Resilient Dynamic Power Management under Uncertainty

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Overview

- Introduction
- Stochastic Decision Making Framework
- Resilient Dynamic Power Management
- Experimental Results
- Conclusion

Introduction

- **PVT variations pose a major challenge**
  - **Design of reliable systems**
  - **Robustness of DPM techniques**
- **Stress/aging results in unacceptable safety margins**
  - **Stress (HCI, NBTI, TDDB) changes V_{th} of Trans.**
  - **Trans. characteristics change > 10% over 10 years**
- **Lack of proper modeling and optimization tools**
  - **Transforms low-level variability into system-level uncertainty**
- **Improving accuracy and robustness of the decision making strategy**
  - **Important step to guarantee the quality of DPM solutions**

Some Relevant Prior Work

- **S. Borkar, et al. (DAC 2003)**
  - **Parameter variations and impact on architecture**
- **K. Kang, et al. (DAC 2007)**
  - **Variation resilient circuit design technique**
- **H. Su, et al. (ISLPED 2003)**
  - **Leakage estimation under V & T variations**
- **M. Lie, et al. (ISLPED 2004)**
  - **Probabilistic analysis for impact of variations**
- **F. Marc, et al. (Trans. On Device Reliability 2006)**
  - **Circuit aging simulation technique based on behavioral model**

High Level Explanation of the Problem

- **Many researchers have examined techniques for:**
  - **Variability modeling and control at the low levels (e.g., physical design optimization and/or logic synthesis)**
  - **Dynamic power management with system variables being**
    - **Directly observable**
    - **Deterministic**
- **These techniques suffer from the following:**
  - **System state is not fully observable**
  - **Conventional DPM approaches tend to be less effective because uncertainty modeling is not done**

Overview of the Proposed Solution

- **Develop a resilient power management framework**
  - **The framework accounts for parameter variations during power management**
  - **Effects of uncertainties due to variability/stress are captured by stochastic processes**
- **Our proposed DPM framework is based on:**
  - **Stochastic process model**
  - **Dynamic programming**
  - **Expectation-maximization algorithm**
    - **Enables a power manager to predict uncertain state of a system in a dynamic environment**
- **Roles of the power manager**
  - **Interact with uncertain stochastic environments**
  - **Select appropriate actions (i.e., V-F values)**
  - **Minimize the long term cost (i.e., energy dissipation)**

