positives
  - Combine outputs from multiple monitors to eliminate possibilities (i.e., narrow down the faulty component)

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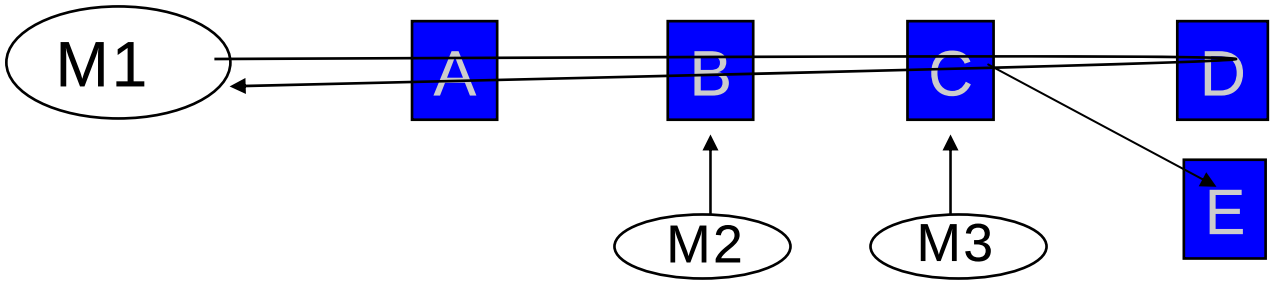
Lessons Learned

- Diagnosis can be difficult: Which component is faulty?



Maybe: A or D

However, could be any, because M1 and M2/M3 may not detect the same fault types

Complexity of coding such rules was getting out of hand

Challenges with Monitors & Diagnosis

- Monitors
  - Different system monitors detect different types of problems => fault hypotheses
    - Monitor outputs and recovery actions can be characterized in terms of these fault hypothesis
  - Monitors do not always detect the problem
    - Must have notion of fault coverage (probability)
  - A general methodology for monitor output fusion is needed
- Diagnosis
  - Typically no absolute knowledge of faulty component
    - Recovery actions must be used to improve diagnosis
    - Performing more monitoring is often a good action to take
  - Automated system must know when to give up

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Challenges in Recovery

- Opaqueness makes diagnosis difficult
  - Multiple tiers span administrative domains
  - Poor localization, false positives and negatives, imperfect coverage
  - Each monitoring technique has different strengths
  - Result: uncertainty about true system state
- Multiple choices of recovery actions
  - Varying cost
    - Restart component vs. reboot host
    - Act now or wait until later?
    - Ordering constraints between component restarts
  - Varying benefit - not all failures are equal
    - Different components are valued differently depending on their customer impact.
- What if the automated system becomes unstable?
  - Ad-hoc vs. theoretically founded approaches

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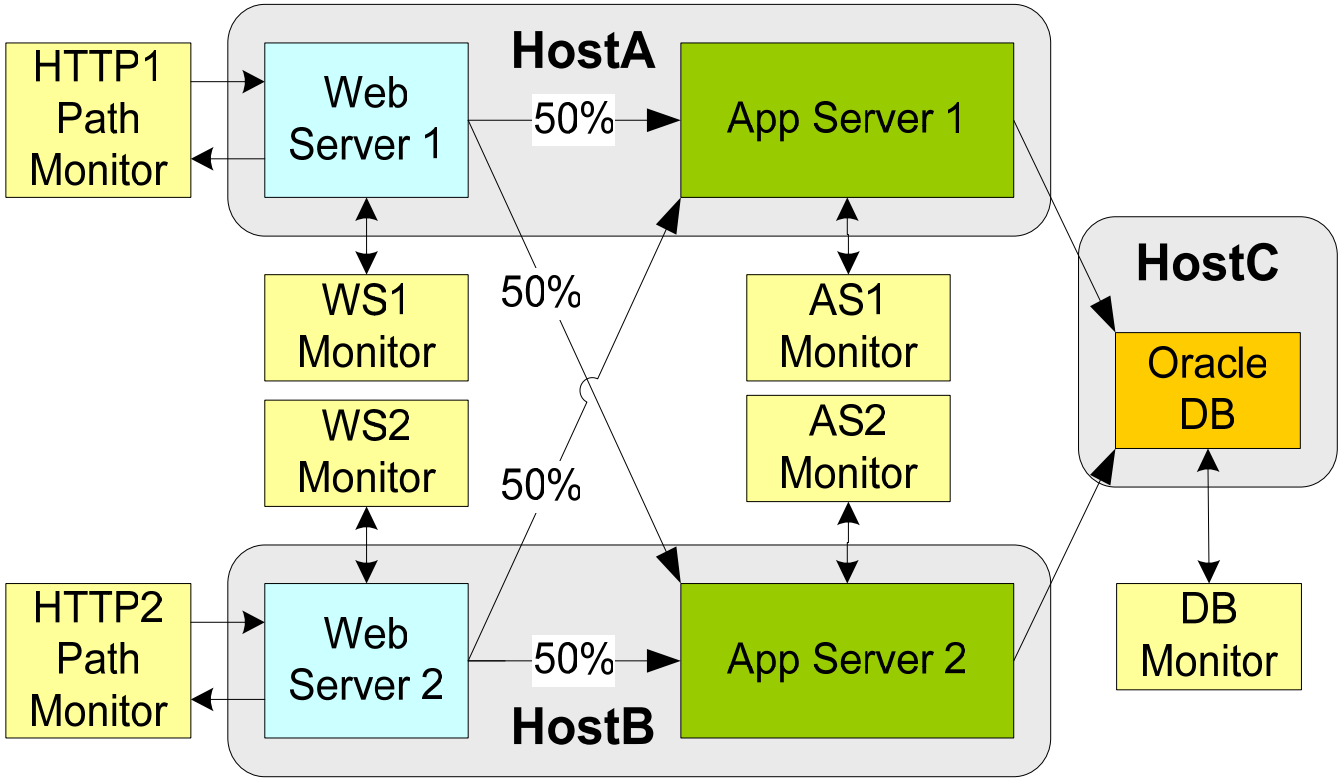
Abstracted Example: An E-commerce System



