NANYANG TECHNOLOGICAL UNIVERSITY

PROGRESS REPORT FOR QUALIFYING EXAMINATION

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Abstract

In the internet-of-things (IoT) era, the edge computing encourages the development of application-specific integrated circuit (ASIC) based accelerators. However, based on the modified Amdahl's law which considers the effect of communication and synchronization in multicore systems [?], the communication bottleneck damps the speedup gained by parallelism and computation acceleration. To connect different processing elements (PE) in the accelerator, network-on-chip (NoC) is generally deployed. Nevertheless, considering the performance demand (i.e., latency and throughput) and cost budget (i.e., power and area), the conventional NoCs with hop-by-hop traversal cannot achieve these two targets simultaneously for ASIC. The performance and cost of traditional NoC are limited by two issues. One is the hop-by-hop arbitration and buffering result in time- and power-consuming communication, especially for the long distance data transmission. The other is network contention among packets with shared links which can result in huge delay and drastically degrade the NoC performance, especially for communication-intensive applications. To address these two issues, we propose a novel NoC architecture, CDless NoC. Specifically, we design the configurable router together with cluster-based controllers to replace the distributed per-hop arbitration. Also, we propose matched routing algorithms for the controller with the consideration of the run-time network state. With the help of our proposed hardware/software co-design, the single-cycle long-distance communication path can be efficiently established, which fully boost the system performance efficiency.

Table of Contents

List of Figures

List of Tables

Table 0.1: Notations Used in This Paper

Notation	**Description**
$\mathcal{V}, \mathcal{E}$	The set of tasks nodes and edges.
m, p, l	The set of message, packet and flit.
$\lvert . \rvert$	The number of elements.
$\mathcal{A}$	The set of processing elements.
$\tau_{v,a}$	$= q_v/ep_a$. The execution time of v on a.
$\mathcal{F}, \mathcal{G}$	The mapping and routing algorithm.
γ_m	The route to transmit data of message m.
L	The latency related to transmission.
E	The energy used for transmission.
t_r, t_w	The router-stage latency and propagation delay.
$\mathcal{M}, \mathcal{R}$	The mapping and routing result
$\mathcal{M}(t)$	Processing element mapped to task t

Chapter 1

Introduction

1.1 Background

1.2 Motivation and Objectives

1.2.1 Objectives

1.3 Organization of the Report

Chapter 2

Literature Review

2.1 NoC and its Communication

2.2 Related Works

2.3 Motivation

Chapter 3

Proposed CDless NoC Architecture

3.1 Architecture Overview

3.2 Discussion

Chapter 4

Algorithm Description

This chapter will introduce algorithms we used in our work, including the design of heterogeneous NoC, the main process of exploring the mapping-routing combined search space by Tabu search, and computing the best route of each map result by reinforcement learning.

4.1 Heterogeneous NoC design

Most of the existing researches about task mapping and routing are based on homogeneous NoC. In reality, heterogeneous NoCs are increasingly appearing in people's life, especially on smart phones. Figure 4.1 is a heterogeneous example, which is big.LITTLE architecture proposed by ARM and is widely used in various devices. Threads with high priority or requiring high computing speed can be assigned to high-performance CPU cores, while threads with low priority or low computing speed requirements (such as background tasks) are completed by low-power CPU cores.

In this paper, We used the method proposed by Shoukat Ali to practice our heterogeneous

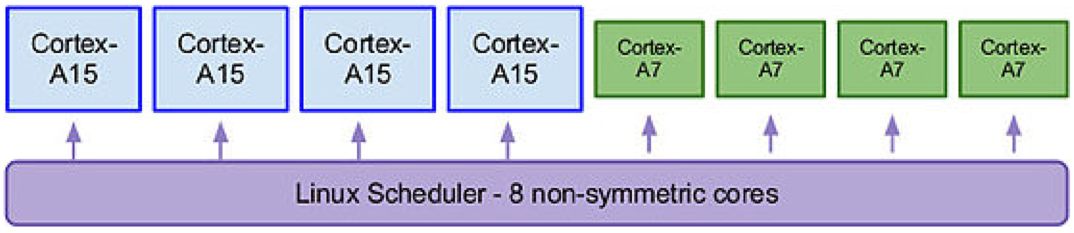


Figure 4.1: big.LITTLE architecture

NoC design[]. Specifically, we use a coefficient-of-variation-based(CVB) generation method to get a matrix of expected time to compute(ETC). In ETC matrix, the element ETC[i][j] is the expected execution time of task i on PE j. PE's number calculation method is defined as the following formula:

$$PE's\ Number = (row - 1) \times mesh\ size + (column - 1)$$

For example, the number of PE in the second row and third column in 8x8 mesh network is (2-1)x8+(3-1)=10.

The CVB generation method is described as the following pseudo code:

```
Algorithm 1: CVB generation method
  Input: $q$, the vector of average execution time of all tasks
  $t$, number of tasks
  $V_{machine}$, NoC heterogeneity coefficient
  $m$, number of PEs
  Output: $ETC$, the matrix of expected time to compute
1 $\alpha_{machine} = \frac{1}{V_{machine}^2}$
2 for $i \in [0, t-1]$ do
3     $\beta_{machine}[i] = \frac{q[i]}{\alpha_{machine}}$
4     for $j \in [0, m-1]$ do
5         $ETC[i, j] = Gamma(\alpha_{machine}, \beta_{machine}[i])$
6         /*$Gamma(\cdot)$ is Gamma distribution, independent sampling each time*/
7     end
8 end
```

4.2 Tabu search

4.2.1 Original Tabu search

4.2.2 Robust Tabu search

As a variant of the original Tabu Search, The Robust Tabu search was proposed in [1] to explore search space in a more efficient method. In chapter X, we mentioned that the mapping problem, which is the problem of the mapping relationship between the Processing Element(PE) and the calculation task, is a quadratic assignment problem(QAP). Some existing studies, by comparing kinds of algorithms, have shown that the most efficient methods to solve a QAP are

Tabu Search and its variants, which take both computational time and the quality of solution into consideration[2][3][4]. Based on these studies, we were inspired to explore the effect of Tabu Search in the joint search space of mapping and routing.

