

Neuromorphic Computing

8. Case Study: Real Hardware- Software Design of 3D-NoC- Based Neuromorphic System

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1. Introduction
2. R-NASH System
3. R-NASH Hardware
4. R-NASH Learning
5. R-NASH Mapping
6. Evaluation results
7. Conclusions

1. Introduction

- This lecture discuss about a case study on the design and evaluation of a reliable three dimensional digital neuromorphic processor (RNASH)
- RNASH consists of:
 - The design methodology
 - Hardware
 - Learning
 - Mapping

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2. R-NASH system

Overview

- The overview of R-NASH are in four phases:
 1. **Software modeling:** building the software model of the SNN application and perform the offline training to validate the model
 2. **Mapping:** generating the configuration from the software model to be able to port into the R-NASH hardware
 3. **Porting to hardware:** using the configuration to perform inference in the hardware
 4. **Runtime maintenance:** fault management for R-NASH

2. R-NASH system

System Phases

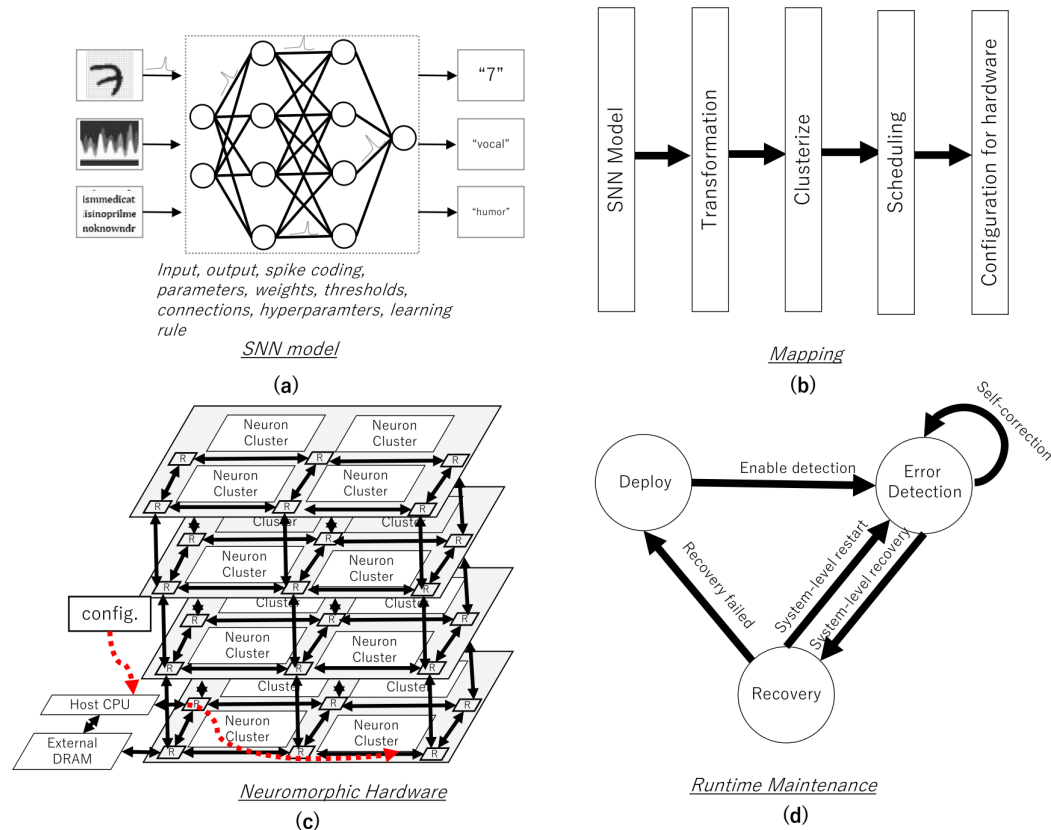


Fig. 8.2: R-NASH system platform. (a) SNN model. (b) Mapping into the neuromorphic hardware. (c) Our neuromorphic hardware in 3D-ICs. (d) Runtime maintenance for R-NASH.

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3. R-NASH hardware

Overview

- R-NASH is based on 3D Mesh Network-on-Chip for the communication.
- Communication is based on Address Event Representation protocol.
- Computation is done by the LIF core array for the core (256 LIFs per core).
- SRAM-based synapses are used in R-NASH.

3. R-NASH hardware Overview

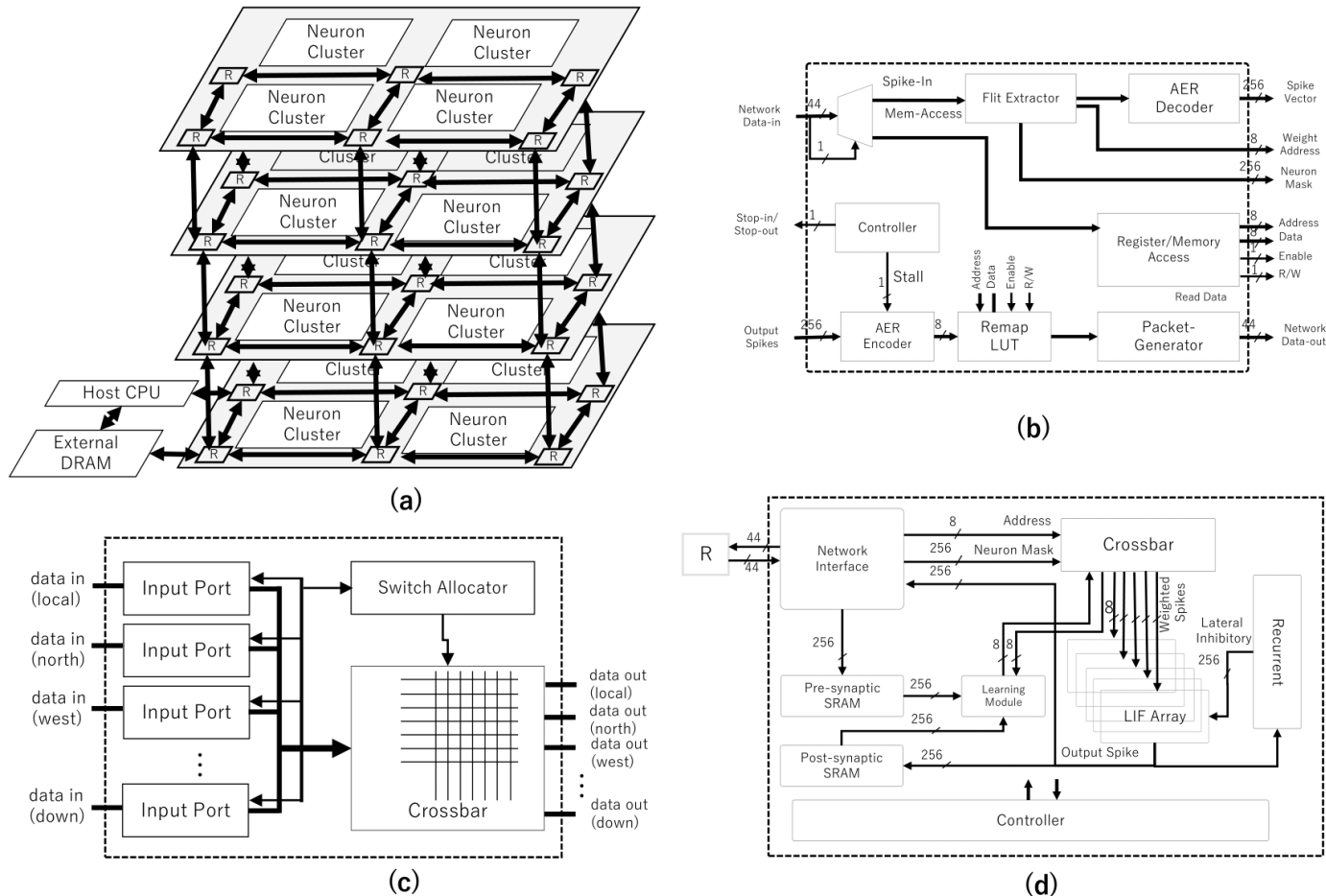


Fig. 8.3: R-NASH architecture. (A) Neuromorphic System. (B) Network-Interface. (C) 3D-Router. (D) SNPC Core

3. R-NASH hardware

Communication

- R-NASH supports two types of flits: **spike** (in AER format) and **memory flits**.
 - The AER format flit is converted to the address of the weight SRAM to extract the weight of the connection
 - Memory flit provides the instruction and the required addresses to read/write to/from the memory cells and registers in the neuron cluster.

