



GDP and More: Thermal and Power Solutions for Multi/Many-Core VLSI Systems

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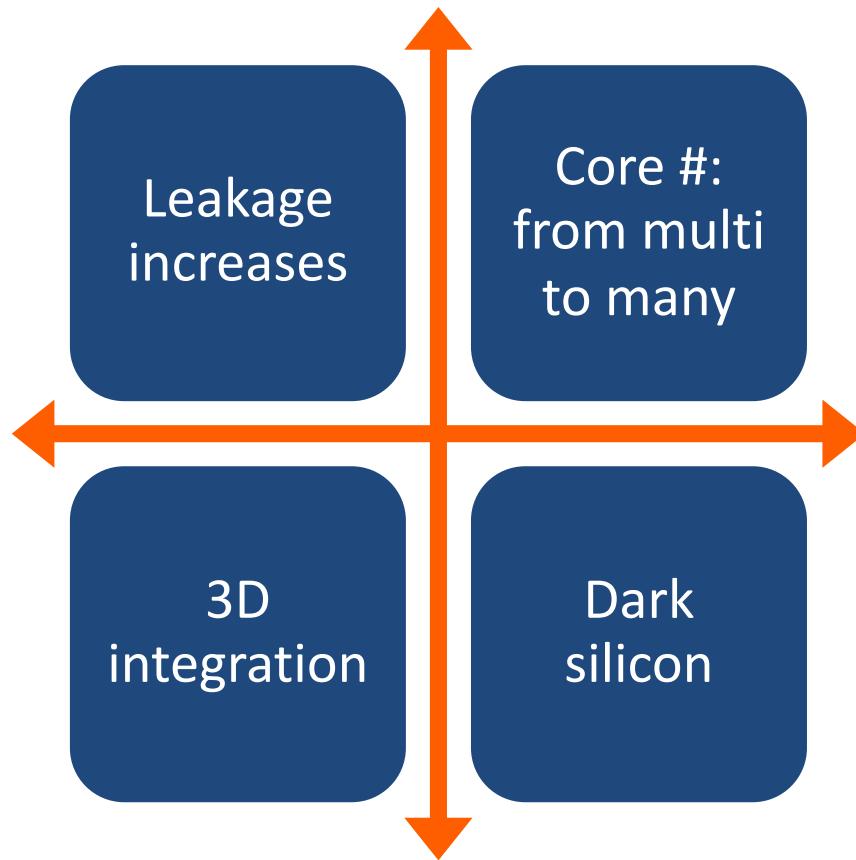
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2019

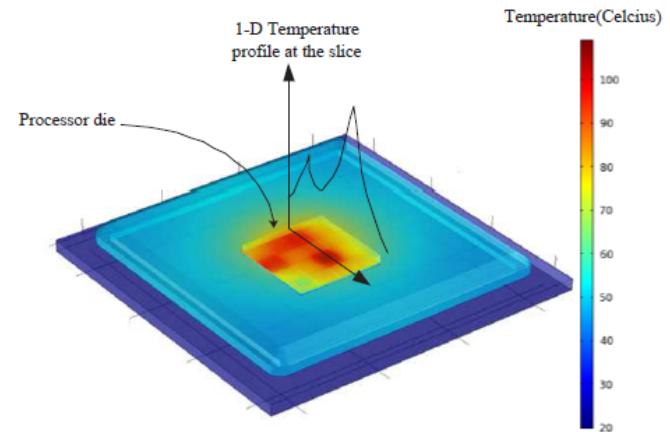
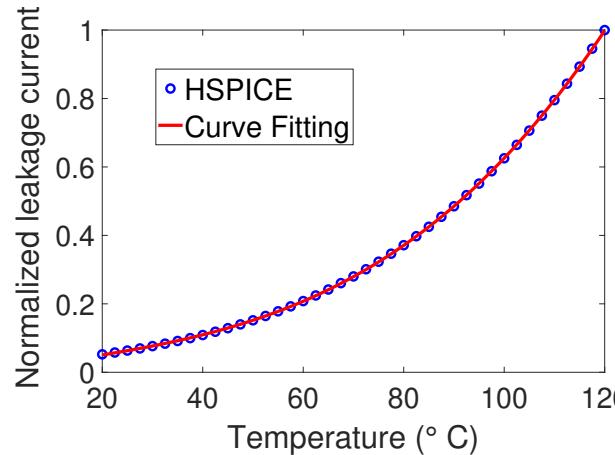
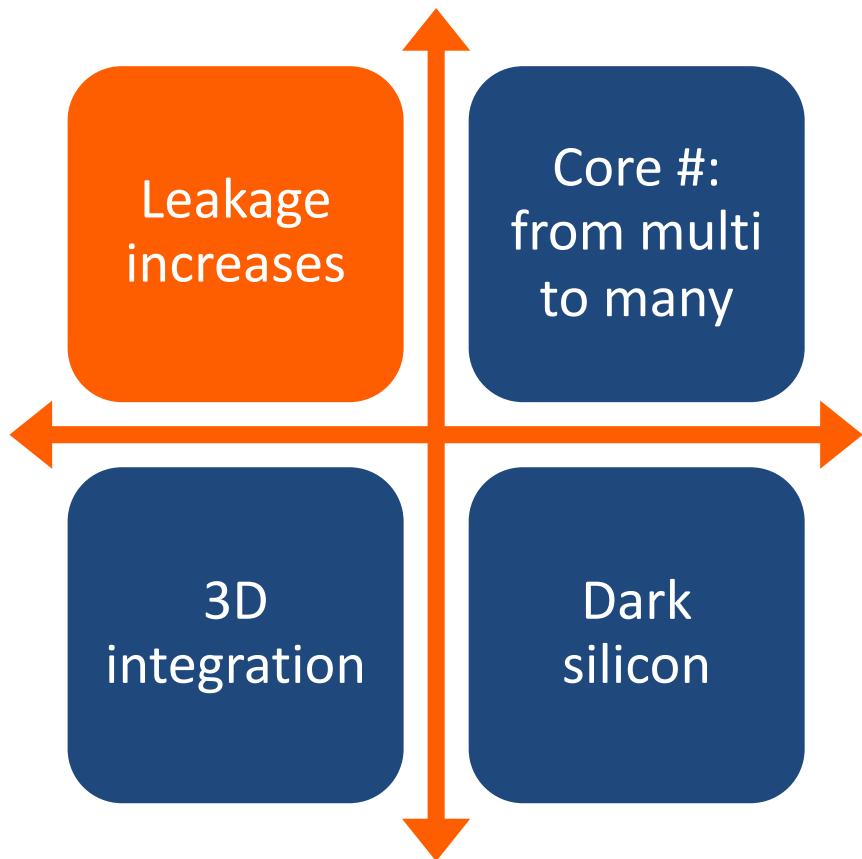
Motivation and Background

The new challenges in IC industry



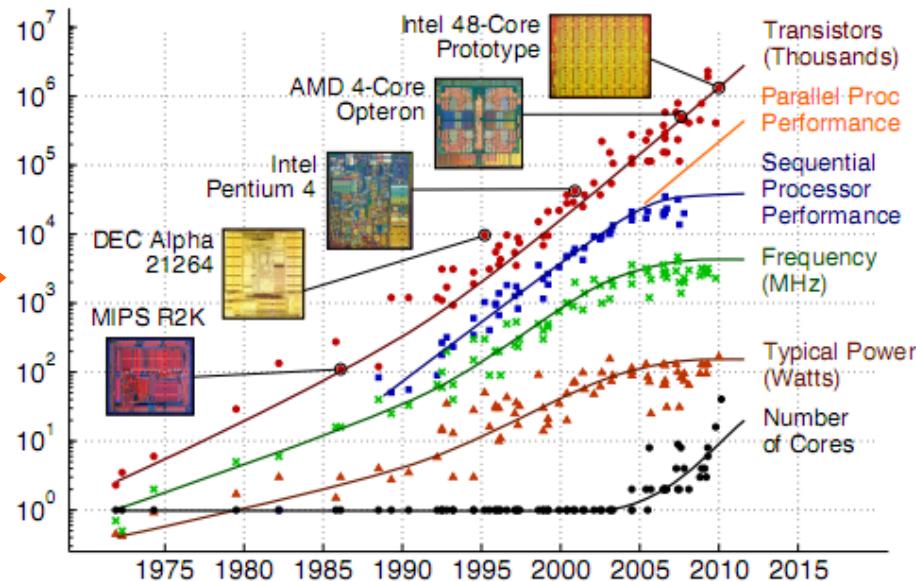
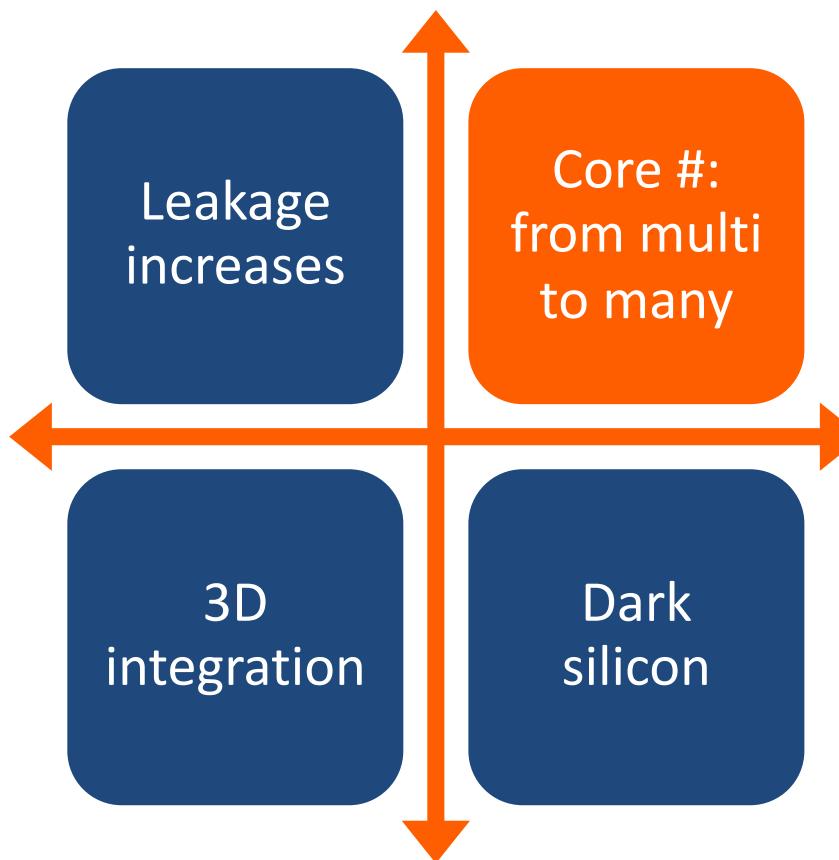
- Scaling causes new challenges in IC industry.
- Solutions needed for new challenges.