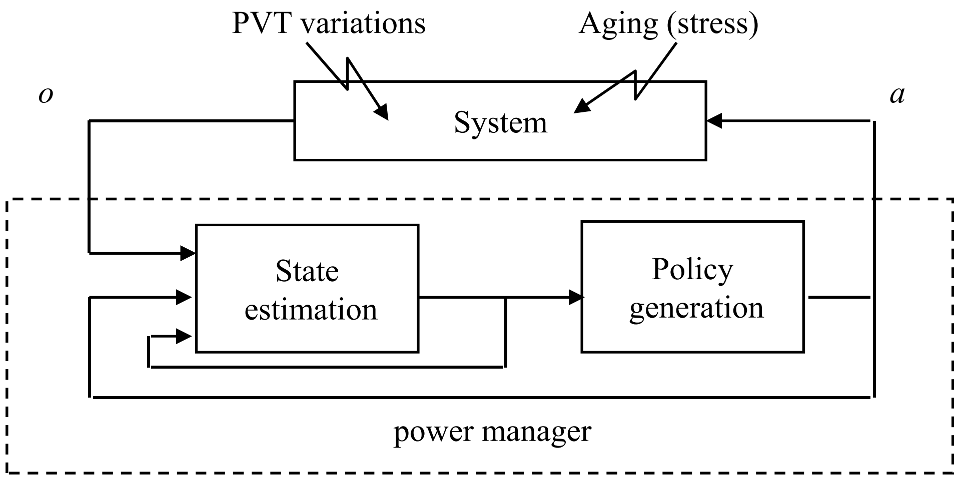
POMDP

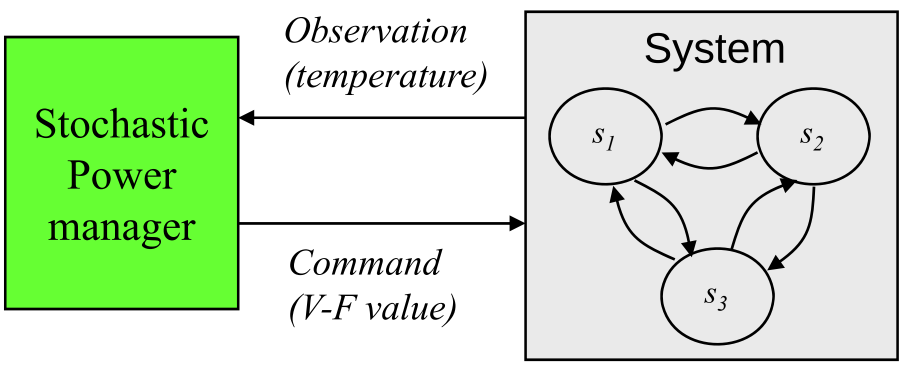
- **POMDP is a tuple (S, A, O, T, Z, c) such that**
  - **S is a finite set of states (power)**
  - **A is a finite set of actions (V-F value)**
  - **O is a finite set of observations (temperature)**
  - **T is a transition probability function**
    - $T(s',a,s) = Prob(s^{t+1} = s' \mid a^t = a, s^t = s)$
  - **Z is an observation function**
    - $Z(o',s',a) = Prob(o^{t+1} = o' \mid a^t = a, s^{t+1} = s')$
  - **c is a cost function**
    - **action *a* in state *s* incurs some cost, *c*(*s*, *a*)**

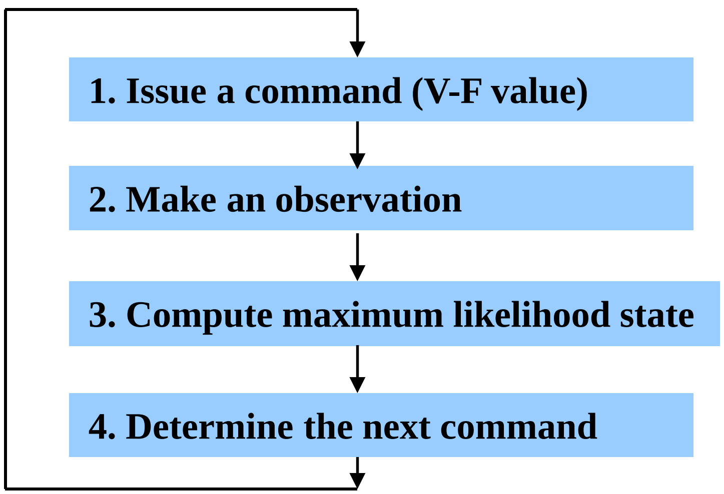
- **POMDP maintains a *belief* state (vector)**
  - **A probability distribution over the possible states**