- Fault models: fail-silent (crash), non fail-silent (zombie) faults
- Recovery Actions: restart component, reboot host.
- Individual component monitors: only detect crashes
- End-to-end path monitors: detect crashes and zombies but poor localization
- Recovery Cost: fraction of “lost” requests (i.e. user-perceived availability)

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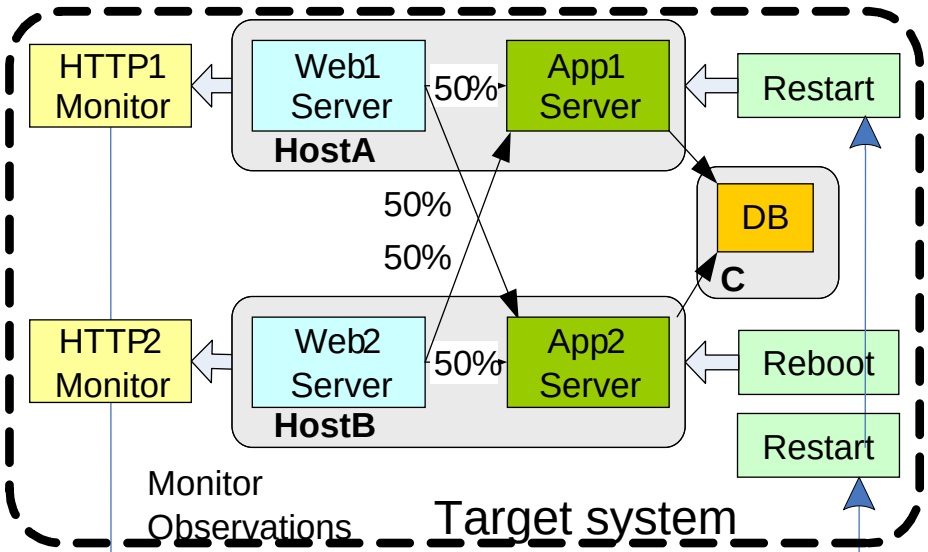
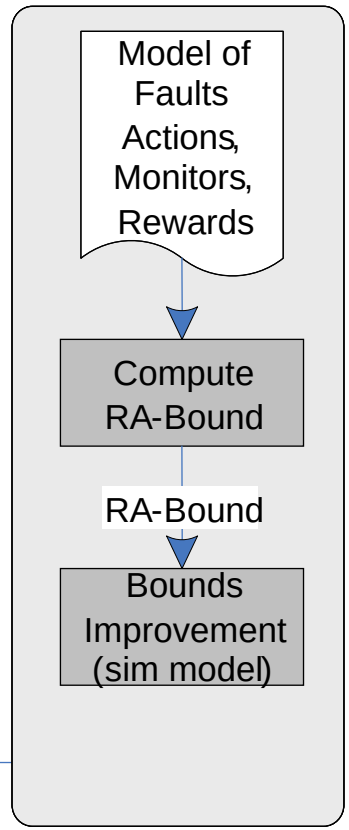
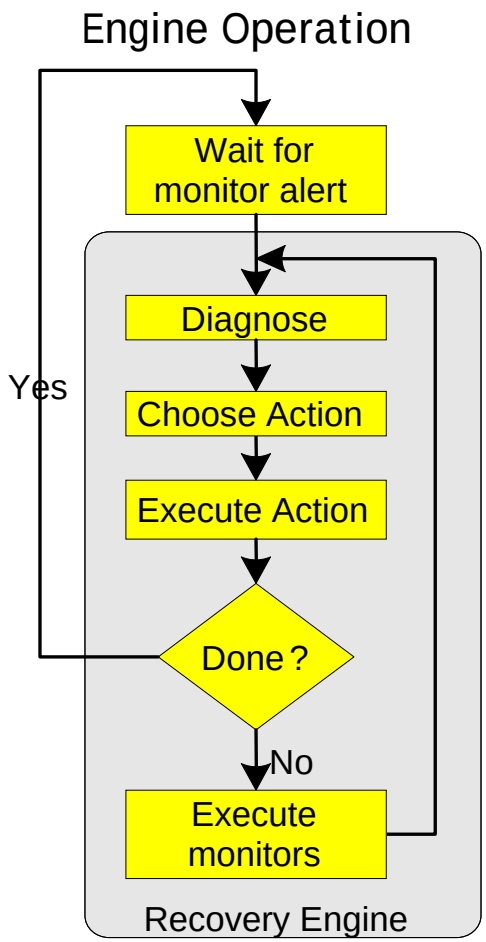
Recovery Engine Architecture