The leakage problems



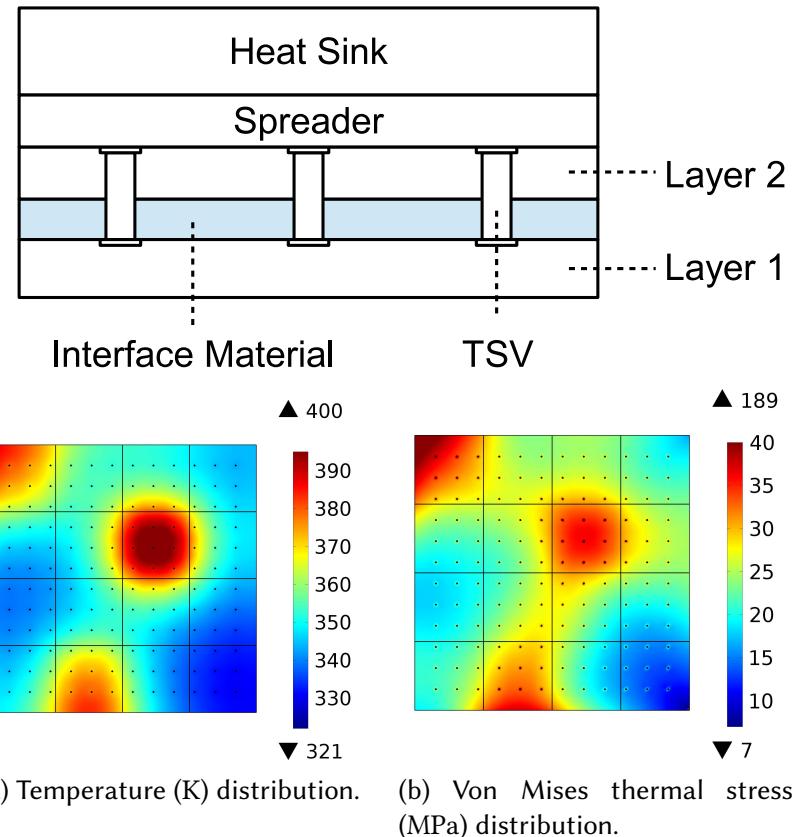
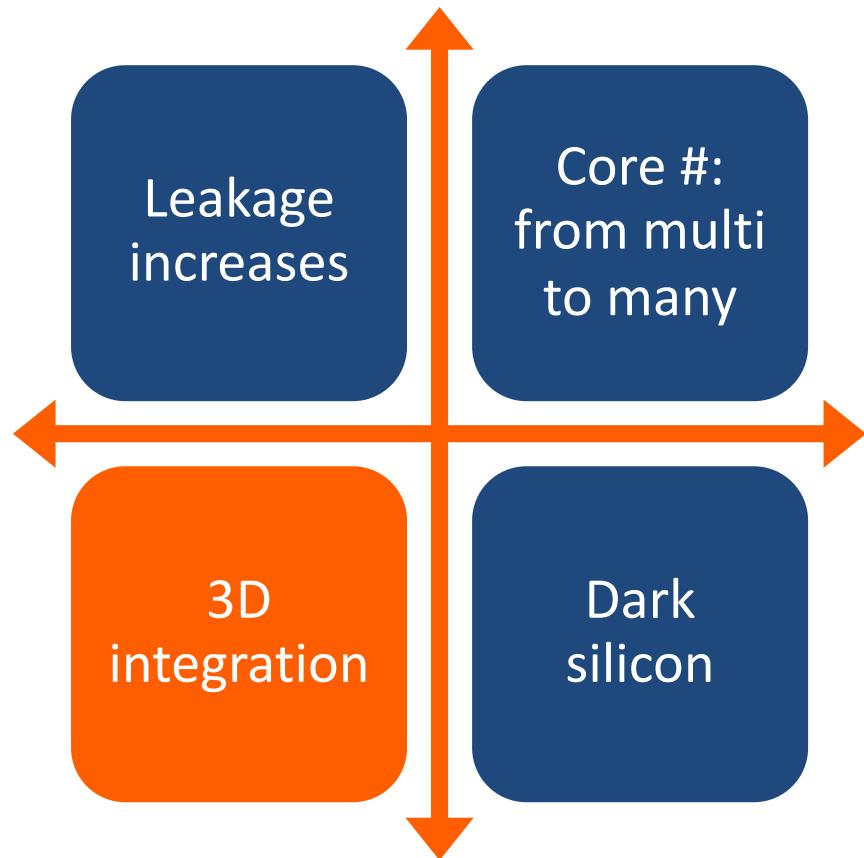
- Leakage power becomes **significant**.
- Leakage power **highly** and **nonlinearly** relates to temperature: dangerous and difficult to model.

The many-core challenge



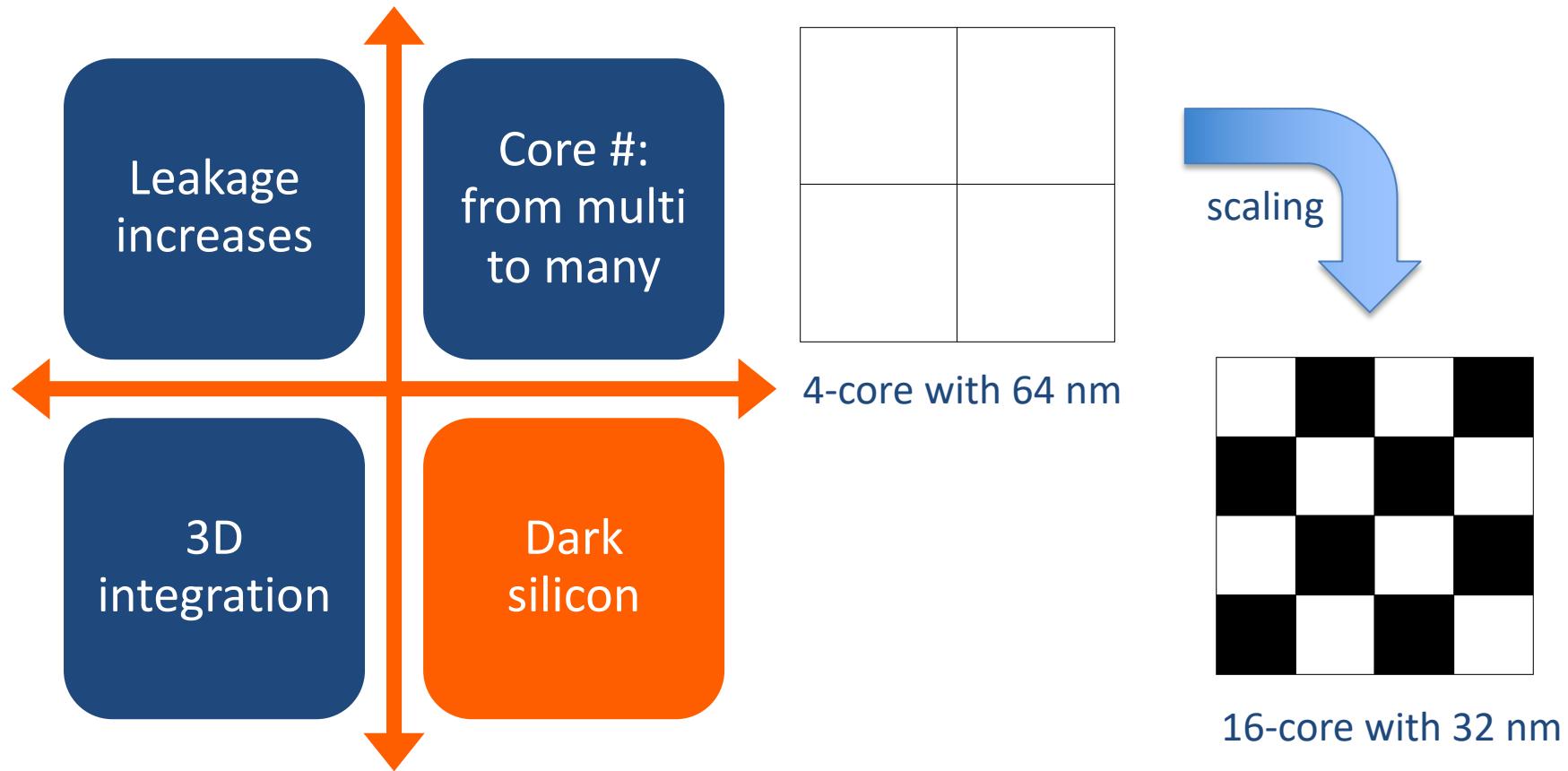
- Core # increases: tens or more cores on a single die.
- Difficult to coordinate cores for best performance under thermal constraint.

