

Towards Multi-Objective Dynamic SPM Allocation

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Execution Time Analysis (WCET), Vienna, Austria*

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- 1 Motivation**

- 2 **Dynamic SPM Allocation (DSA)**

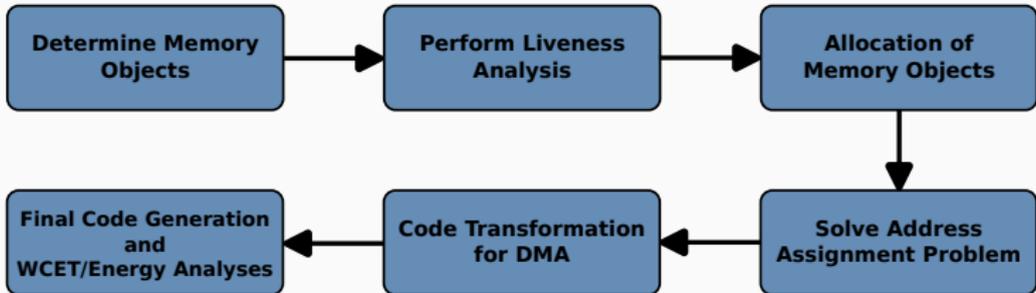
- 3 **Multi-Objective DSA-based Optimization**

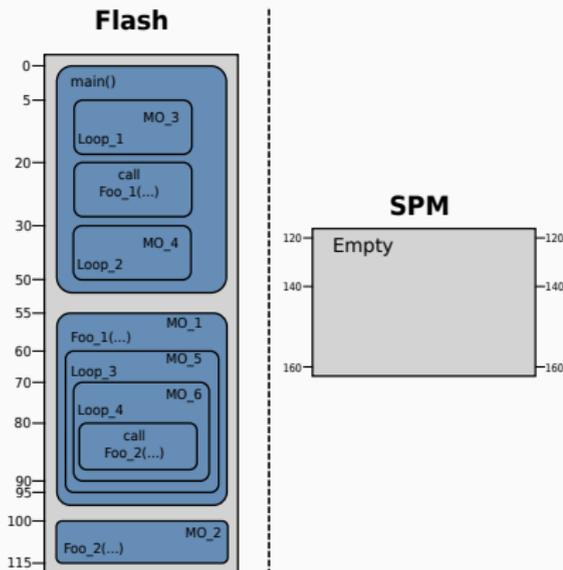
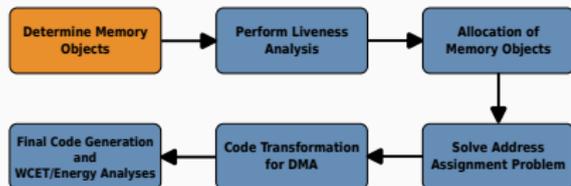
- ⋮
- 4 **Evaluation**

- ⋮
- 5 **Conclusion**

- Worst-Case Execution Time (WCET)
- Energy consumption
- Static SPM allocation constrained by small SPM size

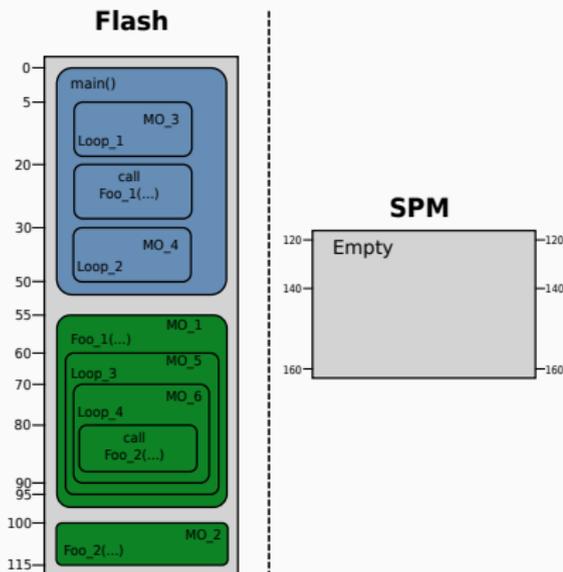
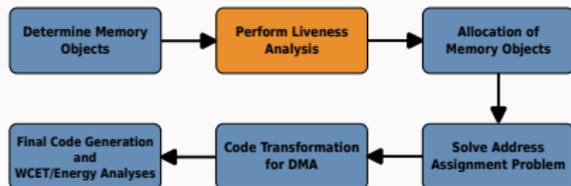
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Memory Objects:

