Outstanding unsolved problems demand new methods for their solution, while powerful new methods beget new problems to be solved. But, as Poincare observed, it is the man, not the method, that solves a problem. -E. T. Bell ("Men of Mathematics")

Optimization Algorithms and Parallel Programming in Physical and Logic Synthesis

Prof. Hai Zhou EECS Northwestern University

25 Jul 2009

1. SoC Design Issues

2. Wire Retiming for Global Interconnects

Block models and problem formulation Incremental retiming algorithms for wire pipelining Experimental results

3. Buffer Insertion for SoC Circuits

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

4. Multicore Parallel CAD

Multicore Revolution and CAD Challenges Nondeterministic Transactional Algorithm Mapping Algorithm to Multicore Program Experimental Results

Outline

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System-on-Chip

- Moore's Law: number of transistor doubles per generation
- Market requires more functionality on a chip
- System-on-Chip is natural both from supply and demand



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• Design productivity lags far behind the technology "What shall we use so many transistors for?"



- Design productivity lags far behind the technology "What shall we use so many transistors for?"
- System Complexity: huge amount of functionality



- Design productivity lags far behind the technology "What shall we use so many transistors for?"
- System Complexity: huge amount of functionality
- Silicon complexity: more physical phenomena to be modeled and considered

Communication Among Components

- Increasing frequencies and die sizes
- Shrinking gate delays
- Interconnect delay dominates circuit performance
- Interconnect optimizations such as buffering are universally applied
- Global communication requests multiple clock cycles

Noise and Crosstalk

- Increasing aspect ratios of wires
- Decreasing distances between wires
- · Capacitive and inductive couplings among wires
- Noises are induced on quiet wires by switching wires
- Wire delays are changing because of crosstalk
- Analog components are sensitive to noises

Power Consumption

- Leakage has become prominent for current and future technology
- Excessive power consumption shortens battery life
- It also increase the cost and the stress of packaging

Thermal Issues

- Excessive power consumption increases temperatures on chip
- Uneven power consumption increases thermal gradients
- High temperature decreases performance and reliability
- It also increases packaging cost
- Leakage increases with high temperatures

Manufacturability

• Many new phenomena and issues in nano-lithography:

Manufacturability

- Many new phenomena and issues in nano-lithography:
- Process variations: random fabrication outcomes
- Resolution Enhancement Techniques (RET)
- Antenna effects
- ...

SoC Design Issues

Wire Retiming for Global Interconnects Buffer Insertion for SoC Circuits Multicore Parallel CAD

SoC Design Requirements

SoC Design Requirements

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• Modeling and analysis techniques

SoC Design Requirements

- Modeling and analysis techniques
- Design optimization techniques

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Wire pipelining

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- VLSI scaling trend
 - Frequency: 2X/generation, Die size: 1.25X/generation
 - Problem: global communication requires multiple clock periods

Wire pipelining

Block models and problem formulation ncremental retiming algorithms for wire pipelining Experimental results

- VLSI scaling trend
 - Frequency: 2X/generation, Die size: 1.25X/generation
 - Problem: global communication requires multiple clock periods
- Recent research

14

• Insert flip-flops (FFs) on wires based on physical needs (Intel, IBM, etc.)

Wire pipelining

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- VLSI scaling trend
 - Frequency: 2X/generation, Die size: 1.25X/generation
 - Problem: global communication requires multiple clock periods
- Recent research
 - Insert flip-flops (FFs) on wires based on physical needs (Intel, IBM, etc.)
 - How to maintain logical (functional) correctness?
 - FF insertion changes computation schedule
 - Synchronization among different computation units may be destroyed

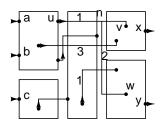
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Wire pipelining by retiming

- Retiming [Leiserson and Saxe '83] relocates FFs w/o changing functionality
 - Re-scheduling computation
- We extend it for pipelining long wires
 - Re-scheduling both computation and communication
- FFs may be added at PI (or PO) and then retimed into the circuit

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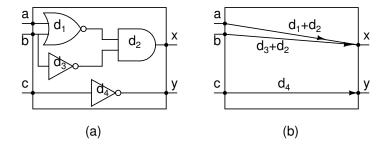
An SOC design example



- Block placement and global routing are given
- Signal directions and register locations, too

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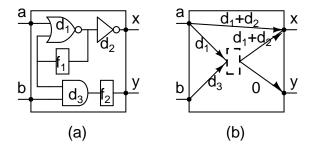
Timing model for a combinational block



• Timing arrows represent pin-to-pin path delays

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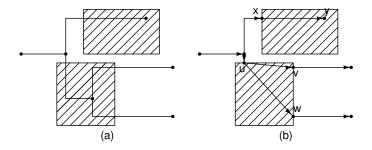
Timing model for a sequential block



- Timing arrows for pin-to-pin combinational paths
- A virtual register introduced for other paths
 - Paths starting or ending at registers

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Timing model for a net



- Nodes for Steiner points
- Nodes for entrances and exits of buffer-forbidden areas

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Optimal wire retiming problem

•
$$G = (V, E), E = E_1 \cup E_2, E_1 \cap E_2 = \emptyset$$

delay: $d(e), \#FF: w(e), \forall e \in E$

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Optimal wire retiming problem

- $G = (V, E), E = E_1 \cup E_2, E_1 \cap E_2 = \emptyset$ delay: $d(e), \#FF: w(e), \forall e \in E$
- $\forall e \in E_2$, d(e) is proportional to its length
 - Since buffers are allowed on E_2

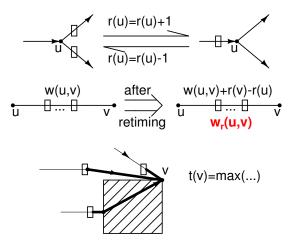
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Optimal wire retiming problem

- $G = (V, E), E = E_1 \cup E_2, E_1 \cap E_2 = \emptyset$ delay: $d(e), \#FF: w(e), \forall e \in E$
- $\forall e \in E_2$, d(e) is proportional to its length
 - Since buffers are allowed on E_2
- Find relocation of FFs
 - No FFs changed on any $e \in E_1$
 - Minimize clock period (= the maximum delay between any two consecutive FFs)

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Introducing decision variables r and t



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Formal problem formulation

Minimize T subject to:

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Formal problem formulation

Minimize T subject to:

• Retiming validity

$$r(u) = r(v) \quad \forall (u, v) \in E_1 \quad (1)$$

$$w_r(u,v) = w(u,v) + r(v) - r(u) \ge 0 \quad \forall (u,v) \in E_2$$
 (2)

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Formal problem formulation

Minimize T subject to:

• Retiming validity

$$r(u) = r(v) \quad \forall (u, v) \in E_1 \quad (1)$$

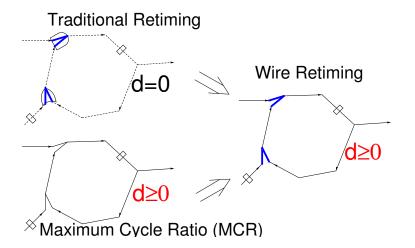
$$w_r(u,v) = w(u,v) + r(v) - r(u) \ge 0 \qquad \forall (u,v) \in E_2 \quad (2)$$