The problem of 3D integration



- 3D IC: go vertical for higher integration density.
- High power density leads to **high temperature, large stress, and reliability issues.**

The dark silicon hazard



- Not all cores can be on simultaneously anymore.
- **Which cores** should be on and how much power can be consumed for best performance?

Outline

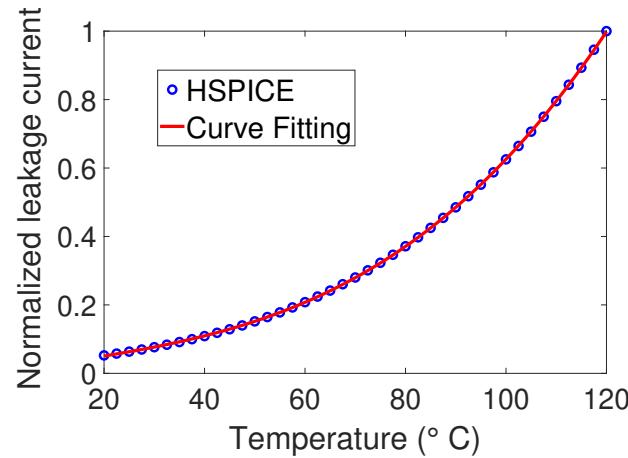
- Leakage Matters:
 - Leakage-aware thermal estimation
(IEEE Trans. on Computers, 2018)
 - Leakage-aware thermal management (white-box model)
(ASP-DAC Best Paper Nomination, 2019)
 - Leakage-aware thermal management (black-box model)
(IEEE Trans. on CAD of Integrated Circuits and Systems, 2019)
- Many-Core Solutions:
 - Hierarchical thermal management
(ACM Trans. on Design Automation of Electronic Systems, 2017)
- 3D Integration:
 - Runtime stress estimation using ANN
(ACM Trans. on Design Automation of Electronic Systems, 2019)
 - STREAM: Stress-aware reliability management
(IEEE Trans. on CAD of Integrated Circuits and Systems, 2018)
- Dark Silicon Hazard:
 - GDP: Greedy based dynamic power budgeting
(IEEE Trans. on Computers 2019)

Leakage Matters

- **Leakage-aware thermal estimation**
H. Wang, J. Wan, *et al.*, “A fast leakage-aware full-chip transient thermal estimation method”, IEEE Trans. on Computers, 2018
- **Leakage-aware thermal management**
 - **White-box model through PWL approximation**
X. Guo, H. Wang, *et al.*, “Leakage-aware thermal management for multi-core systems using piecewise linear model predictive control”, ASP-DAC Best Paper Nomination, 2019
 - **Black-box model using Echo State Network (ESN)**
H. Wang, X. Guo, *et al.*, “Leakage-aware predictive thermal management for multi-core systems using echo state network”, IEEE Trans. on CAD of Integrated Circuits and Systems, 2019

Nonlinear leakage problem in thermal estimation

- Leakage power depends on temperature nonlinearly.



- Difficult to compute temperature
 - Initial guess and iteration needed to solve the nonlinear thermal model (white-box model)!