- Functions: Foo_1() and Foo_2()
- Loops: Loop_1, Loop_2, Loop_3, and Loop_4

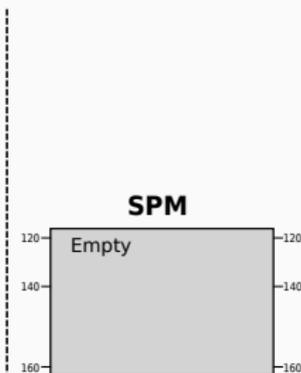
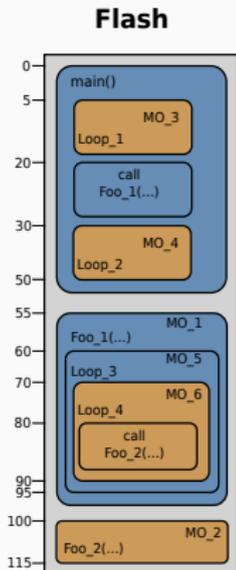
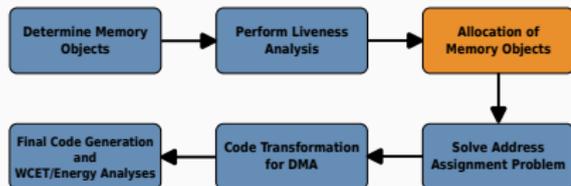


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Liveness conflicts:

- Foo_2(), Loop_3, and Loop_4
- Foo_1() and Foo_2()



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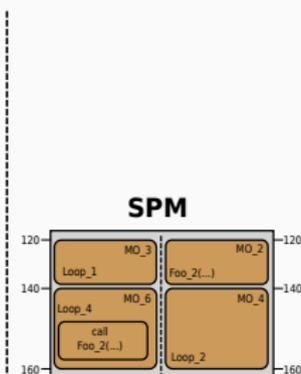
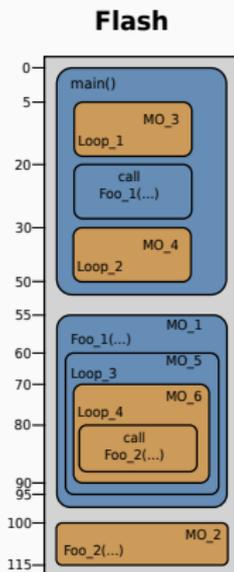
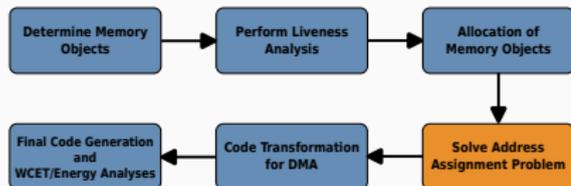
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Memory Object Allocation:

- Flash: Foo_1() and Loop_3()
- SPM: Foo_2(), Loop_1, Loop_2, and Loop_4



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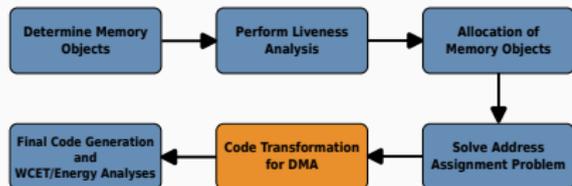
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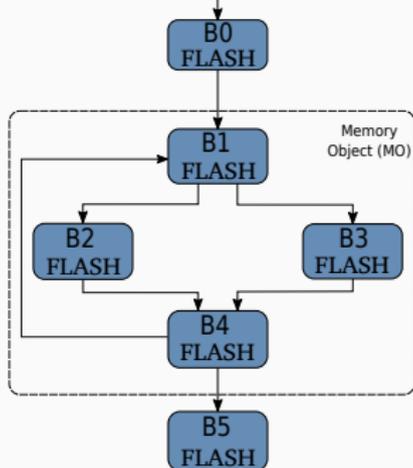
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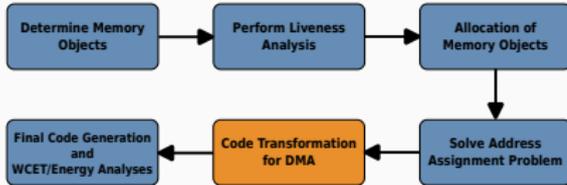
Address Assignment:

