Machine Learning for Interconnect Network Traffic Forecasting: Investigation and Exploitation

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ABSTRACT

Interconnect networks play a key role in high-performance computing (HPC) systems. Parallel discrete event simulation (PDES) has been a long-standing pillar for studying large-scale networking systems by replicating the real-world behaviors of HPC facilities. However, the simulation requirements and computational complexity of PDES are growing at an intractable rate. An active research topic is to build a surrogate-ready PDES framework where an accurate surrogate model built on machine learning can be used to forecast network traffic for improving PDES. In this paper, we make the first attempt to introduce two representative time series methods, the Autoregressive Integrated Moving Average (ARIMA) and the Adaptive Long Short-Term Memory (ADP-LSTM), to forecast the traffic in interconnect networks, using the Dragonfly system as a representative example. The proposed ADP-LSTM can efficiently adapt to the ever-changing network traffic, facilitating the forecasting capability for intricate network traffic, by incorporating a novel online learning strategy. Our preliminary analysis demonstrates promising results and shows that ADP-LSTM can consistently outperform ARIMA with significantly less time overhead.

ACM Reference Format:
Xiongxiao Xu, Xin Wang, Elkin Cruz-Camacho, Christopher D. Carothers, Kevin A. Brown, Robert B. Ross, Zhiling Lan, and Kai Shu. 2023. Machine Learning for Interconnect Network Traffic Forecasting: Investigation and Exploitation. In *ACM SIGSIM Conference on Principles of Advanced Discrete Simulation (SIGSIM-PADS '23), June 21–23, 2023, Orlando, FL, USA*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3573900.3591123

SIGSIM-PADS '23, June 21–23, 2023, Orlando, FL, USA
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ACM ISBN 979-8-4007-0030-9/23/06.
https://doi.org/10.1145/3573900.3591123

1 INTRODUCTION

High-performance computing (HPC) systems rely on efficient and scalable interconnect networks to support unprecedented system size at a reasonable cost. For example, the Dragonfly network is a hierarchical, high-radix, low-diameter topology that can reduce the network cost with high-bandwidth and low-latency service [15, 16]. Such a unique network topology has been widely adopted by various HPC facilities, e.g., the National Energy Research Scientific Computing Center and the Argonne Leadership Computing Facility.

Parallel discrete event simulation (PDES) has been successfully applied for modeling network data flows and hierarchical storage systems, including transportation and mobility applications, internet and cybersecurity simulations, and simulations for hardware co-design [23]. Although PDES modeling frameworks, such as ROSS [3] and CODES [22], can conduct simulations on Dragonfly networks, the high computational complexity hinders its deployment in practice. For example, PDES takes four hours to simulate the 4,096-node MILC running for 122 milliseconds [27].

To address the issue, high-fidelity *surrogate* models are desired to accelerate PDES due to their potential for forecasting network-level performance by capturing temporal correlation in the network traffic. We envision a surrogate-ready PDES where the simulation alternates between two phases: a detailed PDES phase where the application workload is simulated fully and a surrogate phase where the induced traffic is forecasted to fast-forward PDES through the time period forecatsed by the surrogate. However, designing effective surrogate models faces several challenges. First, when simulating multiple HPC applications on a large-scale interconnect network, the fierce contention among the applications for shared resources can have a detrimental effect on the forecasting accuracy of surrogate models [20, 28]. Second, the dynamically-changing network conditions pose additional challenges, requiring the surrogate model to be able to adaptively incorporate evolving network information. Third, PDES events are generated at a rapid pace. There is a pressing need to ensure forecast efficiency from surrogate models, in addition to maintaining effectiveness.

To tackle the above challenges, we make the first attempt to investigate the potential for machine learning frameworks to build surrogate models for interconnect network traffic forecasting. Specifically, we utilize ARIMA and ADP-LSTM, two representative time series forecasting models, as surrogate models to accelerate PDES models, with a 72-node Dragonfly simulation as a case study. The proposed algorithm Adaptive Long Short-Term Memory (ADP-LSTM) integrates the strength of offline learning and online learning to adapt to intricate and dynamic network traffic. In the experiments, we conduct a preliminary study to compare the performance and time overhead of ARIMA and ADP-LSTM. The experimental results show ADP-LSTM can obtain superior performance than ARIMA and ADP-LSTM requires significantly less time overhead.

2 RELATED WORK

In this section, we briefly describe the related work on (1) machine learning for traffic forecasting, and (2) traffic forecasting on interconnect networks.

