Power, Area and Thermal Prediction in 3D Network-on-Chip using Machine Learning

Abhijith C, Anand M K
Department of Computer Science and Engineering
National Institute of Technology Karnataka (NITK)
Surathkal, India
Email: {abhijithc.242cs003, anandmk.242cs008}@nitk.edu.in

I. Experimental Results

This section focuses on the experimental setup, dataset generation, dataset preprocessing, performance of different models, and comparison of their performance.

A. Experimental Setup

The dataset is generated using PAT-Noxim and a shell script.PAT Noxim is a cycle-accurate simulator used to analyze power, area, and thermal metrics in networks-on-chip (NoC) architectures. The entire experiment is executed on a computer setup with the configurations: HP HP EliteDesk 800 G8 Tower PC, 16.0 GiB memory, 11th Gen Intel® Core™ i5-11500 @ 2.70GHz × 12 graphics, Mesa Intel® Graphics (RKL GT1), 1.0 TB disk capacity and Ubuntu 22.04.4 LTS.

B. Dataset Generation

The parameters used in NoC architecture configuration are as follows.

- **dimx/ dimy/ dimz**: Represents the dimensions of the NoC architecture in X, Y, and Z directions.
- **PIR (Packet Injection Rate)**: The rate at which packets are injected into the network.
- **Buffer Size**: Storage capacity of the input buffers in each router.
- **Routing Type**: Represents the packet routing algorithms, such as XYZ routing, OE 3D, or Fully adaptive routing.
  - **XYZ (XYZ Routing)**: Packets are routed in three dimensions sequentially.
  - **OE3D (Odd-Even 3D Routing)**: Extends the 2D odd-even routing strategy to three dimensions.
  - **Fully Adaptive Routing**: The path of each packet is determined based on congestion and link availability.
- **Traffic Type**: Represents the data traffic pattern in the network, such as Random.
  - **Random Traffic**: The source-destination pairs for packet communication are selected randomly.
- **Cycles**: Represents the number of simulation cycles the simulator runs.

The dataset is generated by simulating various configurations on PAT-Noxim. The configurations include mesh sizes ranging from 2 x 2 x 2 to 16 x 16 x 2, pir values from 0.01 to 0.1 with step size of 0.01, and buffer sizes 4, 6, 8, and 10. Three different routing algorithms are used: XYZ, Fully Adaptive, and Odd-Even 3D. The simulations are run for 200000 cycles. The traffic considered is Random.
The simulation output of PAT Noxim consists of the following parameters:

- **Steady State Temperature**: Refers to the final, stabilized temperature reached by the NoC system.
- **Core Average Temperature**: Represents the average temperature of all the processing cores in the NoC.
- **Memory Average Temperature**: Represents the average temperature of the memory units integrated within the NoC.
- **Router Average Temperature**: Represents the average temperature of all routers in the NoC.
- **Average Power**: Represents the total average power consumption of the NoC system.
- **Average Core Power**: Represents the average power consumption of all cores in the NoC.
- **Average Router Power**: Represents the average power consumption of the routers in the NoC.
- **Average Power Per Router**: Refers to the average power consumption per router in the NoC.
- **Layer Area**: Refers to the area occupied by a single layer in a 3D NoC.
- **Total Area**: The overall area used by the entire NoC system.
- **Area Per Core**: Refers to the area of each individual core in the NoC system.

C. Data Preprocessing

The simulation results of PAT-Noxim include various metrics. The parameters considered in this experiment are power metrics such as average power, average core power, average router power, and average power per router; area metrics such as layer area, area per core, and total area; temperature metrics such as steady state temperature, core average temperature, memory average temperature, and router average temperature. The categorical column, such as the routing algorithm, is encoded. The dataset is split into training and test sets (80% train and 20% test). The parameters are standardized to the same scale, which improves the performance of ML models.

D. Experiments conducted

The generated dataset is trained using AdaBoost with Decision Tree as the model. Decision tree regressor is used as a weak learner for the AdaBoost technique. Decision trees are non-linear models that split data based on feature values to predict a target. They are effective for modeling complex relationships between NoC parameters, which makes them ideal for use as base learners for AdaBoost. AdaBoost is an ensemble technique. It assigns weight to misclassified data points so subsequent learners focus on these more complex examples, thus improving accuracy.
The performance of the AdaBoost with decision tree model is then evaluated against a few other models that are trained on the same dataset. The models used are:

- Random Forest
- Decision Tree
- AdaBoost
- Support Vector Regressor (SVR)
- Linear Regression
- K-Nearest Neighbors
- 9-Layer CNN
- RNN (LSTM)
- Feedforward Neural Network(FNN)

E. Performance Metrics

The performance metrics used for evaluating the performance of different models are:

- **Mean Squared Error (MSE)**: Measures the average squared difference between the predicted values ($\hat{y}_i$) and actual values (y_i).