• Timing validity

$$t(v) \ge t(u) + d(u, v) - w_r(u, v)T \quad \forall (u, v) \in E$$
 (3)
 $0 \le t(v) \le T \quad \forall v \in V$ (4)

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Algorithmic view of the problem



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Traditional retiming problem

$$r(u) = r(v), \ \forall (u, v) \in E_1$$
(1)

$$w_r(u, v) = w(u, v) + r(v) - r(u) \ge 0, \ \forall (u, v) \in E_2$$
(2)

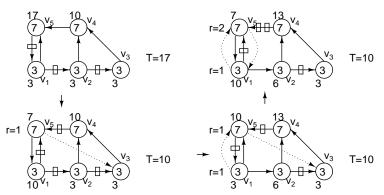
$$t(v) \ge t(u) + d(u, v), \ \forall (u, v) \in E : w_r(u, v) = 0$$

$$0 \le t(v) \le T, \ \forall v \in V$$
(4)

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Zhou's algorithm [ASP-DAC'05]

- Solve traditional retiming incrementally w/o binary search:
 - Initialize T by r = 0
 - Iteratively increment r(v) for $t(v) \geq T$
 - Maintain *m* pointers for optimality checking



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Maximum cycle ratio problem

Minimize T subject to:

$$t(v) \ge t(u) + d(u, v) - w_r(u, v)T \qquad \forall (u, v) \in E(3)$$

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Maximum cycle ratio problem

Minimize T subject to:

$$t(v) \ge t(u) + d(u, v) - w_r(u, v)T \qquad \forall (u, v) \in E(3)$$

- Burns's algorithm [CalTech PhD thesis '91]
- Solve MCR problem by iteratively pushing down T

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Idea for solving wire retiming problem

• Initialize T with r = 0

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Idea for solving wire retiming problem

• Initialize T with r = 0

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• Iteratively reduce T while keeping (1)-(4)

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Idea for solving wire retiming problem

• Initialize T with r = 0

- Iteratively reduce T while keeping (1)-(4)
 - With *r* unchanged
 - Extend Burns's algorithm

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Idea for solving wire retiming problem

• Initialize T with r = 0

- Iteratively reduce T while keeping (1)-(4)
 - With r unchanged
 - Extend Burns's algorithm
 - Change r (retiming)
 - Extend Zhou's algorithm

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Idea for solving wire retiming problem

- Initialize T with r = 0
- Iteratively reduce T while keeping (1)-(4)
 - With r unchanged
 - Extend Burns's algorithm
 - Change r (retiming)
 - Extend Zhou's algorithm
- Certify optimality

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Push down T with r unchanged

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• Retiming validity ((1) and (2)) is kept

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Push down T with r unchanged

- Retiming validity ((1) and (2)) is kept
- Minimize *T* under timing validity:

$$t(v) \ge t(u) + d(u, v) - w_r(u, v)T, \ \forall (u, v) \in E$$
(3)
$$0 \le t(v) \le T, \ \forall v \in V$$
(4)

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- Burns's algorithm [CalTech PhD thesis '91]
 - Returns minimal T under (3)

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$$t(v) \ge t(u) + d(u, v) - w_r(u, v)T, \ \forall (u, v) \in E$$
(3)
$$0 \le t(v) \le T, \ \forall v \in V$$
(4)

- Burns's algorithm [CalTech PhD thesis '91]
 - Returns minimal T under (3)

Extend Burns's to incorporate (4)

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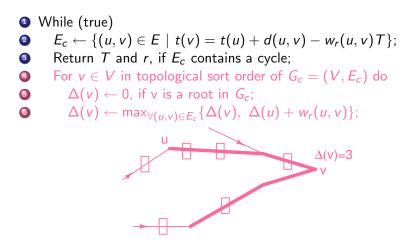
Burns's Algorithm

While (true)

- Return T and r, if E_c contains a cycle;

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Burns's Algorithm



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Burns's Algorithm

While (true) 1 $E_c \leftarrow \{(u, v) \in E \mid t(v) = t(u) + d(u, v) - w_r(u, v)T\};$ 2 Return T and r, if E_c contains a cycle; 3 For $v \in V$ in topological sort order of $G_c = (V, E_c)$ do 4 $\Delta(v) \leftarrow 0$, if v is a root in G_c : 5 $\Delta(v) \leftarrow \max_{\forall (u,v) \in E_r} \{\Delta(v), \ \Delta(u) + w_r(u,v)\};$ 6 0 $\theta \leftarrow \infty$: 8 For each $(u, v) \in E$ do 9 If $(\Delta(u) + w_r(u, v) > \Delta(v))$ then $\theta \leftarrow \min\{\theta, \frac{t(v)-t(u)-d(u,v)+w_r(u,v)T}{\Delta(u)+w_r(u,v)-\Delta(v)}\};$ 0

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Burns's Algorithm

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Modify Burns's to satisfy (4)

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Modify Burns's to satisfy (4)

For each $v \in V$ do $\theta \leftarrow \min\{\theta, \frac{T-t(v)}{\Delta(v)+1}\};$ 12

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Modify Burns's to satisfy (4)

Theoretical importance

Push T down to the minimum, with r unchanged

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Push down T by changing r

Condition

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• $\exists v, t(v) = T$

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Push down T by changing r

Condition

31

- $\exists v, t(v) = T$
- Zhou's algorithm

•
$$r(v) \leftarrow r(v) + 1$$

• Necessary to get a smaller T if it exists

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Push down T by changing r

Condition

- $\exists v, t(v) = T$
- Zhou's algorithm
 - $r(v) \leftarrow r(v) + 1$
 - Necessary to get a smaller T if it exists
 - Regain retiming validity ((1) and (2))
 - Proper r adjustments

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Push down T by changing r

Condition

- $\exists v, t(v) = T$
- Zhou's algorithm
 - $r(v) \leftarrow r(v) + 1$
 - Necessary to get a smaller T if it exists
 - Regain retiming validity ((1) and (2))
 - Proper r adjustments
- Run extended Burns's under new r

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Criteria for certifying optimality

Optimality has been reached if:

- A critical cycle in Burns's
- An *m* cycle in Zhou's

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• $\exists v \in V$, $r(v) > N_{\rm ff}$, the total # of FFs in any simple path

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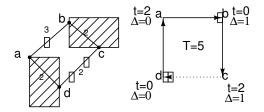
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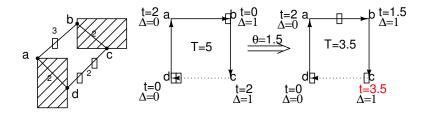
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An example



