Network Flow-based Simultaneous Retiming and Slack Budgeting for Low Power Design

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Outline

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   - Problem Formulation

2. Methodology
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   - Remove Redundant Constraint
   - Convex Cost Dual Flow Algorithm

3. Experimental Results
Timing constraint and Low Power become significant requirement.

- Retiming: relocate flip-flops (FFs)
- Slack Budgeting: relax the timing constraints of components

Simultaneous Retiming and Slack Budgeting
Previous Works

– Retiming:
  - [C.E. Leiserson et al. Algorithmica 1991]: first work
  - [N. Maheshwari et al. TCAD 1998]: flow based Min-area retiming
  - [H. Zhou, ASPDAC 2005]: incremental Min-period retiming
  - [J. Wang & H. Zhou DAC 2008]: incremental Min-period retiming

– Slack Budgeting:
  - [R. Nair et al. TCAD 1989]: ZSA, suboptimal heuristic
  - [C. Chen et al. TCAD 2002]: Maximum-Independent-Set, NP-complete
  - [S. Ghiasi et al. ICCAD 2004]: Flow based algorithm
Previous Works (Cont.)

- **Retiming + Slack Budgeting:**
  - [Y. Hu et al. DAC 2006]: dual-Vdd, MILP
  - [S. Liu et al. ASPDAC 2010]: heuristic; MIS based

- **In previous works:**
  - A few works consider simultaneous Retiming and Slack Budgeting
  - MILP method or heuristic method

- **In our works:**
  - Network-Based Algorithm
  - Speedup
Problem Formulation

**Input:**
- Directed graph $G = (V, E, d, w)$ as synchronous sequential circuit.
  - $i \in V$: combinational gate
  - $e_{ij} \in E$: signal passing from gate $i$ to $j$
  - $d_i$: delay of gate $i$
  - $w_{ij}$: number of FF on edge $e_{ij}$
- period constraint $T$
- power-slack tradeoff for each slack level

**Output:** reallocation represented by $r$, so
- minimize power consumption
- under the period constraint
**MILP Formulation**

**Condition for $\Phi(G) \leq T$**

\[
\begin{align*}
  a_i &\geq d_i + s_i \quad \forall i \in V \\
  a_i &\leq T \quad \forall i \in V \\
  r_i - r_j &\leq w_{ij} \quad \forall (i, j) \in E \\
  a_j &\geq a_i + d_i + s_i \quad \text{if } r_i - r_j = w_{ij}
\end{align*}
\]

Suppose $R_i = r_i + a_i / T$

$\Rightarrow a_i = T \cdot R_i - T \cdot r_i.$

\[
\begin{align*}
  \min \quad & \sum_{i \in V} P(\bar{s}_i) \\
  \text{s.t.} \quad & \bar{R}_i - \bar{r}_i \geq \bar{s}_i \quad \forall i \in V \quad (IIa) \\
  & \bar{R}_i - \bar{r}_i \leq T \quad \forall i \in V \quad (IIb) \\
  & \bar{r}_j - \bar{r}_i \geq -T \cdot w_{ij} \quad \forall (i, j) \in E \quad (IIc) \\
  & 0 \leq \bar{R}_i, \bar{r}_i \leq \bar{N}_{ff} \quad \forall i \in V \quad (IId) \\
  & \bar{s}_i = \{\bar{s}_i^1, \ldots, \bar{s}_i^k\} \quad \forall i \in V \quad (IIe) \\
  & 0 \leq \bar{s}_i \leq T \quad \forall i \in V \quad (IIf) \\
  & \bar{R}_j - \bar{R}_i \geq t_{ij} \quad \forall (i, j) \in E \quad (IIg) \\
  & t_{ij} \geq \bar{s}_j - T \cdot w_{ij} \quad \forall (i, j) \in E \quad (IIh)
\end{align*}
\]
MILP Formulation (cont.)

- Solved by ILP Solver, but unacceptable runtime
- Need more effective method
  - Without two constraints, convex cost dual network algorithm [R. K. Ahuja et al. 2003]
  - Removes constraint ($\text{IIh}$), add penalty function $P(t_{ij})$:
  - Generate new problem ($\text{III}$)