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- **Mean Absolute Error (MAE)**: Measures the average of the absolute differences between the predicted values ($\hat{y}_i$) and actual values (y_i).

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

- **R² (Coefficient of Determination)**: Represents the proportion of variance in the dependent variable (y_i) explained by the independent variables, where $\bar{y}$ is the mean of the actual values.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

F. Results Analysis

1) Temperature Analysis: This section analyzes temperature-related parameters such as steady-state temperature, core average temperature, memory average temperature, and router average temperature. Tables I and II analyze layer one and layer two steady-state temperatures. Layer one and two core average temperature metrics are provided in Tables III and IV. Tables V and VI analyze layer one and layer two memory average temperatures. Layer one and two router average temperature metrics are provided in Tables VII and VIII.

TABLE I: Performance Metrics for Different Algorithms - steady_state_temp_L0

Algorithm	**MSE**	**MAE**	R^2
AdaBoost with Decision Tree	0.0011	0.0125	0.9989
Random Forest	0.0012	0.0154	0.9987
Decision Tree	0.0021	0.0171	0.9978
KNN	0.0380	0.1171	0.9604
SVR	0.0613	0.1250	0.9362
AdaBoost	0.1979	0.3712	0.7939
Linear Regression	0.4100	0.4848	0.5731
9-Layer CNN	0.0252	0.0975	0.9737
RNN (LSTM)	0.0181	0.0813	0.9812
FNN	0.0360	0.1298	0.9635

TABLE II: Performance Metrics for Different Algorithms - steady_state_temp_L1

Algorithm	**MSE**	**MAE**	R^2
AdaBoost with Decision Tree	0.0011	0.0127	0.9988
Random Forest	0.0012	0.0153	0.9987
Decision Tree	0.0020	0.0169	0.9979
KNN	0.0383	0.1175	0.9601
SVR	0.0622	0.1252	0.9353
AdaBoost	0.1931	0.3624	0.7990
Linear Regression	0.4123	0.4862	0.5709
9-Layer CNN	0.0254	0.0981	0.9736
RNN (LSTM)	0.0177	0.0801	0.9816
FNN	0.0362	0.1301	0.9633

TABLE III: Performance Metrics for Different Algorithms - core_avg_temp_L0

Algorithm	**MSE**	**MAE**	R^2
AdaBoost with Decision Tree	0.0077	0.0415	0.9922
Random Forest	0.0069	0.0436	0.9930
Decision Tree	0.0106	0.0506	0.9892
AdaBoost	0.3740	0.4481	0.6203
KNN	0.2283	0.2017	0.7683
SVR	0.4741	0.2536	0.5188
Linear Regression	0.6070	0.4970	0.3839
9-Layer CNN	0.0276	0.1096	0.9720
RNN (LSTM)	0.0398	0.1269	0.9596
FNN	0.0378	0.1323	0.9627

2) Power Analysis: This section analyzes power-related parameters such as average power, average core power, average power per router, and average router power. Table IX analyzes the average core power. Average power metrics are provided in Table X. Table XI analyzes the average power per router. Average router power metrics are provided in Table XII.

3) Area Analysis: This section analyzes area-related parameters such as layer area, total area, and area per core. Table XIII analyzes the layer area. Total area metrics are provided in Table XIV. Table XV analyzes the area per core.