2.1 Machine Learning for Traffic Forecasting

The research field of traffic forecasting has existed for many years [13, 17, 24, 29, 37]. The earlier researchers utilize statistical method ARIMA [1, 18, 19, 30, 31] to forecast traffic. Afterward, the researcher employ traditional machine learning, such as neural network [6, 8] and Support Vector Machine (SVM) [4, 14]. However, the classical statistical and traditional machine learning approaches are relatively weak due to their oversimplified assumptions and limited representation capabilities, respectively. Nowadays, deep learning methods are popular in traffic forecasting due to its strong expressive capabilities. The existing deep learning methods for traffic forecasting can be classified into Feedforward Neural Network (FNN) [9, 36, 40], Convolutional Neural Network (CNN) [33, 35, 39], Recurrent Neural Network (RNN) and LSTM [7, 21, 35], Graph neural network (GNN) [5, 34, 44] and Transformer [26, 38, 41, 43].

2.2 Network Traffic Forecasting

A few studies have been conducted on network traffic prediction. Huang et al. [12] propose a table-driven framework called Network Traffic forecasting Table (NTPT) to predict traffic in the on-chip interconnect network. Huang et al. [11] propose a table-based traffic predictor which can capture application traffic patterns. Zhou et al. [42] design a traffic forecasting strategy and propose three latency trade-off models. Other studies focus on traffic forecasting on software defined network. Azzouni et al. [2] propose the NeuTM, a model based on Long Short-Term Memory Recurrent Neural Networks (LSTM RNNs), for network traffic matrix forecasting. The existing studies mainly focus on tile-based network-on-chip or wide-area network at a small scale. Different from the existing research, we target the traffic forecasting problem in the Dragonfly interconnect network which features a hierarchical topology. In the case study shown in Section 4, we investigate the network traffic forecasting on a 252-port dragonfly network. To the best of our knowledge, this is the first paper to focus on network traffic forecasting in the Dragonfly network.

3 NETWORK TRAFFIC FORECASTING

In this section, we formally define the problem, and assess two machine learning aproaches based surrogate models.

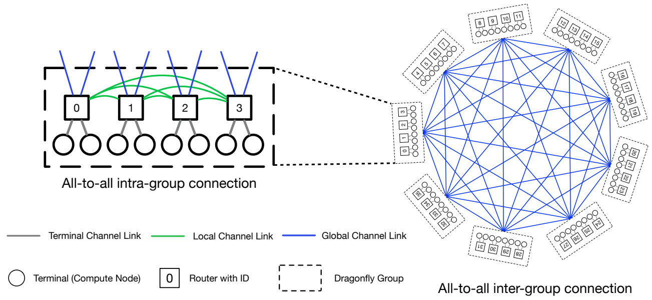


Figure 1: The illustration of the 1D Dragonfly network.

3.1 Problem Definition

We focus on the 1D Dragonfly network as shown in Figure 1 with n routers $R_i \in \{R_1, R_2, ..., R_n\}$. Each router R_i has m ports, including terminal ports, local ports, and global ports. We denote terminal ports as $T_{j_T} \in \{T_1, T_2, ..., T_{m_T}\}$, local ports as $L_{j_L} \in \{L_1, L_2, ..., L_{m_L}\}$, and global ports as $G_{j_G} \in \{G_1, G_2, ..., G_{m_G}\}$. The $t \in \{1, 2, ..., T\}$ is defined as the set of time intervals. In a time interval, application processes on the ports communicate with each other, creating traffic on the network. We define the traffic as the size of the packet in/out of a port during a time interval. Formally, we use $y^t_{i,j}$ to denote the total traffic of port j on the router i in a time interval t. Since we only focus on port-level forecasting in this paper, we ignore the i and j in the following descriptions. Our study considers *a k-step delay*, meaning at time t our forecast model can access the data at $t - k$ and before. We formally define the problem as follows:

Problem Statement: Given historical data $\mathcal{H}_{t-k} = \{y_1, y_2, \ldots, y_{t-k}\}$ of port j on router i, the network traffic forecasting problem aims to forecast traffic y_t of port j on router i at time interval t (*k-step delay*).

3.2 Surrogate Modeling

To capture the complex network traffic, we investigate two types of surrogate methods: ARIMA and ADP-LSTM, due to success in traffic forecast scenarios such as road traffic forecasting [1, 35].

ARIMA (AutoRegressive Integrated Moving Average) [1] is a classical statistical time series forecasting method and has been widely adopted in traffic forecasting. The $ARIMA(p, d, q)$ has three parameters: p, d, and q. p is the order of the autoregressive model; q is the order of the moving-average model; d is the degree of differentiation, which enables ARIMA to model non-stationary signals.