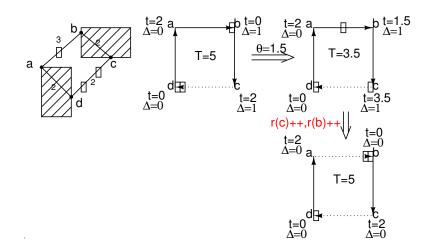
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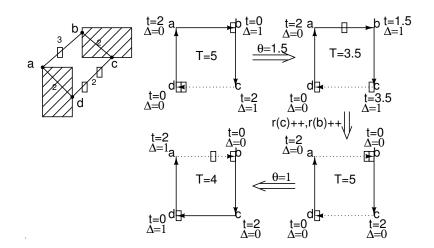
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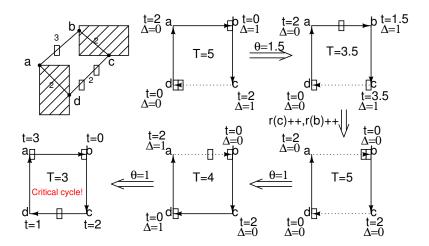
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An example



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An example



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Computation complexity

- Complexity per iteration
 - $O(|V|^2|E|)$

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Computation complexity

- Complexity per iteration
 - $O(|V|^2|E|)$
- # of iterations

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• $O(|V| \cdot N_{\mathrm{ff}})$, where N_{ff} is the total # of FFs in any simple path

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Computation complexity

- Complexity per iteration
 - $O(|V|^2|E|)$
- # of iterations
 - $O(|V| \cdot N_{\rm ff})$, where $N_{\rm ff}$ is the total # of FFs in any simple path
- Entire algorithm
 - $O(|V|^3|E|\cdot N_{\rm ff})$ in the worst case

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Computation complexity

- Complexity per iteration
 - $O(|V|^2|E|)$
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 - $O(|V| \cdot N_{\rm ff})$, where $N_{\rm ff}$ is the total # of FFs in any simple path
- Entire algorithm
 - $O(|V|^3|E| \cdot N_{\rm ff})$ in the worst case
 - Remarkable efficiency in practice

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Benchmark

• ISCAS-89

- 1st test set: treat gates as blocks
- 2nd test set: circuits w/ non-complete bipartite blocks

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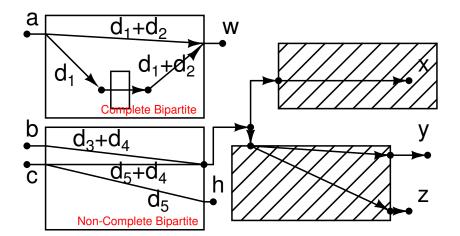
Benchmark

• ISCAS-89

- 1st test set: treat gates as blocks
- 2nd test set: circuits w/ non-complete bipartite blocks
 - Use hMETIS to partition a circuit into groups
 - Treat each group as a block

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Block models



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Optimal clock period

| Circuit | V | E | N _{ff} | w/o non-CB | | w/ non-CB | | | | | | |
|---------|-------|-------|-----------------|------------|--------------------|-----------|-------|--------------------|--|--|--|--|
| | | | | #Step | T^{opt} | #Par | #Step | T^{opt} | | | | |
| s386 | 519 | 700 | 6 | 13 | 51.1 | 50 | 1 | 55.0 | | | | |
| s400 | 511 | 665 | 21 | 120 | 32.2 | 50 | 1 | 50.6 | | | | |
| s444 | 557 | 725 | 21 | 289 | 35.2 | 40 | 1 | 63.2 | | | | |
| s838 | 1299 | 1206 | 32 | 2 | 76.0 | 130 | 1 | 84.0 | | | | |
| s953 | 1183 | 1515 | 29 | 31 | 60.6 | 110 | 2 | 69.5 | | | | |
| s1488 | 2054 | 2780 | 6 | 11 | 70.6 | 200 | 1 | 73.3 | | | | |
| s1494 | 2054 | 2792 | 6 | 63 | 76.9 | 160 | 1 | 79.9 | | | | |
| s5378 | 7205 | 8603 | 179 | 26 | 111.2 | 500 | 1 | 115.3 | | | | |
| s13207 | 19816 | 22999 | 669 | 129 | 239.5 | 1000 | 1 | 292.8 | | | | |
| s35932 | 46097 | 58266 | 1728 | 68 | 148.3 | 2000 | 1 | 163.2 | | | | |
| s38584 | 53473 | 66964 | 1452 | 126 | 204.0 | 2000 | 1 | 264.0 | | | | |

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Running time comparison (in seconds)

• t_{bs1} [ICCAD'03], t_{bs2} [DATE'04], precision=0.1

| Circuit | w/o n | on-CB b | olocks | w/ non-CB blocks | | | |
|---------|--------------|--------------|--------------|------------------|--------------|--------------|--|
| | $t_{ m bs1}$ | $t_{ m bs2}$ | $t_{ m new}$ | $t_{ m bs1}$ | $t_{ m bs2}$ | $t_{ m new}$ | |
| s386 | 1.97 | 0.01 | 0.00 | 3.67 | 0.01 | 0.00 | |
| s400 | 1.64 | 0.01 | 0.03 | 3.38 | 0.01 | 0.00 | |
| s444 | 2.23 | 0.03 | 0.09 | 4.31 | 0.01 | 0.00 | |
| s838 | 8.79 | 0.03 | 0.00 | 33.42 | 0.02 | 0.00 | |
| s953 | 9.76 | 0.04 | 0.02 | 17.56 | 0.07 | 0.00 | |
| s1488 | 35.17 | 0.08 | 0.08 | 98.88 | 0.05 | 0.00 | |
| s1494 | 34.13 | 0.08 | 0.06 | 62.86 | 0.09 | 0.00 | |
| s5378 | 684.6 | 0.24 | 0.31 | 1344.74 | 0.29 | 0.00 | |
| s13207 | - | 1.07 | 3.46 | - | 206.52 | 0.02 | |
| s35932 | - | 18.63 | 7.55 | - | 6.19 | 0.19 | |
| s38584 | - | 7.44 | 30.17 | - | 21992.67 | 0.19 | |

Optimization Algorithms and Parallel Programming in Physical a

Prof. Hai Zhou EECS Northwestern University

Block models and problem formulation Incremental retiming algorithms for wire pipelining Experimental results

Summary

- Scaling trend introduces more multiple clock period interconnects
- Retiming is a critical technique for wire pipelining with correctness

Block models and problem formulation Incremental retiming algorithms for wire pipelining Experimental results

Summary

- Scaling trend introduces more multiple clock period interconnects
- Retiming is a critical technique for wire pipelining with correctness
- An efficient new algorithm is proposed and tested
 - Without binary search
 - Exact optimality
 - Polynomial time bounded
 - Simple implementation
 - Efficient in practice
 - Incremental in nature

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Outline

1. SoC Design Issues

2. Wire Retiming for Global Interconnects

Block models and problem formulation Incremental retiming algorithms for wire pipelining Experimental results

3. Buffer Insertion for SoC Circuits

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

4. Multicore Parallel CAD

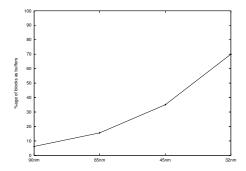
Multicore Revolution and CAD Challenges Nondeterministic Transactional Algorithm Mapping Algorithm to Multicore Program Experimental Results

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Buffers Are Everywhere

Saxena et al. TCAD04

Projected that as many as 70% cells could just be buffers.