G. Comparison study

1) Temperature Analysis: This section compares the performance of different models across parameters such as steady-state temperature, core average temperature, memory average

TABLE IV: Performance Metrics for Different Algorithms - core_avg_temp_L1

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0.0034	0.0267	0.9966
Random Forest	0.0027	0.0265	0.9973
Decision Tree	0.0043	0.0307	0.9958
SVR	0.3460	0.2720	0.6582
KNN	0.2191	0.2000	0.7835
AdaBoost	0.2557	0.4098	0.7474
Linear Regression	0.9037	0.5865	0.1072
9-Layer CNN	0.0213	0.0898	0.9790
RNN (LSTM)	0.0229	0.0896	0.9774
FNN	0.0310	0.1200	0.9696

TABLE V: Performance Metrics for Different Algorithms - mem_avg_temp_L0

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0.0064	0.0432	0.9936
Random Forest	0.0051	0.0398	0.9949
Decision Tree	0.0082	0.0471	0.9918
KNN	0.4311	0.2576	0.5710
AdaBoost	0.1985	0.3481	0.8025
SVR	0.9742	0.3193	0.0304
Linear Regression	0.8829	0.4742	0.1213
9-Layer CNN	0.0349	0.1198	0.9653
RNN (LSTM)	0.0323	0.1170	0.9679
FNN	0.0510	0.1589	0.9511

TABLE VI: Performance Metrics for Different Algorithms - mem_avg_temp_L1

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0.0020	0.0212	0.9980
Random Forest	0.0017	0.0198	0.9983
Decision Tree	0.0030	0.0235	0.9971
KNN	0.2512	0.2029	0.7556
AdaBoost	0.1464	0.2762	0.8576
SVR	0.3990	0.2770	0.6118
Linear Regression	1.0030	0.5763	0.0242
9-Layer CNN	0.0195	0.0804	0.9810
RNN (LSTM)	0.0166	0.0774	0.9838
FNN	0.0314	0.1182	0.9695

TABLE VII: Performance Metrics for Different Algorithms - router_avg_temp_L0

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0.0047	0.0313	0.9952
Random Forest	0.0050	0.0362	0.9950
Decision Tree	0.0075	0.0413	0.9925
KNN	0.2341	0.1797	0.7651
AdaBoost	0.2079	0.3494	0.7915
SVR	0.5236	0.2204	0.4748
Linear Regression	0.5870	0.4415	0.4112
9-Layer CNN	0.0233	0.0906	0.9766
RNN (LSTM)	0.0229	0.0940	0.9770
FNN	0.0416	0.1258	0.9593

TABLE VIII: Performance Metrics for Different Algorithms - router_avg_temp_L1

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0.0020	0.0193	0.9981
Random Forest	0.0020	0.0211	0.9981
Decision Tree	0.0033	0.0244	0.9968
KNN	0.2300	0.1786	0.7807
AdaBoost	0.1616	0.3120	0.8459
SVR	0.3708	0.2496	0.6464
Linear Regression	0.9080	0.5579	0.1340
9-Layer CNN	0.0156	0.0688	0.9851
RNN (LSTM)	0.0155	0.0653	0.9853
FNN	0.0379	0.0851	0.9630

TABLE IX: Performance Metrics for Different Algorithms - avg_cores_power

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0.0004	0.0063	0.9996
Random Forest	0.0004	0.0076	0.9996
Decision Tree	0.0007	0.0081	0.9993
SVR	0.0027	0.0429	0.9974
KNN	0.0062	0.0614	0.9939
AdaBoost	0.0695	0.2264	0.9309
Linear Regression	0.1159	0.2551	0.8849
9-Layer CNN	0.0043	0.0497	0.9958
RNN (LSTM)	0.0030	0.0390	0.9970
FNN	0.0004	0.0076	0.9996

TABLE X: Performance Metrics for Different Algorithms - avg_power

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0.0007	0.0086	0.9993
Random Forest	0.0007	0.0101	0.9993
Decision Tree	0.0012	0.0108	0.9988
SVR	0.0029	0.0427	0.9971
KNN	0.0066	0.0611	0.9933
AdaBoost	0.1072	0.2854	0.8927
Linear Regression	0.1355	0.2651	0.8644
9-Layer CNN	0.0045	0.0499	0.9955
RNN (LSTM)	0.0039	0.0424	0.9961
FNN	0.0006	0.0096	0.9994

TABLE XI: Performance Metrics for Different Algorithms - avg_power_per_router

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0.0040	0.0204	0.9959
Random Forest	0.0079	0.0371	0.9919
KNN	0.0080	0.0368	0.9918
Decision Tree	0.0121	0.0393	0.9877
SVR	0.0143	0.0796	0.9854
AdaBoost	0.1188	0.2933	0.8785
Linear Regression	0.1873	0.3189	0.8085
9-Layer CNN	0.0139	0.0795	0.9858
RNN (LSTM)	0.0197	0.0947	0.9799
FNN	0.0063	0.0337	0.9936

