Recurrent Neural Network Based Dynamic Resource Reallocation of BBU Pools in 5G C-RAN ROADM Networks

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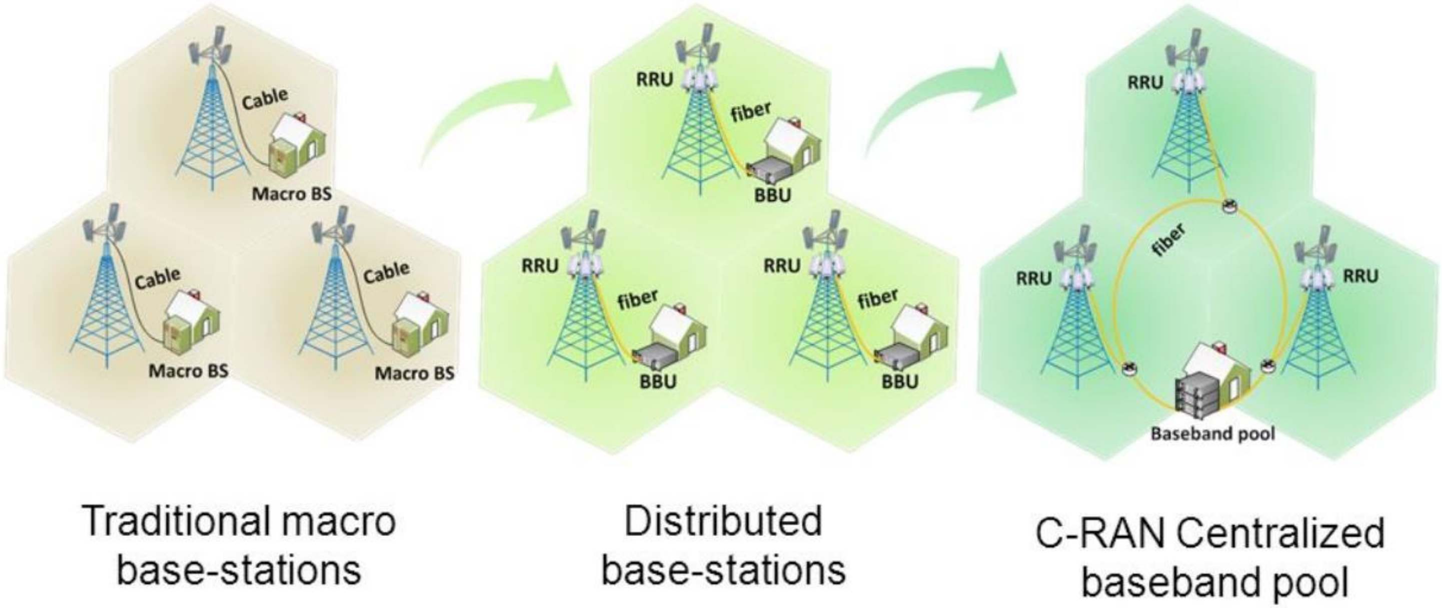
Background

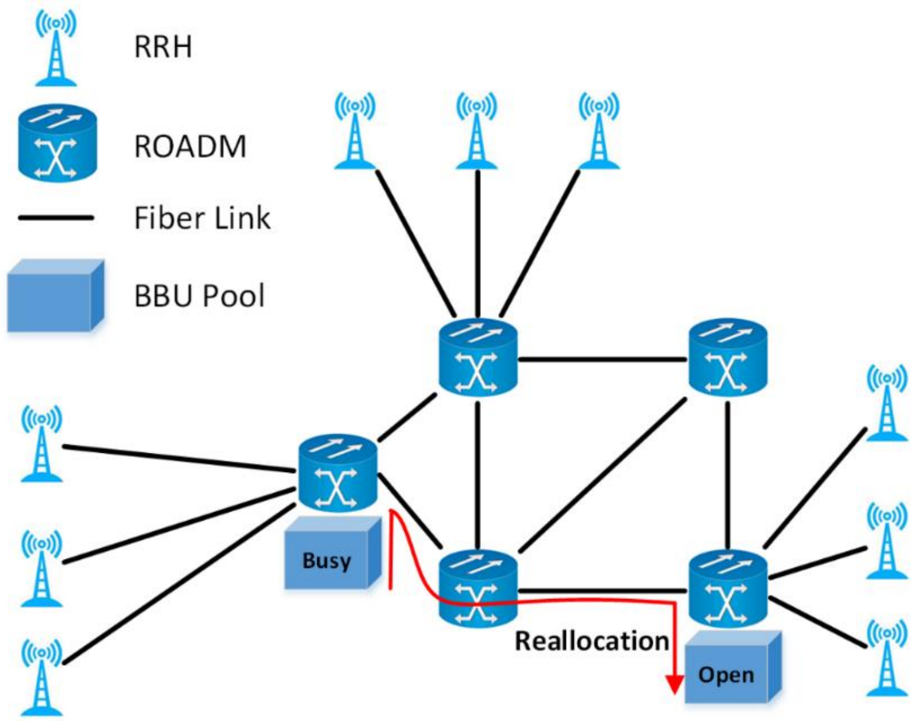
- 5G=orders of magnitude more capacity
- Legacy RAN=low resource utilization
- Centralized or Cloud RAN=better resource utilization
- Moved to centralized locations (BBU pools) for sharing of power and computational resources