POMDP-based Power Manager

- **Structure of the proposed power manager**

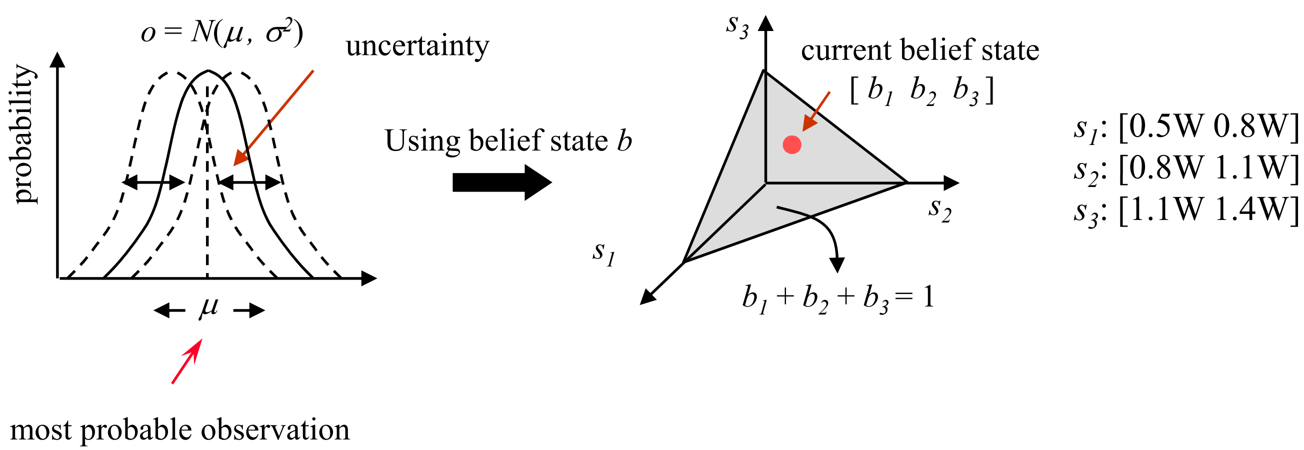






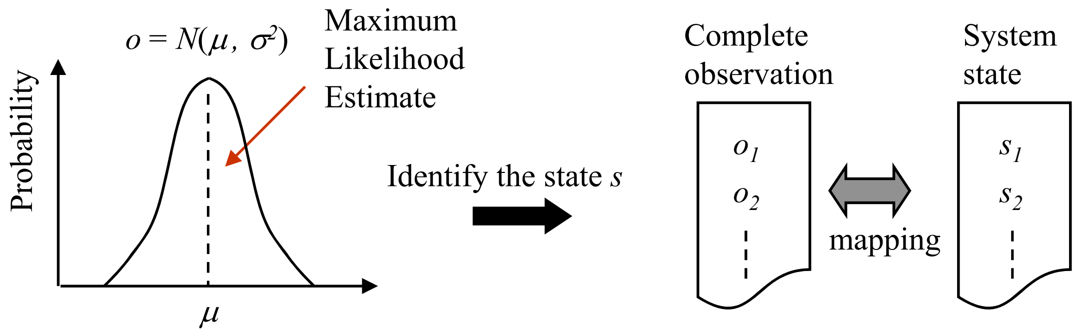
Power Management Framework (1/2)

- **Partial observation and its effect on the probability density function**
  - **Computing the belief state:** $b^{t+1}(s') = \dfrac{Z(o',s',a)\sum_s b^t(s)T(s',a,s)}{\sum_{s,s''} Z(o',s'',a) b^t(s) T(s'',a,s)}$
  - **Complexity of computing the belief state grows rapidly with the number of states**
  - **Solving a belief-state based DPM problem is quite expensive**



Power Management Framework (2/2)

- To avoid the complexity of solving the belief-state based DPM problem
  - We adopt a state estimation technique based on the expectation-maximization (EM) algorithm
  - The EM algorithm deals with uncertain information when computing the maximum likelihood estimate (MLE) of the system state
- Forming the complete observation with MLE
  - MLE enables determination of the system state without using belief states



EM-based State Estimation (1/3)

- **The goal is to obtain estimation of the complete observation by using the EM algorithm**
  - ***o*: observed data (i.e., noisy measurement)**
  - ***m*: missing date (i.e., hidden source of variation that affects the power state of the system)**
  - **Together *o* and *m* constitute the complete data**
  - **EM algorithm finds an observation estimate *θ* that maximizes the complete-data likelihood, which is defined as:**

$$p(o, m \mid \theta) = p(m \mid o, \theta)\, p(o \mid \theta)$$

- **Identify the system state from the complete data through a pre-defined observation-state mapping table**
  - **The mapping table is obtained by doing extensive simulation at design time**

Backup slide: EM algorithm (2/3)