Figure 4.2 shows how Robust Tabu search works to get the result. In order to show our algorithm in a more specific way, we provide both a flowchart and pseudo code to make it more convenient for readers. In order to avoid being overly complicated and easy to read, we split the flowchart into two parts. In flowcharts, you could simply replace Figure 4.3 with "Expand Neighborhood" in Figure 4.2. The pseudo code is at the end of this section.

The rounded rectangles represent the beginning state and the end state. The end state has been marked by the "end" word, so the other one is the beginning state. We randomly select a PE for each task, and then map the task to the PE. It is possible for multiple tasks to be mapped to the same PE, of course, this behavior is not advocated, due to its negative impact on program parallelism. After this work is completed, We use this randomly generated mapping result $\mathcal{M}_0$ as the initial state.

After the initial operation, it comes to the iterative process. In Tabu search, the neighborhood of a certain state $\mathcal{M}$ is defined as a set which is all possible states that can be obtained after one operation of the state $\mathcal{M}$. Based on this definition, the operation in our algorithm is, first randomly select a task t, then move this task to the PE adjacent to $\mathcal{M}(t)$. In 2D-mesh NoC, each PE has up to eight adjacent PEs. In extreme cases, it will be reduced to three. Therefore, based on this setting, each neighborhood has three to eight possible states to explore.

After the process of expand neighborhood, the algorithm should choose the best state from neighborhood. As a co-optimization algorithm, our algorithm will integrate mapping and routing to select the best state. Specifically, we will compute a best route for each mapping result by our routing algorithm mentioned in section 4.3, then consider these two aspects together.

To define how good a result is ,we define a parameter p which consists of two parts. The first part p_1 corresponds to mapping, it is the sum of the execution time of all tasks on the PE mapped to. The second part p_2 corresponds to routing, it is the sum of the waiting time caused by contention when transmitting data after a task is finished.

As we mentioned in section 4.1, the NoC we are experimenting with is heterogeneous, so the same task is mapped on different PEs, or the same PE is processing different tasks, and the execution time is both different. Our algorithm is expected to find the result that minimizes the execution time of all tasks, so p_1, the the sum of the execution time of all tasks, should

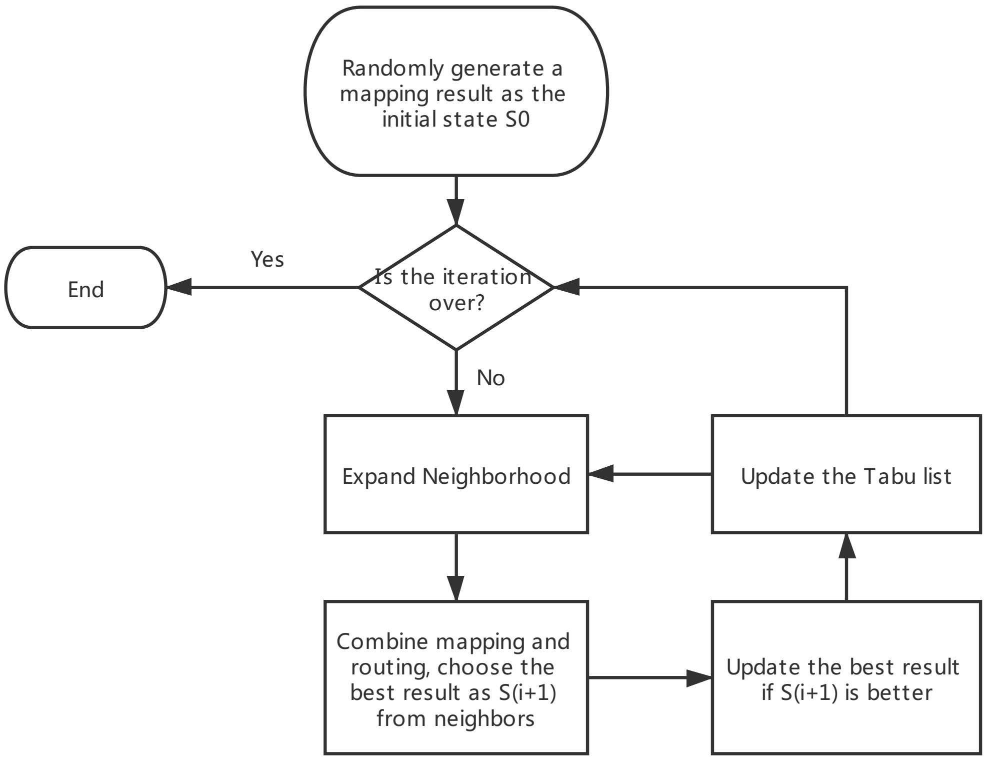

Randomly generate a mapping result as the initial state S0
Is the iteration over?
Yes
End
No
Expand Neighborhood
Update the Tabu list
Combine mapping and routing, choose the best result as S(i+1) from neighbors
Update the best result if S(i+1) is better