From legacy RAN to C-RAN

Problem Statement

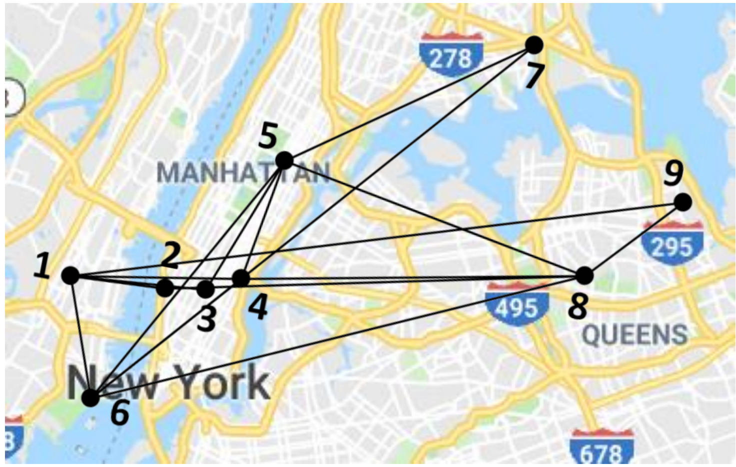
- High capacity + Low latency = ROADM networks
- ROADM networks take minutes for wavelength reconfigurations
- Dynamic reallocation require traffic prediction in advance
- Machine learning solution: Long short-term memory (LSTM) networks



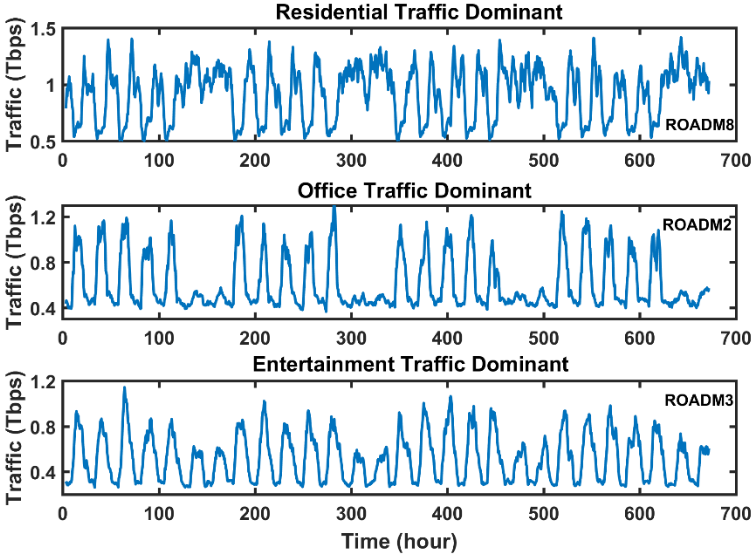
C-RAN network architecture with resource reallocation