TABLE XII: Performance Metrics for Different Algorithms - avg_routers_power

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0.0012	0.0123	0.9987
Random Forest	0.0023	0.0170	0.9976
Decision Tree	0.0034	0.0186	0.9965
SVR	0.0058	0.0494	0.9941
KNN	0.0085	0.0552	0.9913
AdaBoost	0.2717	0.4722	0.7219
Linear Regression	0.2406	0.3368	0.7537
9-Layer CNN	0.0066	0.0550	0.9933
RNN (LSTM)	0.0075	0.0504	0.9923
FNN	0.0019	0.0159	0.9981

TABLE XIII: Performance Metrics for Different Algorithms - layer_area

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	3.37E-32	2.77E-17	1.0000
Random Forest	8.04E-05	0.0029	0.9999
Decision Tree	0.0003	0.0025	0.9997
SVR	0.0041	0.0568	0.9960
KNN	0.0057	0.0594	0.9944
AdaBoost	0.0335	0.1462	0.9673
Linear Regression	0.1023	0.2403	0.9000
9-Layer CNN	0.0042	0.0493	0.9959
RNN (LSTM)	0.0025	0.0375	0.9976
FNN	0.0001	0.0036	0.9999

TABLE XIV: Performance Metrics for Different Algorithms - total_area

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	1.81E-10	6.88E-07	1.0000
Random Forest	8.04E-05	0.0029	0.9999
Decision Tree	0.0003	0.0025	0.9997
SVR	0.0041	0.0568	0.9960
KNN	0.0057	0.0594	0.9944
AdaBoost	0.0333	0.1469	0.9674
Linear Regression	0.1023	0.2403	0.9000
9-Layer CNN	0.0043	0.0504	0.9957
RNN (LSTM)	0.0023	0.0354	0.9977
FNN	0.0001	0.0036	0.9999

TABLE XV: Performance Metrics for Different Algorithms - area_per_core

Algorithm	MSE	MAE	R^2
AdaBoost with Decision Tree	0	0	1
AdaBoost	0	0	1
Random Forest	0	0	1
Decision Tree	0	0	1
SVR	0	0	1
KNN	0	0	1
Linear Regression	0	0	1
9-Layer CNN	0	0	1
RNN (LSTM)	0	0	1
FNN	0	0	1

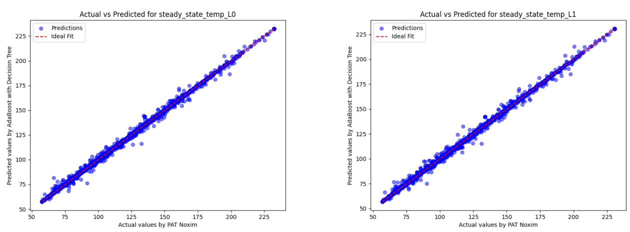
temperature, and router average temperature. After studying Tables I and II, it is evident that AdaBoost with Decision Tree and Random Forest achieved minimal errors (MSE, MAE) and the highest R^2 values ($\geq$0.998 $\geq$0.998) for both layers. Algorithms like KNN and SVR had higher errors and lower R^2 values. Tables III, IV, V, VI, VII, and VIII show that AdaBoost with Decision Tree and Random Forest performs well with minimal MSE and MAE values and R^2 values close to 1 across both layers. Linear regression and SVR show the worst performance.

2) Power Analysis: This section compares the performance of different models across parameters such as average power, average core power, average power per router, and average router power. After studying Table IX, it is evident that AdaBoost with Decision Tree and Random Forest show close to zero errors (MSE, MAE) and the highest R^2 values ($\geq$0.99). Algorithms like Linear regression and KNN had higher errors and lower R^2 values. Tables X, XII, and XI show that AdaBoost with Decision Tree performs better than all other algorithms with minimal MSE and MAE values and R^2 values close to 1 for average power metrics. Linear regression and KNN show the worst performance with relatively high errors.

3) Area Analysis: This section compares the performance of different models across parameters such as layer area, total area, and area per core. After studying Tables XIII and XIV, it is evident that AdaBoost with Decision Tree and Random Forest show near-perfect performance with close to zero errors (MSE, MAE) and R^2 values close to 1. Algorithms like SVR and KNN had higher errors and lower R^2 values. Table XV shows that all algorithms made perfect predictions with MSE and MAE values as 0 and R^2 value as 1 because the area per core is a constant value.