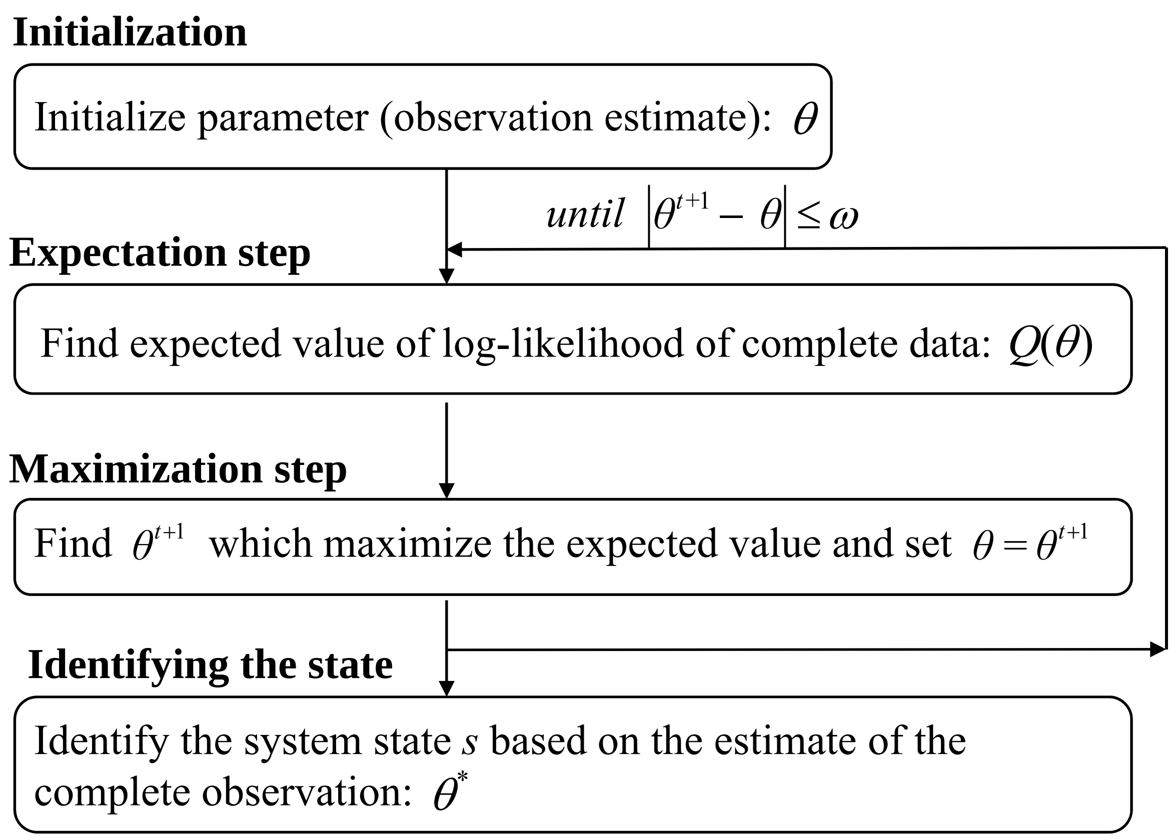
- **The EM algorithm iteratively improves an observation estimate *θ* as follows:** $\theta^{t+1} = \arg\max_{\theta} Q(\theta)$
  - ***θ*** ***t+1*** **: the value that maximizes the conditional expectation of log-likelihood of the complete data given the observed variables**
  - ***Q(θ)*** **: the expected value of the log-likelihood of complete data**
- **We cannot determine the exact value of the log-likelihood since we do not know the complete data**
  - **We calculate an expected value of the log-likelihood of complete data for the given values *o***

$$Q(\theta) = E_m\left(\log p(o, m \mid \theta) \middle| o\right)$$

$$= \int_{-\infty}^{\infty} p(m \mid o) \log p(o, m \mid \theta) dm$$

EM-based State Estimation (3/3)

- **The flow of the state estimation by the EM algorithm**
  - **Expectation step + Maximization step**



Policy Generation (1/2)

- **Policy generation deals with the cost function**
  - **A dynamic programming technique is used to solve the problem since it exhibits the property of optimal sub-structure cost**

- **The optimum cost is defined as follows:**
  - **The expected discounted sum of cost that an agent accrues**

$$\Psi^*(s) = \min_{\pi} E\left(\sum_{t=0}^{\infty} \gamma^t \cdot c(t)\right)$$

  - γ**: a discount factor, 0 ≤** γ **< 1**
  - ***c*(*t*): cost at time *t***

- **In our problem setup, the cost function is defined as:**

$$\Psi^*(s) = \min_{a}\left(C(s,a) + \gamma \sum_{s' \in S} T(s',a,s)\Psi^*(s')\right) \quad \forall s \in S$$

Policy Generation (2/2)

- **Given the cost function, the optimal action can be obtained by**

$$\pi^*(s) = \arg\min_a \left(C(s,a) + \gamma \sum_{s' \in S} T(s',a,s)\Psi^*(s') \right)$$