Figure 4.2: The main process of Tabu search

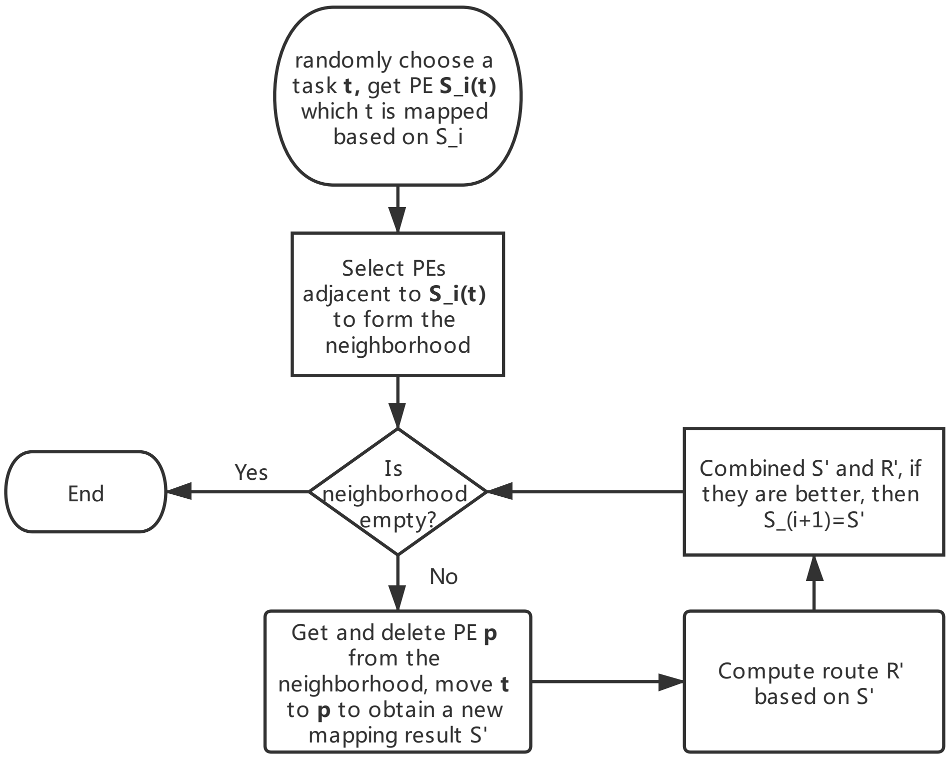
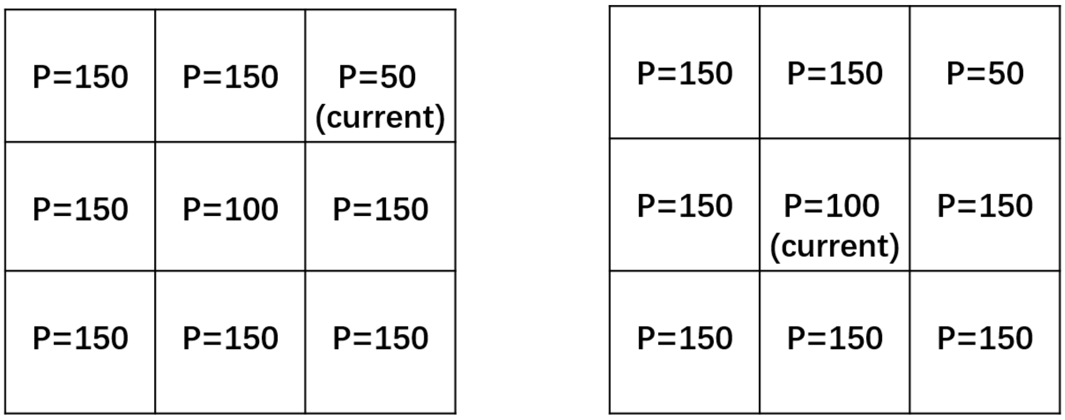

randomly choose a task t, get PE S_i(t) which t is mapped based on S_i
Select PEs adjacent to S_i(t) to form the neighborhood
Is neighborhood empty?
Yes
End
No
Get and delete PE p from the neighborhood, move t to p to obtain a new mapping result S'
Compute route R' based on S'
Combined S' and R', if they are better, then S_(i+1)=S'

Figure 4.3: Expand Neighborhood



(a) state 1 (b) state 2

Figure 4.4: Example for explaining tabu list

be as small as possible. In order to avoid all tasks being concentrated to compete for certain PEs with strong computing ability, we punished this situation that multiple tasks are mapped on the same PE. In detail, when calculating p_1, The execution time of task t will be multiplied by a coefficient, which is the number of tasks mapped on PE $\mathcal{M}(t)$. In this case, only multiple tasks are mapped on the same PE will be punished.

Our algorithm is a contention-aware algorithm, so p_2 is waiting time caused by contention. Different from the simulator which calculates cycle by cycle, we adopted another faster method to estimate waiting time. Detailed instructions will be mentioned in section 4.3.

According to the above description, the parameter p is given by the following formula:

$$p = \sum_t^{\mathcal{V}} ET[t][\mathcal{M}(t)] * task\_num(\mathcal{M}(t)) + contention\_time$$

The smaller the parameter p, the better the quality of this result. At the mapping level, this means finding a PE with strong computing ability; at the routing level, this means that there is less contention in the result we find.

When we find the best result among the neighborhood in the current state, we set it to the state of the next iteration, and then add this operation to the tabu list. The operation in tabu list will never be adopted until it is released from tabu list. This effectively ensure that our algorithm does not fall into local optima. To explain this more clearly, we use Figure 4.4 to give an example.

In Figure 4.4(a), the current state falls in the first row and third column. It's neighborhood has three elements, the best one is located in the second row and second column, the state in the next iteration has moved to this position. After this move operation, the current state falls in the second row and the second column, as shown in Figure 4.4(b). If we do not add this operation to the tabu list, the algorithm will still return to the first row and third column in the next iteration, because this is the best one in current neighborhood. The algorithm will move back and forth between these two positions, thus falling into an endless loop. The significance of the tabu list is to force the algorithm to accept a certain state that is not particularly good, so as to move to a new position to explore other search spaces in order to find the best state.

Finally, we record the best state $\mathcal{M}_b$ that has occurred during the iteration as the final mapping result. Then we use the routing algorithm mentioned in section 4.3 to obtain the corresponding route $\mathcal{R}(\mathcal{M}_b)$, so as to get the solution to this task graph.