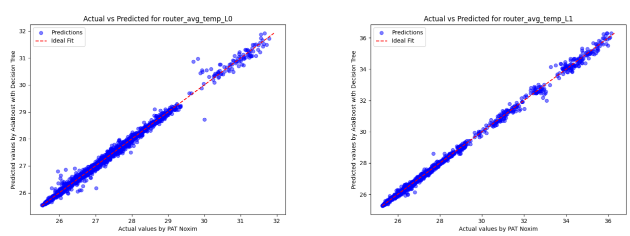
AdaBoost with Decision Tree and Random Forest consistently outperformed all other models with the lowest MSE and MAE values and the highest R^2 values across the prediction of all the power, area, and thermal metrics. Random Forest shows slightly less performance than AdaBoost with Decision Tree. Linear Regression and SVR show the worst performance with higher errors and low R^2 values. It is concluded that AdaBoost with Decision Tree is the most consistent and accurate model among all other models. This model works by training a series of 50 decision trees, each aimed at reducing the overall prediction error. Each round assigns higher weights to the samples, which are hard to predict. The subsequent trees give more importance to those challenging cases. The final prediction is the aggregation of each tree, which overall makes a robust prediction model.

Figures 1 to 7 compare actual values from PAT Noxim and predicted values from the AdaBoost model with the decision tree. The blue dots are individual data points from the test dataset, where each dot shows how closely the model's predictions match the actual values. The red dashed line represents the ideal fit where the model's predictions match the actual values. If points are closely clustered around the red line, this suggests that the model's predictions are relatively accurate.A larger spread from the red line indicates higher prediction errors. Figures 1 to 4 show that the actual and predicted values are almost identical for the temperature parameters. Temperature is measured in degrees Celsius. The blue points and red lines are nearly perfectly aligned. Figures 5 and 6 illustrate that the predicted and actual values are perfectly aligned, highlighting the effectiveness of the AdaBoost model with the decision tree in predicting power values. Power is calculated in (J/cycle).Figure 7 demonstrates that the area is perfectly predicted by the AdaBoost model with the decision tree. The area is measured in (μm^2).



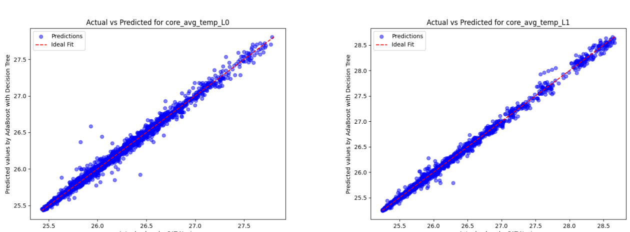
(a) Actual vs Predicted for steady_state_temp_L0 (b) Actual vs Predicted for steady_state_temp_L1

Fig. 1: Actual vs Predicted for steady_state_temp_L0 and steady_state_temp_L1



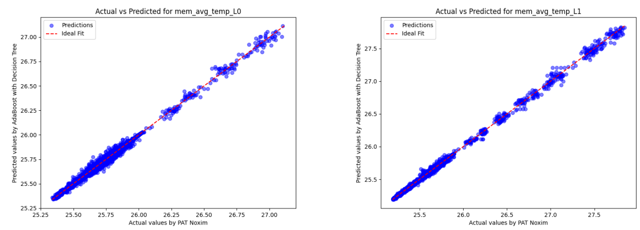
(a) Actual vs Predicted for router_avg_temp_L0 (b) Actual vs Predicted for router_avg_temp_L1

Fig. 2: Actual vs Predicted for router_avg_temp_L0 and router_avg_temp_L1



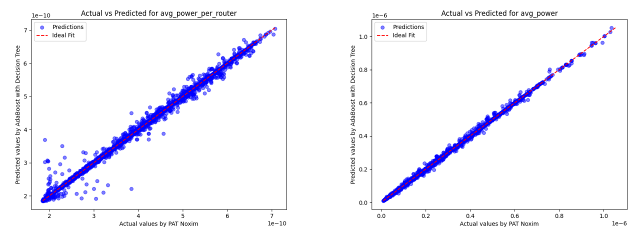
(a) Actual vs Predicted for core_avg_temp_L0 (b) Actual vs Predicted for core_avg_temp_L1