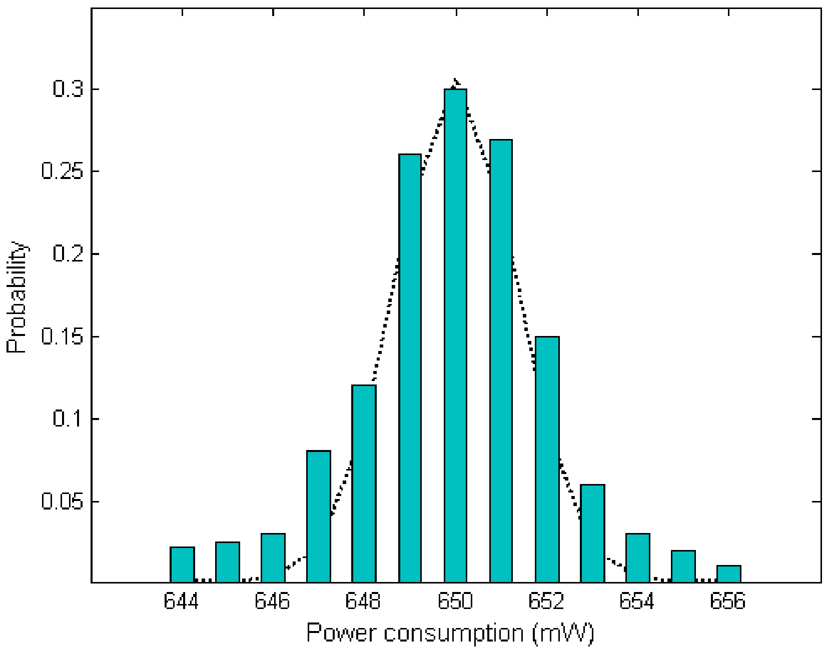
- **One way to solve Markov decision problem is to use value iteration method**
  - **Value iteration method consists of a recursive update of the value function to choose an action**

initialize $\Psi(s)$ arbitrarily
  loop until a stopping criterion is met
    loop for $\forall s \in S$
      loop for $\forall a \in A$
        $Q(s,a) = C(s,a) + \gamma \sum_{s' \in S} T(s',a,s)\Psi(s')$
        $\Psi(s) = \min_a Q(s,a)$
      end loop
    end loop
  end loop

The value iteration algorithm

Experimental Results (1/5)

- **Apply the proposed DPM technique to a RISC processor realized with 65nm CMOS**
- **Analyze possible variations of the processor power**
  - **Vary process corners during simulation**
  - **Probability density function for power ~*N*(650, 3.1)**



Experimental Results (2/5)

- **Set the parameter values**

State	Description [W]
s_1	[0.5 0.8]
s_2	(0.8 1.1]
s_3	(1.1 1.4]

Obs.	Description [°C]
o_1	[75 83]
o_2	(83 88]
o_3	(88 95]

cost $c(s, a)$ [pJ]			
	s_1	s_2	s_3
a_1	[541	500	470]
a_2	[465	423	381]
a_3	[450	508	550]

(a_1 = [1.08V/150MHz], a_2 = [1.20V/200MHz], a_3 = [1.29V/250MHz])

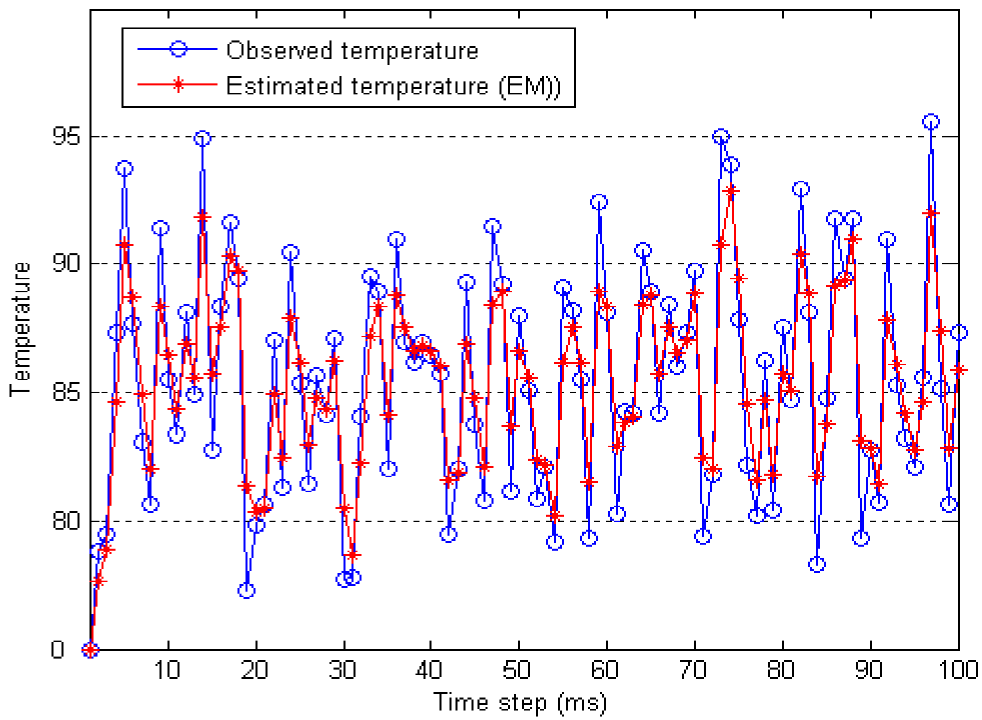
- **PBGA package thermal performance data (T_A=70 °C)**