Algorithm 2: Robust Tabu Search

```
   Input:  $\mathcal{V}, \mathcal{E}$, The set of tasks nodes and edges.
           $\mathcal{A}$, The set of processing elements.
   Output: Best mapping result $\mathcal{M}_b$ and its corresponding routing result $\mathcal{R}_b$
 1 Initialize Randomly generate a $\mathcal{M}_0$ as the initially state
    Tabu list($TL$)=$\emptyset$
 2 for $i \in [0, max\_iteration]$ do
 3     $t = Random(\mathcal{V})$ //randomly choose a task from $\mathcal{V}$
 4     $\mathcal{M}' = \emptyset, j' = 0$
 5     for $j \in Neig(\mathcal{M}_i(t))$ AND $(\mathcal{M}_i(t), j) \notin TL$ do
 6         $\mathcal{M}_i(t) = j$
 7         $\mathcal{R}_i = \mathcal{G}(\mathcal{M}_i)$
 8         if $\mathcal{M}_i$ and $\mathcal{R}_i$ is better then
 9             $\mathcal{M}' = \mathcal{M}_i, j' = j$
10         end
11         restore $\mathcal{M}_i$
12     end
13     $\mathcal{M}_{i+1} = \mathcal{M}'$
14     if $TL$ is full then
15         delete $TL[0]$
16     end
17     add $(\mathcal{M}_i(t), j')$ to $TL$'s tail
18     if $\mathcal{M}_{i+1}$ is better than $\mathcal{M}_b$ then
19         $\mathcal{M}_b = \mathcal{M}_{i+1}$
20         $\mathcal{R}_b = \mathcal{G}(\mathcal{M}_b)$
21     end
22 end
```

4.3 Routing algorithm

Our routing algorithm is based on Advantage Actor Critic(A2C) which is a reinforcement learning algorithm. This section will introduce reinforcement learning, A2C and how do we apply them to routing algorithm.

4.3.1 Reinforcement learning

Reinforcement learning is a algorithm aims to maximize the cumulative reward, it is studied in many disciplines, such as game theory, multi-agent systems and control theory. The basic reinforcement learning model should include:

- The set of environment and agent states S, beginning with initial state s_0;
- A action function $A(s_t)$ gives all possible actions when agent is in state s_t;
- A reward function $R(s_t)$ gives reward of current state s_t;
- A transition model $P(s_{t+1}|s_t, a_t)$ gives the probability of state s_t to state s_{t+1} through action a_t

In this section, all s and its variants with superscript or subscript represent state, all a and its variants with superscript or subscript represent action.

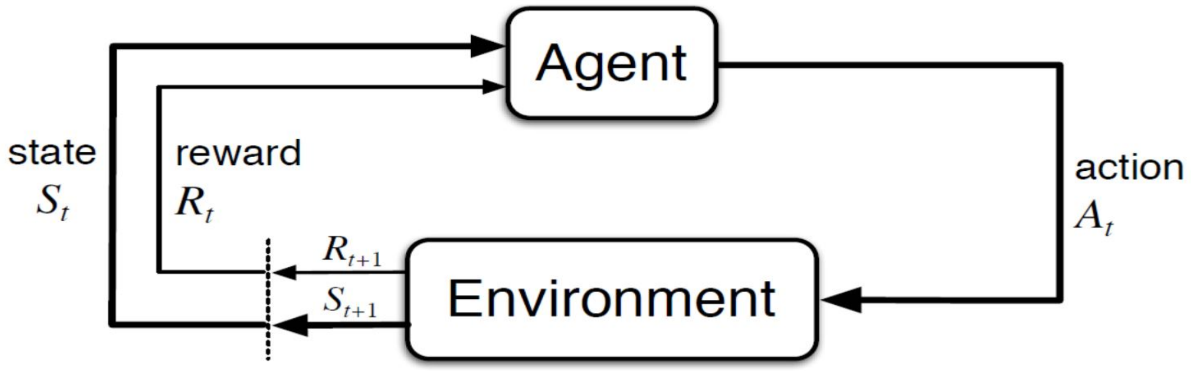


Figure 4.5: How agent and environment interact

The way agent and environment interact is shown in the Figure 4.. At time step t, agent observes state s_t and produce action a_t, then it gets resulting reward r_{t+1} and next state s_{t+1}.

Figure 4. gives a timeline summary of multiple time steps. The probability of reach s_{t+1} from s_t depends only on current state s_t and action a_t, not any other past states or actions.

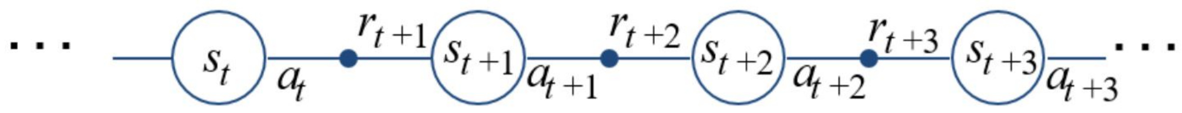


Figure 4.6: Timeline of multiple time steps

The algorithm design ideas of reinforcement learning are very similar to human thinking. In the beginning, the computer know nothing about everything, and learn from mistakes after constant trial and error, and finally found the pattern, thus having the ability to solve this type of problem.

When the computer makes an action a from state s to state $s^{'}$, the reward function will give a definite reward to tell the computer whether it is good or bad to perform action a in state s. The computer will remember this evaluation and update its own strategy. When in the state s again, the computer will make better decisions based on past experience. Different from the supervised learning with labels on training samples, the data has no labels during the training process of reinforcement learning, and only learns through rewards and punishments given by the environment.

There are two basic methods in reinforcement learning, which are **value-based** and **policy-based**. Value-based algorithm record the corresponding reward after each action. When the agent need to perform action, value-based algorithm will directly select the most valuable action based on previous experience. It is usually used to deal with the situation where the action space is discrete, and when the action space is continuous, it can do nothing, because it can no longer record the corresponding value for every action.

In the case that the action space is continuous, we usually use the policy-based algorithm to solve the problem. Policy-based algorithm will analyze the current state, and then give the probability of various actions to be taken in the next step, after that take actions based on this probability distribution. In the training process, the policy-based algorithm will modify its parameters according to the reward of each action executed, and then it will give better results when the probability distribution of all actions needs to be given again.