3. R-NASH hardware

Flit format

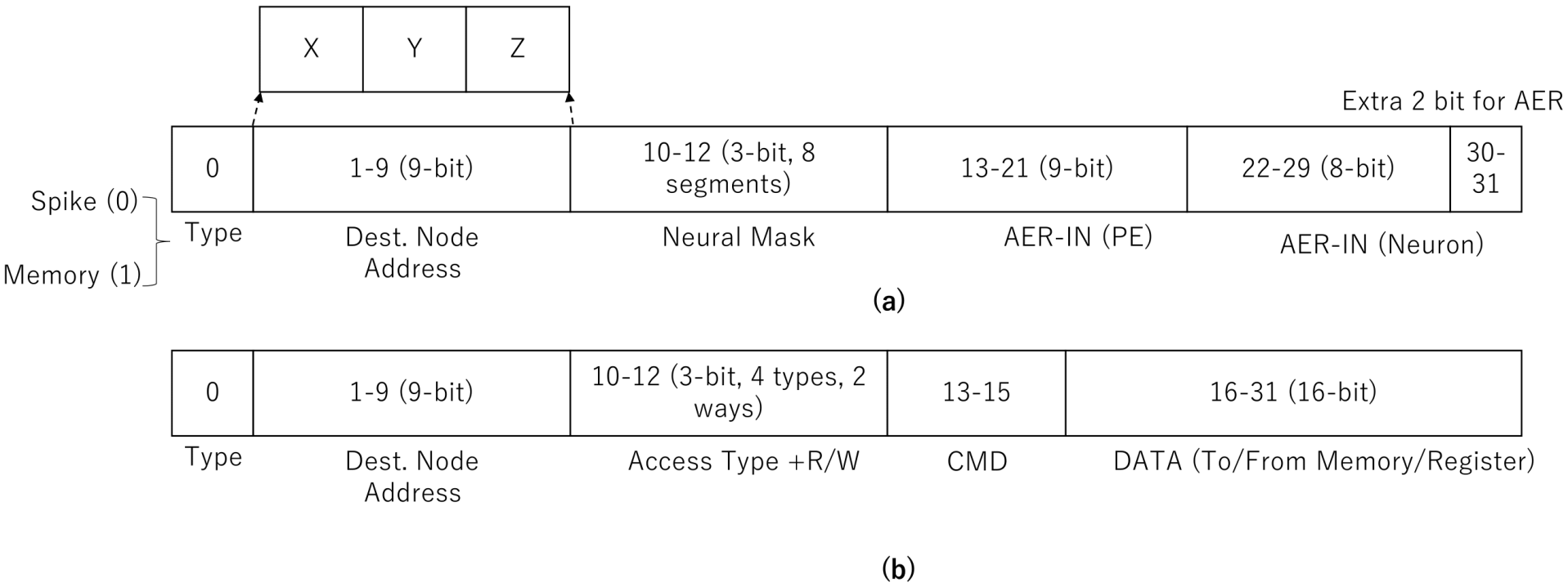


Fig. 8.4: R-NASH Flit Formats

3. R-NASH hardware Router

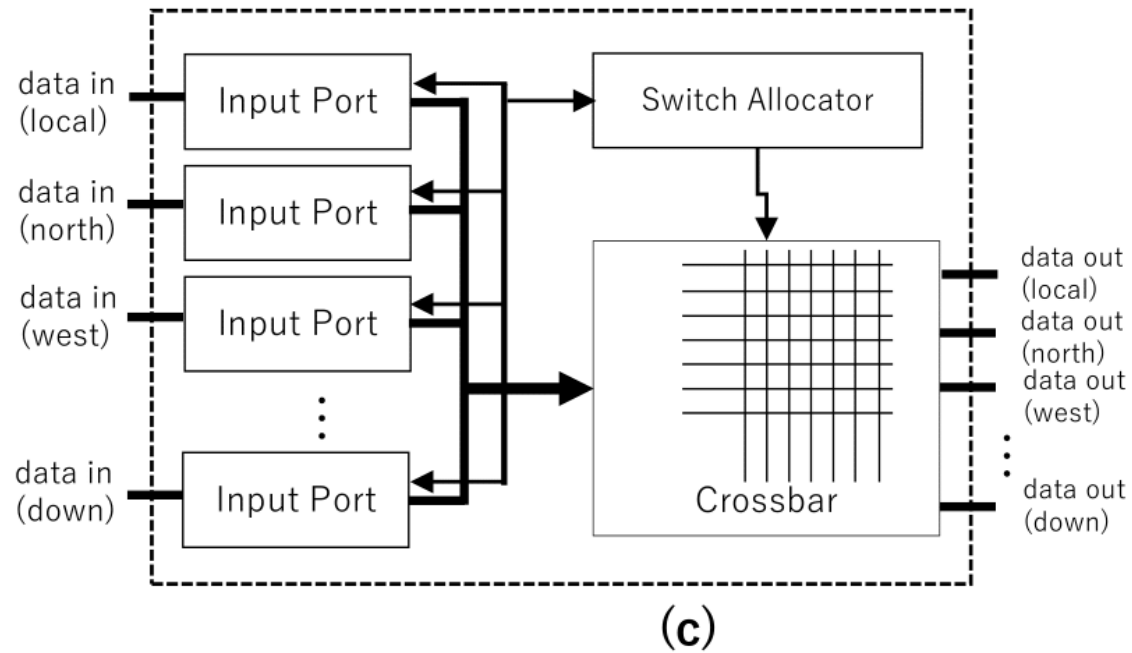


Fig. 8.3(c): Router architecture.

3. R-NASH hardware Network Interface

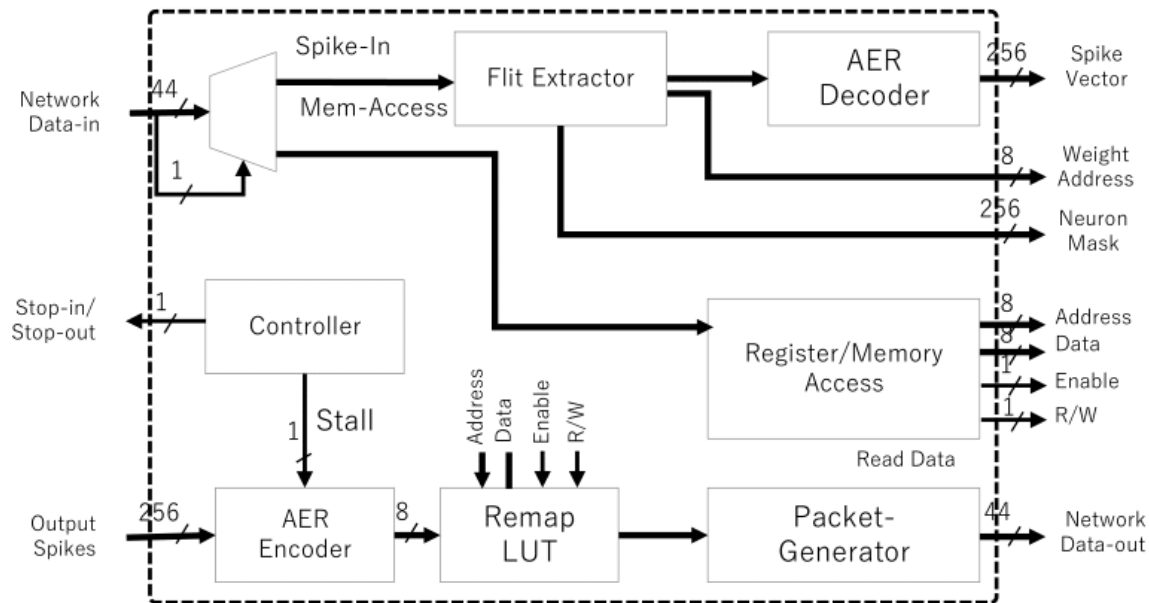


Fig. 8.3 (b): NI architecture.