- First-Fit Heuristic
- Best-Fit Heuristic

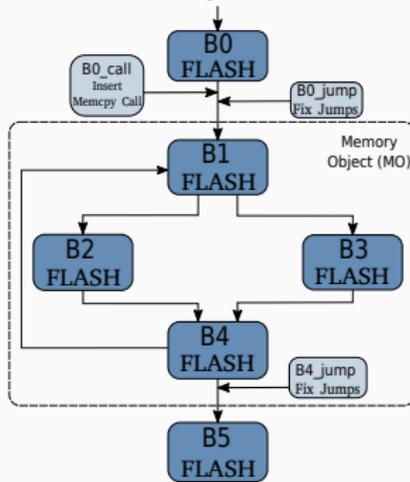


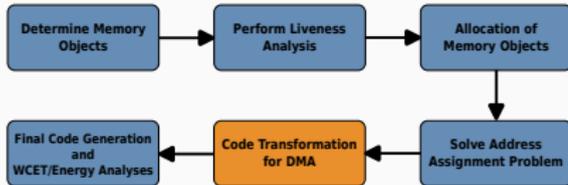
At Compile Time



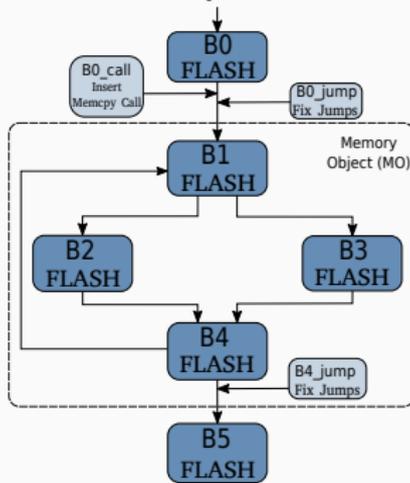


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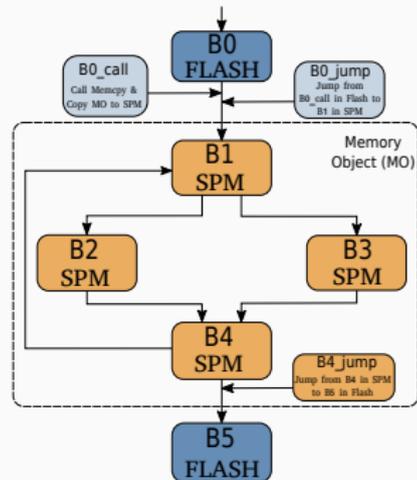


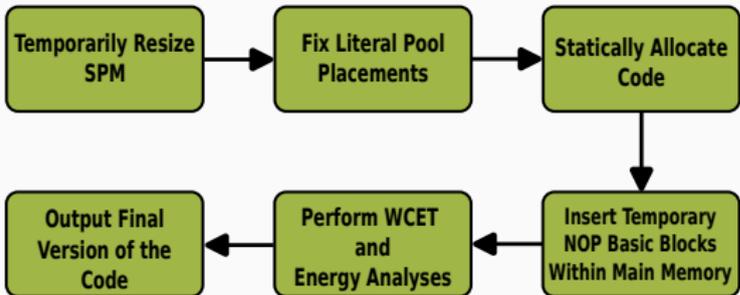
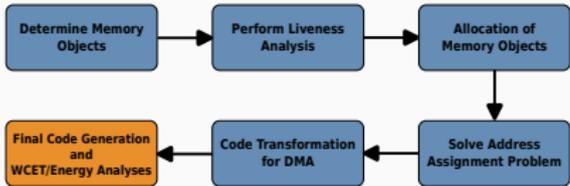


At Compile Time



During Runtime





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- * $x \in X \in \{0, 1\}^d$

Multi-Objective Optimization Problem

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- **Objective Space:**

- * $\Theta = \{F(x) = (F_1(x), F_2(x)) | x \in X\}$

- Where, $F_1(x)$ = WCET objective and $F_2(x)$ = Energy objective

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- **Minimization function:**

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- **Search Space Constraint:**