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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Efficient and Effective Techniques Are Needed

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Efficient and Effective Techniques Are Needed

- Most prior researches focusing on buffering a single net:
 - van Ginneken ISCAS90
 - Shi et al. DAC03

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

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- Most prior researches focusing on buffering a single net:
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- However, how to buffer a whole circuit is the ultimate issue

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Efficient and Effective Techniques Are Needed

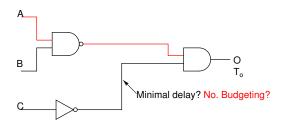
- Most prior researches focusing on buffering a single net:
 - van Ginneken ISCAS90
 - Shi et al. DAC03

- However, how to buffer a whole circuit is the ultimate issue
- "Budgeting + buffering each net" won't work since we do not know budgeting cost a priori

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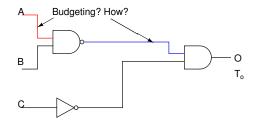
Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Simply Buffering Each Net Optimally is Overkill



Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Simply Buffering Each Net Optimally is Overkill



Our Goal

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Problem

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Given a combinational circuit, insert minimal number of buffers such that the timing constraint is satisfied.

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Our Goal

Problem

Given a combinational circuit, insert minimal number of buffers such that the timing constraint is satisfied.

• It is NP-hard [Liu et al. ICCD99]

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Our Goal

Problem

44

Given a combinational circuit, insert minimal number of buffers such that the timing constraint is satisfied.

- It is NP-hard [Liu et al. ICCD99]
- So, we just want to solve effectively and efficiently but not optimally

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Limited Existing Approaches

- Lagrangian relaxation based [Liu et al. ICCD99, DATE00]
- Path-based [Sze et al. DAC05]

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Lagrangian relaxation based [Liu et al. ICCD99, DATE00]

• Objective function: $\alpha \sum_{e \in E} K_e$.

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Lagrangian relaxation based [Liu et al. ICCD99, DATE00]

• Objective function: $\alpha \sum_{e \in E} K_e$.

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• Objective function after LR: $\sum_{e \in E} (\alpha K_e + \beta_e d_e)$.

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Lagrangian relaxation based [Liu et al. ICCD99, DATE00]

- Objective function: $\alpha \sum_{e \in E} K_e$.
 - Objective function after LR: $\sum_{e \in E} (\alpha K_e + \beta_e d_e)$.
 - Sensitive to α

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Lagrangian relaxation based [Liu et al. ICCD99, DATE00]

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 - Sensitive to α

46

• How to determine α ?

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Lagrangian relaxation based [Liu et al. ICCD99, DATE00]

- Objective function: $\alpha \sum_{e \in E} K_e$.
 - Objective function after LR: $\sum_{e \in E} (\alpha K_e + \beta_e d_e)$.
 - Sensitive to $\boldsymbol{\alpha}$

- How to determine α ?
- Lagrangian relaxation based: expensive, over-buffering

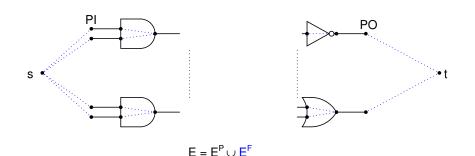
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Path based [Sze et al. DAC05]

- Select a set of critical paths
- How to determine the number of critical paths?
- Performance compared with Lagrangian relaxation based?

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Problem formulation



Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Problem formulation

$$Minimize \qquad \sum_{(i,j)\in E^P} K_{ij} \tag{5}$$

s.t.
$$a_i + d_{ij} \le a_j \quad \forall (i,j) \in E$$
 (6)
 $a_t - a_s \le REQ$ (7)

where K_{ij} is the number of buffers on edge (i, j), a_i is the arrival time at vertex *i*, d_{ij} is the delay of edge (i, j), and *REQ* is the timing constraint.

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Difficulty in buffering

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• It's a discrete optimization problem

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

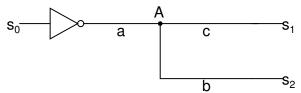
Difficulty in buffering

- It's a discrete optimization problem
- Buffering on a branch influences delays of other branches

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Difficulty in buffering

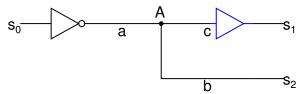
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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Difficulty in buffering

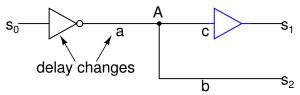
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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Difficulty in buffering

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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

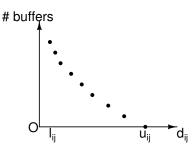
Our Approach

- Treat buffering as substitute one wire by another with different buffers
- Iterative budgeting with actual buffering cost

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Our Approach

- Treat buffering as substitute one wire by another with different buffers
- Iterative budgeting with actual buffering cost



Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Simplified situation

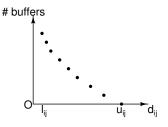
- Fixed module delay
- Two-pin nets

Reformulation

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

• constraint graph: add one edge from t to s with weight -REQ

• $K_{ij} = C_{ij}(d_{ij})$



Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Reformulation

Problem

Given a constraint graph G(V, E)

$\begin{array}{ll} \textit{Minimize} \quad \sum_{(i,j)\in E} \mathcal{C}_{ij}(d_{ij}) \\ \textit{s.t.} \quad t_j \geq t_i + d_{ij} \quad \forall (i,j) \in E \end{array}$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Reformulation

Problem

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Given a constraint graph G(V, E)

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- The dual of the convex cost flow problem
 - \mathcal{C}_{ij} : a discrete domain with integer range
 - No existing techniques can solve this

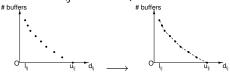
Buffer Insertion for Soc Multicore Parall Reformulation Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

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- The dual of the convex cost flow problem
 - C_{ij} : a discrete domain with integer range
 - No existing techniques can solve this
- Linearize C_{ii} : convex piece-wise linear



Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Optimality condition

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Karush-Kuhn-Tucker (KKT)

$$t_{j} \geq t_{i} + d_{ij} \qquad \forall (i,j) \in E \qquad (8)$$

$$\exists \mathbf{x} : -\mathcal{C}^{+}_{ij}(d_{ij}) \leq x_{ij} \leq -\mathcal{C}^{-}_{ij}(d_{ij}) \qquad \forall (i,j) \in E \qquad (9)$$

$$\sum_{(i,j)\in E} x_{ij} - \sum_{(j,i)\in E} x_{ji} = 0 \qquad \forall i \in V \qquad (10)$$

$$x_{ij} \geq 0 \qquad \forall (i,j) \in E \qquad (11)$$

$$x_{ij}(t_{j} - t_{i} - d_{ij}) = 0 \qquad \forall (i,j) \in E \qquad (12)$$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Optimality condition

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• x_{ii}: network flow

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Optimality condition

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$$x_{ij} \geq 0 \qquad \forall (i,j) \in E \qquad (11)$$

$$x_{ij}(t_{j} - t_{i} - d_{ij}) = 0 \qquad \forall (i,j) \in E \qquad (12)$$

• x_{ii}: network flow

• Condition (12):
$$x_{ij} \neq 0 \Rightarrow t_j = t_i + d_{ij}$$
.