Regardless of value-based or policy-based, our goal is finding a policy function $\pi(s)$ to give the excellent action that an agent takes in any given state s. However, when measuring the quality of a state s, we cannot only focus on the reward of this state s, but also the rewards of other states that can be reached through this state, which is the "potential" of this state s. We discount the individual state rewards by a factor γ which is between 0 and 1, so we have the expected sum of discounted rewards $G(s_t)$. $G(s_t)$ is based on the assumption that the agent will execute the optimal policy from state s_t. It is shown by the following formula:

$$G(s_t) = R(s_t) + \gamma R(s_{t+1}) + \gamma^2 R(s_{t+2}) + ... = \sum_{i=t}^{\infty} \gamma^{i-t} R(s_i)$$

If our current state is s, the state that may be reached after s is s', then the optimal policy will be :

$$\pi^*(s) = \underset{a \in A(s)}{argmax} \sum_{s'} P(s'|s,a) G(s')$$

4.3.1.1 Value-based algorithm

For value-based algorithm, our goal is learning a policy $\pi(a|s)$ via a value function $Q(s,a)$. The value function $Q(s,a)$ is used to measure the value of performing action a in state s. Take Q-learning as an example, this algorithm will maintain a Q table to get the best action $argmax_{a^*} Q(s,a)$. A simple Q table is shown as Table 4.1.

Table 4.1: A simple Q table

Q-table	a_1	a_2
s_1	1	5
s_2	2	3
s_3	4	6

When the agent is in state s_1, $\pi(a|s)$ will choose the action with a large Q value to execute, that is, a_2. When the agent transitions to a new state, it will still choose the action it will perform according to the Q table until the end. The classic methods of updating the value of the status include Monte Carlo Method and Temporal Difference Learning.

In Monte Carlo method, The update formula for the value is as follows:

$$V(s_t) \leftarrow V(s_t) + \alpha \left[G_t - V(s_t) \right]$$

where $G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$ is the actual reward from time step t and α is the given learning

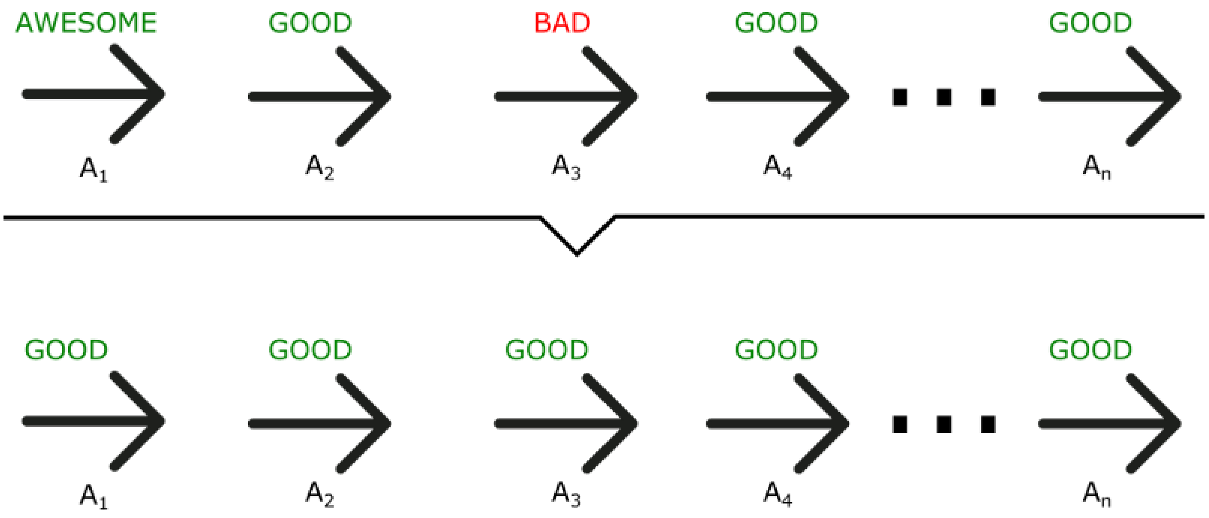


Figure 4.7: An example for the disadvantage in Monte Carlo

rate.

the reward will be calculated after the episode ends and then the model will be updated. This method has a disadvantage. When the model gets a high reward, the model will think all actions it takes are excellent, even if there are some actions is not good. Figure 4. gives a example to explain this phenomenon. Although A_3 is a bad action, the total reward is still high due to the excellent performance of other actions. In this situation, the model will consider A_3 as a good action.

In this situation, we need a large number of samples and enough learning time to make the model converge, which is undoubtedly disadvantageous. We hope to be able to update at each time step, so Temporal Difference Learning was proposed.

Temporal Difference Learning(TD Learning) is usually used to calculate the value of the state. When the time step transits from t to $t+1$, TD learning could immediately update $V(s_t)$ based on the observed reward R_{t+1} and estimated value $V(s_{t+1})$ as follows:

$$V(s_t) \leftarrow V(s_t) + \alpha \left[R_{t+1} + \gamma V(s_{t+1}) - V(s_t)\right]$$

where α is given learning rate and γ is attenuation coefficient.

Based on these considerations, we use TD Learning to update Q table. Given learning rate α, for state s, action a and the next state s' of s through action a, we firstly get the reward r from state s performing action a, then update $Q(s, a)$ by following formula based on TD

Learning:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \cdot [r + \gamma \cdot max_{a'} Q(s',a') - Q(s,a)]$$

Based on this process, the pseudo code is shown in Algorithm 3.

Algorithm 3: value-based algorithm

```
Input: $S$, the set of environment and agent states
       $A(\cdot)$, the action function
       $R(\cdot)$, the reward function
       $P(s'|s,a)$, the transition model
Output: $Q(s,a)$, Q table
1  Initialize $Q(s,a)$ arbitrarily
2  for $i \in [0, max\_episodes]$ do
3      Initialize $s = s_0$
4      while $s$ is not terminal do
5          $a = \underset{a_i}{argmax}\, Q(s,a_i)$
6          Take action $a$, observe reward $r$, next state $s'$
7          $Q(s,a) \leftarrow Q(s,a) + \alpha \cdot [r + \gamma \cdot max_{a'} Q(s',a') - Q(s,a)]$
8          $s \leftarrow s'$
9      end
10 end
```

4.3.1.2 Policy-based algorithm

For policy-based algorithm, we directly study a policy mapping states to actions, which is different from value-based algorithm. Generally, we learn a parameterized policy with parameter θ that can select actions from action space without consulting a value function. We define $\pi(a|s,\theta) = P(A_t = a|S_t = s, \theta_t = \theta)$ with parameter θ is the probability that action a is taken at time step t and the environment is in state s at time step t.