ADP-LSTM (Adaptive Long Short-Term Memory) is developed based on the LSTM [10] framework. LSTM is shown to be effective in addressing the gradient vanishing problem and capable of capturing long-term dependency [25]. However, the network traffic on the interconnect networks such as Dragonfly networks is intricate since the Dragonfly network has a more complex topology. To capture the complex network traffic, we propose ADP-LSTM which can dynamically update parameters and adapt to the evolving network traffic, by incorporating an online learning strategy into the standard offline learning. Specifically, offline learning means the model is trained before the inference, and online learning denotes the trained model is dynamically adjusted based on the newly accessible data during the inference. Such flexibility enables the capacity of adapting dynamically to complex network traffic and further facilitating the traffic forecasting performance.

3.3 Model Training and Inference

ARIMA. During the training, ARIMA fits the data stream with a fixed-length historical data window; in the inference, ARIMA forecasts the traffic based on the fitted model. ARIMA forecasts one-step traffic at a time. By sliding the historical data window and iterating the above processes, ARIMA can continuously perform forecasting to get multi-step traffic.

ADP-LSTM. As shown in Algorithm 1, the training of ADP-LSTM includes two phases: an offline learning phase and an online learning phase. In the offline learning phase (lines 2 – 4), we obtain a small portion of data for the training of a desirable ADP-LSTM. The remaining data is for the inference (lines 5 – 11). In the online learning phase (lines 8 – 10), we tune ADP-LSTM with a single newly accessible data to adapt dynamically to the changing traffic. In the inference, ADP-LSTM forecasts one-step traffic at a time and continuously forecasts to obtain the multi-step traffic by sliding a fixed window.

Note that in the setting of a k-step delay, our surrogate models can only access the actual data with a delay of k intervals. The historical data window consists of the actual data when available and the subsequent forecasted data.

Algorithm 1 The algorithm of ADP-LSTM

```
Require: Historical data $\mathcal{H}_T = \{y_1, y_2, ..., y_T\}$ in a time period $T$
    and $l$ denoting the fixed length of historical data window.
 1: Split historical data $\mathcal{H}_T$ into $\mathcal{H}_{train}$ and $\mathcal{H}_{test}$
 2: while offline learning phase do
 3:     Train ADP-LSTM with $((y_{t-l}, y_{t-l+1}, ..., y_{t-1}), y_t)$ in $\mathcal{H}_{train}$
 4: end while
 5: while inference do
 6:     Forecast traffic $\tilde{y}_t$ at time $t$ based on a historical data window, concatenated by actual data $(y_{t-l}, y_{t-l+1}, ..., y_{t-k})$ and
        forecasted data $(\tilde{y}_{t-k+1}, \tilde{y}_{t-k+2}, ..., \tilde{y}_{t-1})$
 7:     Access a newly acquired data $y_{t-k+1}$
 8:     while online learning phase do
 9:         Tune ADP-LSTM with the newly accessible data
            $((y_{t-(k+l-1)}, y_{t-(k+l-2)}, ..., y_{t-k}), y_{t-k+1})$
10:     end while
11: end while
```

4 EXPERIMENTAL EVALUATION

Network Simulator. We utilize CODES to generate the network traffic data. CODES [22] is a packet-level, high-fidelity simulation tool that can collect detailed network information on Dragonfly networks. We simulate both Jacobi 3D and MILC which run simultaneously on a 72-node Dragonfly system. Each application occupies half of all the compute nodes. We collect the aggregated traffic volume that each port routed in a series of time intervals. The time interval size is set to 300 microseconds.

Network Topology. The Dragonfly network (see Figure 1) has a hierarchical design, consisting of the all-to-all inter-group connection and intra-group connection. In the network, the 72 compute nodes and 36 routers are averagely divided into 9 groups, which are all-to-all connected. Within a group, the routers are also all-to-all connected. Each router has 7 ports, including 2 terminal ports, 3 local ports, and 2 global ports. The total number of ports is 252.

Applications. Our workload includes two widely-used applications [27]: (1) **Jacobi 3D** is a widely used scientific application. The processes of Jacobi 3D are formed in a $4 \times 3 \times 3$ Cartesian grid and every process communicates with 6 neighbors at each iteration, and (2) **MILC** is developed by the MIMD Lattice Computation (MILC) collaboration for quantum chromodynamics (QCD). It executes simulations of four-dimensional SU (3) lattice gauge theory.

Job Placement. We investigate two job placement policies [28]: (1) *Contiguous Placement* selects computer nodes consecutively for the processes of the job to occupy, and (2) *Random Placement* selects computer nodes randomly for the processes of the job to occupy.