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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Convex-cost flow based buffering algorithm

Algorithm MinCost-Buffering

$$d_{ij} \leftarrow u_{ij} \ \forall (i,j) \in E$$

 $c_{(i,j)} \leftarrow -C_{ij}^-(d_{ij}) \ \forall (i,j) \in E \land s_{ij} < 0$
 $c_{(i,j)} \leftarrow 0 \ \forall (i,j) \in E \land s_{ij} \ge 0$
while there exist positive cycles in G
Augment maximal flows using s as the source
and t as the sink;
Select a min-cut M;
Insert one buffer into $(i,j) \ \forall (i,j) \in M$;
UpdateTimingSlack(G);
 $c_{(i,j)} \leftarrow -C_{ij}^-(d_{ij}) - f_{ij} \ \forall (i,j) \in E \land s_{ij} < 0$
 $c_{(i,j)} \leftarrow 0 \ \forall (i,j) \in E \land s_{ij} \ge 0$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Convex-cost flow based buffering algorithm

• No need of the explicit representation of C_{ii} : efficiency

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Convex-cost flow based buffering algorithm

- No need of the explicit representation of C_{ij} : efficiency
- No backward flow: component delays NEVER increase, efficiency

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Convex-cost flow based buffering algorithm

- No need of the explicit representation of C_{ij} : efficiency
- No backward flow: component delays NEVER increase, efficiency

•
$$f_{ij} = -\mathcal{C}^-_{ij}(d_{ij}) \ \forall (i,j) \in M$$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Optimality conditions

Theorem

The solution generated by MinCost-Buffering satisfies the conditions (4)-(7).

$$t_{j} \geq t_{i} + d_{ij} \qquad \forall (i,j) \in E \qquad (4)$$

$$\exists \mathbf{x} : -\mathcal{C}^{+}_{ij}(d_{ij}) \leq x_{ij} \leq -\mathcal{C}^{-}_{ij}(d_{ij}) \qquad \forall (i,j) \in E \qquad (5)$$

$$\sum_{(i,j)\in E} x_{ij} - \sum_{(j,i)\in E} x_{ji} = 0 \qquad \forall i \in V \qquad (6)$$

$$x_{ij} \geq 0 \qquad \forall (i,j) \in E \qquad (7)$$

$$x_{ij}(t_{j} - t_{i} - d_{ij}) = 0 \qquad \forall (i,j) \in E \qquad (8)$$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Min-cut based buffering algorithm

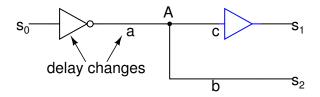
Algorithm MinCut-Buffering $d_{ii} \leftarrow u_{ii} \quad \forall (i,j) \in E$ $c_{(i,i)} \leftarrow -\mathcal{C}^{-}_{ii}(d_{ij}) \ \forall (i,j) \in E \land s_{ij} < 0$ $c_{(i,i)} \leftarrow 0 \quad \forall (i,j) \in E \land s_{ii} \geq 0$ while there exist positive cycles in G Augment maximal flows using s as the source and t as the sink: Select a min-cut M; Insert one buffer into $(i, j) \ \forall (i, j) \in M$; UpdateTimingSlack(G); $[c_{(i,i)} \leftarrow -\mathcal{C}^{-}_{ii}(d_{ii}) - f_{ii} \quad \forall (i,j) \in E \land s_{ii} < 0]$ $c_{(i,i)} \leftarrow -\mathcal{C}^{-}_{ii}(d_{ii}) \ \forall (i,j) \in E \land s_{ii} < 0$ $c_{(i,i)} \leftarrow 0 \ \forall (i,j) \in E \land s_{ij} \geq 0$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Difficulty in buffering

• Objective function is non-separable:

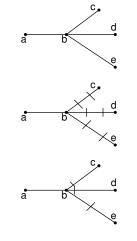
$$K_{ij} = f(d_1, d_2, \ldots, d_k)$$



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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ii}^{-}(d_{ij}))$

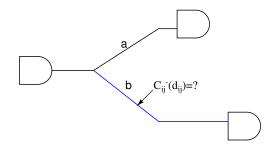


$$(a \rightarrow b \rightarrow e) >> (a \rightarrow b \rightarrow c) = (a \rightarrow b \rightarrow d)$$

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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

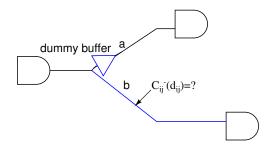
Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$



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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$



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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$

• Enforce that at most one wire of a net is in the min-cut

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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$

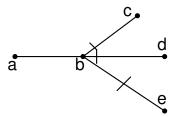
- Enforce that at most one wire of a net is in the min-cut
- Decouple other branches when inserting buffer on a branch

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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$

- Enforce that at most one wire of a net is in the min-cut
- Decouple other branches when inserting buffer on a branch



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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}(d_{ij}))$

• δ_e : the delay change of edge e when a new buffer is inserted into e

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$

• δ_e : the delay change of edge e when a new buffer is inserted into e

$$\delta_e = 0 \ \forall e \in E^F$$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$

• δ_e : the delay change of edge e when a new buffer is inserted into e

 $\delta_e = 0 \ \forall e \in E^F$

• T_e : The maximal delay change of e and its fanin edge $T_e = \delta_e \ \forall e \in E^F$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$

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 $\delta_e = 0 \ \forall e \in E^F$

- T_e : The maximal delay change of e and its fanin edge $T_e = \delta_e \ \forall e \in E^F$
- Delay sensitivity computation: $1/T_e$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$

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 $\delta_e = 0 \ \forall e \in E^F$

- T_e : The maximal delay change of e and its fanin edge $T_e = \delta_e \ \forall e \in E^F$
- Delay sensitivity computation: $1/T_e$

$$= \infty \ \forall e \in E^F$$

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Delay sensitivity computation $(-C_{ij}^{-}(d_{ij}))$

• δ_e : the delay change of edge e when a new buffer is inserted into e

 $\delta_e = 0 \ \forall e \in E^F$

- T_e : The maximal delay change of e and its fanin edge $T_e = \delta_e \ \forall e \in E^F$
- Delay sensitivity computation: 1/T_e
 = ∞ ∀e ∈ F^F
- Buffer-forbidden area is handled transparently

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Network flow based buffering algorithm framework

```
Algorithm NetworkBIN
maxdelay \leftarrow ComputeTimingAndSlack(G);
SetCapacity(G);
while maxdelay> REQ
  Find a min-cut of G;
  for each wire (u, v) in the found min-cut
     Insert one buffer into (u, v);
     Decouple the other wires that connect from u;
  UpdateCapacity(G);
```