If we use $J(\theta)$ to measure the performance of policy $\pi(a|s,\theta)$, then $J(\theta)$ is our objective function, we could use the gradient descent method to update θ with given learning rate α:

$$\theta_{t+1} = \theta_t + \alpha \nabla J(\theta_t)$$

We use average reward to define $J(\theta)$. Assuming $p_\pi(s)$ is the probability of state s occurs when executed according to policy π, $\pi(a|s,\theta)$ is the probability of taking action a in state s according to policy π, $Q_\pi(s,a)$ is is the value obtained by taking action a in state s according to policy π (it is similar with $Q(s,a)$ in value-based algorithm). Then $\sum_a \pi(a|s,\theta) Q_\pi(s,a)$ is the average value obtained by performing various actions in state s. In this case, $J(\theta)$ will be :

$$J(\theta) = \sum_s p_\pi(s) \sum_a \pi(a|s,\theta) Q_\pi(s,a)$$

According to policy gradient theorem[], $\nabla J(\theta)$ is proportional to $\nabla_\theta \pi(a|s,\theta)$. Since $p_\pi(s)$ is a probability, we replace the sum of s with mathematical expectation:

$$\nabla J(\theta) \propto \sum_s p_\pi(s) \sum_a Q_\pi(s,a) \nabla_\theta \pi(a|s,\theta) = \mathbb{E}_\pi \left[\sum_a Q_\pi(s_t,a) \nabla_\theta \pi(a|s_t,\theta) \right]$$

Now we could use Monte Carlo method to approximate this expected value. $\pi(a|s_t,\theta)$ is also probability, so we use the same method to replace the sum of a:

$$\begin{aligned}
\nabla J(\theta) &\propto \mathbb{E}_\pi \left[\sum_a Q_\pi(s_t,a) \nabla_\theta \pi(a|s_t,\theta) \right] \\
&= \mathbb{E}_\pi \left[\sum_a \pi(a|s_t,\theta) Q_\pi(s_t,a) \frac{\nabla_\theta \pi(a|s_t,\theta)}{\pi(a|s_t,\theta)} \right] \\
&= \mathbb{E}_\pi \left[Q_\pi(s_t,a_t) \frac{\nabla_\theta \pi(a_t|s_t,\theta)}{\pi(a_t|s_t,\theta)} \right] \\
&= \mathbb{E}_\pi \left[G_t \frac{\nabla_\theta \pi(a_t|s_t,\theta)}{\pi(a_t|s_t,\theta)} \right] \\
&= \mathbb{E}_\pi \left[G_t \nabla_\theta ln\ \pi(a_t|s_t,\theta) \right]
\end{aligned}$$

where $G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$, represents the value of state s_t.

In conclusion, now we have the update formula for gradient descent:

$$\theta_{t+1} = \theta_t + \alpha G_t \nabla_\theta ln\ \pi(a_t|s_t,\theta)$$

According to this formula, we could train our policy function $\pi(a|s,\theta)$ and make it smarter than smarter. The pseudo code of A2C is shown in algorithm 4..

On the basis of these two methods, Actor-Critic, which combines the advantages of these two methods, was created. It is also the prototype of the Advantage Actor Critic we used. The detailed introduction is in section 4.3.2.

Algorithm 4: Policy-based algorithm

```
1 Initialize $\theta$ randomly
2 for each episode $\{s_0, a_0, r_1, ..., s_{T-1}, a_{T-1}, r_T\} \sim \pi(a|s, \theta)$ do
3     for $t \in [0, T-1]$ do
4         $G_t = \sum_{k=0} \gamma^k r_{t+k+1}$
5         $\theta \leftarrow \theta + \alpha G_t \nabla_\theta ln\ \pi(a_t|s_t, \theta)$
6     end
7 end
```

4.3.2 Advantage Actor-Critic

Actor-Critic consists of two networks, actor and critic. Actor accepts the state s_t of the agent in step t as input, and then outputs the action a_t that the agent will take in this state. Critic will evaluate this action a_t made by Actor and give a specific value $Q(s_t, a_t)$ to measure this action. Figure 4. gives a schematic diagram of Actor-Critic.

As we mentioned in section 4.3.1, critic is a value-based function with parameter w, it could be state value function $V_w(s)$ or state-action value function $Q_w(s, a)$. Actor is a policy-based function $\pi_\theta(a|s)$ with parameter θ, it updates the parameter θ according to the suggestions given by critic. The update parameter method of value-based algorithm and policy-based algorithm is mentioned in section 4.3.1.1 and 4.3.1.2.