3. R-NASH hardware

LIF neuron architecture

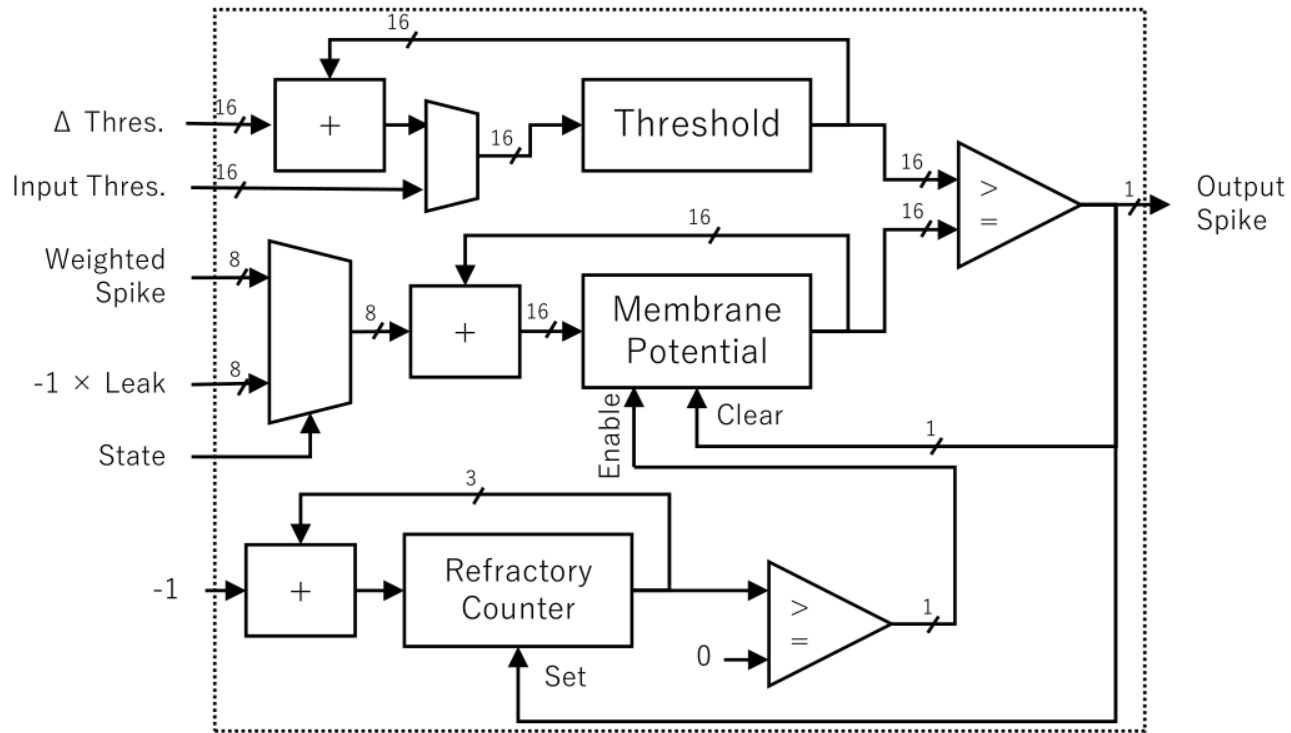


Fig. 8.5: LIF neuron architecture.

3. R-NASH hardware

STDP learning architecture

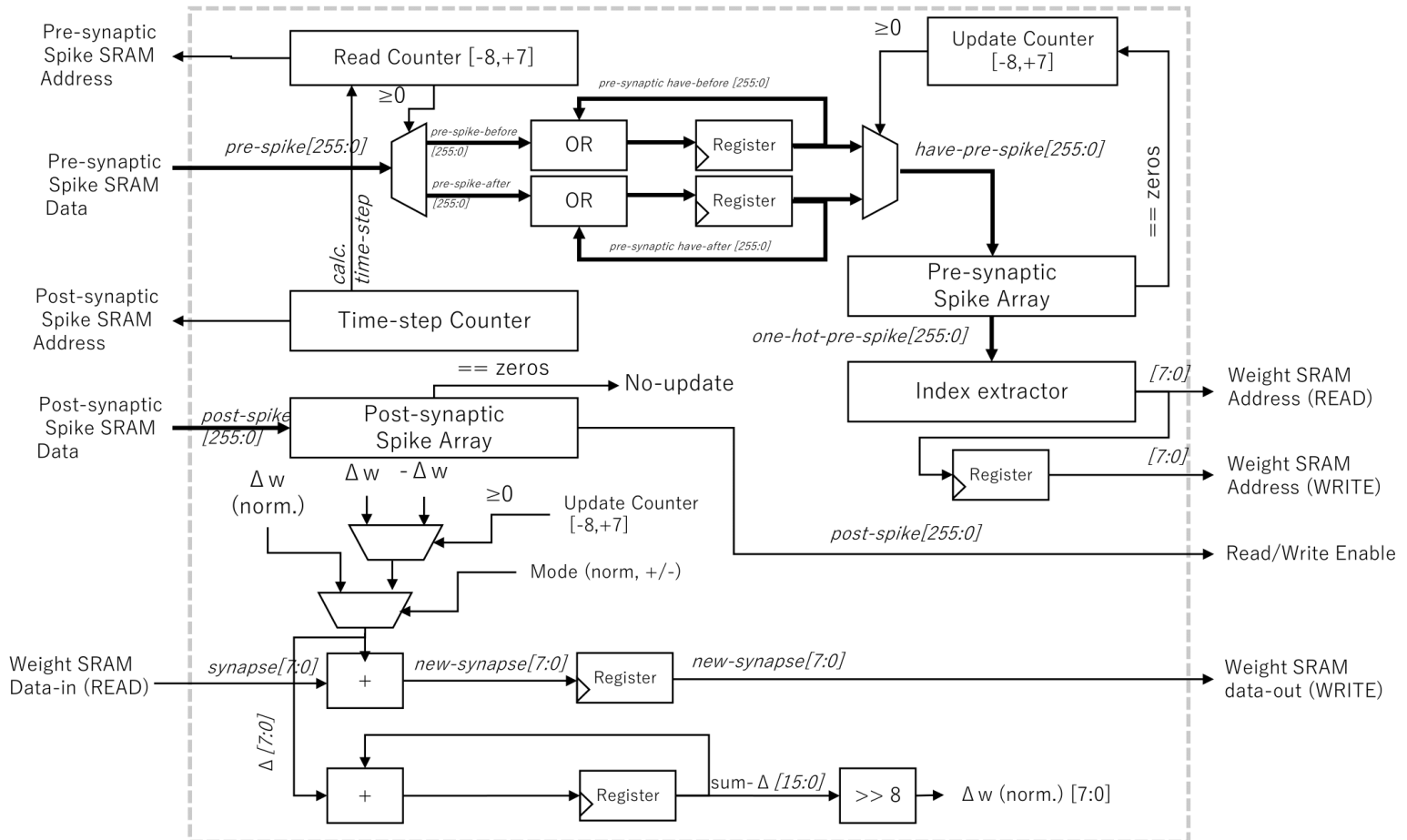


Fig. 8.7: On-chip STDP learning architecture

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4. R-NASH learning

Overview

- R-NASH supports two types of learning:
 - **Off-chip learning:** weights are trained off-line and then download to the chip
 - **On-chip learning with STDP:** R-NASH core support on-chip learning with the ability to update the weight during operation.
- The on-chip learning STDP will follow the simplified rules for unsupervised learning:
 - Weight adjustment will be fixed.
 - Weight normalization will be performed.