Fig. 3: Actual vs Predicted for core_avg_temp_L0 and core_avg_temp_L1



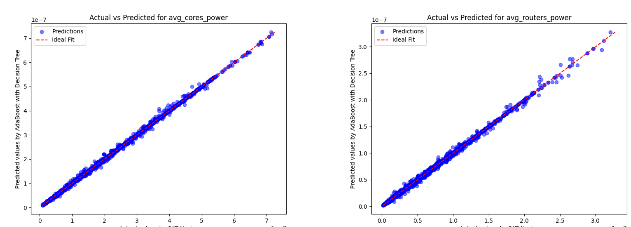
(a) Actual vs Predicted for mem_avg_temp_L0 (b) Actual vs Predicted for mem_avg_temp_L1

Fig. 4: Actual vs Predicted for mem_avg_temp_L0 and mem_avg_temp_L1



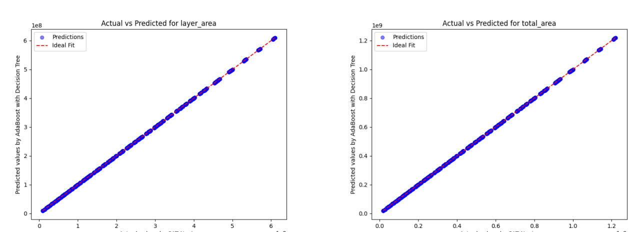
(a) Actual vs Predicted for avg_power_per_router (b) Actual vs Predicted for avg_power

Fig. 5: Actual vs Predicted for avg_power_per_router and avg_power



(a) Actual vs Predicted for avg_cores_power (b) Actual vs Predicted for avg_routers_power

Fig. 6: Actual vs Predicted for avg_cores_power and avg_routers_power



(a) Actual vs Predicted for layer_area (b) Actual vs Predicted for total_area

Fig. 7: Actual vs Predicted for layer_area and total_area

H. Execution Time Comparison

The prediction time of the AdaBoost with Decision Tree model is compared with the simulation time of PAT Noxim simulator for various configurations. The configurations include sqaure mesh sizes ranging from 2 x 2 x 2 to 16 x 16 x 2, pir value of 0.1 and buffer size 8. The routing algorithm are used is XYZ. The simulations are run for 200000 cycles. The traffic considered is Random. The time is recorded in seconds.

Mesh Size	PAT Noxim (s)	Proposed Method (s)
2x2x2	13	0.3359
3x3x2	13	0.3069
4x4x2	18	0.4791
5x5x2	26	0.5367
6x6x2	33	0.3252
7x7x2	47	0.5013
8x8x2	78	0.3649
9x9x2	158	0.3459
10x10x2	231	0.1781
11x11x2	318	0.4136
12x12x2	443	0.3890
13x13x2	539	0.3383
14x14x2	673	0.2346
15x15x2	833	0.2697
16x16x2	992	0.4806

TABLE XVI: Simulation time for PAT Noxim and prediction time for the proposed method across different mesh sizes.

It is observed from Table XVI that the predicted time of the proposed method is much less compared to the simulation time for the PAT Noxim simulator.

I. Scalability

The PAT Noxim simulator can only simulate a restricted range of mesh sizes up to 16 x 16 x 2. In comparison to the PAT Noxim, the proposed method can predict Power, Area, and Thermal metrics for much larger mesh sizes. The configurations include pir value of 0.05 and buffer size 10. The routing algorithm are used is XYZ. The results of predictions for higher configurations are given in Table XVII.

Parameter	32*32*2	50*50*2	64*64*2
Steady State Temp L0	395.228485	441.352966	481.141815
Steady State Temp L1	378.136719	402.036530	425.022980
Router Avg Temp L0	29.939732	31.092331	32.057034
Router Avg Temp L1	28.664806	29.063614	29.503901
Core Avg Temp L0	26.688856	26.758017	26.829973
Core Avg Temp L1	26.616013	26.842722	27.072412
Mem Avg Temp L0	25.991127	26.057503	26.102097
Mem Avg Temp L1	25.969568	26.130873	26.268902
Total Area	3.295609e+09	5.513879e+09	7.208206e+09
Avg Power	3.00e-06	4.00e-06	5.00e-06
Avg Cores Power	2.00e-06	3.00e-06	4.00e-06
Avg Routers Power	7.01e-07	1.00e-06	1.00e-06
Avg Power Per Router	9.69e-10	1.22e-09	1.44e-09
Layer Area	1644980000	2725601000	3552910000
Area Per Core	4695230	4695230	4695230