\[
\begin{align*}
\min & \quad \sum_{i \in V} P(\bar{s}_i) \\
\text{s.t.} & \quad \bar{R}_i - \bar{r}_i \geq \bar{s}_i & \forall i \in V & (\text{IIa}) \\
& \quad \bar{R}_i - \bar{r}_i \leq T & \forall i \in V & (\text{IIb}) \\
& \quad \bar{r}_j - \bar{r}_i \geq -T \cdot w_{ij} & \forall (i, j) \in E & (\text{IIc}) \\
& \quad 0 \leq \bar{R}_i, \bar{r}_i \leq \bar{N}_{ff} & \forall i \in V & (\text{IIId}) \\
& \quad \bar{s}_i = \{\bar{s}_i^1, \ldots, \bar{s}_i^k\} & \forall i \in V & (\text{IIe}) \\
& \quad 0 \leq \bar{s}_i \leq T & \forall i \in V & (\text{IIf}) \\
& \quad \bar{R}_j - \bar{R}_i \geq t_{ij} & \forall (i, j) \in E & (\text{IIg}) \\
& \quad t_{ij} \geq \bar{s}_j - T \cdot w_{ij} & \forall (i, j) \in E & (\text{IIh})
\end{align*}
\]
MILP Formulation (cont.)

- Solved by ILP Solver, but unacceptable runtime
- Need more effective method
- Without two constraints, convex cost dual network algorithm [R. K. Ahuja et al. 2003]
- Removes constraint (IIh), add penalty function $P(t_{ij})$:
- Generate new problem (III)

\[
\begin{align*}
\text{min} & \quad \sum_{i \in V} P(\bar{s}_i) \\
\text{s.t.} & \quad \bar{R}_i - \bar{r}_i \geq \bar{s}_i \quad \forall i \in V \tag{IIa} \\
& \quad \bar{R}_i - \bar{r}_i \leq T \quad \forall i \in V \tag{IIb} \\
& \quad \bar{r}_j - \bar{r}_i \geq -T \cdot w_{ij} \quad \forall (i, j) \in E \tag{IIc} \\
& \quad 0 \leq \bar{R}_i, \bar{r}_i \leq \bar{N}_{ff} \quad \forall i \in V \tag{IId} \\
& \quad \bar{s}_i = \{\bar{s}_i^1, \ldots, \bar{s}_i^k\} \quad \forall i \in V \tag{IIe} \\
& \quad 0 \leq \bar{s}_i \leq T \quad \forall i \in V \tag{IIf} \\
& \quad \boxed{R_j - R_i \geq t_{ij}} \quad \forall (i, j) \in E \tag{IIg} \\
& \quad t_{ij} \geq \bar{s}_j - T \cdot w_{ij} \quad \forall (i, j) \in E \tag{IIh}
\end{align*}
\]
MILP Formulation (cont.)

\[
\begin{align*}
\min \quad & \sum_{i \in V} P(\bar{s}_i) + \sum_{(i,j) \in E} P(t_{ij}) \quad (III) \\
\text{s.t.} \quad & (IIa) - (IIg) \\
& t_{ij} \geq -T \cdot w_{ij}, \quad \forall (i, j) \in E \\
\end{align*}
\]

Given solutions of (III), heuristic generate solution of (II):

\[
\bar{s}_j = \min(t_{ij} + T \cdot w_{ij}, \bar{s}_j), \quad \forall i \in FL(j)
\]
Remove Redundant Constraint

- Denote \( s_i^* \) where \( P(\bar{s}_i) \) is minimum
- Define \( Q(\bar{s}_i) \):
  \[
  Q(\bar{s}_i) = \begin{cases} 
  P(\bar{s}_i^*) & \text{if } \bar{s}_i \leq s_i^* \\
  P(\bar{s}_i) & \text{if } \bar{s}_i > s_i^*
  \end{cases}
  \]
- Consider new problem (III'), which replaces (IIa) and (IIb) by \( \bar{R}_i - \bar{r}_i = \bar{s}_i \)

\[
\begin{align*}
\min & \sum_{i \in V} Q(\bar{s}_i) + \sum_{(i,j) \in E} P(t_{ij}) \\
\text{s.t.} & (IIc) - (Ilg) \\
& \bar{R}_i - \bar{r}_i = \bar{s}_i \quad \forall i \in V \\
& t_{ij} \geq -T \cdot w_{ij} \quad \forall (i,j) \in E
\end{align*}
\]

\[
\begin{align*}
\min & \sum_{i \in V} P(\bar{s}_i) + \sum_{(i,j) \in E} P(t_{ij}) \\
\text{s.t.} & (IIa) - (Ilg) \\
& t_{ij} \geq -T \cdot w_{ij} \quad \forall (i,j) \in E
\end{align*}
\]

**Theorem 1**
For every optimal solution \( (\bar{R}, \bar{r}, \bar{s}) \) of problem (III), there is an optimal solution \( (\bar{R}, \bar{r}, \hat{s}) \) of problem (III'), and the converse also holds.