$$GT(t) + C \frac{dT(t)}{dt} = BP(T, t),$$
$$Y(t) = LT(t),$$

Piecewise linear based thermal estimation

- Build local linear thermal models by Taylor expansion

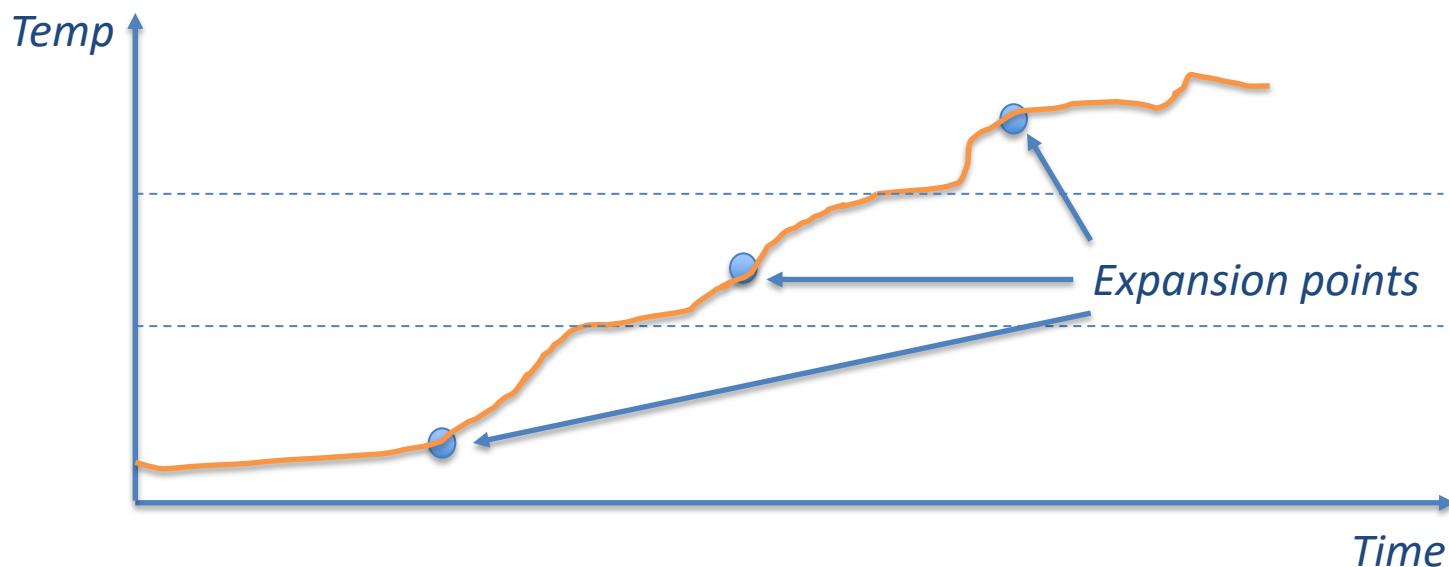
$$P_s = P_0 + A_s T,$$

$$G_l T(t) + C \frac{dT(t)}{dt} = B(P_d(t) + P_0),$$
$$Y(t) = LT(t).$$



$$G_l = G - BA_s$$

- Change Taylor expansion points on the fly

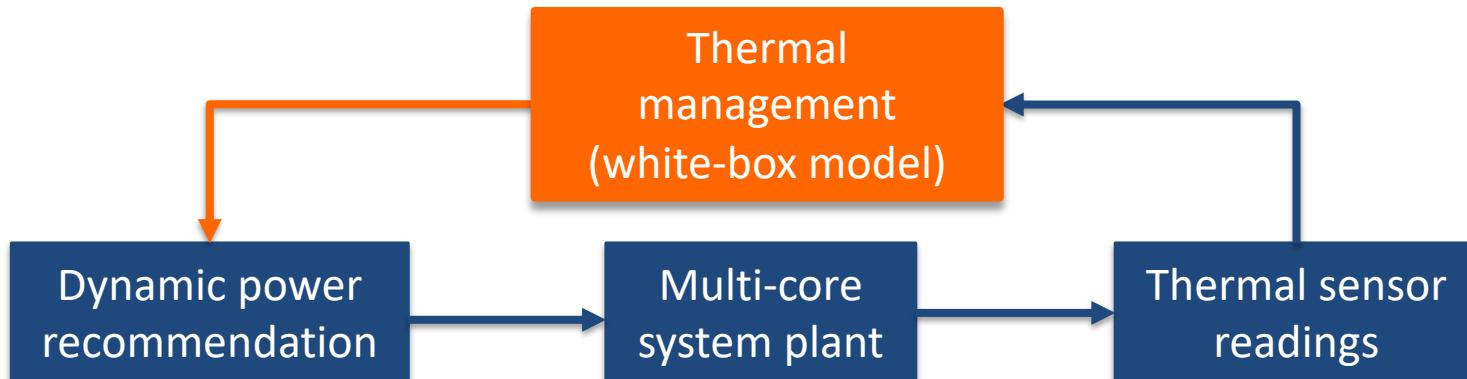


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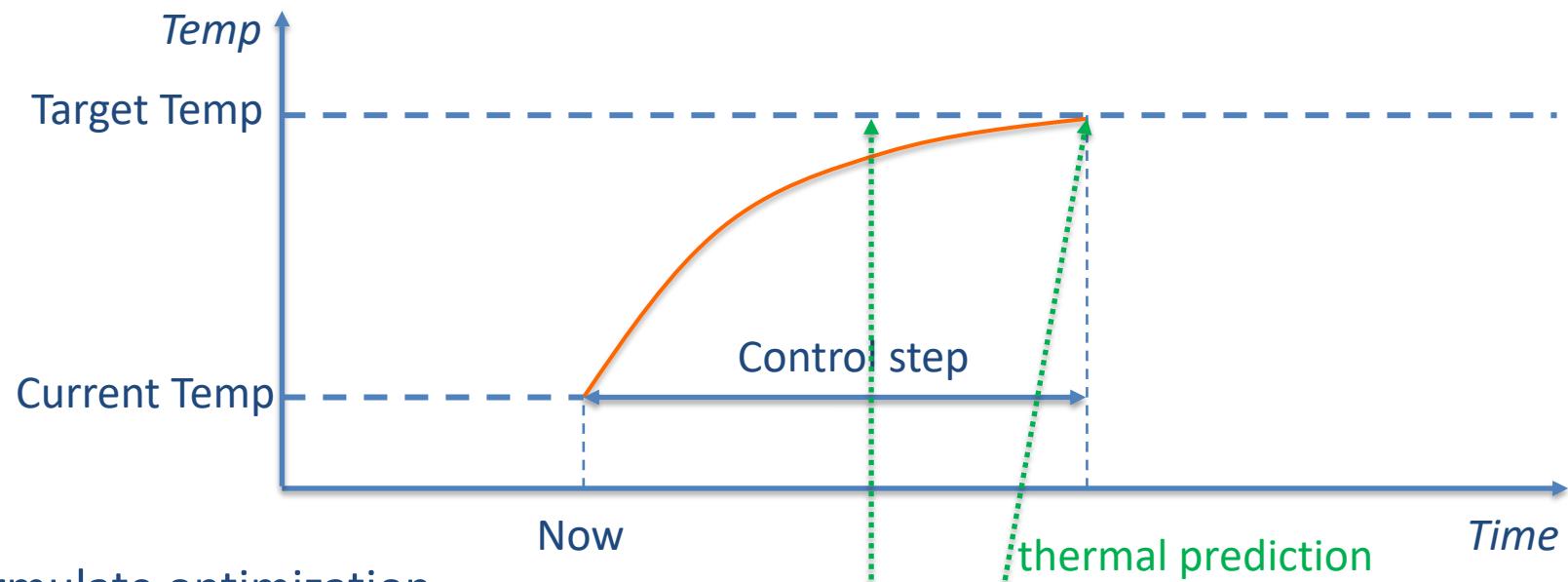
Leakage-aware thermal management problem

- Dynamic power is **controllable**
 - Change core's V/f
 - Switch tasks by scheduling
- Leakage power is **uncontrollable**
 - Depends mainly on temperature
- How to compute the **dynamic power recommendation** in leakage-aware thermal management?



Basic framework of Predictive DTM

- The basic idea of predictive DTM
 - Compute the dynamic power recommendation P_d , which tracks the given target temperature
 - P_d can be solved by optimization using thermal prediction

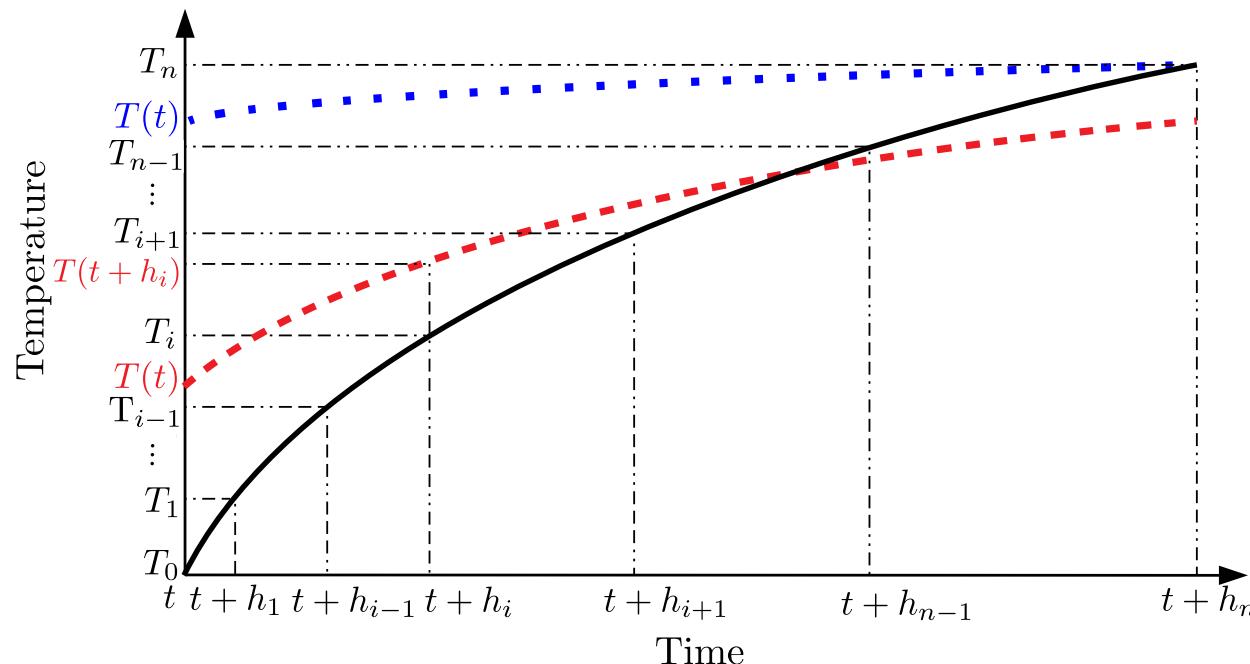


Formulate optimization
using white-box
thermal model

$$\text{minimize} \quad \mathcal{J} = (\mathcal{Y}_g - \mathcal{Y})^T (\mathcal{Y}_g - \mathcal{Y})$$

Determine expansion points in thermal management

- Build PWL white-box thermal model for DTM
- A systematic way to choose Taylor expansion points
 - Simulate the extreme curve (black) to determine points
 - Normal curves (orange, blue) share the points of the extreme

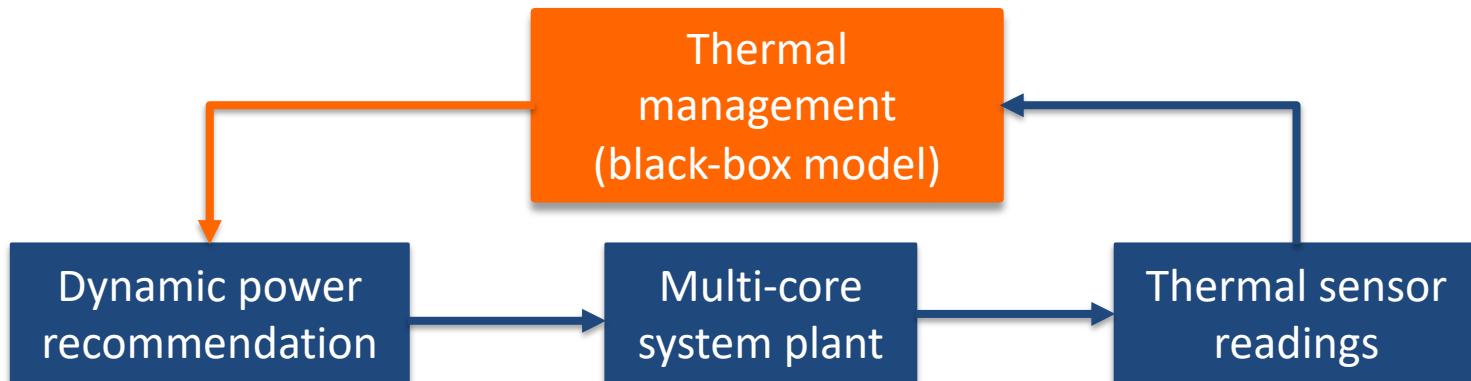


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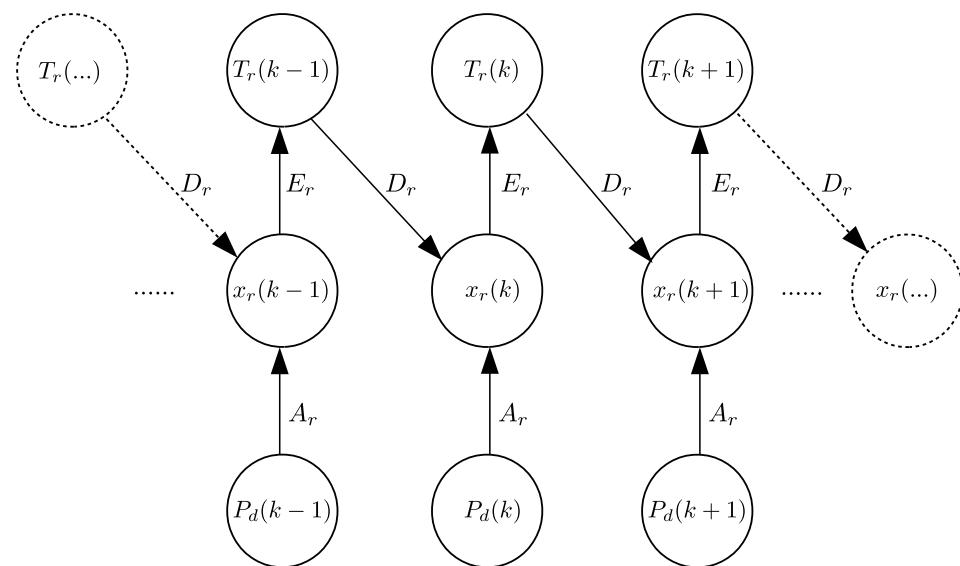
Using black-box model for DTM