C-RAN Simulations

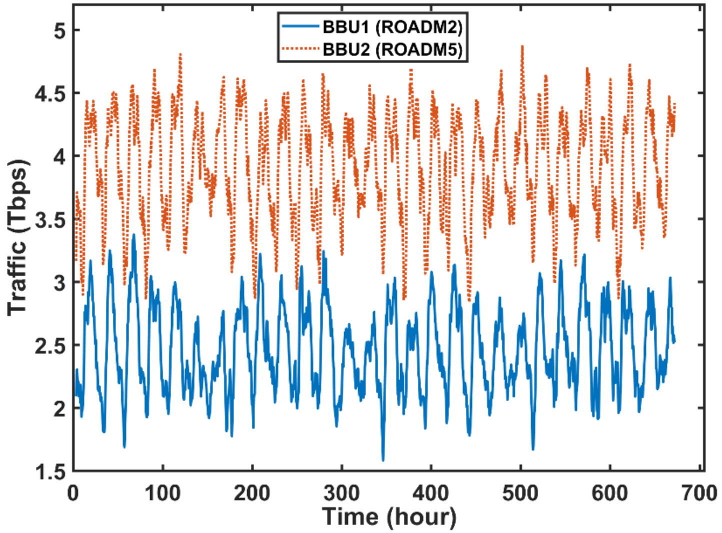
- New York City incumbent local exchange carrier (ILEC) network
- 9 ROADMs, 400 km^2, average degree=3.5
- Modified K shortest path, k=5
- 64 23Gbps small cells directly routed to each ROADM, 2 BBU pools (ROADM 2 and ROADM 5)
- 12060 connections following Poisson distributions over 28 days
- Residential, office, and entertainment traffic is distributed based on geographical locations



New York City regional ILEC topology (from zayo.com)



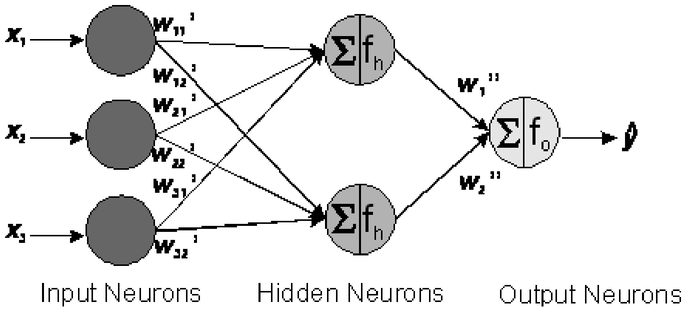
Traffic at different ROADMs



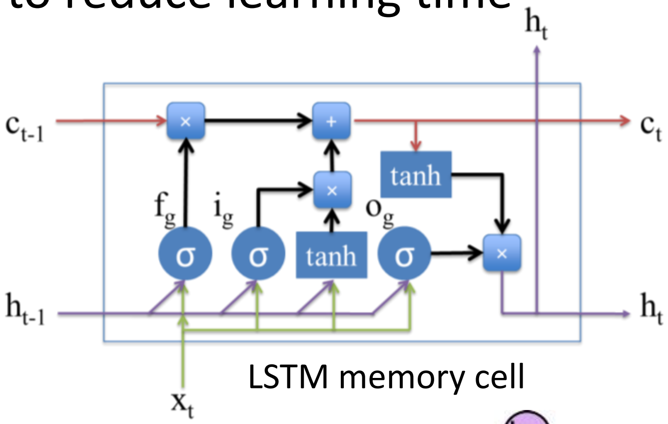
Traffic at two BBU pools

LSTM Network

- Recurrent neural networks (RNN) predict time series data
- RNN face "gradient vanishing"
- LSTM introduces memory cells to control the input information
- Truncated backpropagation through time to reduce learning time