4. R-NASH learning STDP learning model

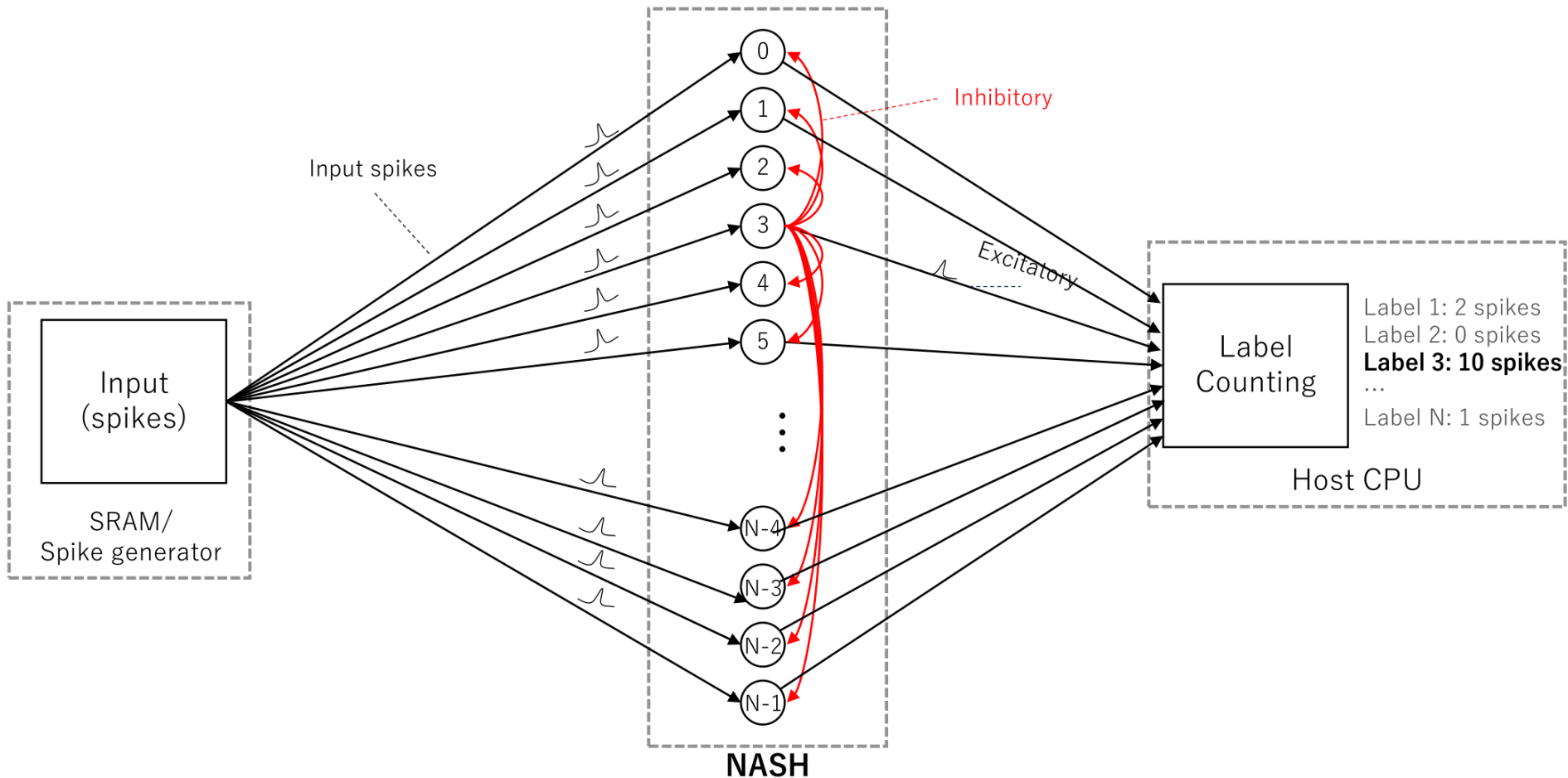


Fig. 8.6: On-chip STDP learning model

4. R-NASH learning

STDP learning weight adjustment

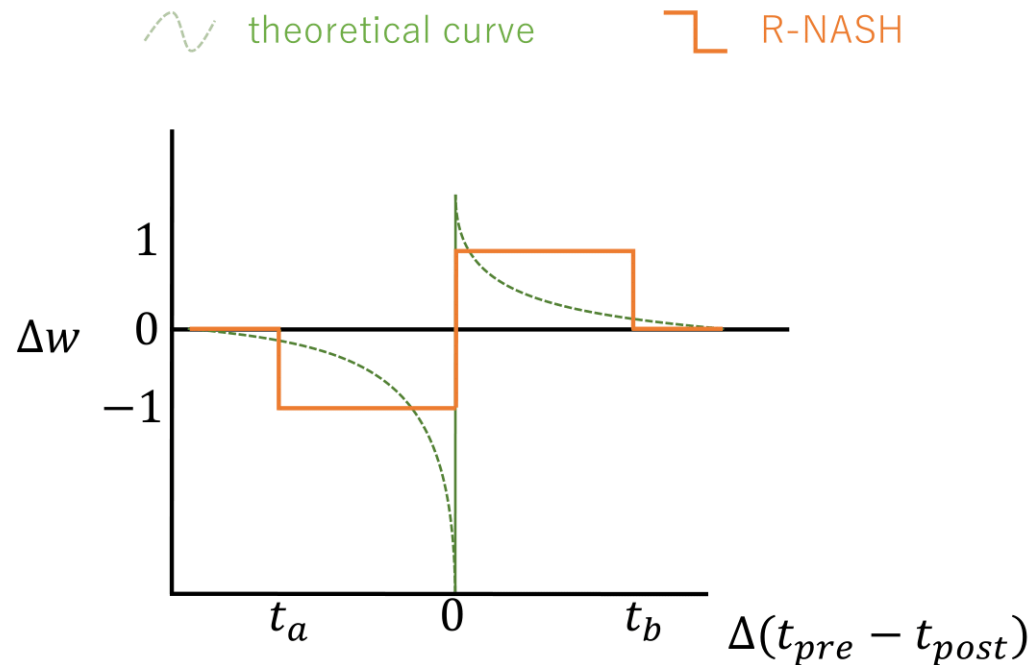


Fig. 8.8: On-chip STDP learning mechanism

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5. R-NASH mapping

Overview

- As we break the neuromorphic system into groups of neurons connected via a Network-on-Chip, dividing and placing are essential issues since they can heavily affect the performance.
 - For instance, placing two connected neurons far apart can lead to a critical delay path in the system.
- In R-NASH, we use Genetic Algorithm to perform mapping.