- When detailed structure unavailable
 - Build black-box thermal model
 - Training using input (power) and output (temp.) pairs
- Remarks
 - Input should be **dynamic power**
 - Model should be **nonlinear**
 - Leakage handled implicitly inside model

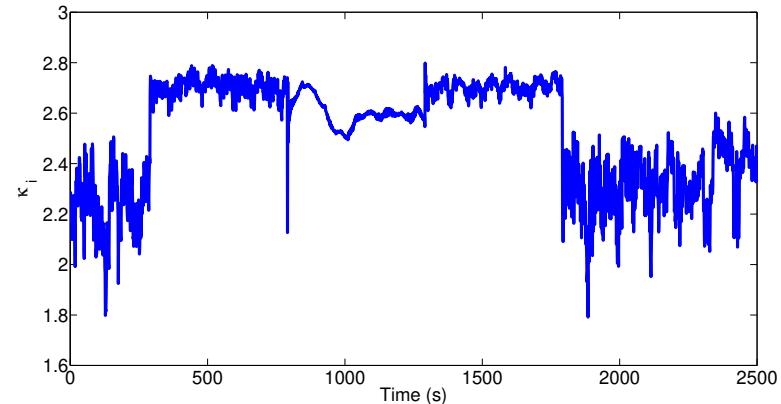


First try (failed): RNN based model

- Using recurrent neural network (RNN)
 - Nonlinear model specially for dynamic system modeling
 - Training using back propagation through time (BPTT)
 - First try **failed!** Due to exploding gradient in training
 - Large error using RNN



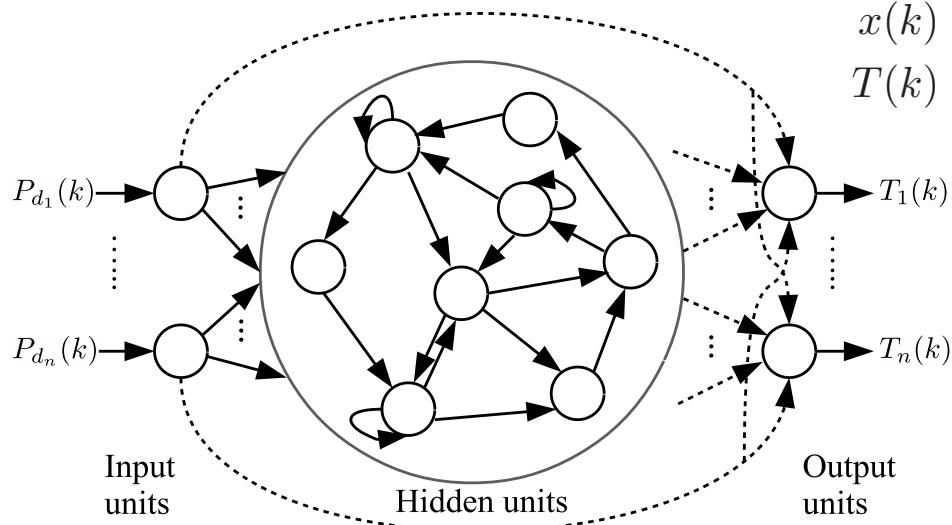
$$x_r(k) = f(A_r P_d(k) + D_r T_r(k-1) + \alpha),$$
$$T_r(k) = E_r x_r(k) + \beta,$$



Singular value > 1: exploding gradient

ESN to avoid exploding gradient

- Echo State Network (ESN) is a special RNN
 - Fixing the recurrent weights in hidden units
 - Only train the input and output weights
 - Training does **not** propagate through time (vs. BPTT)
 - Good accuracy in leakage-aware thermal modeling



$$x(k) = (1 - \gamma)x(k - 1) + \gamma f(AP_d(k) + Dx(k - 1)),$$
$$T(k) = Ex(k) + HP_d(k),$$

Simple training via least square,
No exploding gradient problem:

$$S = \begin{bmatrix} x(1), x(2), \dots, x(n_k) \\ P_{tr}(1), P_{tr}(2), \dots, P_{tr}(n_k) \end{bmatrix}^T$$

$$O = [T_{tr}(1), T_{tr}(2), \dots, T_{tr}(n_k)]^T$$

$$W_{out} = (S^\dagger O)^T$$

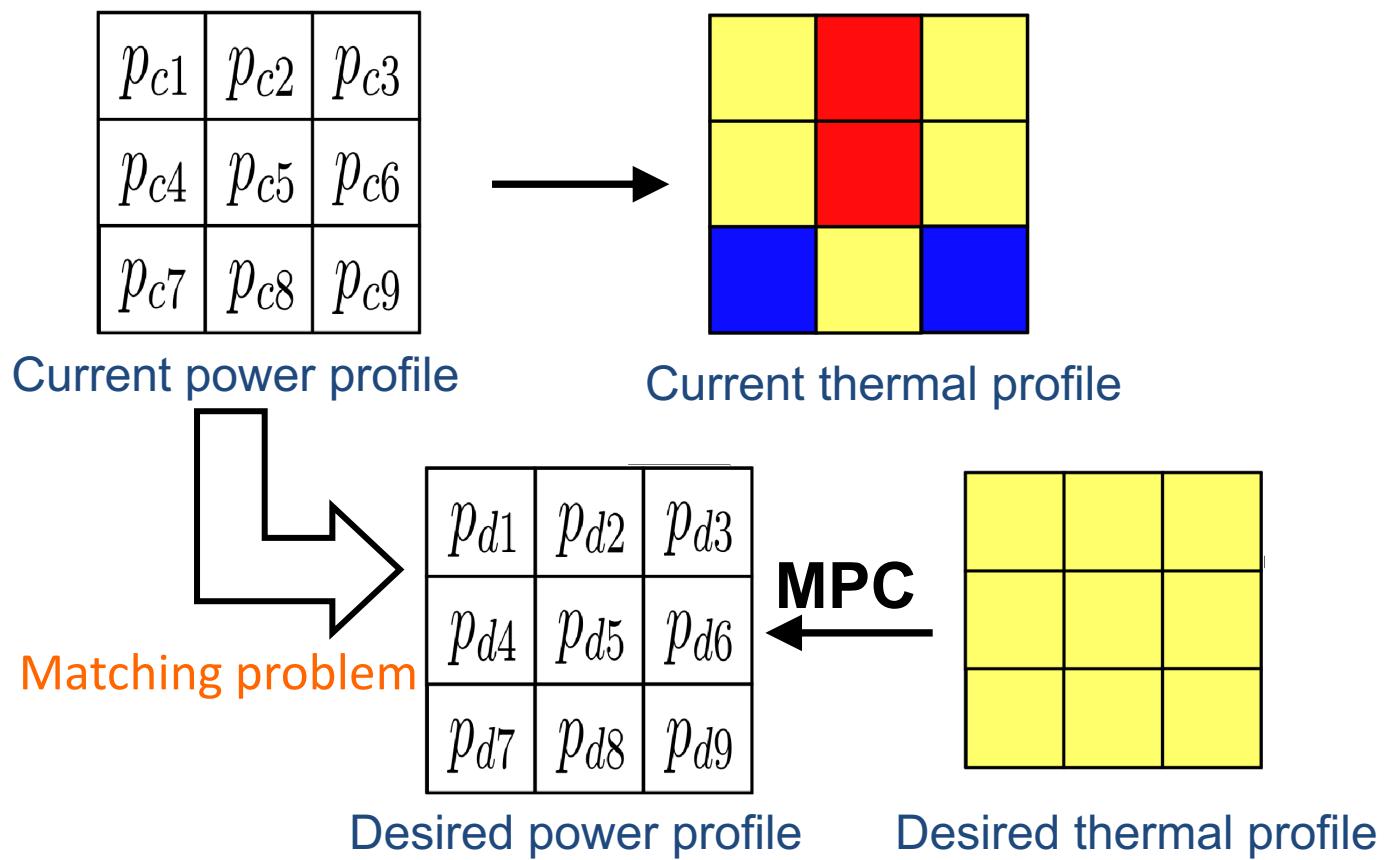
Many-Core Solutions

- **Hierarchical thermal management**

H. Wang, J. Ma, *et al.*, “Hierarchical dynamic thermal management method for high-performance many-core microprocessors”, ACM Trans. on Design Automation of Electronic Systems, 2017