Adaptive routing [28] is adopted in our simulation. It routes packets along the minimal path or the non-minimal path based on the network congestion state. When a non-minimal path is selected, the packets will be minimally routed into a randomly intermediate router, then minimally forwarded to their destinations. Accordingly, we denote the two settings as *cont-adp* and *random-adp*.

Model Training and Testing. The dataset consist of 1,580 and 1,630 data for *cont-adp* and *random-adp*, respectively. We use the first 200 data for training and the rest for testing. For ARIMA, the hyperparameters p, d and q are set to 13, 1 and 5, respectively. For ADP-LSTM, the hidden dimension and learning rate are set to 64 and 0.001, respectively. The historical data window lengths for ARIMA and LSTM are 200 and 13, respectively.

Evaluation Metrics. We use the following metrics to assess the effectiveness and efficiency of the aforementioned surrogate models.

- **MSE** (Mean Square Error) and **MAE** (Mean Absolute Error) are two metrics to evaluate the performance of the forecasting models in the forecasting problem [32, 35, 38]
- **Time Overhead** measures the overall time overhead of the forecasting models on a port. For ARIMA, it includes the time of calculating parameters and the time of estimating network traffic. For ADP-LSTM, it includes the offline training cost, the online training cost, and the inference overhead.

4.1 Experimental Results

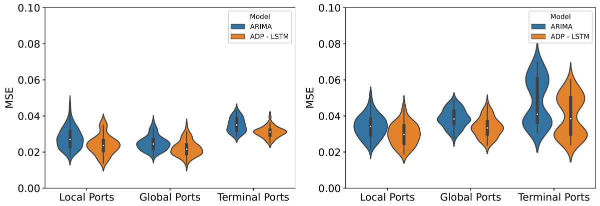
In the following, we describe our results in two aspects: port level analysis and network level analysis. In port level analysis, we analyze the results of some representative ports; in network level analysis, we present an overall perspective for all ports on all routers. Note that we consider the one-step delay (i.e., $k = 1$) for the following results and will perform a sensitivity analysis in section 4.2.

4.1.1 Port Level Analysis. We evaluate the performance and time overhead of ARIMA and ADP-LSTM on all ports of all routers. Due to page limits, we show the results of three routers and three ports for each router, and the results are shown in Table 1.

Performance. From Table 1, we can clearly observe that ADP-LSTM outperforms ARIMA consistently. The reason is that ADP-LSTM can leverage powerful capabilities of deep learning to capture complex patterns implied in network traffic while ARIMA based on the statistical algorithm is relatively limited in handling such intricate traffic. More importantly, ADP-LSTM can dynamically adapt to complex network traffic, which boosts the forecasting capability for network traffic.

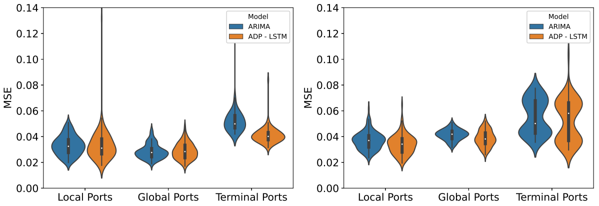
Table 1: Accuracy and time overhead results of port L_0, G_0 and T_0 on Router R_0, R_{18} and R_{35} when $k = 1$. T.O. means time overhead. IMPROVEMENT(Δ) indicates the improvement of ADP-LSTM compared to the ARIMA.