TABLE XVII: Higher Configuration Results for Different Dimensions

J. Adaptability

1) Adaptability to routing algorithms: The proposed method is capable of predicting for configurations that include different routing algorithms such as XYZ, OE 3D, and Fully Adaptive routing. Tables XVIII, XIX, and XX represent the predicted results of the proposed model and simulation results of PAT Noxim with XYZ, OE 3D, and Fully Adaptive as routing algorithms for the following configurations: Mesh size 8 x 8 x 2, buffer size 10, PIR 0.05, minimum packet size 4, maximum packet size 8, and traffic type random.

Parameter	Proposed Method	PAT Noxim
Steady State Temp L0	167.580813	167.580813
Steady State Temp L1	165.214625	165.474859
Router Avg Temp L0	29.136848	29.136848
Router Avg Temp L1	28.640883	28.640883
Core Avg Temp L0	26.962495	26.962495
Core Avg Temp L1	26.725548	26.726645
Mem Avg Temp L0	26.008092	26.008092
Mem Avg Temp L1	25.879767	25.879767
Total Area	304998000.0	304998000.0
Avg Power	3.073450e-07	3.073450e-07
Avg Cores Power	2.224900e-07	2.226330e-07
Avg Routers Power	8.526710e-08	8.526710e-08
Avg Power Per Router	6.661490e-10	6.661490e-10
Layer Area	152499000.0	152499000.0
Area Per Core	4695230.0	4695230.0

TABLE XVIII: XYZ Routing

Parameter	Proposed Method	PAT Noxim
Steady State Temp L0	124.186594	124.186594
Steady State Temp L1	122.930750	122.930750
Router Avg Temp L0	26.989448	26.989448
Router Avg Temp L1	26.759092	26.759092
Core Avg Temp L0	26.195203	26.195203
Core Avg Temp L1	26.057848	26.057848
Mem Avg Temp L0	25.795822	25.795822
Mem Avg Temp L1	25.700916	25.700916
Total Area	304998000.0	304998000.0
Avg Power	2.051910e-07	2.051910e-07
Avg Cores Power	1.617970e-07	1.615370e-07
Avg Routers Power	4.365420e-08	4.365420e-08
Avg Power Per Router	3.410490e-10	3.410490e-10
Layer Area	152499000.0	152499000.0
Area Per Core	4695230.0	4695230.0

TABLE XIX: OE 3D Routing

2) Adaptability to 2D: The proposed method is capable of predicting Power, Area, and Thermal metrics for 2D mesh sizes as shown in Table XXI.

Parameter	Proposed Method	PAT Noxim
Steady State Temp L0	105.046969	105.053375
Steady State Temp L1	104.180359	104.180359
Router Avg Temp L0	26.174891	26.174891
Router Avg Temp L1	26.033525	26.033525
Core Avg Temp L0	25.92038	25.92038
Core Avg Temp L1	25.812806	25.812806
Mem Avg Temp L0	25.739359	25.739359
Mem Avg Temp L1	25.651266	25.651266
Total Area	304998000.0	304998000.0
Avg Power	1.602690e-07	1.602880e-07
Avg Cores Power	1.348980e-07	1.348900e-07
Avg Routers Power	2.538780e-08	2.538780e-08
Avg Power Per Router	1.982700e-10	1.983420e-10
Layer Area	152499000.0	152499000.0
Area Per Core	4695230.0	4695230.0

TABLE XX: Fully Adaptive Routing

Parameter	Value
Dim X	4
Dim Y	4
Buffer Size	10
Packet Size Min	4
Packet Size Max	8
Routing Type	XYZ
Selection Strategy	Thermal
Traffic Type	Random
Injection Rate	0.05
Steady State Temp L0	99.3473
Router Avg Temp L0	27.754863
Core Avg Temp L0	26.844844
Mem Avg Temp L0	25.852469
Total Area	76249500.0
Avg Power	7.773150e-08
Avg Cores Power	6.081240e-08
Avg Routers Power	1.691910e-08
Avg Power Per Router	5.287230e-10
Layer Area	38124800.0
Area Per Core	4695230.0

TABLE XXI: Results for 2D mesh size