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

CostBIN and CutBIN

- CostBIN: consider the historical flow
 - Use the timing constraint as the required time at t
 - The flow only flows through the edges with slacks less than 0
- CutBIN: no historical flow
 - Use the current maximal delay from s to t as the required time at t ($s_{ij} \ge 0$)
 - The flow only flows through the edges with slacks less than S_{th}
 - S_{th} is used to speed up the algorithm

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Experiment setup

- 100-nano technology
- Random graph generator used by [Liu99]
- Timing constraint: 1.2 times the minimal delay that can be achieved by buffering

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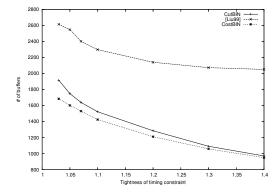
Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Comparison results of CutBIN, CostBIN and [Liu99]

| circuit | | [Liu99] | | CutBIN | | | | CostBIN | | | |
|---------|-------|---------|------|--------|------|--------|--------------|---------|-------|--------|-------------|
| #M | #W | #B | T(s) | #B | T(s) | Reduce | Spd up | #B | T (s) | Reduce | Spd up |
| 22 | 98 | 172 | 0 | 146 | 0.01 | 15% | $1 \times$ | 127 | 0.01 | 26% | $1 \times$ |
| 44 | 197 | 305 | 5 | 176 | 0.02 | 43% | 250× | 145 | 0.01 | 52% | 500× |
| 81 | 398 | 606 | 16 | 306 | 0.06 | 50% | 267× | 276 | 0.04 | 54% | 400× |
| 159 | 799 | 887 | 10 | 464 | 0.14 | 48% | $71\times$ | 449 | 0.11 | 49% | 91× |
| 258 | 1037 | 1096 | 28 | 767 | 0.25 | 30% | $112 \times$ | 709 | 0.34 | 35% | 82× |
| 505 | 2039 | 2140 | 20 | 1251 | 1.04 | 42% | 19× | 1137 | 1.80 | 47% | $11 \times$ |
| 2514 | 10039 | 10297 | 170 | 5612 | 20 | 45% | 9× | 5206 | 40 | 49% | 4× |
| 5034 | 20038 | 21201 | 344 | 10059 | 58 | 53% | 6× | 9403 | 142 | 56% | 2× |
| Avg | | | | | | 41% | | | | 46% | |

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

The influence of the tightness of timing constraint



Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Extensions to handle multiple buffer types and fixed buffering candidate locations

| circuit | | [Liu00] | | | CostBIN | | NetBIN | CutBIN | |
|---------|--------|---------|-------|---------|---------|-----------|--------|---------|---------|
| | # Cand | Area | Time | Area | Time | Reduction | Area | Area | Time |
| c1 | 695 | 598.5 | 151 | 333.5 | 0.17 | 44% | 629 | 340.5 | 0.17 |
| c2 | 1278 | 659.0 | 90 | 368.0 | 0.37 | 44% | 773.5 | 381.0 | 0.40 |
| c3 | 2564 | 1955.0 | 256 | 643.5 | 2.58 | 67% | 1473.0 | 660.0 | 2.98 |
| c4 | 5168 | 2636.0 | 979 | 1089.0 | 5.54 | 59% | 3096.0 | 1092.0 | 8.49 |
| c5 | 5579 | 2933.5 | 859 | 1594.5 | 16.43 | 46% | - | 1668.0 | 11.05 |
| c6 | 11163 | 4842.5 | 1855 | 2604.0 | 32.83 | 46% | - | 2762.0 | 25.00 |
| c7 | 53612 | 24272.0 | 4662 | 11234.0 | 682.73 | 54% | - | 11823.0 | 555.51 |
| c8 | 107931 | 66592.0 | 21000 | 21191.5 | 2635.43 | 68% | - | 22418.0 | 1716.93 |
| Avg | | | | | | 54% | | | |

Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

Summary

- Effective and efficient techniques for buffering a whole circuit is needed for SoC designs
- Minimal buffering under timing constraint has a similar structure as the dual of a convex cost flow problem
- Iterative network flows are proposed for buffering a whole circuit
- Two efficient buffering algorithms based on network flow are implemented:
 - CostBIN (convex cost flow based) and CutBIN (min-cut based);
 - $\bullet~46\%$ and 41% reductions on the number of buffers.
 - 54% reductions on buffers in realistic cases.

Multicore Revolution and CAD Challenges Nondeterministic Transactional Algorithm Mapping Algorithm to Multicore Program Experimental Results

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Block models and problem formulation Incremental retiming algorithms for wire pipelining Experimental results

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Motivation and Problem Formulation Efficient Algorithms Based on Network Flow Experimental Results

4. Multicore Parallel CAD

Multicore Revolution and CAD Challenges Nondeterministic Transactional Algorithm Mapping Algorithm to Multicore Program Experimental Results

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Multicore Revolution

- $\bullet\,$ Since 2004, μP frequency scaling has been flattened
- Only more cores in new generations

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Multicore Revolution

- Since 2004, μP frequency scaling has been flattened
- Only more cores in new generations
- Applications will not speed up automatically
- Who wants to upgrade?
- We are all doomed if computers are like washing machines
 - No industry growth
 - No exciting projects
 - No funding

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CAD Challenges

- CAD problems are huge
- CAD problems are computationally intensive
- CAD software traditionally depends heavily on frequency scaling

Salvation

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Parallel programming is the only rescue!

Salvation

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• Automated parallelization is in general a failure

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- Message passing based programming is too low level

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Parallel programming is the only rescue!

Parallel programming is very very difficult!

- Automated parallelization is in general a failure
- Message passing based programming is too low level
- Multithreading is hard to get right due to data racing

Thinking Parallel

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To get parallelism, we have to think parallel

Thinking Parallel

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To get parallelism, we have to think parallel

• With a small skull, we cannot think about true parallel

Thinking Parallel

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To get parallelism, we have to think parallel

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 - Number of possible scenario are exponential

Thinking Parallel

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To get parallelism, we have to think parallel

- With a small skull, we cannot think about true parallel
 - Number of possible scenario are exponential
- Nondeterministic Transactional Model is the best possible

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Nondeterministic Transactional Model in UNITY

- An algorithm is an initialization followed by a loop
- The loop is an iterative execution of any command with a true guard
- Execution is atomic (i.e. a transaction)
- Order of execution is arbitrary (nondeterministic)

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Ancient Wisdom

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• Euclid's GCD Algorithm $(a, b \in \mathbf{N})$ Euclid's alg. { x, y := a, bdo /* GCD(x, y) = GCD(a, b) */ $x > y \rightarrow x := x - y$ $x < y \rightarrow y := y - x$ od /* $GCD(x, y) = GCD(a, b) \land x = y$ */ output x }

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Min-Cost Flow Problem

• Timing-constrained optimization problems in CAD:

$$\begin{array}{ll} \textit{Min} & \sum_{(i,j)\in E} \textit{cost}_{ij}(d(i,j)) \\ \textit{s.t.} & \forall (i,j)\in E: p(i) + d(i,j) \leq p(j) \end{array}$$