Setting	Router	Port	ARIMA			ADP-LSTM			IMPROVEMENT (Δ)		
			MSE	MAE	T.O. (s)	MSE	MAE	T.O. (s)	$\Delta(MSE)$	$\Delta(MAE)$	$\Delta(T.O.)$
cont-adp	$\mathbf{R_0}$	$\mathbf{L_0}$	0.0321	0.1410	2,255	0.0219	0.0939	26	46.72%	50.13%	85
		$\mathbf{G_0}$	0.0271	0.1238	1,796	0.0234	0.0912	25	15.77%	35.81%	69
		$\mathbf{T_0}$	0.0359	0.1411	1,998	0.0317	0.1127	25	13.32%	25.22%	78
	$\mathbf{R_{18}}$	$\mathbf{L_0}$	0.0321	0.1401	2,087	0.0284	0.1274	25	12.88%	10.00%	82
		$\mathbf{G_0}$	0.0287	0.1339	1,925	0.0233	0.1154	25	23.49%	16.09%	76
		$\mathbf{T_0}$	0.0333	0.1431	2,055	0.0313	0.1367	25	6.32%	4.70%	80
	$\mathbf{R_{35}}$	$\mathbf{L_0}$	0.0231	0.1145	1,983	0.0217	0.1009	26	6.86%	13.56%	75
		$\mathbf{G_0}$	0.0226	0.1166	1,908	0.0171	0.0947	26	32.11%	23.14%	73
		$\mathbf{T_0}$	0.0367	0.1506	2,076	0.0353	0.1474	26	3.97%	2.16%	79
random-adp	$\mathbf{R_0}$	$\mathbf{L_0}$	0.0332	0.1479	2,263	0.0298	0.1386	25	11.43%	6.66%	90
		$\mathbf{G_0}$	0.0334	0.1468	2,241	0.0275	0.1301	25	21.54%	12.78%	89
		$\mathbf{T_0}$	0.0621	0.2012	2288	0.0501	0.1800	25	23.85%	11.79%	91
	$\mathbf{R_{18}}$	$\mathbf{L_0}$	0.0407	0.1630	2,186	0.0372	0.1536	25	9.53%	6.10%	86
		$\mathbf{G_0}$	0.0361	0.1539	2193	0.0313	0.1426	25	15.30%	7.91%	86
		$\mathbf{T_0}$	0.0557	0.1938	2246	0.0477	0.1797	25	16.80%	7.83%	87
	$\mathbf{R_{35}}$	$\mathbf{L_0}$	0.0315	0.1403	2,192	0.0228	0.1087	26	38.18%	29.04%	85
		$\mathbf{G_0}$	0.0328	0.1451	2,170	0.0265	0.1277	26	23.62%	13.60%	82
		$\mathbf{T_0}$	0.0396	0.1505	2,148	0.0320	0.1161	26	23.79%	29.69%	81



(a) *con-adp* setting w.r.t. MSE (b) *random-adp* setting w.r.t. MSE

Figure 2: Forecast accuracy distributions ($k = 1$).



(a) *con-adp* setting w.r.t. MSE (b) *random-adp* setting w.r.t. MSE

Figure 3: Forecast accuracy distributions ($k = 5$).

Time Overhead. From Table 1, we observe that the time overhead of ADP-LSTM is significantly less than ARIMA. The great gap is due to the following reason. Although AIRMA does not require any offline training, it needs to calculate parameters by fitting a set of historical data per step. Such a model fitting process is more computationally expensive compared to ADP-LSTM which only needs to be tuned by a single newly accessible data per step.

4.1.2 Network Level Analysis. To assess the consistency of the forecast results across all ports and routers, we show the distributions of the forecast accuracy results, grouped by local ports, global ports, and terminal ports, as shown in Figure 2. From the figure, we can obtain consistent results with the port level analysis. The ADP-LSTM is more effective than ARIMA, on local ports, global ports, and terminal ports. It further demonstrates the effectiveness of ADP-LSTM as a surrogate model compared to ARIMA.

4.2 Sensitivity Analysis

We investigate the effect of the delay k on forecast accuracy. Due to the page limit, we only show the results when $k = 5$ in Figure 3. First, we observe that some ports have very large MSE e.g., in $cont-adp$ setting, R_8L_2 : 0.6339 and $R_{13}L_2$: 15.5494 for ADP-LSTM; in $random - adp$ setting, $R_{29}T_0$: 81457340.7567 for ARIMA, $R_{14}T_0$: 3.0814 and $R_{23}T_0$: 85.4369 for ADP-LSTM. Second, the proposed ADP-LSTM still outperforms ARIMA when $k = 5$. In addition, compared to Figure 2, the accuracy of ARIMA and ADP-LSTM both diminish. It may be because as k increases, the proportion of actual data in the historical data window decreases, resulting in reduced usage of the actual data for surrogate modeling.

5 CONCLUSION AND FUTURE WORK

In this paper, we investigate the potential of machine learning surrogate models to accelerate PDES, by forecasting the intricate traffic in the Dragonfly network. Several key research questions remain open: (i) how to improve forecasting accuracy by taking into account additional network features and the temporal/spatial correlation among ports in the dragonfly, (ii) how to improve long-term forecast accuracy as the delay step k grows, and (iii) how to integrate and coordinate Python based surrogate modeling with C/C++ based PDES modeling.

Acknowledgement: This work is supported by US National Science Foundation grant CCF-2109316, and the Director, Office of Advanced Scientific Computing Research, Office of Science, of the U.S. Department of Energy under Contract No. DE-AC02-06CH11357 and the "Kronos: Enabling Long Timescale PDES Simulations via Multi-Resolution Methods" project.

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