5. R-NASH mapping Mapping Algorithm

Algorithm 6 Genetic algorithm for neurons mapping

```
// initialize phase
70 S1: load the system configuration
71 S2: randomize the  $K$  mapping solutions
    // evolve phase
72 for (generation  $g_i$  in 1 to  $G$ ) do
73     S3: remove the wrong mapping solutions
74     S4: calculate cost function (communication cost) for each solution of the population
75     S5: select the  $B$  best out of  $K$  solutions based on the cost function
76     S6: mutate the  $B$  best solutions to have new  $K$  solutions
77     S6: crossover the new  $K$  solutions to have new population
78     S7: check if it satisfies the communication cost or does not improve over several generations
    // finalize phase
79 S7: calculate cost function for each solution of the population
    S8: select the  $B = 1$  best out of  $K$  solutions based on the cost function
```

5. R-NASH mapping

Gene, Cross-over and Mutation

String structure 

(a)

Member 1 

Member 2 

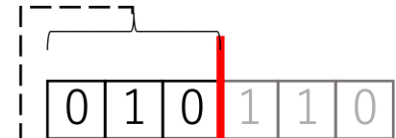
Member 3 

⋮

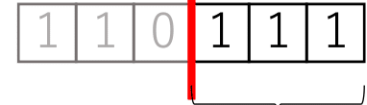
Member M 

(b)

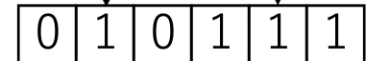
Member 1



Member 2

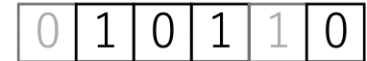


Offspring

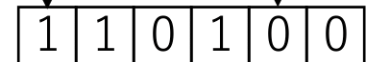


(c)

Member 1



Mutated member



(d)

Fig. 8.9: Genetic algorithm (GA): (a) an example string structure; (b) initialization process; (c) cross-over and (d) mutation

5. R-NASH mapping

Example of crossover and mutation

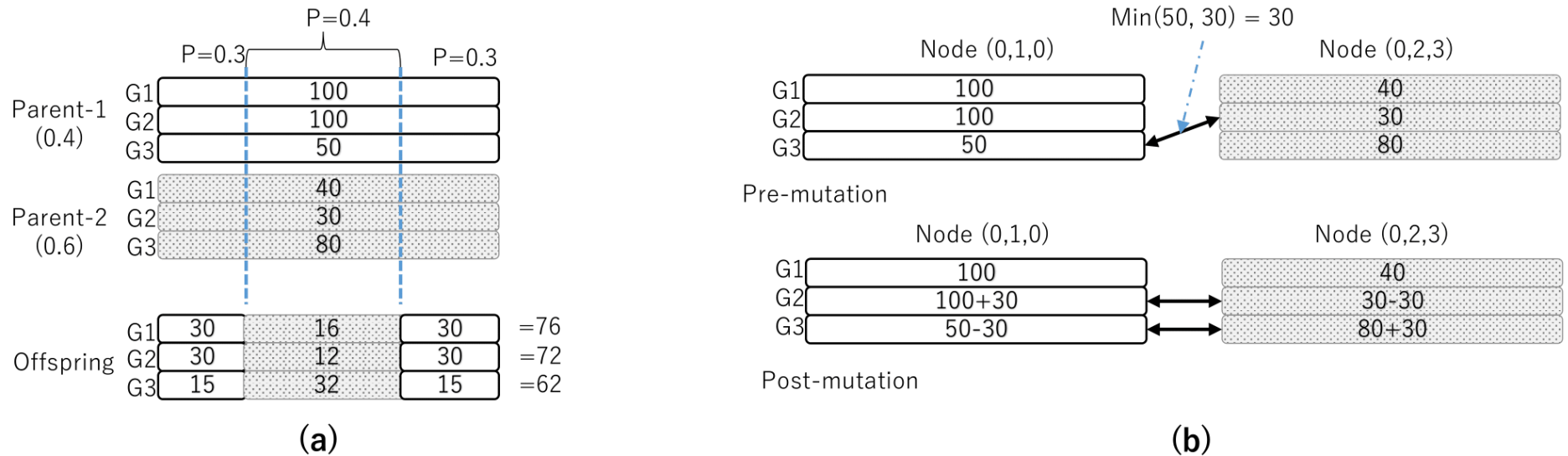


Fig. 8.10: Crossover and mutation method for GA mapping. (A) Crossover. (B) Mutation

5. R-NASH mapping

Fault-tolerance features

- To tackle defective routing, R-NASH offers:
 - Fault tolerance mechanism inside router (input buffer, crossbar).
 - Error Correction Code in the flit (2xSECEDED(22, 16)).
 - Soft error tolerance in the routing unit
- To tackle defective neurons, R-NASH offer remapping to use spare neurons as replacements.

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6. Evaluation

Genetic Algorithm for Initial Mapping

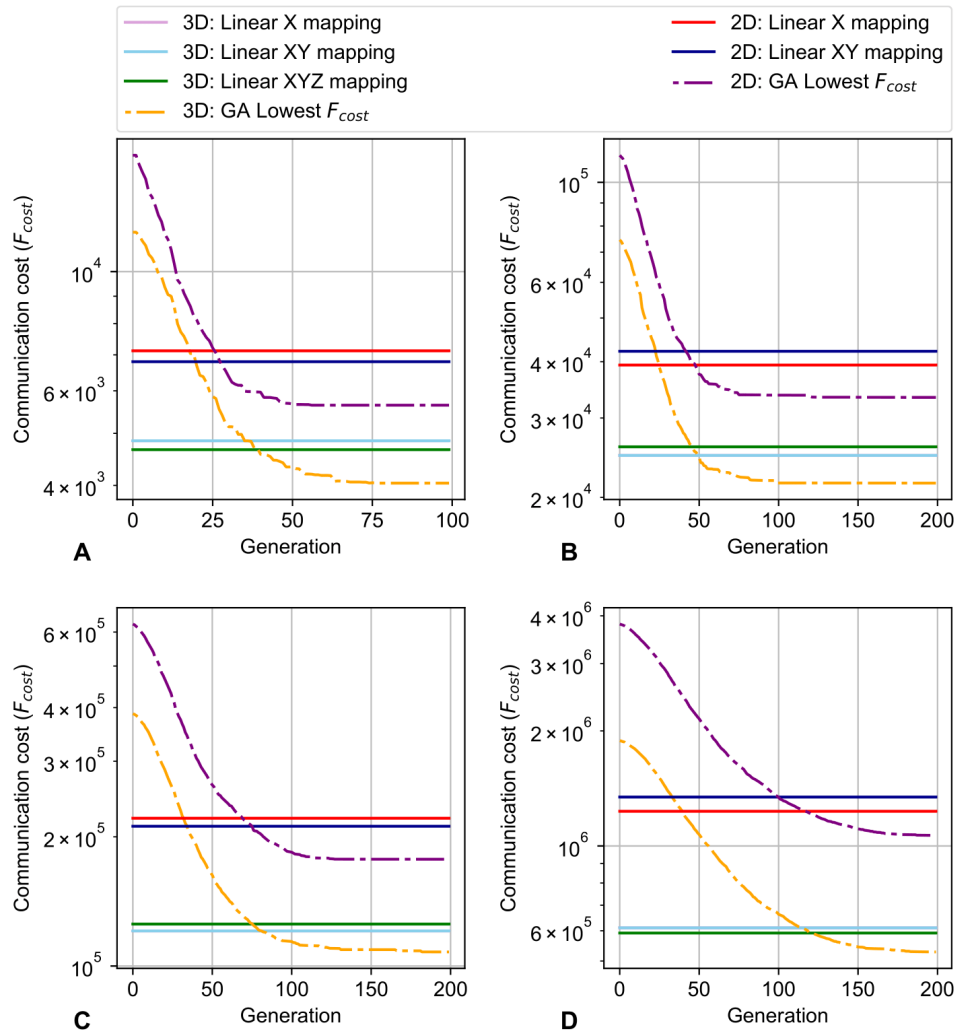


Fig. 8.12: Genetic Algorithm Result for initial mapping. (A) $4 \times 4 \times 4$ NoC-based, 256 neurons/node. (B) $6 \times 6 \times 6$ NoC-based, 256 neurons/node. (C) $8 \times 8 \times 8$ NoC-based, 256 neurons/node. (D) $10 \times 10 \times 10$ NoC-based, 256 neurons/node.