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Min-Cost Flow Problem

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$$\begin{array}{ll} \textit{Min} & \sum_{(i,j)\in E} \textit{cost}_{ij}(d(i,j)) \\ \textit{s.t.} & \forall (i,j)\in E: p(i) + d(i,j) \leq p(j) \end{array}$$

• Dual: min-cost flow problem:

$$\begin{array}{ll} \textit{Min} & \sum_{(i,j)\in E} w(i,j)f(i,j) \\ \textit{s.t.} & \forall (i,j)\in E: 0 \leq f(i,j) \leq c(i,j) \\ & \forall j\in V: \sum_{(i,j)\in E} f(i,j) = \sum_{(j,k)\in E} f(j,k) \end{array}$$

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Optimality Condition

Karush-Kuhn-Tucker condition for min-cost flow

$$P0 \stackrel{\Delta}{=} \forall (i,j) \in E : 0 \le f(i,j) \le c(i,j)$$

$$P1 \stackrel{\Delta}{=} \forall j \in V : \sum_{(i,j) \in E} f(i,j) = \sum_{(j,k) \in E} f(j,k)$$

$$P2 \stackrel{\Delta}{=} \forall (i,j) \in E(f) : w^{p}(i,j) (\stackrel{\Delta}{=} w(i,j) - p(i) + p(j)) \ge 0$$

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Optimality Condition

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$$P2 \stackrel{\Delta}{=} \forall (i,j) \in E(f) : w^{p}(i,j) (\stackrel{\Delta}{=} w(i,j) - p(i) + p(j)) \ge 0$$

• ϵ -optimality (optimal if $\epsilon < 1/|V|$)

$$P2(\epsilon) \stackrel{\Delta}{=} \forall (i,j) \in E(f) : w^p(i,j) \geq -\epsilon$$

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Parallelism by Nondeterministic Transactions

• Valid guarded commands can be execute in parallel if there is no conflict.

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Parallelism by Nondeterministic Transactions

- Valid guarded commands can be execute in parallel if there is no conflict.
- Non-deterministic transactional programming for multicore algorithm design
 - Easy to reason (focus on isolated atomic commands)
 - Guaranteed correctness
 - Rich parallelism

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Designing Min-Cost Flow Algorithm

• Post-condition revisited:

$$\begin{array}{rcl} \mathsf{P0} &\triangleq & \forall (i,j) \in \mathsf{E} : \mathsf{0} \leq f(i,j) \leq c(i,j) \\ \mathsf{P1} &\triangleq & \forall j \in \mathsf{V} : \sum_{(i,j) \in \mathsf{E}} f(i,j) = \sum_{(j,k) \in \mathsf{E}} f(j,k) \\ \mathsf{P2}(\epsilon) &\triangleq & \forall (i,j) \in \mathsf{E}(f) : w^{\mathsf{p}}(i,j) \geq -\epsilon \\ \mathsf{Post} &\triangleq & \mathsf{P0} \land \mathsf{P1} \land \mathsf{P2}(\epsilon) \land \epsilon < 1/|\mathsf{V}| \end{array}$$

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Designing Min-Cost Flow Algorithm

• Post-condition revisited:

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$$\begin{array}{rcl} \mathsf{P0} &\triangleq & \forall (i,j) \in \mathsf{E} : 0 \leq f(i,j) \leq c(i,j) \\ \mathsf{P1} &\triangleq & \forall j \in \mathsf{V} : \sum_{(i,j) \in \mathsf{E}} f(i,j) = \sum_{(j,k) \in \mathsf{E}} f(j,k) \\ \mathsf{P2}(\epsilon) &\triangleq & \forall (i,j) \in \mathsf{E}(f) : w^{\mathsf{P}}(i,j) \geq -\epsilon \\ \mathsf{Post} &\triangleq & \mathsf{P0} \land \mathsf{P1} \land \mathsf{P2}(\epsilon) \land \epsilon < 1/|\mathsf{V}| \end{array}$$

• Design strategy: use P0 as invariant, and all the other conditions as loop goals.

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To Satisfy Loop Goals

• For *P*1

- Push out excess $X(j) \triangleq \sum_{(i,j) \in E} f(i,j) \sum_{(j,k) \in E} f(j,k)$
- Keeping $P2(\epsilon)$: push only on admissible edge with $w^{p}(i,j) < 0$
- If nowhere to push, increase self price: $p(i) = p(i) + \epsilon/2$

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- For P2(ε)

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• Remove residue edge by filling its capacity: f(i,j) = c(i,j)

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To Satisfy Loop Goals

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- For P2(ε)

- Remove residue edge by filling its capacity: f(i,j) = c(i,j)
- For $\epsilon < 1/|V|$
 - Half ϵ when P1 and P2(ϵ)

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Nondeterministic Transactional Algorithm

Goldberg's algorithm

$$\begin{array}{l} f, p, \epsilon := 0, 0, \max_{(i,j) \in E} |w(i,j)| \\ \text{do} \quad /* \ P0 \ */ \\ \exists (i,j) \in E(f) : X(i) > 0 \land -\epsilon \leq w^p(i,j) < 0 \\ \rightarrow push(i,j) \\ \exists i \in V : X(i) > 0 \land \forall (i,j) \in E(f) : w^p(i,j) \geq 0 \\ \rightarrow p(i) := p(i) + \epsilon/2 \\ \exists (i,j) \in E(f) : w^p(i,j) < -\epsilon \\ \rightarrow f(i,j) := f(i,j) + c_f(i,j) \\ P1 \land P2(\epsilon) \land \epsilon \geq 1/|V| \rightarrow \epsilon := \epsilon/2 \\ \text{od} \ /* \ P0 \land P1 \land P2(\epsilon) \land P3 \ */ \end{array}$$

Good Features

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- Correctness by construction
 - Post-condition is true when algorithm ends.

Good Features

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- Correctness by construction
 - Post-condition is true when algorithm ends.
- Termination

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• No node distance decreases more than 3|V| times for one ϵ .

Good Features

Multicore Revolution and CAD Challenges Nondeterministic Transactional Algorithm Mapping Algorithm to Multicore Program Experimental Results

- Correctness by construction
 - Post-condition is true when algorithm ends.
- Termination
 - No node distance decreases more than 3|V| times for one ϵ .
- Parallelism exposed
 - 2|E| + |V| + 1 guarded commands, many of which are independent.

General Principle

Multicore Revolution and CAD Challenges Nondeterministic Transactional Algorithm Mapping Algorithm to Multicore Program Experimental Results

• General ideas

- Bind one thread to each core.
- Thread has same life span as program.

General Principle

Multicore Revolution and CAD Challenges Nondeterministic Transactional Algorithm Mapping Algorithm to Multicore Program Experimental Results

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- Each thread can execute every guarded command.
- Executed command depends on available data on a core.

General Principle

Multicore Revolution and CAD Challenges Nondeterministic Transactional Algorithm Mapping Algorithm to Multicore Program Experimental Results

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 - Data (or their tokens) move among cores.