**Theorem 2**
The constraint (IIb) in problem (III) can be removed.
Remove Redundant Constraint

- Denote $s_i^*$ where $P(\bar{s}_i)$ is minimum
- Define $Q(\bar{s}_i)$:

$$Q(\bar{s}_i) = \begin{cases} 
P(\bar{s}_i^*) & \text{if } \bar{s}_i \leq s_i^* \\
P(\bar{s}_i) & \text{if } \bar{s}_i > s_i^*
\end{cases}$$

- Consider new problem (III'), which replaces (IIa) and (IIb) by $\bar{R}_i - \bar{r}_i = \bar{s}_i$

$$\min \sum_{i \in V} Q(\bar{s}_i) + \sum_{(i,j) \in E} P(t_{ij}) \quad (III')$$

\text{s.t.} (IIc) - (Ilg)

$$\bar{R}_i - \bar{r}_i = \bar{s}_i \quad \forall i \in V$$

$$t_{ij} \geq -T \cdot w_{ij} \quad \forall (i, j) \in E$$

\text{Theorem 1}

For every optimal solution $(\bar{R}, \bar{r}, \bar{s})$ of problem (III), there is an optimal solution $(\bar{R}, \bar{r}, \hat{s})$ of problem (III'), and the converse also holds.

\text{Theorem 2}

The constraint (IIb) in problem (III) can be removed.
Solve problem (III) by Convex Cost Dual Flow$^a$:
Step 1: Transformation to Primal Network Flow Problem
- Split vertex $i$ into two vertex $\bar{r}_i$ and $\bar{R}_i$
- $\left( \bar{r}_i, \bar{R}_i \right) \in \bar{E}_1$, $\left( \bar{R}_i, \bar{R}_j \right) \in \bar{E}_2$, $\left( \bar{r}_i, \bar{r}_j \right) \in \bar{E}_3$
- Further simplify problem as follow:

$$\min \sum_{(i,j) \in \bar{E}} P(s_{ij}) \quad (IV)$$

subject to:

- $\mu_j - \mu_i \geq s_{ij} \quad \forall (i,j) \in \bar{E} \quad (IVa)$
- $0 \leq \mu_i \leq \bar{N}_{ff} \quad \forall i \in \bar{V} \quad (IVb)$
- $l_{ij} \leq s_{ij} \leq u_{ij} \quad \forall (i,j) \in \bar{E} \quad (IVc)$

MILP Formulation
Remove Redundant Constraint
Convex Cost Dual Flow Algorithm

Primal Network Flow Problem (cont.)

Step 1: Transformation to Primal Network Flow Problem (cont.)

\[
\min \sum_{(i,j) \in \bar{E}} P(s_{ij}) \tag{IV}
\]

s.t. \( \mu_j - \mu_i \geq s_{ij} \) \( \forall (i, j) \in \bar{E} \) \( \tag{IVa} \)

0 \( \leq \mu_i \leq \bar{N}_f \) \( \forall i \in \bar{V} \) \( \tag{IVb} \)

\( l_{ij} \leq s_{ij} \leq u_{ij} \) \( \forall (i, j) \in \bar{E} \) \( \tag{IVc} \)

Remove constraints by \( \bar{P}(s_{ij}) \) and \( B(\mu_i) \)

\[
\bar{P}(s_{ij}) = \begin{cases} 
P(u_{ij}) + M(s_{ij} - u_{ij}) & \text{if } s_{ij} > u_{ij} \\
\bar{s}_{ij} > s_{ij} > l_{ij} & \text{if } 0 \leq \bar{s}_{ij} \leq T \\
P(s_{ij}) & \text{if } \bar{s}_{ij} < l_{ij}
\end{cases}
\]

\[
B(\mu_i) = \begin{cases} 
M \cdot (\mu_i - \bar{N}_f) & \text{if } \mu_i > \bar{N}_f \\
0 & \text{if } 0 \leq \bar{\mu}_i \leq \bar{N}_f \\
-M \cdot \mu_i & \text{if } \mu_i < 0
\end{cases}
\]

Get Primal Network Flow Problem:

\[
\min \sum_{(i,j) \in \bar{E}} \bar{P}(s_{ij}) + \sum_{i \in \bar{V}} B(\mu_i) \tag{V}
\]

s.t. \( \mu_j - \mu_i \geq s_{ij} \) \( \forall (i, j) \in \bar{E} \)
Primal Network Flow Problem (cont.)