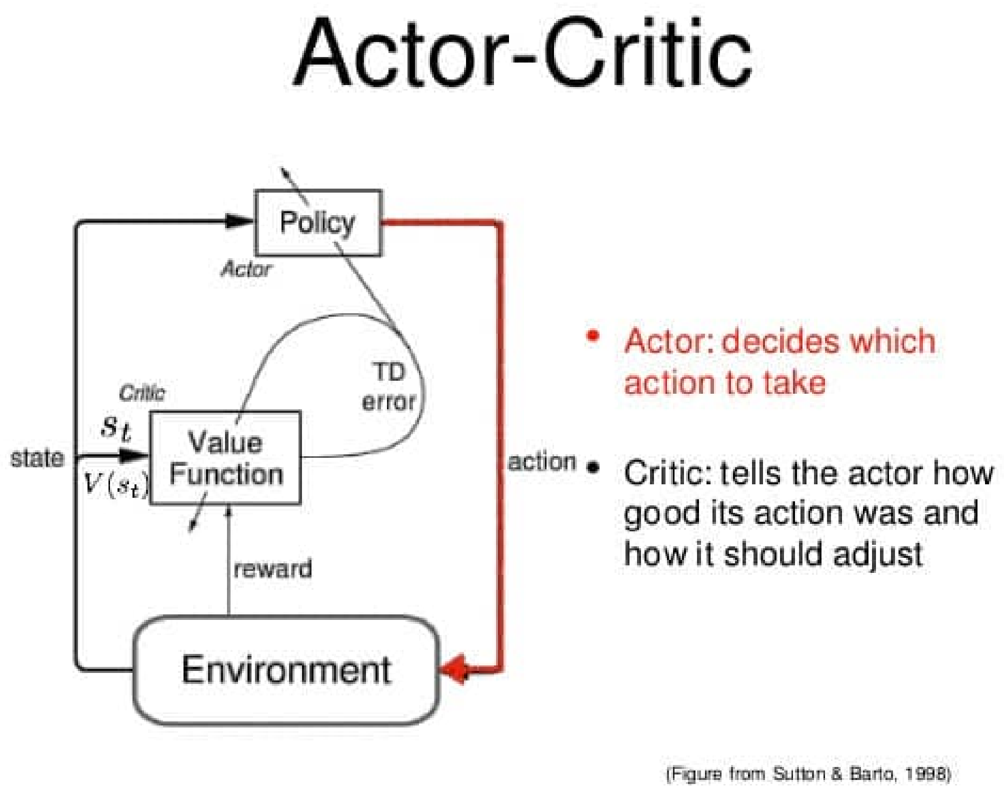
In this paper, we used Advantage Actor-Critic(A2C). It differs from basic Actor-Critic in that the value function in critic is replaced with advantage value $A_w(s, a)$. It is defined by the following formula:

$$A_w(s, a) = Q_w(s, a) - V_w(s)$$

In this formula, $V_w(s)$ is the state value, which is the sum of the state-action values corresponding to all possible actions in state s multiplied by the probability of taking the action, in other words, $V_w(s) = \sum_{a' \in A(s)} \pi(a'|s) \cdot Q_w(s, a')$, is a mathematical expectation. Q_w is the state-action value corresponding to the action a in state s.

So, the advantage value $A_w(s, a)$, is the advantage of current action a over the average action in state s. If the advantage value $A_w(s, a)$ is greater than zero, then the action a is better than the average action in state s. If the advantage function $A_w(s, a)$ is less than zero, then the current action a is not as good as the average action.

However, we usually do not calculate state-action value $Q_w(s, a)$ and state value $V_w(s)$



Actor-Critic

- Actor: decides which action to take
- Critic: tells the actor how good its action was and how it should adjust

(Figure from Sutton & Barto, 1998)

Figure 4.8: The structure of Actor-Critic

separately. Because in this case we need to train two networks at the same time, one for calculating state-action value and one for calculating state value, which will increase the amount of calculation.

The usual practice is to replace $Q_w(s, a)$ with $r + \gamma V_w(s')$, where r is the reward obtained by the agent performing action a in state s, s' is the next state the agent moves to after performing action a in state s and γ is the attenuation coefficient. In this case, we only need to train a network to calculate the state value, and the advantage value will be:

$$A_w(s, a) = r + \gamma V_w(s') - V_w(s)$$

Regarding the update method of policy-based algorithm, we have already mentioned it in section 4.3.1.2, in the actor it has the following form:

$$\theta_{t+1} = \theta_t + \alpha Q_w(s, a) \nabla_\theta ln\ \pi_\theta(a_t|s_t)$$

For the update method of value-based algorithm, critic, we only need to update according to the direction of the gradient descent of the value function:

$$w_{t+1} = w_t + \alpha A_w(s_t, a_t) \nabla_w Q_w(s_t, a_t)$$

The pseudo code of A2C is shown in algorithm 4..

Algorithm 5: Advantage Actor-Critic

```
1  **Initialize** $\theta, w$ randomly
2  **for** $i \in [0, max\_episodes]$ **do**
3      $s = s_0$
4      **while** $s$ *is NOT terminal* **do**
5          Sample action $a \sim \pi_\theta(a|s)$
6          Take action $a$, observe reward $r$, next state $s'$
7          $\theta \leftarrow \theta + \alpha Q_w(s, a) \nabla_\theta ln\ \pi_\theta(a|s)$
8          $A_w(s, a) = r + \gamma V_w(s') - V_w(s)$
9          $w \leftarrow w + \alpha A_w(s, a) \nabla_w Q_w(s, a)$
10         $s = s'$
11     **end**
12 **end**
```

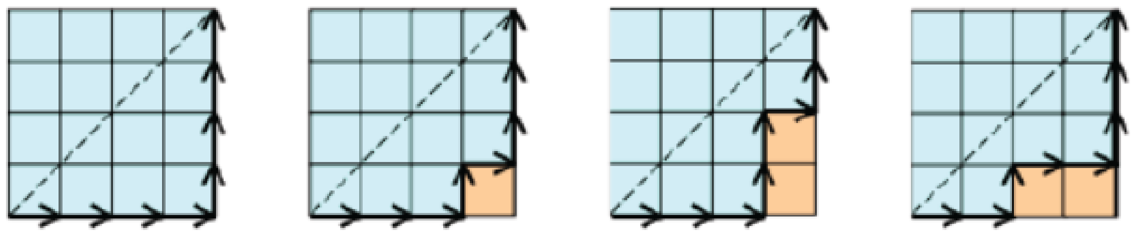


Figure 4.9: Different route for same start and end points

4.3.3 Route solving

In this section, we will introduce how to model the route problem and how to use reinforcement learning to solve it.

Given a task graph and determined NoC architecture, when the mapping result is determined, we need to plan the route according to the transmission in the task graph. Although the start and end points have been determined, the exploration space of the route is still very large. Figure 4. shows an example. We expect to calculate a route with as little contention as possible for all transmissions.

Without considering going in the opposite direction of destination, the number of times of data transmission along the X or Y axis are determined. For example, the transmission in Figure 4. transmit 4 times along the X axis and 4 times along the Y axis. These two numbers are certain regardless of the route. Different routes only affect the order in which data moves along the X axis or Y axis appears during transmission.