General Principle

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- General ideas
 - Bind one thread to each core.
 - Thread has same life span as program.
 - Each thread can execute every guarded command.
 - Executed command depends on available data on a core.
 - Data (or their tokens) move among cores.
- Advantages

- Long live threads to avoid overhead on creating/destroying threads
- Thread bound to core to avoid preemption
- Cores are keeping busy

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Multicore Min-Cost Flow Program

```
    Same program for each core

  while \epsilon > 1/|V|
      if get some active nodes V_a
          for i \in V_{a}
              for (i, j) \in E(f)
                  {if (w^{p}(i,j) < -\epsilon) f(i,j) := f(i,j) + c_{f}(i,j)
                  elseif (w^p(i,j) < 0) push(i,j)
              end for
              if (X(i) > 0) {relabel(i)}
          end for
      elseif Sync on idle
          \epsilon := \epsilon/2
          activate V
  end while
```

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Scheduling for Each Thread

• Iteratively fetch active nodes from a global queue Q

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Scheduling for Each Thread

- Iteratively fetch active nodes from a global queue Q
- Check active nodes for enabled commands

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Scheduling for Each Thread

- Iteratively fetch active nodes from a global queue Q
- Check active nodes for enabled commands
- Execute each enabled command atomically

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Scheduling for Each Thread

- Iteratively fetch active nodes from a global queue Q
- Check active nodes for enabled commands
- Execute each enabled command atomically
- Put new active node into the global queue

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Atomicity Enforcement

- Atomic semantics of commands
 - Transactional memory: natural but immature
 - Mutual exclusion by atomic Compare-And-Swap if(node->token.compare_and_swap(BUSY, IDLE) == IDLE) -> the command;

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How to Detect Termination

- No thread can terminate if there is one busy
- Take a global snapshot: Termination Detection Barrier
 - TDBarrier holds a counter implemented by atomic integer
 - Counter initialized to zero

- Once a thread idle/active, it decrements/increments counter
- Counter being zero means global condition achieved

Load Balancing

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• Dynamically adjust length of local $b_k = q_{in}/q_{out}$

if $n_{active} \le n_{total} \times 0.75$ $b_k = b_k/2$ else if $n_{active} + L/b_k \ge n_{total}$ $b_k = b_k \times 2$

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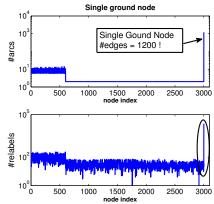
Performance Improvement

- Speed-up excellent on random networks
- Speed-up not as expected on voltage island assignment

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Performance Improvement

- Speed-up excellent on random networks
- Speed-up not as expected on voltage island assignment
- Caught by huge connectivity of ground node.

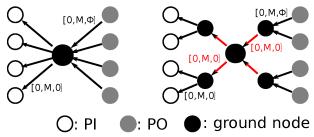


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Performance Improvement

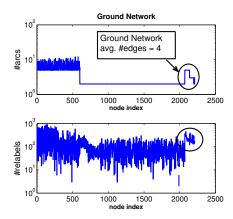
• Convert ground node to a ground network

Single Ground Ground Network



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Performance Improvement



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Experiment Setup

- Implemented in multithreaded (TBB) C++.
- Compiled once and runs for different number of cores

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Experiment Setup

- Implemented in multithreaded (TBB) C++.
- Compiled once and runs for different number of cores
- Application: voltage island assignment [Ma and Young ICCAD08]

$$Min \qquad \sum_{(i,j)\in E} power_{ij}(v(i,j))$$

$$\begin{aligned} \text{s.t.} & \forall (i,j) \in E : p(i) + d_{ij}(v(i,j)) \leq p(j) \\ & \forall i \in V : 0 \leq p(i) \leq \phi \\ & \forall (i,j) \in E : v(i,j) \in \textit{Voltage} \end{aligned}$$

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Experiment Setup

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- Compiled once and runs for different number of cores
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$$\begin{array}{ll} \textit{Min} & \sum_{(i,j)\in E}\textit{power}_{ij}(v(i,j)) \\ \textit{s.t.} & \forall (i,j)\in E:p(i)+d_{ij}(v(i,j))\leq p(j) \\ & \forall i\in V: 0\leq p(i)\leq \phi \\ & \forall (i,j)\in E:v(i,j)\in\textit{Voltage} \end{array}$$

• Linux server with two dual-core 3.0GHz CPUs and 2GB RAM, up to 4 cores.

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Effectiveness of Ground Network

| Cases | Single G | fround | Ground Network | | | |
|-------|--------------|------------|----------------|------------|--|--|
| | #Contentions | 4C Speedup | #Contentions | 4C Speedup | | |
| n10 | 0.00 | 1.25 | 0.00 | 0.93 | | |
| n30 | 58.50 | 1.03 | 4.50 | 1.25 | | |
| n50 | 196.75 | 1.25 | 5.00 | 1.42 | | |
| n100 | 908.75 | 1.31 | 51.75 | 1.46 | | |
| n200 | 6111.00 | 1.07 | 94.75 | 2.26 | | |
| n300 | 8809.00 | 1.02 | 116.50 | 1.90 | | |

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Speedup Rates on Voltage Island Assignment

| Cases | V / E | Speedup Rate of 2C | | | Speedup Rate of 4C | | |
|-------|-------------|--------------------|------|------|--------------------|------|------|
| | | AVG | MIN | MAX | AVG | MIN | MAX |
| n200 | 1344/2329 | 1.61 | 1.40 | 1.81 | 2.26 | 1.99 | 2.96 |
| n300 | 2209/3834 | 1.44 | 1.17 | 1.84 | 1.90 | 1.31 | 2.44 |
| n600 | 4414/7662 | 1.46 | 1.26 | 1.60 | 2.24 | 1.87 | 2.64 |
| n800 | 5376/9322 | 1.73 | 1.52 | 1.99 | 2.78 | 2.32 | 3.31 |
| n900 | 6619/11490 | 1.44 | 1.15 | 1.97 | 2.15 | 1.65 | 2.51 |
| n1000 | 6720/11653 | 1.76 | 1.51 | 2.02 | 2.92 | 2.36 | 3.30 |
| n1200 | 8824/15318 | 1.53 | 1.27 | 1.95 | 2.54 | 2.17 | 3.41 |
| n1400 | 9410/16319 | 1.83 | 1.67 | 2.03 | 3.16 | 2.86 | 3.44 |
| n1600 | 10752/18646 | 1.57 | 1.47 | 1.69 | 2.72 | 2.30 | 3.05 |
| AVG | - | 1.59 | 1.38 | 1.88 | 2.52 | 2.09 | 3.01 |

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Summary

- Parallel CAD unavoidable under multicore revolution
- Parallelism better explored in Nondeterministic Transactional algorithms
- A systematic multicore implementation based nondeterministic transactional algorithm
- Min-cost flow solver with application on voltage assignment demonstrates effectiveness
- Extending to other CAD applications

Thank you

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Any questions?