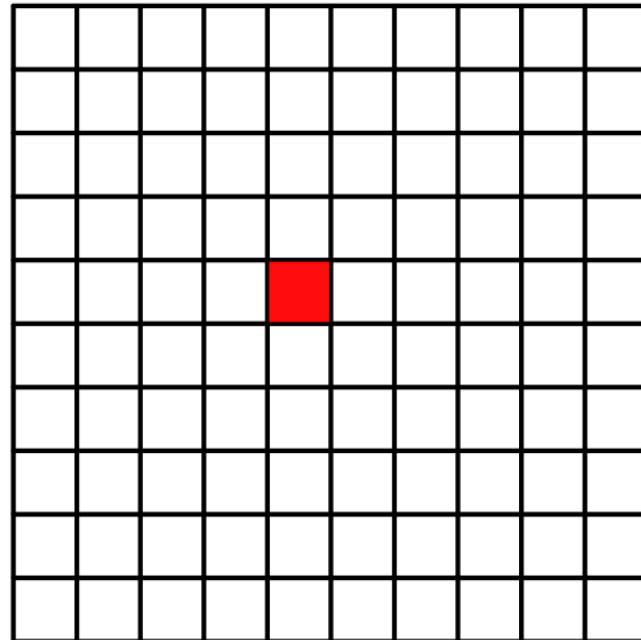
Model predictive control in thermal management

- We want to match the desired power profile using current power profile, by using task migration and DVFS.



The many-core system DTM problem

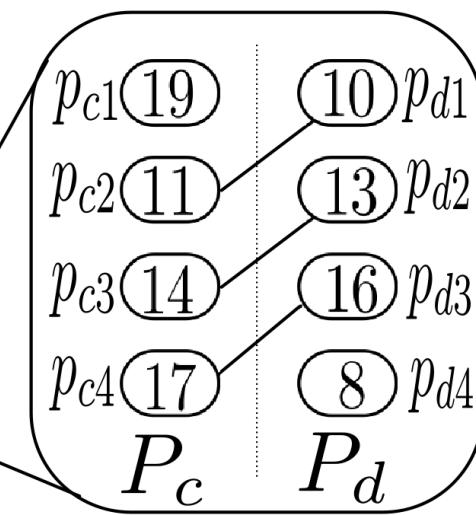
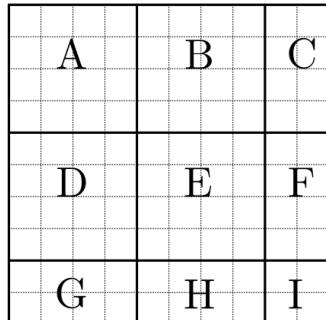
- Computing time increases as core number increases
- Large control delay reduces efficiency



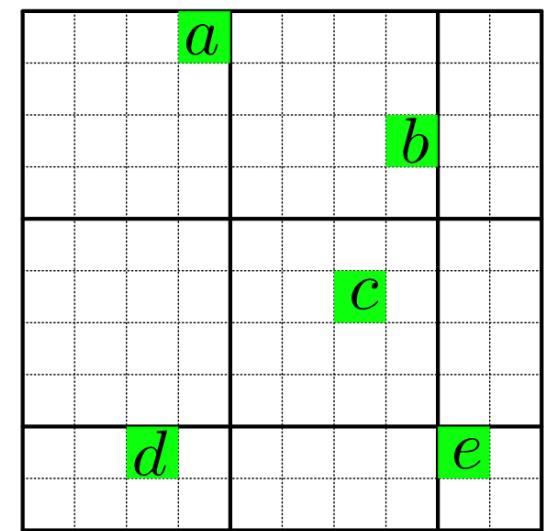
An example of 100-core chip, assuming core in red is in charge of the DTM computing.

Two-level Hierarchical method

- Lower level matching
 - Simply group spatially adjacent cores into blocks.
 - Do matching inside each block (intra block)
- Upper level matching
 - Do Matching using lower level unmatched ones (inter block)



Lower level matching



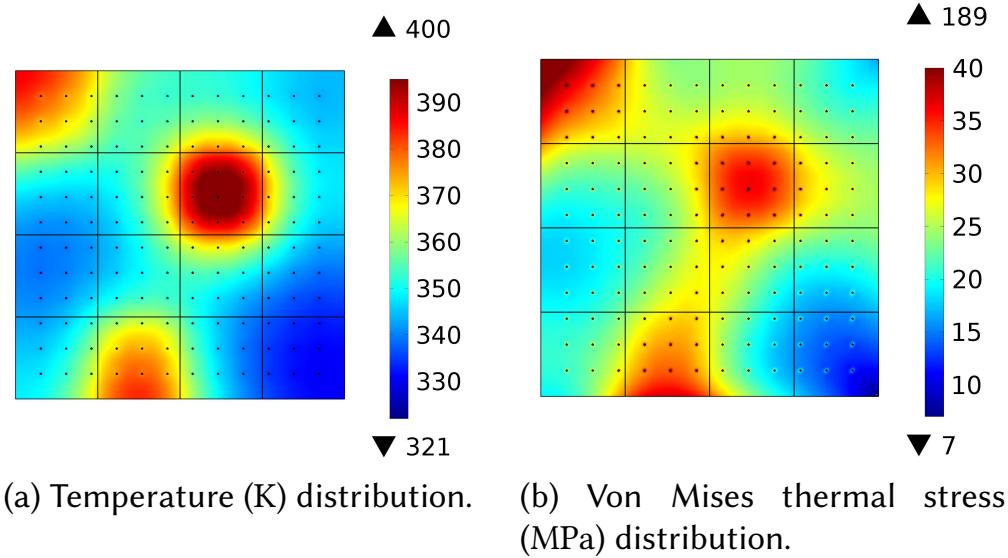
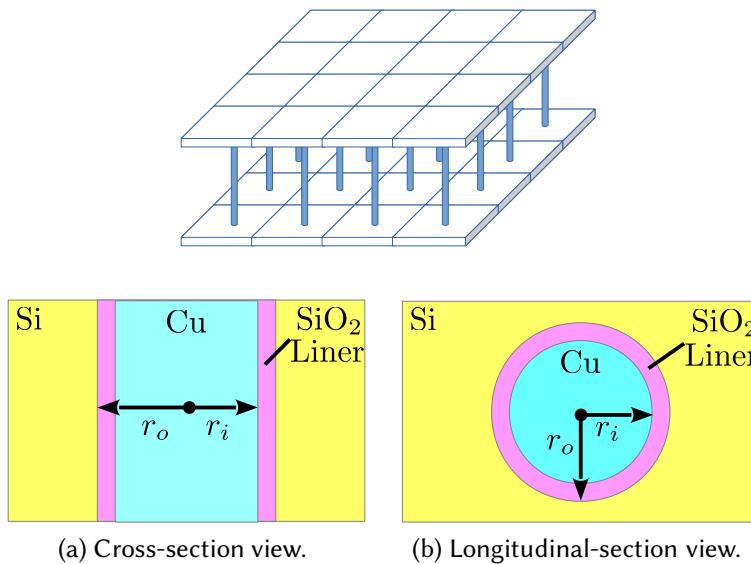
Upper level matching

3-D Integration

- Runtime stress estimation using ANN
H. Wang, T. Xiao, D. Huang, L. Zhang, *et al.*, “Runtime stress estimation for 3D IC reliability management using artificial neural network”, ACM Trans. on Design Automation of Electronic Systems, 2019
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Stress problem in 3D IC

- Stress is significant around Through silicon via (TSV)
- Stress changes with temperature in space and time
- Temperature changes significantly in multi-core systems
- Runtime stress estimation needed

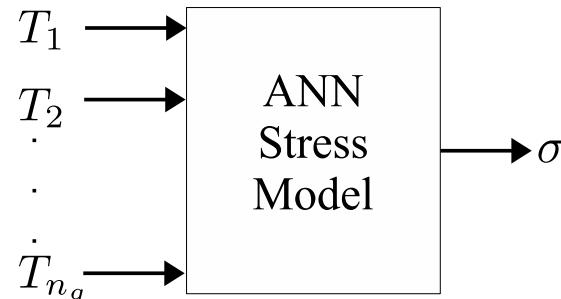


A 3D IC (up) with its TSV structure (down)