Step 1: Transformation to Primal Network Flow Problem (cont.)

\[
\begin{aligned}
\min & \quad \sum_{(i,j) \in \bar{E}} P(s_{ij}) \\
\text{s.t.} & \quad \mu_j - \mu_i \geq s_{ij} \quad \forall (i, j) \in \bar{E} \\
& \quad 0 \leq \mu_i \leq \bar{N}_{ff} \quad \forall i \in \bar{V} \\
& \quad l_{ij} \leq s_{ij} \leq u_{ij} \quad \forall (i, j) \in \bar{E}
\end{aligned}
\]

Remove constraints by \(P(s_{ij})\) and \(B(\mu_i)\)

\[
\bar{P}(s_{ij}) = \begin{cases} 
P(u_{ij}) + M(s_{ij} - u_{ij}) & \text{if } \bar{s}_{ij} > u_{ij} \\
P(s_{ij}) & \text{if } 0 \leq \bar{s}_{ij} \leq T \\
P(l_{ij}) - M(s_{ij} - l_{ij}) & \text{if } \bar{s}_{ij} < l_{ij}
\end{cases}
\]

\[
B(\mu_i) = \begin{cases} 
M \cdot (\mu_i - \bar{N}_{ff}) & \text{if } \mu_i > \bar{N}_{ff} \\
0 & \text{if } 0 \leq \bar{\mu}_i \leq \bar{N}_{ff} \\
-M \cdot \mu_i & \text{if } \mu_i < 0
\end{cases}
\]

Get Primal Network Flow Problem:

\[
\begin{aligned}
\min & \quad \sum_{(i,j) \in \bar{E}} \bar{P}(s_{ij}) + \sum_{i \in \bar{V}} B(\mu_i) \\
\text{s.t.} & \quad \mu_j - \mu_i \geq s_{ij} \quad \forall (i, j) \in \bar{E}
\end{aligned}
\]
Step 2: Lagrangian Relaxation

- Lagrangian relaxation to eliminate constraints
- Lagrangian sub-problem:

\[
L(\vec{x}) = \sum_{e(i,j) \in \bar{E}} \bar{P}(s_{ij}) + \sum_{i \in \bar{V}} B_i(\mu_i) - \sum_{e(i,j) \in \bar{E}} (\mu_j - \mu_i - s_{ij})x_{ij}
\]

- Introduce start node \( v_0 \)
- Final Lagrangian subproblem:

\[
L(\vec{x}) = \min \sum_{e(i,j) \in E} [P_{ij}(s_{ij}) + x_{ij}s_{ij}] \quad (1)
\]

s.t.
\[
\sum_{j: e(i,j) \in E} x_{ij} - \sum_{j: e(j,i) \in E} x_{ji} = 0 \quad \forall i \in V
\]

\[
x_{ij} \geq 0 \quad \forall (i,j) \in E_1 \cup E_2 \cup E_3
\]
Convex Cost-scaling Approach

Step 3: Convex Cost-scaling Approach

- Define function \( H_{ij}(x_{ij}) = \min_{s_{ij}} \{ P_{ij}(s_{ij}) + x_{ij}s_{ij} \} \):
  - \( H_{ij}(x_{ij}) \) is concave, so \( C_{ij}(x_{ij}) = -H_{ij}(x_{ij}) \) is convex
  - Final problem is a min-cost flow problem:

  \[
  L(\tilde{x}) = \min_{e(i,j) \in E} \sum_{e(i,j) \in E} C_{ij}(x_{ij}) \\
  \text{s.t.} \sum_{j : e(i,j) \in E} x_{ij} - \sum_{j : e(j,i) \in E} x_{ji} = 0 \quad \forall i \in V \\
  0 \leq x_{ij} \leq M \quad \forall (i,j) \in E_1 \cup E_2 \cup E_3 \\
  -M \leq x_{ij} \leq M \quad \forall (i,j) \in E_4
  \]

- For optimal flow \( x^* \), construct residual network \( G(x^*) \)
- In \( G(x^*) \), solve shortest path distance \( d(i) \)
- Apply \( \mu(i) = d(i) \) and \( s_{ij} = \mu(i) - \mu(j) \)
- Final solve the problem!!
### Experiments Setup

- Implemented in C++
- 3.0GHz CPU and 6GB Memory
- 19 cases from the ISCAS89

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# Experimental Results

## Results for Power Consumption and Total Slacks

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</tbody>
</table>

| Avg | 9249.3 | 14070 | 11947.9 | 5457.7 | 3744.3 | 4573.8 |
| Diff | 1 | +52% | +29% | 1 | -31% | -16% |

1 S.Liu et al., ”Simultaneous slack budgeting and retiming for synchronous circuits optimization”, ASPDAC 2010
Experimental Results

Results for Runtime:

<table>
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<th>Runtime(s)</th>
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Thank You!