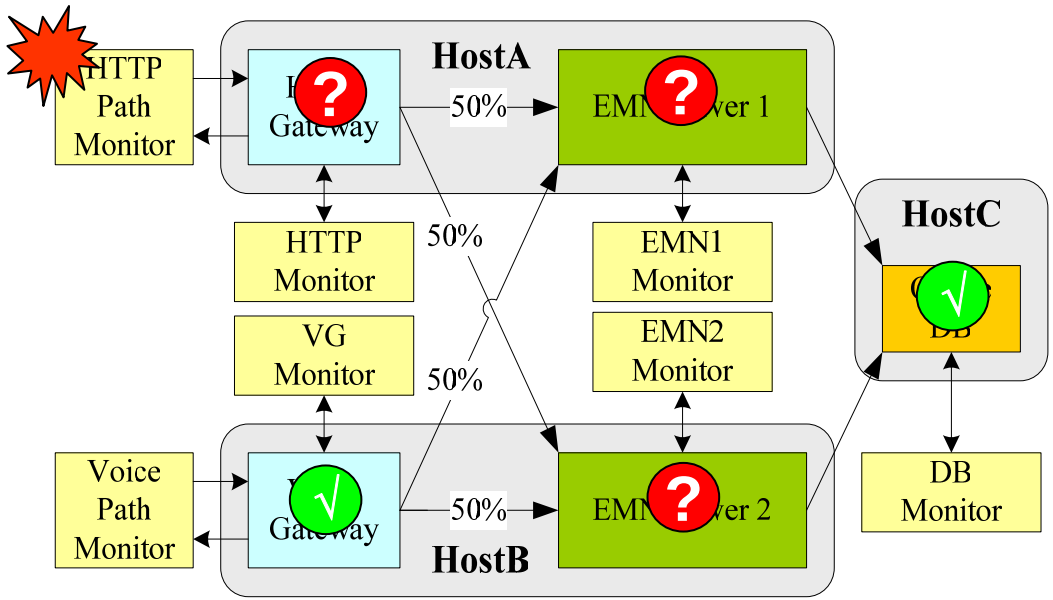






- Action that maximizes value function tree is chosen at each step
- What to use for remaining cost at the leaves of the tree?
  - Zero cost, heuristic cost, bound?

Probabilistic Bayesian Diagnosis



- Precise diagnosis often impossible due to monitor limitations
- Use Bayes rule to compute "diagnosis vector" {P[fh_1],⋯ ,P[fh_n]}
  - Each entry: probability of *fh* given current monitor outputs
  - Using monitor coverage models P[*m*|*fh*] and prior diagnosis
  - If no prior knowledge of which fault, use P[*fh*]=1/|*FH*|
  - Keep track of commonly occurring faults to choose better priors

Monitor Models

- Need to know coverage: P[*m* | *fh*]
- Dependency graph based
  - Probability of touching failed node in a request graph
- Queuing network based
  - Probability of observed response time, load
  - Statistical test
- Statistically learned models in general

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POMDP Formulation for Recovery