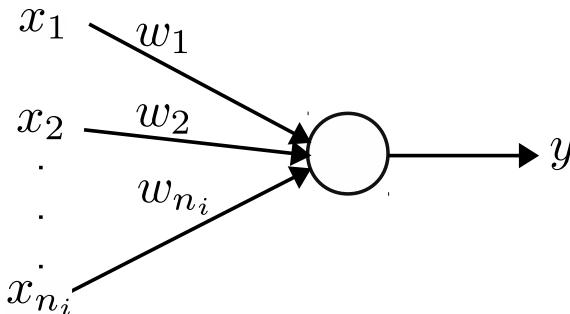
Stress changes with temperature

Framework of ANN stress model

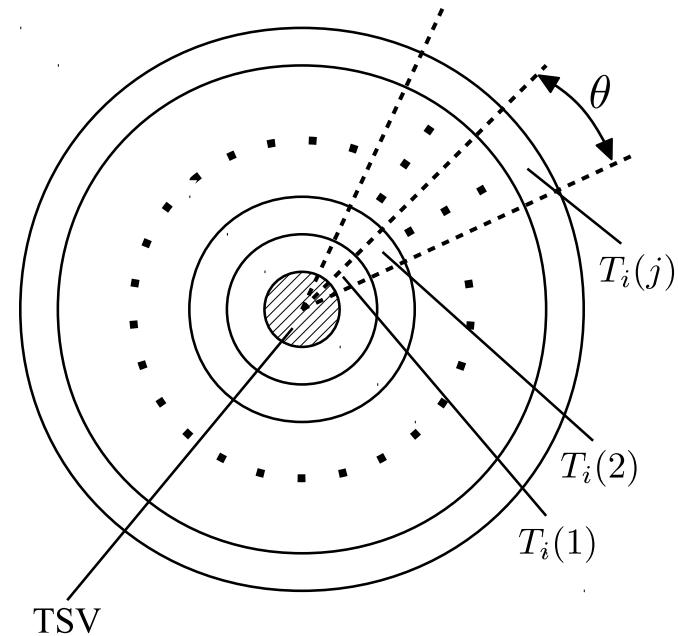
- Input: temperatures around each TSV
- Output: maximum stress
- Inside: neurons with different connections



ANN stress model framework



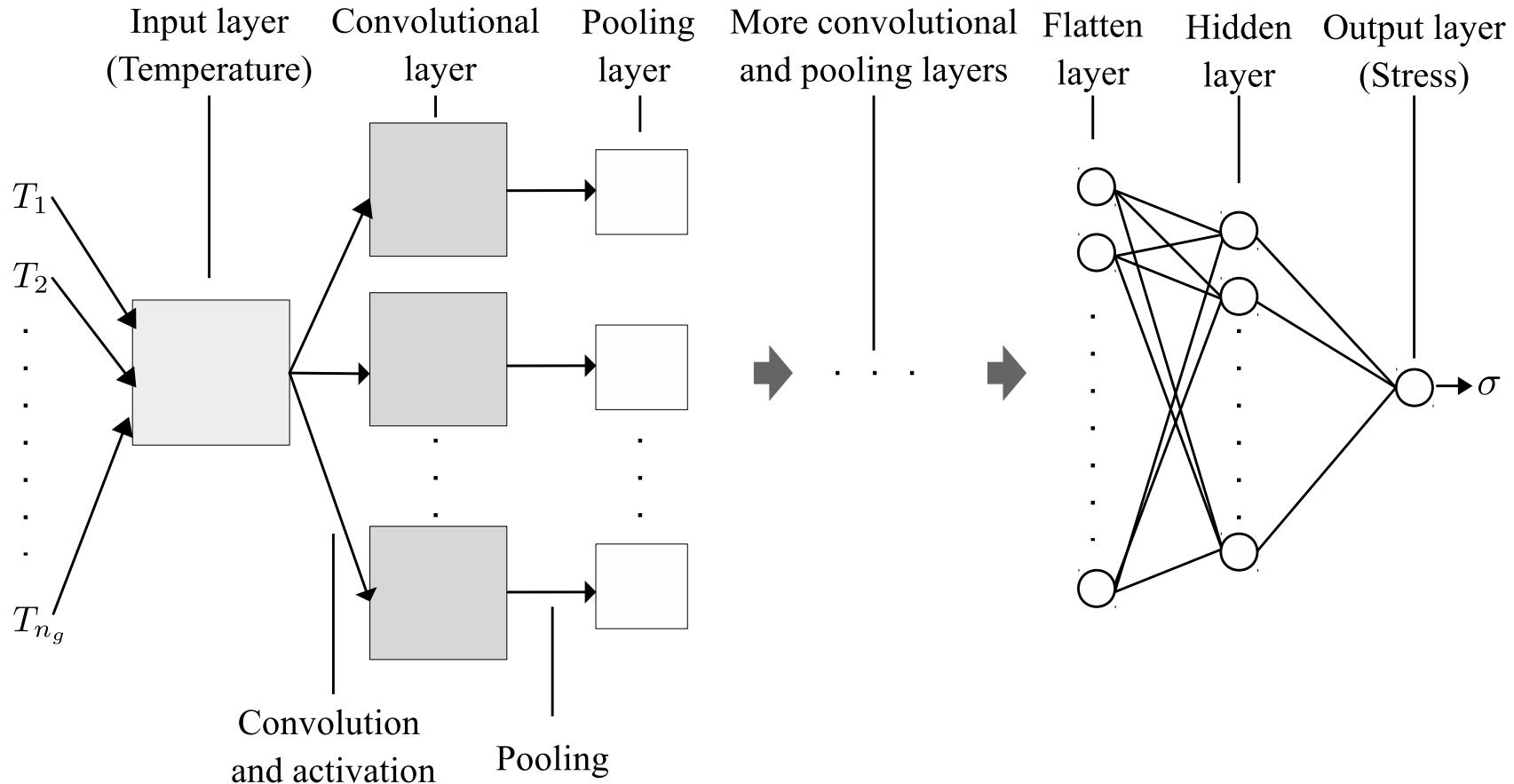
Neural inside ANN stress model



Model input: temperatures
around each TSV

Example: CNN stress model

- Different neural connections leads to different models
- CNN stress model works best in our test

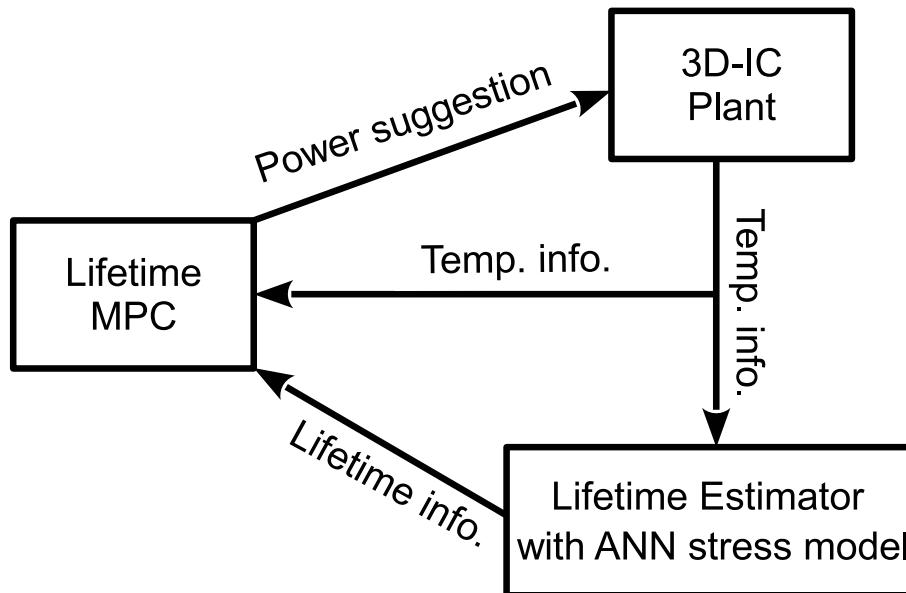


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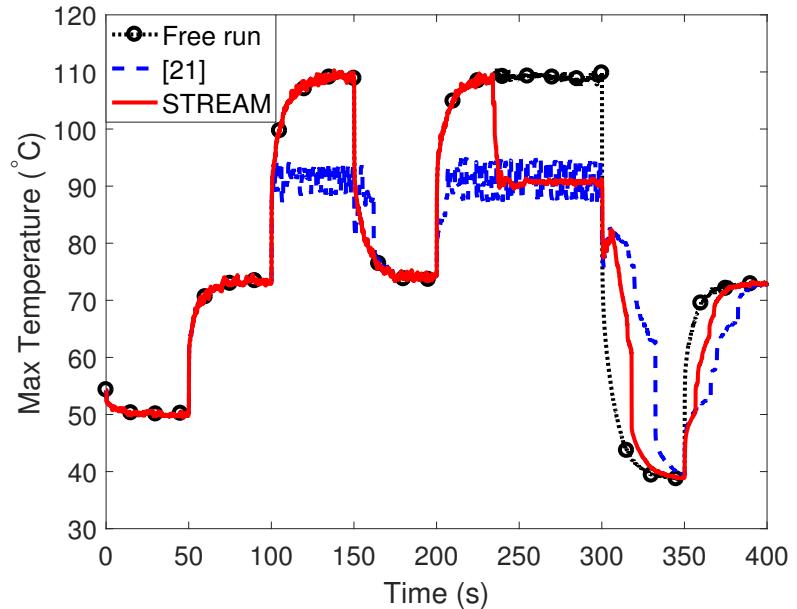
Boost 3D IC performance with ANN stress model

- We can estimate 3D IC lifetime with ANN stress model
- When the expected lifetime is
 - longer than designed: boost performance
 - shorter than designed: limit performance

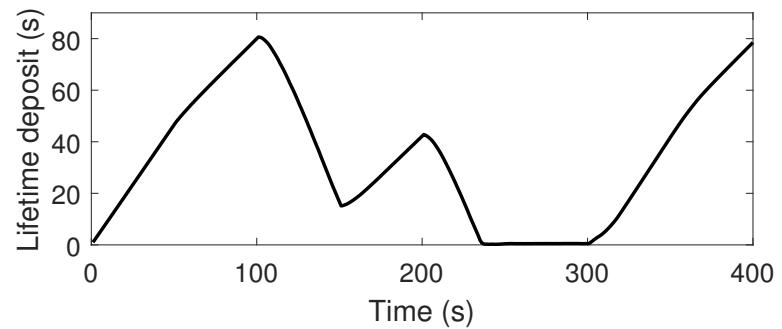


Lifetime banking with lifetime MPC

- Lifetime banking
 - Deposit lifetime
 - Consume lifetime
 - Lifetime deposit should never be negative
- Lifetime model predictive control (MPC)
 - Compute the power recommendation for 3D IC
 - DVFS performed to match the power recommendation



(a) Max temperature of synthetic workload with STREAM, existing method [21] and free run without any reliability management.