Air velocity m/s	Air velocity ft/min	T_{J_max}[°C]	T_{T_max}[°C]	ψ_{JT} [°C/W]	θ_{JA} [°C/W]
0.51	100	107.9	106.7	0.51	16.12
1.02	200	105.3	104.1	0.53	15.62
2.03	300	102.7	101.2	0.65	14.21

- ψ_{JT} : Junction-to-top of package thermal characterization parameter
- θ_{JA} : Thermal resistance for junction-to-ambient

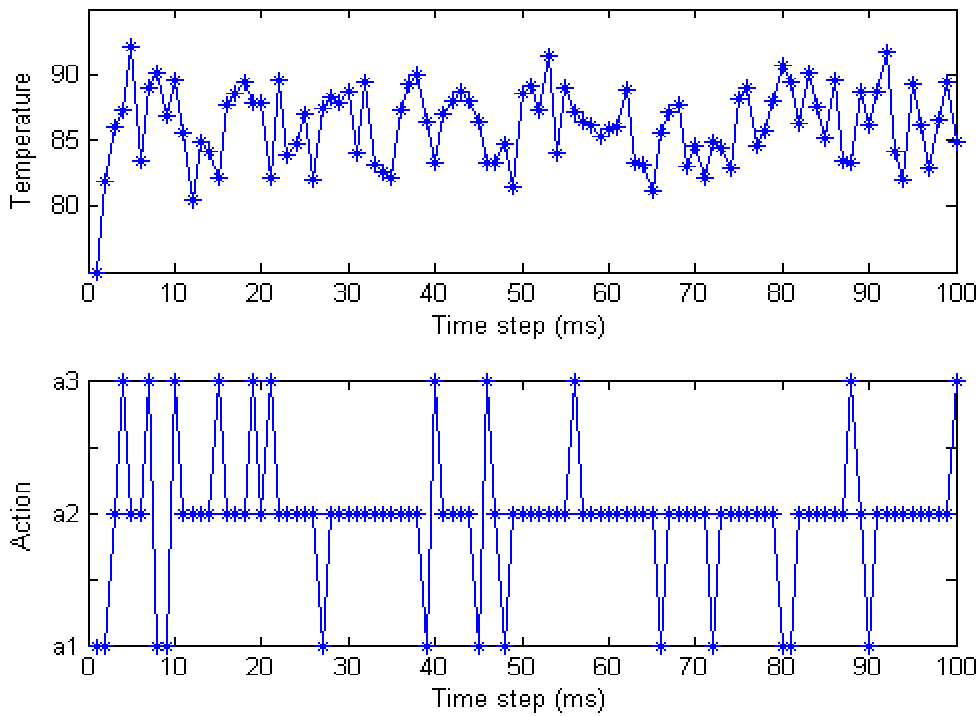
Experimental Results (3/5)

- **Trace of temperatures from the observation and from the MLE estimate**
  - **Calculate T_{chip} *from* $T_{chip} = T_A + P \cdot (\theta_{JA} - \psi_{JT})$, where $P \sim N(P_{sim}, (\Delta P)^2)$**



Experimental Results (4/5)

- **Effectiveness of the policy generation algorithm**
  - **Optimal action is chosen to minimize the cost function by using observations and the EM algorithm to determine the MLE of the system state**



Experimental Results (5/5)

- **Demonstrate the effectiveness of the DPM technique**
  - **Compare with worst and best operating conditions**
  - **Evaluate how the proposed approach can handle variability**
  - **The worst case assumption under-estimates the performance and hence results in the largest EDP value for the DPM solution**

	Minimum Power	Maximum power	Average Power	Energy (normalized)	EDP (normalized)
Our approach	0.71W	1.12W	0.97W	1.14	1.34
Worst case	0.77W	1.26W	1.02W	1.47	2.30
Best case	0.96W	1.31W	1.15W	1.00	1.00

Conclusion

- Proposed a resilient DPM technique which guarantees to select an optimal policy under variability
- The proposed DPM framework brings uncertainty to the forefront of decision-making strategy
- Being able to handle various sources of uncertainty would improve the accuracy and robustness of the design
- The proposed DPM technique ensures energy efficiency, while reducing the uncertain behavior of the system