- A POMDP is a tuple $(S, A, O, p(s'|s,a), q(o|s,a), c(s,a))$
  - States (S): which fault (or null fault) has occurred
  - Observations (O): monitor outputs $\{o_m\}$
  - Transition function $p(s'|s,a)$: effect of recovery action on system and fault state
  - Observation probabilities $q(o|s,a)$: probability that o is generated (monitor models)
  - Cost Function $c(s,a)$: recovery cost, e.g., availability, requests lost/denied etc
- System evolution
  - $(s_0, a_0, o_0, \ldots s_n, a_n, o_n)$
  - But controller can't see s – it tracks "belief state"
  - Belief state $\pi = [\pi(s_0), \ldots, \pi(s_n)]$: state occupancy probability vector (i.e., diagnosis vector)

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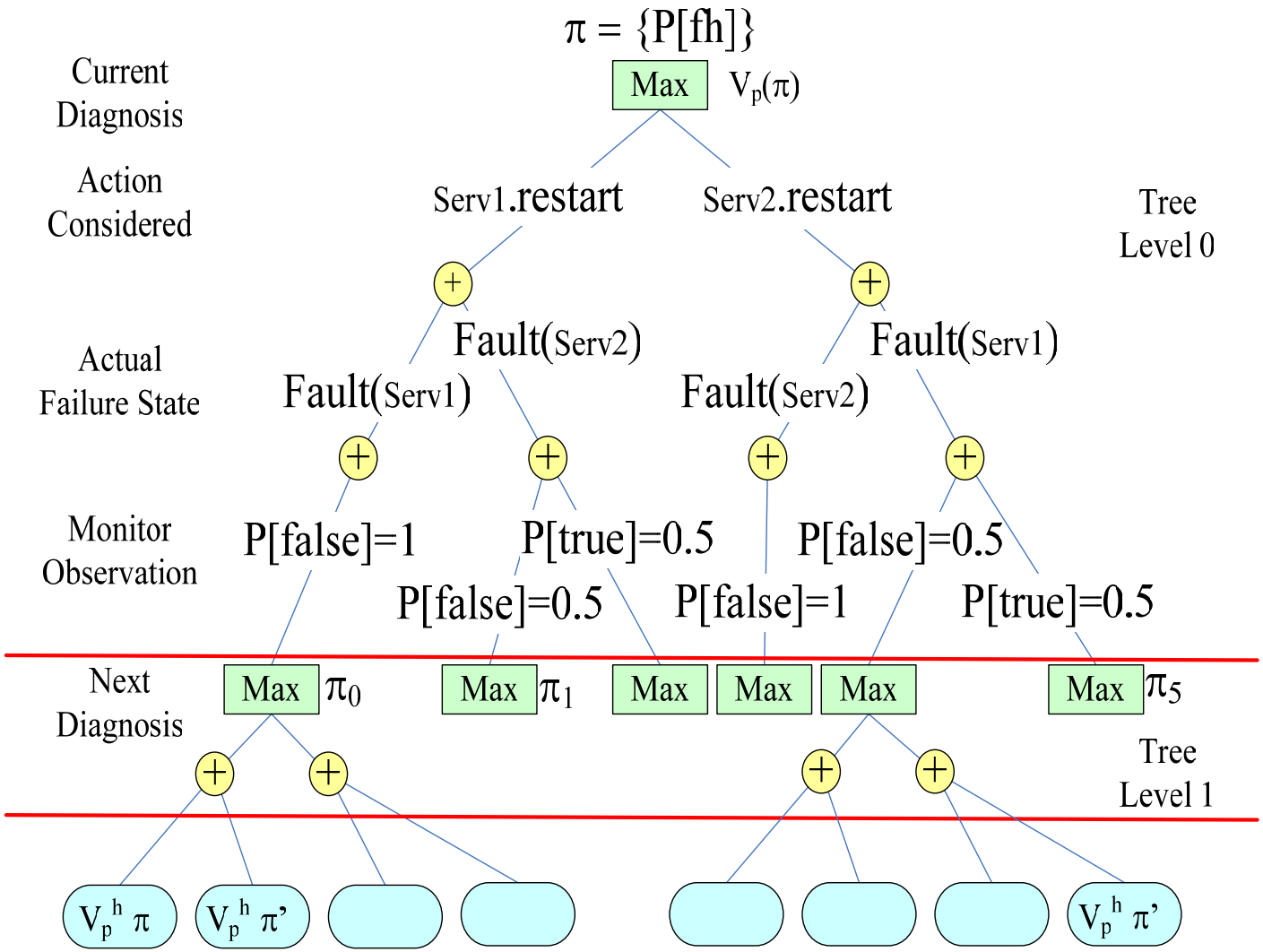
Optimal Value Functions