6. Evaluation

Genetic Algorithm for Initial Mapping

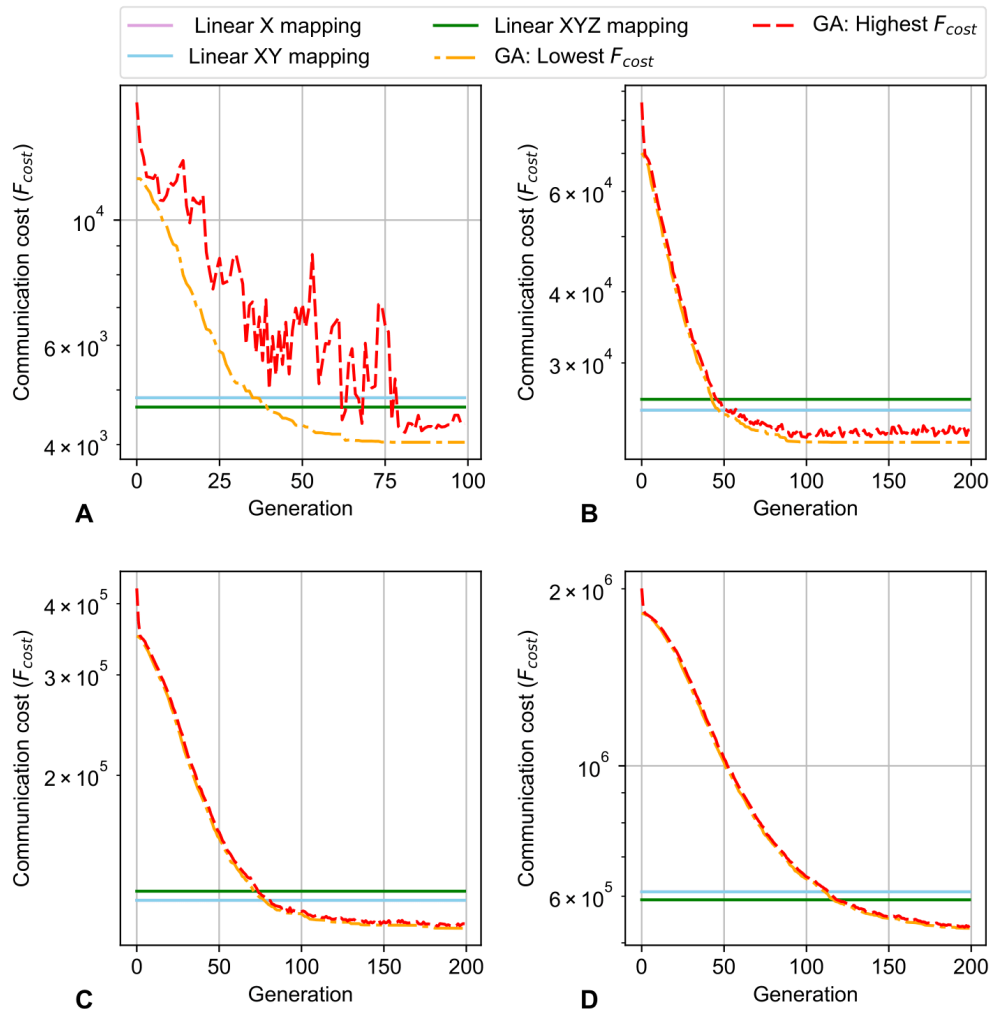


Fig. 8.13: Genetic Algorithm Result of the initial mapping of 3D NoC-based. (A) $4 \times 4 \times 4$, 256 neurons/node. (B) $4 \times 4 \times 8$, 128 neurons/node. (C) $4 \times 8 \times 8$, 64 neurons/node. (D) $4 \times 8 \times 8$, 32 neurons/node.

6. Evaluation

Genetic Algorithm for Initial Mapping

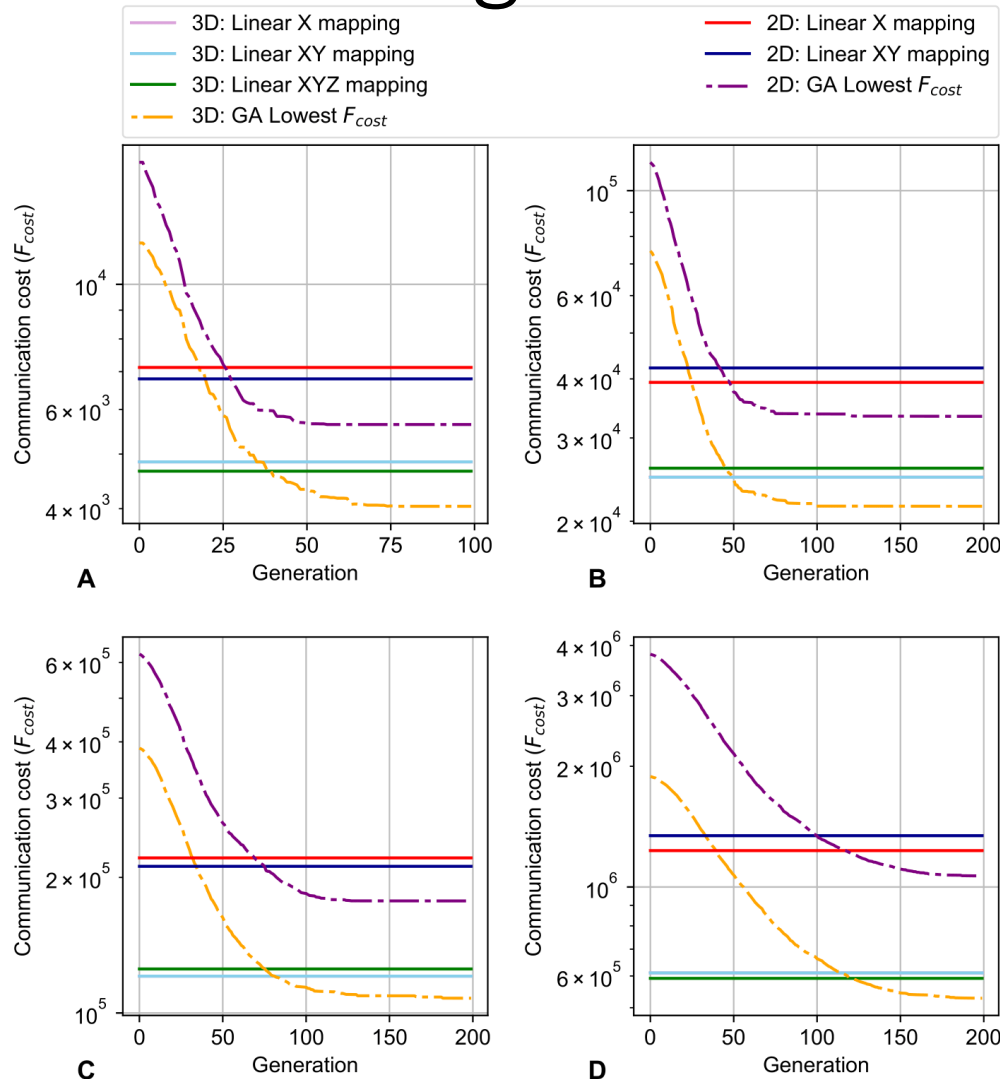


Fig. 8.14: Comparison between 3D and 2D mapping. (A) 64 nodes ($4 \times 4 \times 4$ and 8×8) NoC-based, 256 neurons/node. (B) 128 nodes ($4 \times 4 \times 8$ and 8×16) NoC-based, 256 neurons/node. (C) 256 nodes ($4 \times 8 \times 8$ and 16×16) NoC-based, 256 neurons/node. (D) 512 nodes ($8 \times 8 \times 8$ and 16×32) NoC-based, 256 neurons/node.