Based on this consideration, we only need to let our reinforcement learning model tell the data that, when it reaches a router, the next step should be along the X axis or along the Y axis. The direction of movement is towards the destination, so the data will definitely reach the destination it should go, and will not get lost in the wrong place.

Clarify the concepts in reinforcement learning, our environment is links in NoC. Some of them may have been occupied by other transmissions in a certain period of time. Given an edge e in task graph that needs to calculate route, our agent is data to be transferred of this edge and the state is the use of links in NoC. Specifically, we use a $N \times 4$ matrix to represent the state. N is the number of PEs, '4' represents 4 links connected to each PE (PE at the border has less than 4 links). When data arrives at a PE and starts to use a certain link connected to this PE for transmission, the corresponding position in the matrix will be set to 1. Links not used in the matrix correspond to 0.

The agent has two actions to choose from in each state, moving along the X axis or along the Y axis. This action will use the link in NoC, so after performing an action, set the corresponding position in the matrix to 1, and then move to the next state. Reward is the opposite number of contention times when transmitting in the route given by next state.

We devised a simple method to estimate contention times during transmission of a certain edge in the task graph. First, we need to record the usage status L of each link,that is, during which time period the link is occupied. Given an edge e that needs to calculate contention times, we find the latest available time t_1 among the links that need to be used by e according to L. Then we get the completion time t_2 of the task corresponding to the start point of this edge. After that, we subtract t_2 from t_1 to get the estimated contention times of edge e.

We use breadth first search to access each edge in the task graph that needs to be calculated for the route.

Regarding the order in which we calculate the route for edges in task graph, we sort according to the end time of the start point of edges. The sooner the task is completed, the sooner the data to be sent by this task can be calculated for the route.

Figure 4. is a flowchart of the routing algorithm.

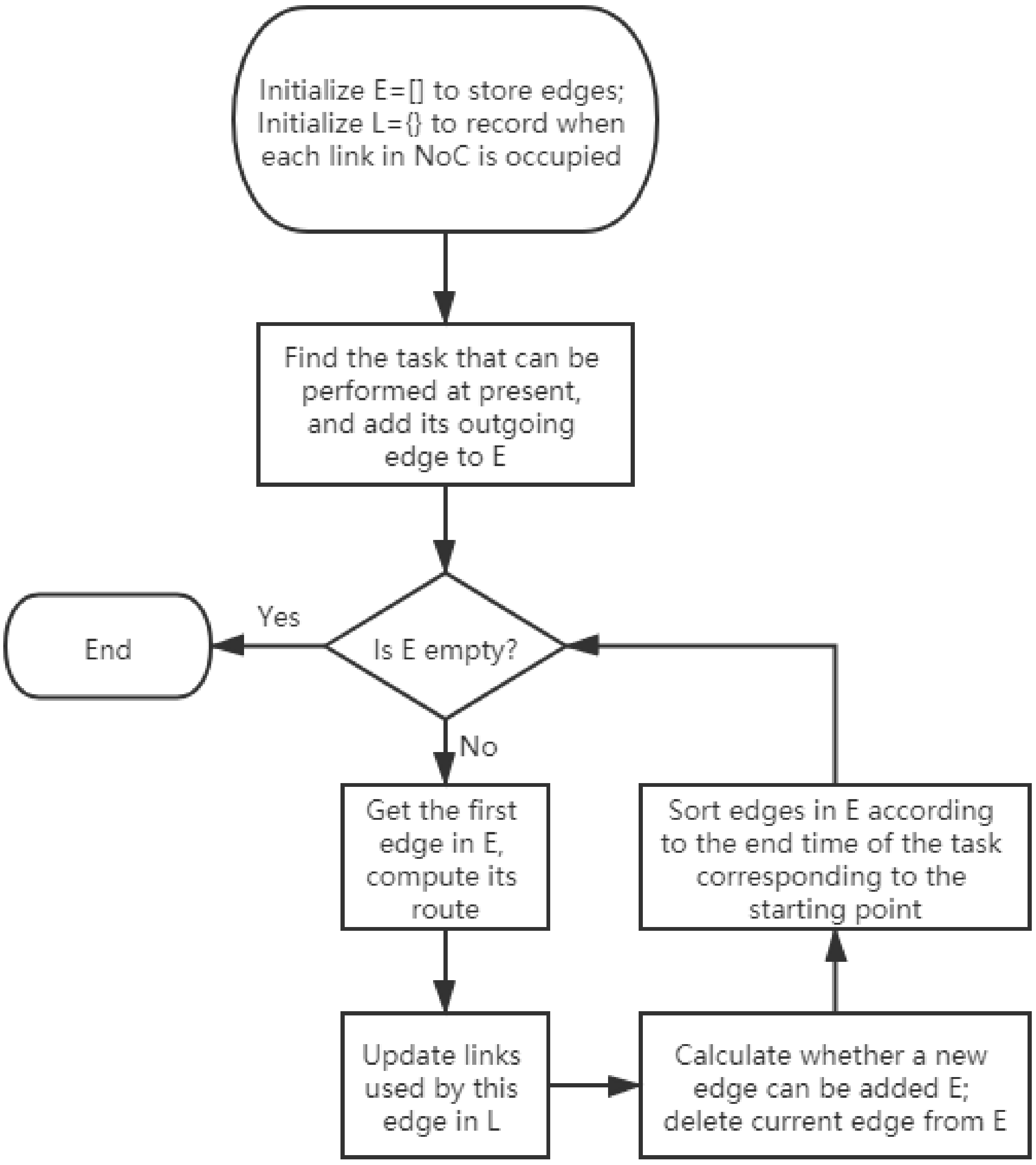

Initialize E=[] to store edges; Initialize L={} to record when each link in NoC is occupied
Find the task that can be performed at present, and add its outgoing edge to E
Is E empty?
Yes
End
No
Get the first edge in E, compute its route
Update links used by this edge in L
Calculate whether a new edge can be added E; delete current edge from E
Sort edges in E according to the end time of the task corresponding to the starting point

Figure 4.10: Routing algorithm

Chapter 5

Experiments and Discussion

5.1 Experimental Evaluation

Chapter 6

Conclusion and Future Work

6.1 Conclusion