- * $X_{(F+1):(F+L)} = X_{(F+1):(F+L)} + \tau$

- Where,

$$\tau_l = \begin{cases} 1, & \text{if } x_{F+l} = 0 \text{ \& } (\exists f \mid \lambda_{F+l} \subseteq \lambda_f \in \Lambda_{1:F}) \text{ \& } x_f = 1 \\ 0, & \text{otherwise} \end{cases}$$

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- **Address Assignment Algorithm Constraint:**

- * $(\mathcal{T} - \eta) = 0$

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To solve multi-objective DSA-based optimization problem, we use:

- Flower Pollination Algorithm (FPA)
- Strength Pareto Evolutionary Algorithm (SPEA)

Algorithm Multi-Objective DSA-based optimization

- 1: Collect *memObj*, perform Liveness Analysis, and randomly initialize initial population of size N
 - 2: **for** $n = 1 : N$ **do**
 - 3: Generate DSA code
 - 4: **while** Stopping criteria is not reached **do**
 - 5: Update Individual using respective update operators
 - 6: **for** Each updated Individual **do**
 - 7: Generate DSA code
 - 8: Update to next generation using selection operator
 - 9: **return** Pareto-optimal solution set
-

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- Proposed multi-objective DSA-based optimization (MO_D)
→Solved using:
 - FPA
 - SPEA
- Multi-objective static SPM allocation-based optimization (MO_S)
→Solved using:
 - FPA
 - SPEA
- ILP-based single objective dynamic SPM allocation (SO_D)

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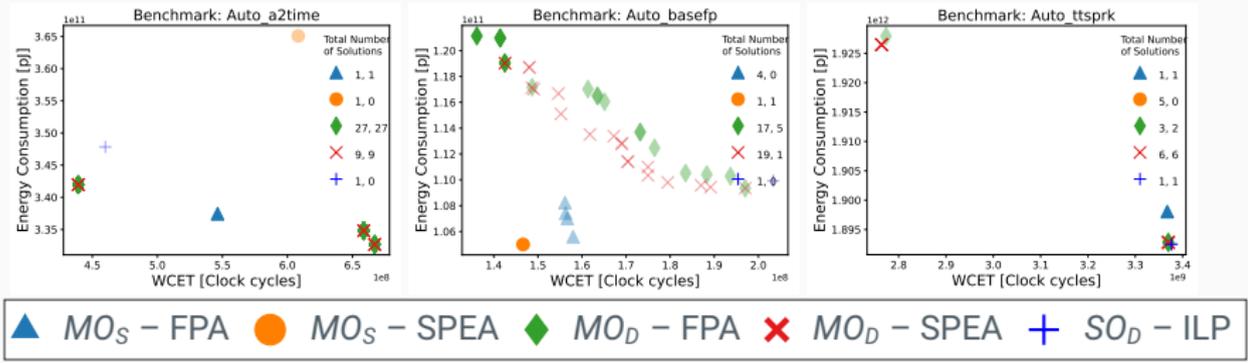


Figure 1: Solutions Obtained from MO_S , MO_D , and SO_D optimization runs

The following percent of solutions were on the final Pareto front

- MO_S -FPA: 3.62%
- MO_S -SPEA: 5.26%
- SO_D -ILP: 0.66%
- MO_D -FPA: 70.4%
- MO_D -SPEA: 20.1%

→ MO_D -FPA found most number of solution on the final Pareto front

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- Coverage: $\mathcal{C} = 1 - \frac{|\{a \in A : \exists p \in \mathcal{P}, a \preceq p\}|}{|A|}$
- Non-Dominance Ratio: $NDR = \frac{|\mathcal{P} \cap A|}{|\mathcal{P}|}$
- Non-Dominated Solutions: $NDS = \frac{|a \in A : a \in \mathcal{P}|}{|A|}$

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From overall Evaluations, in terms of Quality Indicators:

- MO_D performed much better than SO_D
- MO_D performed slightly better than MO_S

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Overheads due to dynamic copying in MO_D optimization run:

- WCET overheads on average: 24.39%
- Energy overheads on average: 22.65%

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- Proposed compiler-level DSA-based multi-objective optimization
- WCC performs WCET and energy analysis of DSA code
- MO_D is solved using FPA and SPEA
- MO_D outperforms SO_D
- MO_D performs slightly better than MO_S

Future Work

- Reducing the WCET and energy overheads by using DMA
- Reducing the compilation time needed by multi-objective DSA-based optimization

Thank You