6. Evaluation Layout

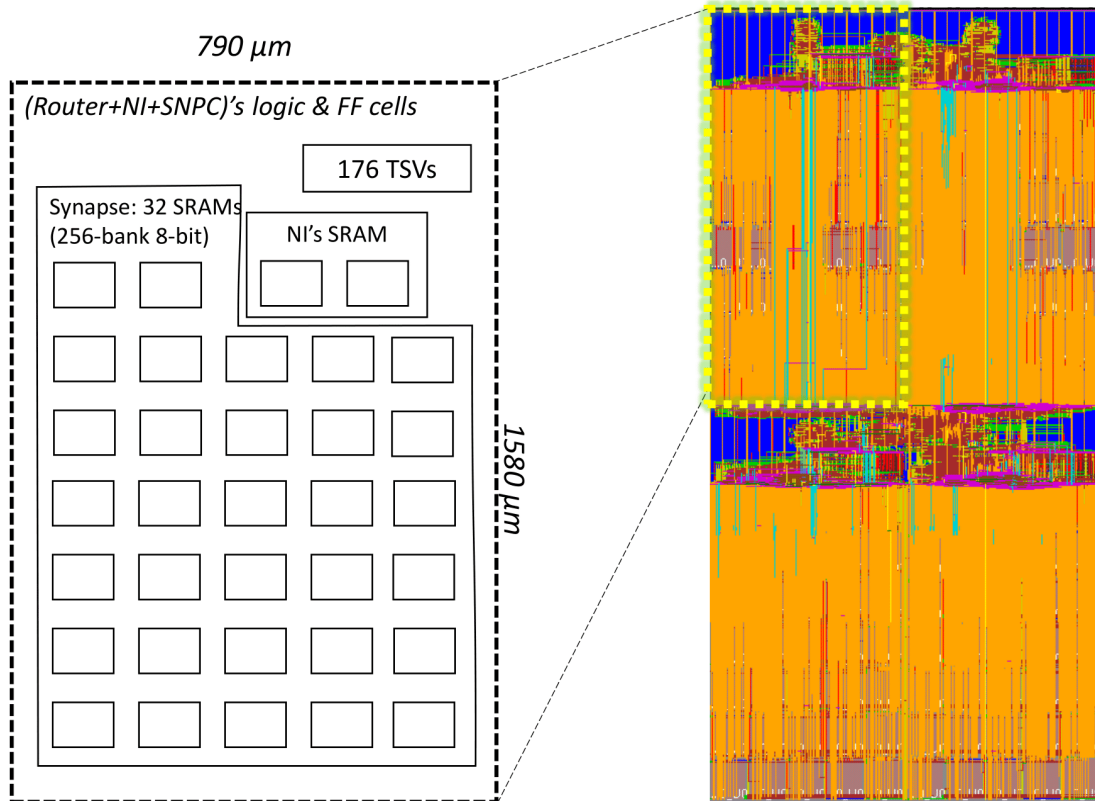


Fig. 8.16: Layout of a 2×2 3D-NoC-based R-NASH layer. A tile's size is $790\ \mu\text{m} \times 1580\ \mu\text{m}$

6. Evaluation

Off-chip learning

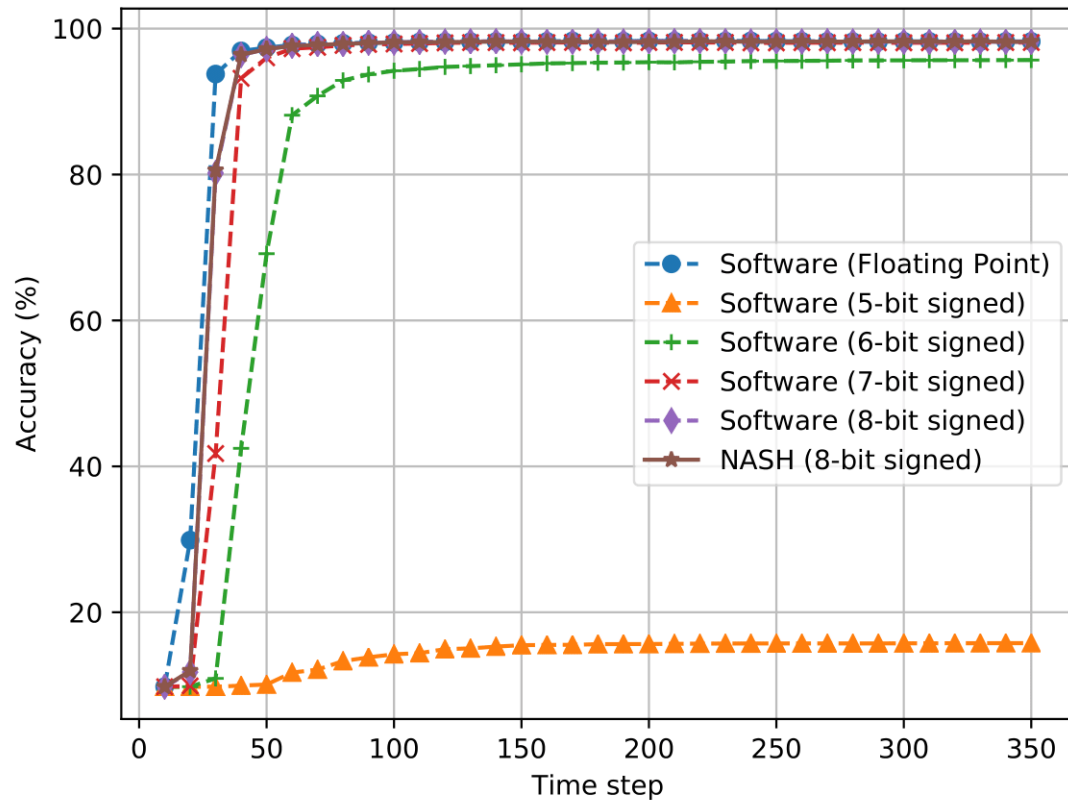


Fig. 8.17: Accuracy result of offline training for MNIST dataset with the network model 784:1024:10.