- Policy ρ specifies what action to take in each belief state
  - Optimal policy ρ^* minimizes mean accumulated cost starting from all belief states
  - ρ^* is Markovian in belief state (i.e. current diagnosis vector)
- Optimal ρ^* computation
  - Bellman dynamic programming recursion
  - $C_m(\pi) = min_a\{c(s,a) + H_{s'}[C_m(\pi')]\}$
  - $p'(\pi'|\pi,a) = \sum_s q(o|s,a)\sum_{s'} p(s|s',a)\pi(s')$ *if* π'=*BayesNextBelief*(π,a,o)
    $= 0$ *otherwise*
  - $c'(\pi,a) = \sum_s c(s,a)\pi(s)$
- Tractability is a problem.
  - Dynamic programming defined over all π
  - There could be infinite π even for trivial S!
  - Exact techniques scale only up to few thousand states

Finite Depth Online POMDP Solution



Leaves are assigned heuristically chosen or bounded cost

Recovery Engine Guarantees

- Desired Guarantees:
  - Safety: recovery engine does not execute unsafe actions
  - Guaranteed recovery: engine does not terminate before recovery is successful (can only be guaranteed w.r.t. model)
  - Finite termination: recovery terminates in a finite amount of time
  - Optimal performance (ideal): recovery cost is minimized
  - Performance guarantee (practical): recovery cost may not be optimal, but is lower than a promised value
- POMDP based recovery engine using finite depth solution
  - Safety can be ensured at model level by disabling dangerous actions
  - Heuristic value at leaves: we can make no guarantees
  - Lower bounds of true value: probabilistically guaranteed recovery, finite termination, average performance guarantee

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Value Function Lower Bounds: RA-Bound

- Previously: Bounds on discounted rewards
  - Discounted reward: $V(\pi) = \max_a\{r(s,a) + \beta\, H_{s'}[V(\pi')]\}$
  - Previous techniques: BI-POMDP, blind action
  - Always finite – even when controller never terminates!
  - Difficult to determine "good" β – weak relation to reality
- New (DSN'06): Bounds on undiscounted accumulated reward
  - Value function may be infinite
  - BI-POMDP, blind action not always finite even for finite valued recovery models
  - We develop a new bound (RA-bound) and conditions under which it works for recovery models
  - Can evaluate risk of terminating recovery too early

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Key Practical Benefits

- Model based – allows separation of concerns monitoring and recovery during specification
- Reward based recovery considers both cause and impact – precise root cause identification may not be critical
- Recovery is Sequential – natural way to deal with mistakes
- Ability to look multiple time-steps ahead – knows when to wait for additional information
- Formal framework – provides strong guarantees about stability and goodness of adaptation