(b) Lifetime deposit information of STREAM.

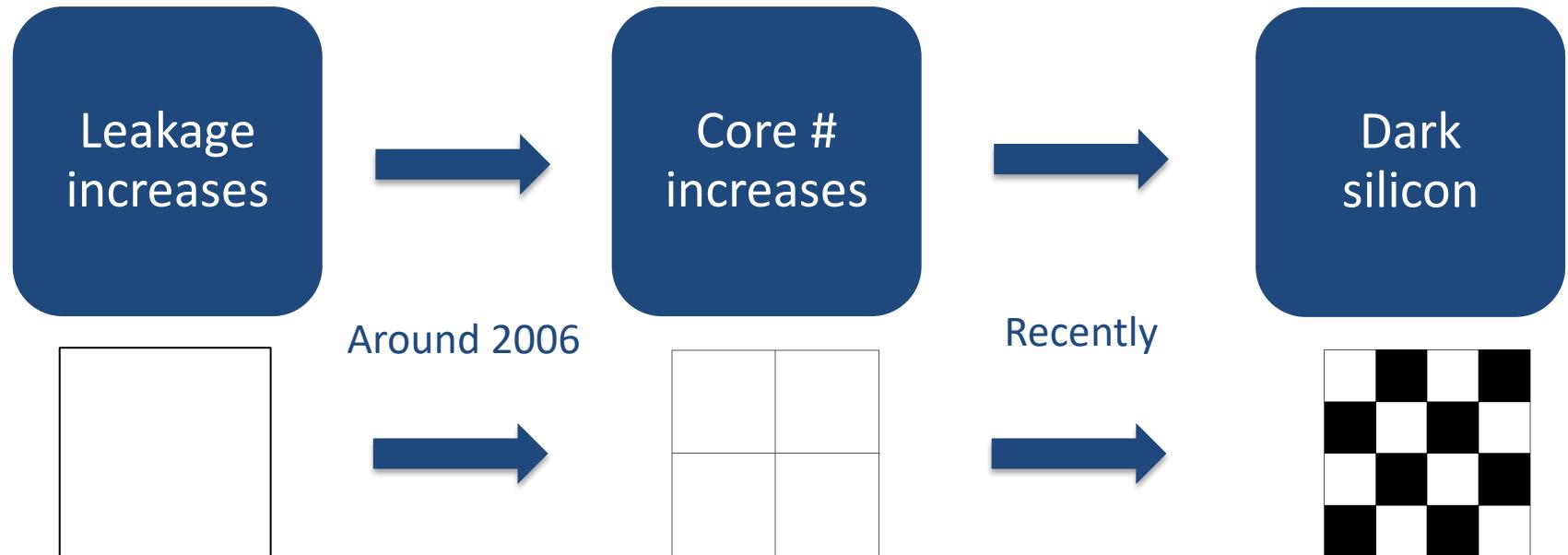
Dark Silicon Hazard

- GDP: Greedy based dynamic power budgeting

H. Wang, D. Tang, M. Zhang, *et al.*, “GDP: A greedy based dynamic power budgeting method for multi/many-core systems in dark silicon”, IEEE Trans. on Computers, 2019

Two battles lost against leakage

- Leakage power does not scale like dynamic power
 - Power density increases with scaling (Dennard scaling lost)
- Power (heat) removal ability remains the same



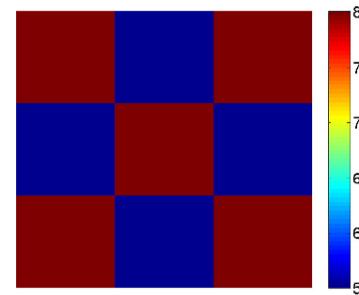
Fix core #
Increase frequency
Best days in performance increase!

Fix frequency
Increase core #

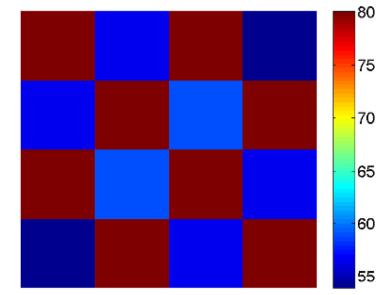
Not all cores operates
@ full freq anymore
We lost Dennard scaling
Solutions needed!

Power budgeting for dark silicon

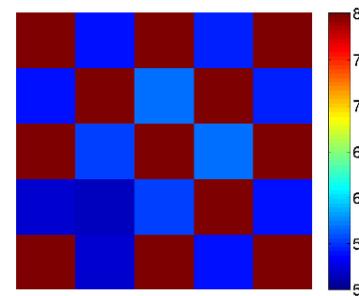
- Activating different cores leads to different power budget
- How to determine the active core distributions and power budget?
- Our solution: Greedy Dynamic Power (GDP)
 - Locate active core positions at runtime
 - Compute power budget for each core



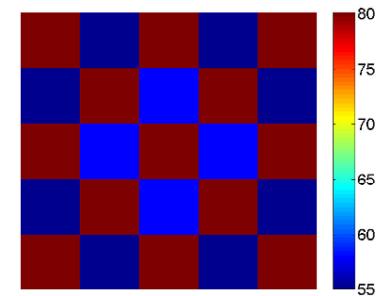
(a) 9-core system with 5 active cores.



(b) 16-core system with 8 active cores.



(c) 25-core system with 12 active cores.



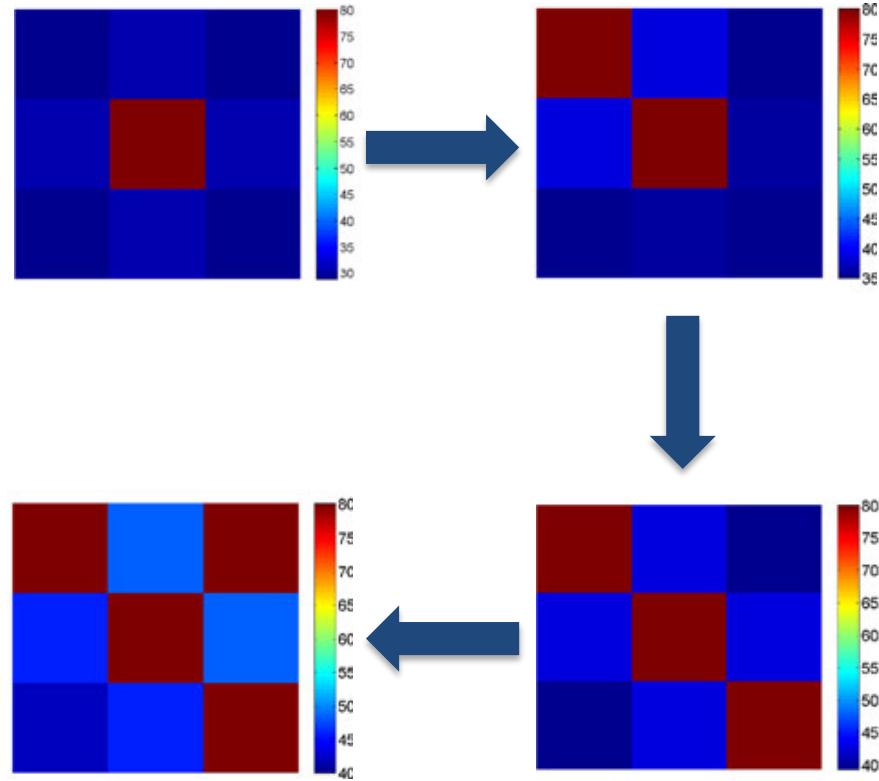
(d) 25-core system with 13 active cores.

The greedy iteration in GDP

- Searching for the best distribution is expensive
- Search the local best one instead!

- Locate the first best one and fix its position
- Search for the second best one and fix its position
- Continue this greedy iteration

- Transient temp. effects considered at runtime



9-core system's first 4 GDP iterations

Thank you!