6. Evaluation

Off-chip learning

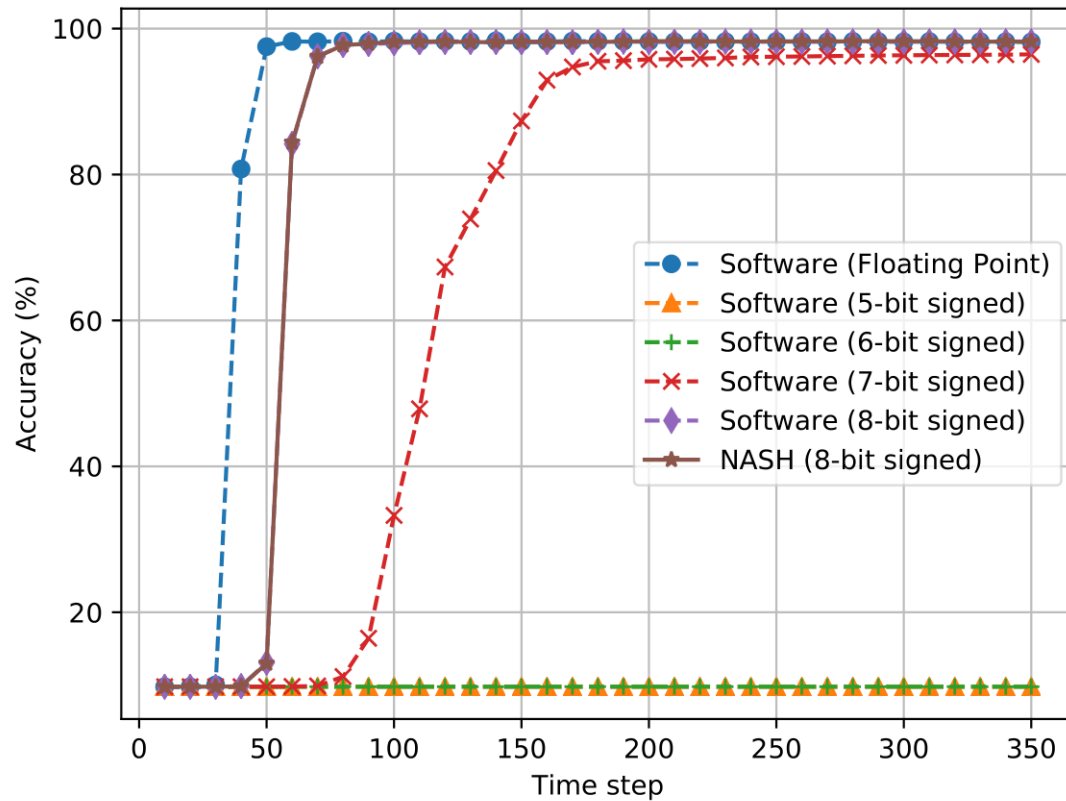


Fig. 8.18: Accuracy result of offline training for MNIST dataset with the network model 784:1024:1024:10.

6. Evaluation

Off-chip learning

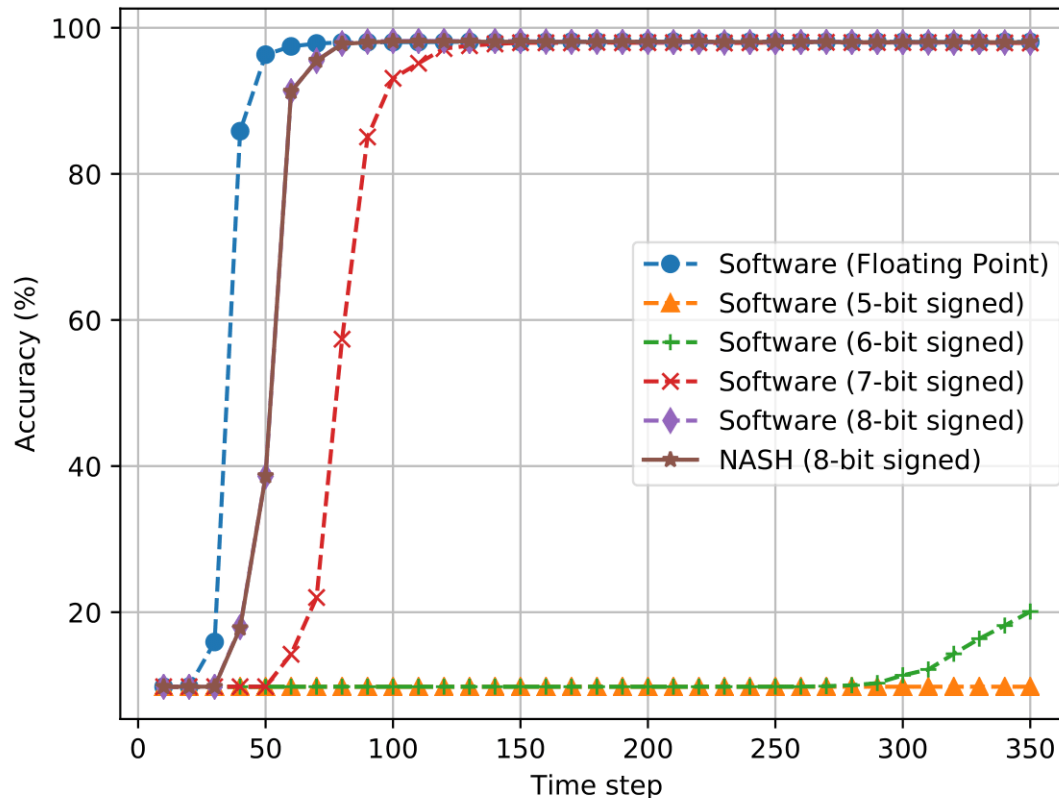


Fig. 8.19: Accuracy result of offline training for MNIST dataset with the network model 784:1024:1024:1024:10.

5. R-NASH mapping

Genetic Algorithm for Initial Mapping

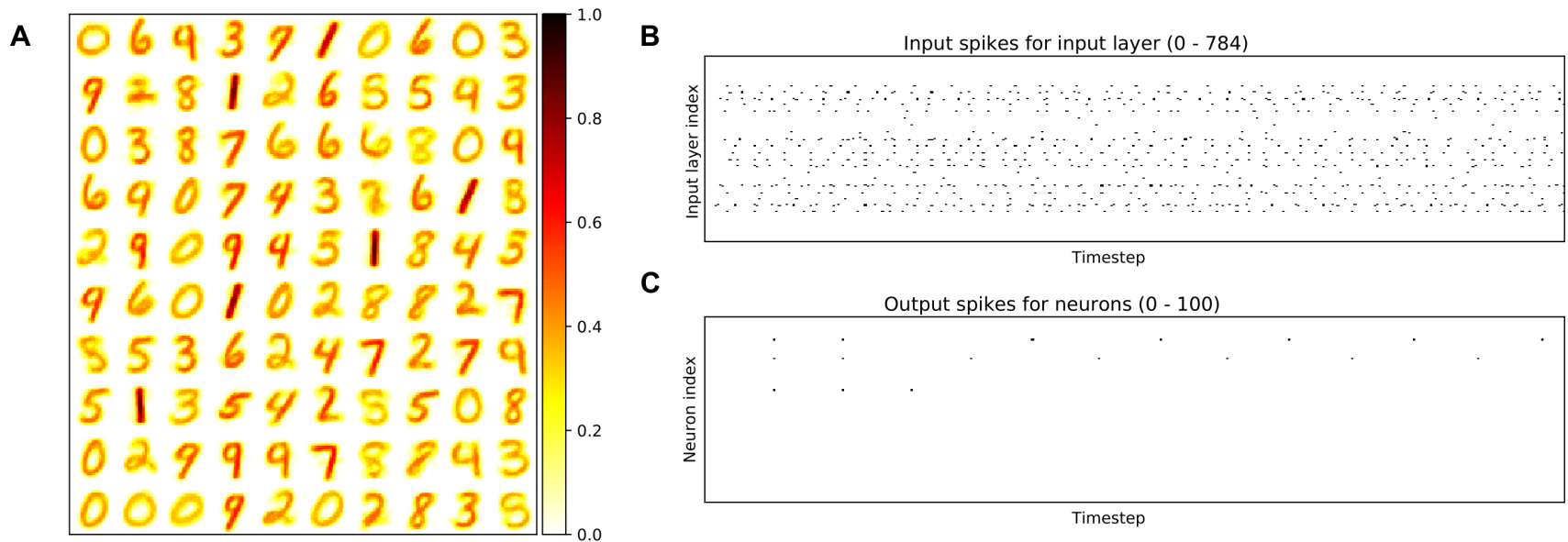


Fig. 8.20: Illustration of the STDP learning model. (A) the final weights. (B) Illustration of input spikes for the first test image (number 8). (C) Illustration of output spikes.

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7. Conclusions

- This lecture shows a case study of R-NASH:
 - 3D NoC based neuromorphic architecture.
 - Fault-tolerance features
- It supports two types of learning:
 - **Off-chip learning & On-chip learning with STDP**
- R-NASH also support initial mapping using GA.
- R-NASH provide protection in the routing unit (routers) and computing unit (neurons)

7. Readings

- F. Akopyan et al., "TrueNorth: Design and Tool Flow of a 65 mW 1 Million Neuron Programmable Neurosynaptic Chip," in IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, vol. 34, no. 10, pp. 1537-1557, Oct. 2015, doi: 10.1109/TCAD.2015.2474396.

<https://ieeexplore.ieee.org/abstract/document/7229264>