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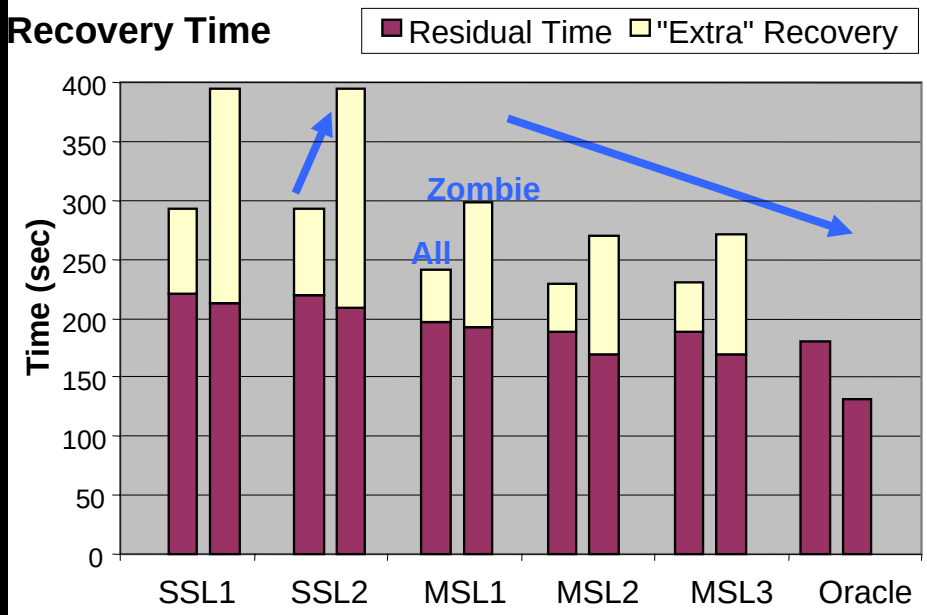
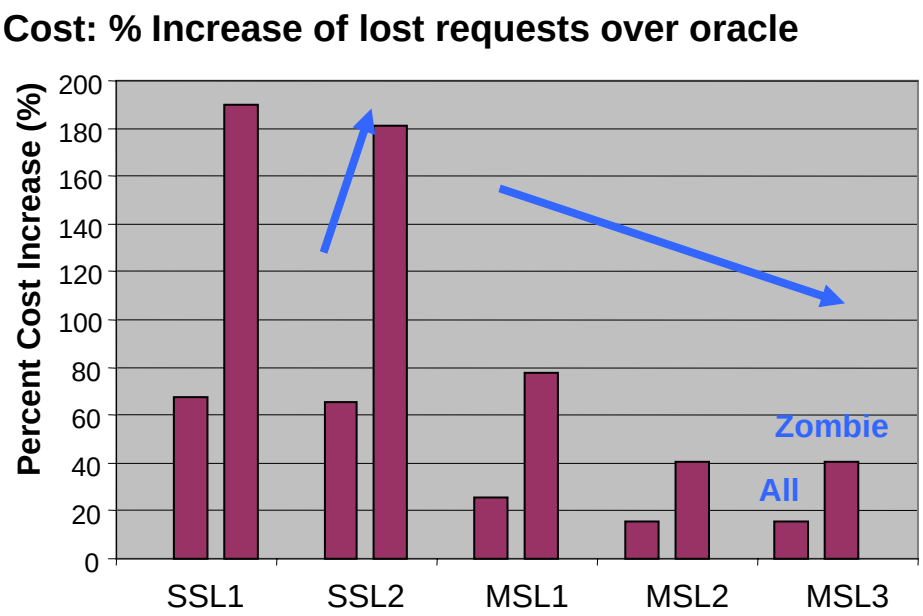
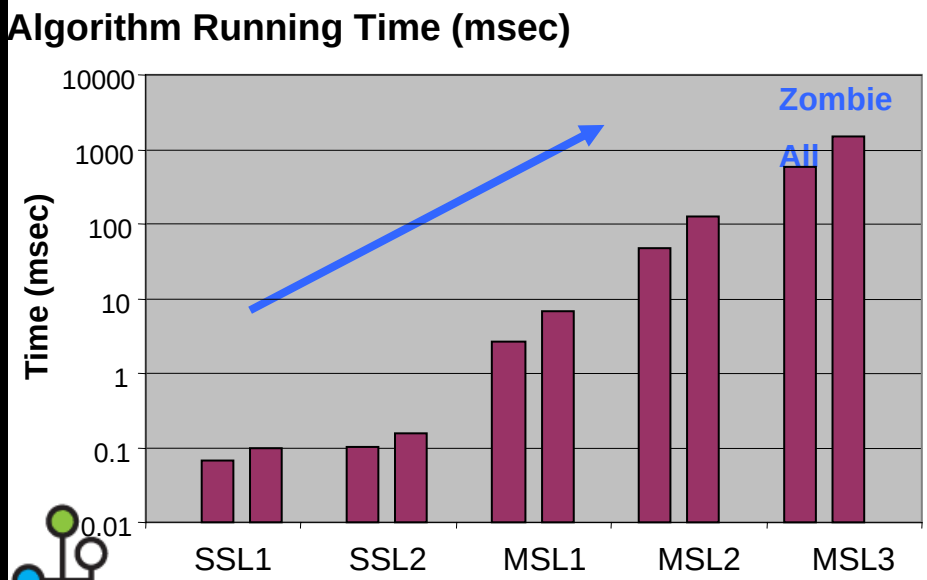
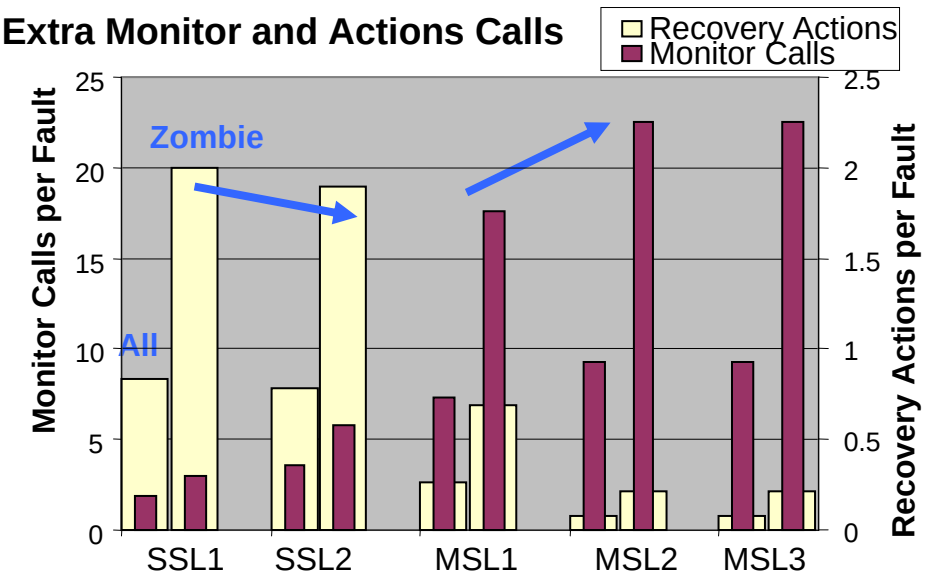
Greedy vs. POMDP (heuristic): Per-Fault Metrics (SRDS '05)