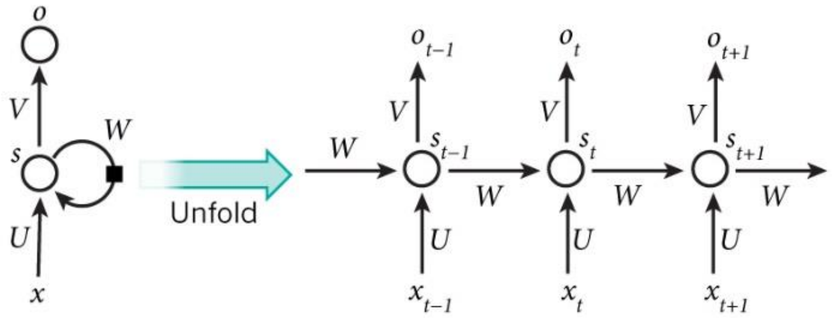


Feedforward neural network

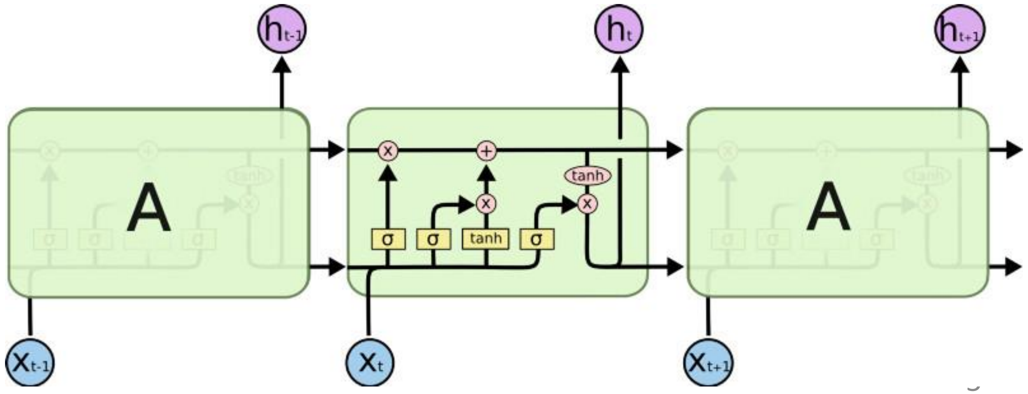


LSTM memory cell

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right)$$
$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right)$$
$$c_t = f_t c_{t-1} + i_t \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right)$$
$$o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o\right)$$
$$h_t = o_t \tanh(c_t)$$



Recurrent neural network



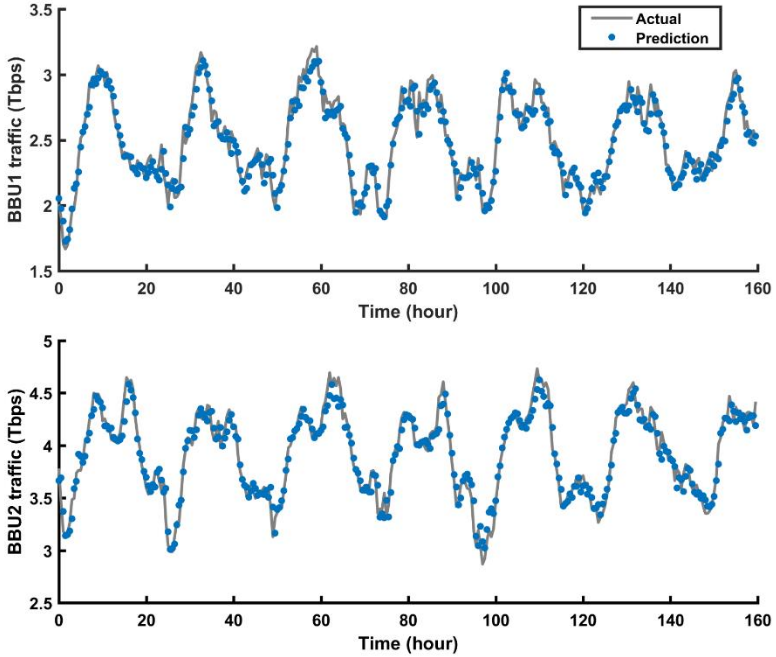
LSTM unfolded through time

LSTM Network Training and Prediction

- 740 training samples (55%), 268 validation samples (20%), 336 test samples (25%)
- 60 previous time steps are used to predict the next time step
- Predict the peak traffic in each BBU pool 30 minutes in advance
- Stochastic gradient descent with mini-batch size of 20 over 1000 epochs (training time=3 minutes)
- Use dropout=0.2 to prevent overfitting
- RMSE = 96.9 Gbps, MAE = 84.2 Gbps

Parameter	Value
Learning rate	0.0005
Dropout	0.2
Activation function	LSTM cell->Linear
Number of epochs	1000
Mini-batch size	20
Cost function	Root mean square error (RMSE)

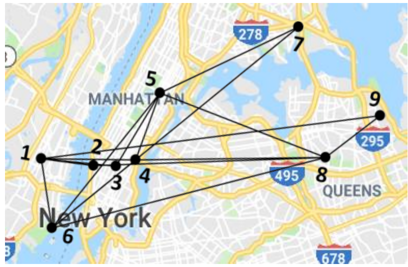
LSTM network parameters

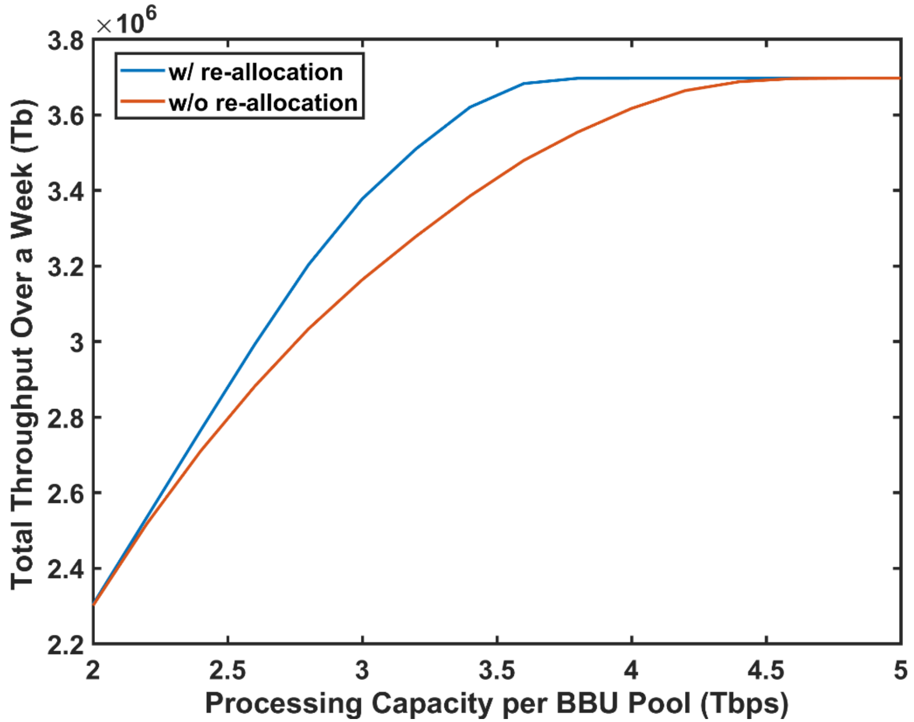


BBU pool traffic prediction with LSTM network

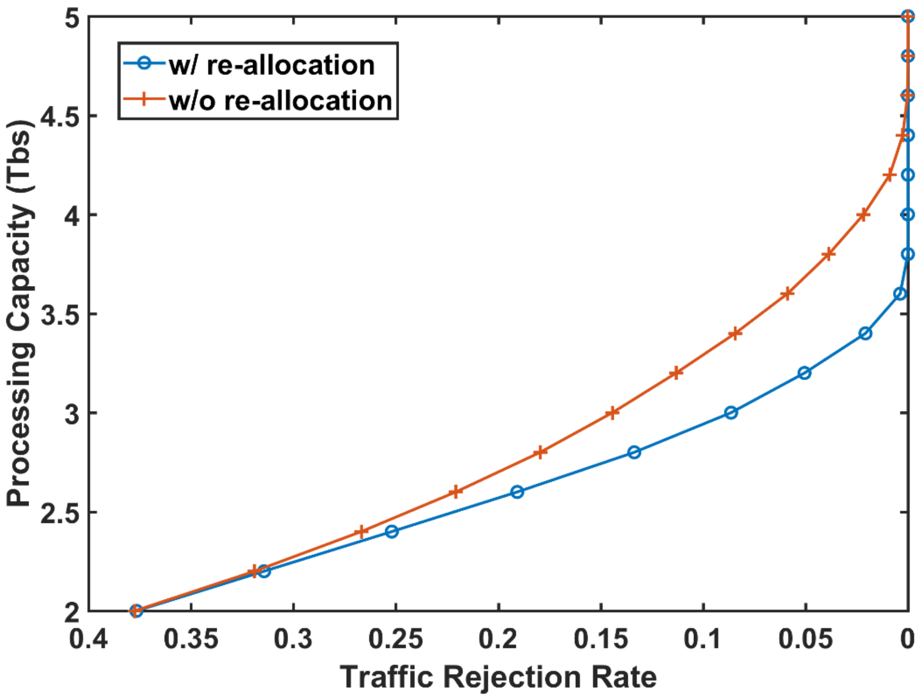
Simulation Results

- Vary the peak resource processing capacity per BBU pool
- 7% maximum improvement of 5G traffic throughput
- 18% resource reduction while achieving 0% traffic rejection rate





5G throughput improvement



Reduced traffic rejection

Conclusion

- The 5G throughput can be improved by dynamic resource reallocation through ROADM network configurations

- Heterogeneous 5G traffic patterns can be accurately predicted 30 minutes in advance by an LSTM network

- 7% increase in network throughput and an 18% reduction of processing resources are achieved

- Future work will investigate the performance of LSTM networks with commercial data in large-scale networks

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Thank you

Normalized traffic