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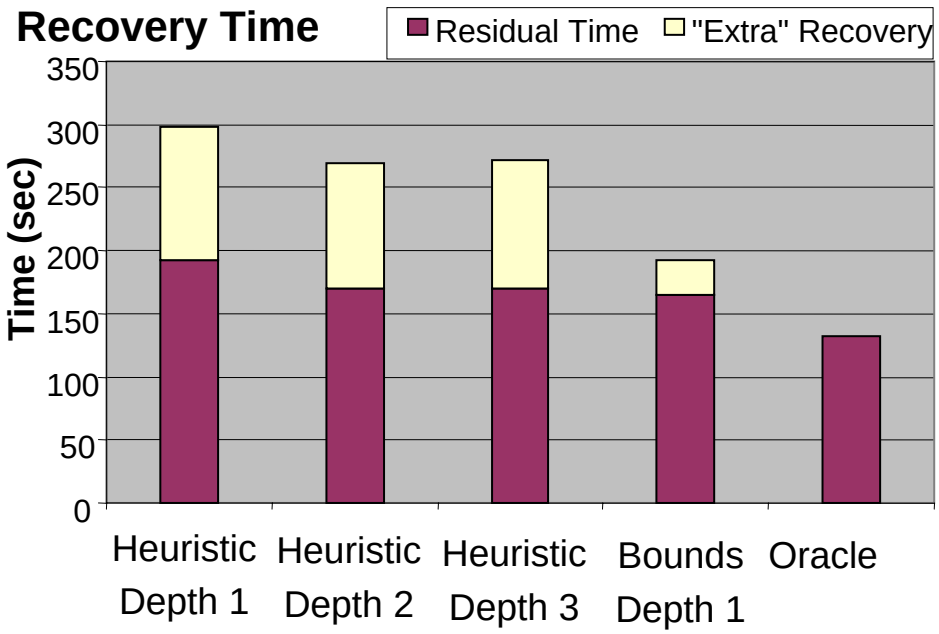
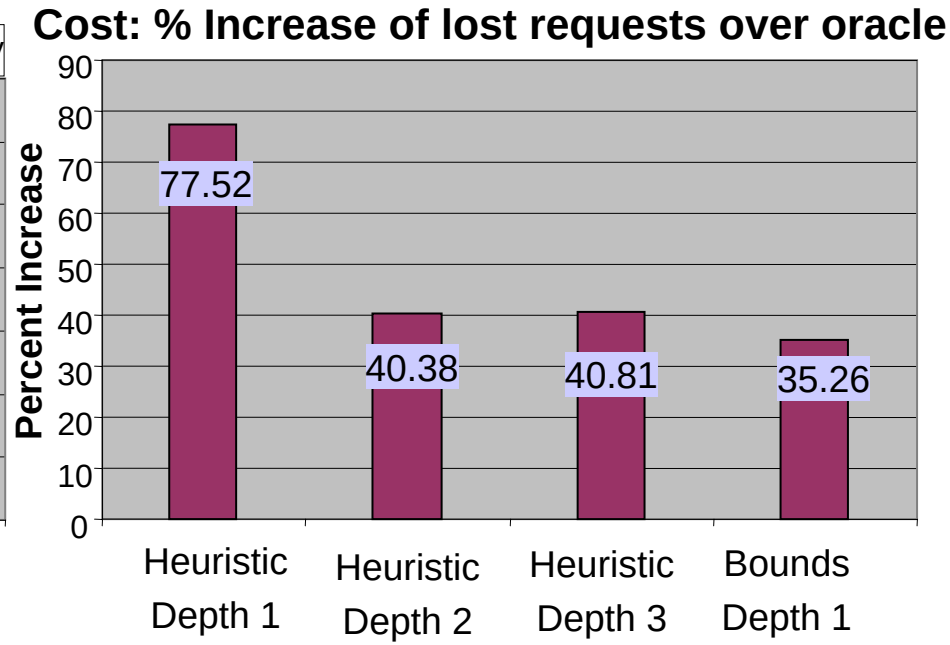
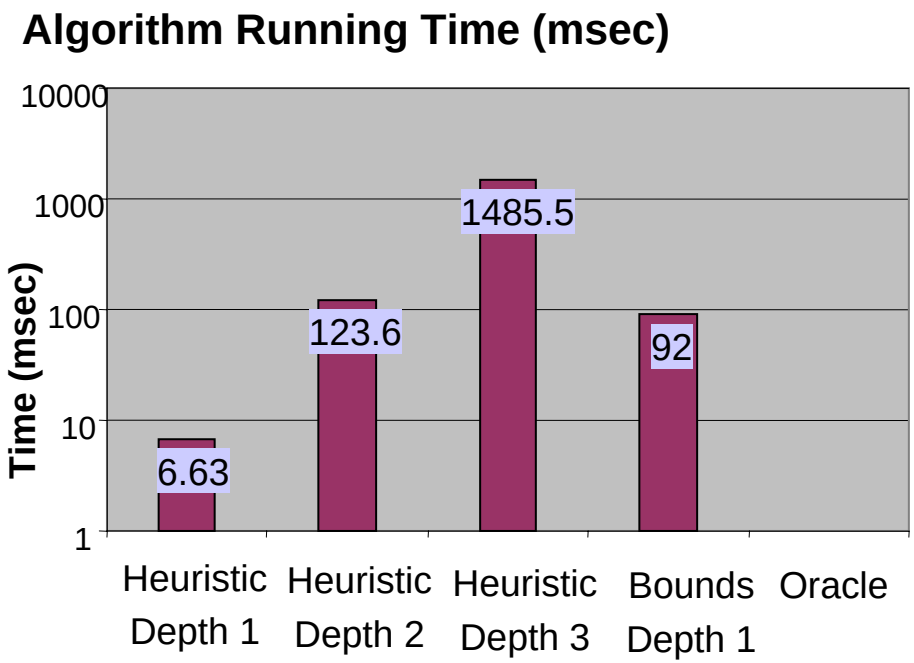
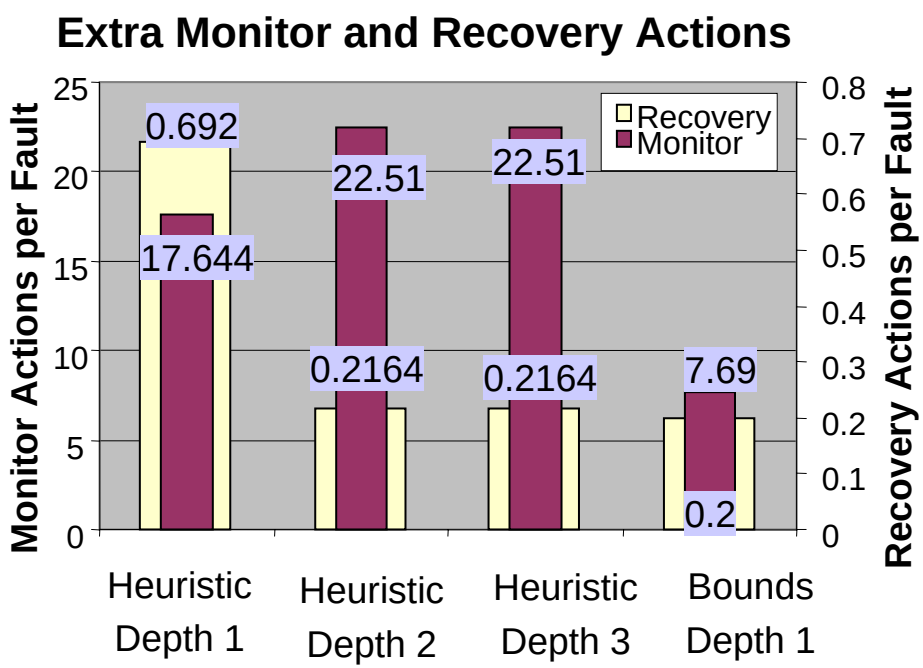
POMDP (heuristic vs. bounds, zombie only) (DSN'06)





POMDP (heuristic vs. bounds, zombie), cont. (DSN'06)





Future work

Model extensions:

- Continuous time: allowing independent system evolution

Engine extensions:

- Dealing with real monitors' outputs: textual, non-standard
  - Combine rule-based and probabilistic reasoning
  - Rules good when no uncertainty of the problem
- Some monitors cannot be invoked at will
- Must wait for the "next scheduled" output
  - Sometimes monitors only give failure alarms but do not report recovery - Absence of alarm for a period of time = all OK
- System specification in general format (XML)
  - Components, their relationships, monitors, fault hypotheses, coverage, allowed actions, ..
  - Different system configurations
- Load-aware monitors for performance failures (queuing model based)

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Conclusions

- A model-based solution for system diagnosis and automatic recovery develop based on needs identified in a real system (SRDS 05)
- New technique developed for solving models efficiently and accurately (DSN 06)
- Extensions underway to address issues in realistic systems
  - Key concern: building appropriate models
- Other application areas possible; evaluation part of future work

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Questions?

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