Delay-Aware Backpressure Routing using Graph Neural Networks

Zhongyuan Zhao, Bojan Radojičić§, Gunjan Verma†, Ananthram Swami †, Santiago Segarra**

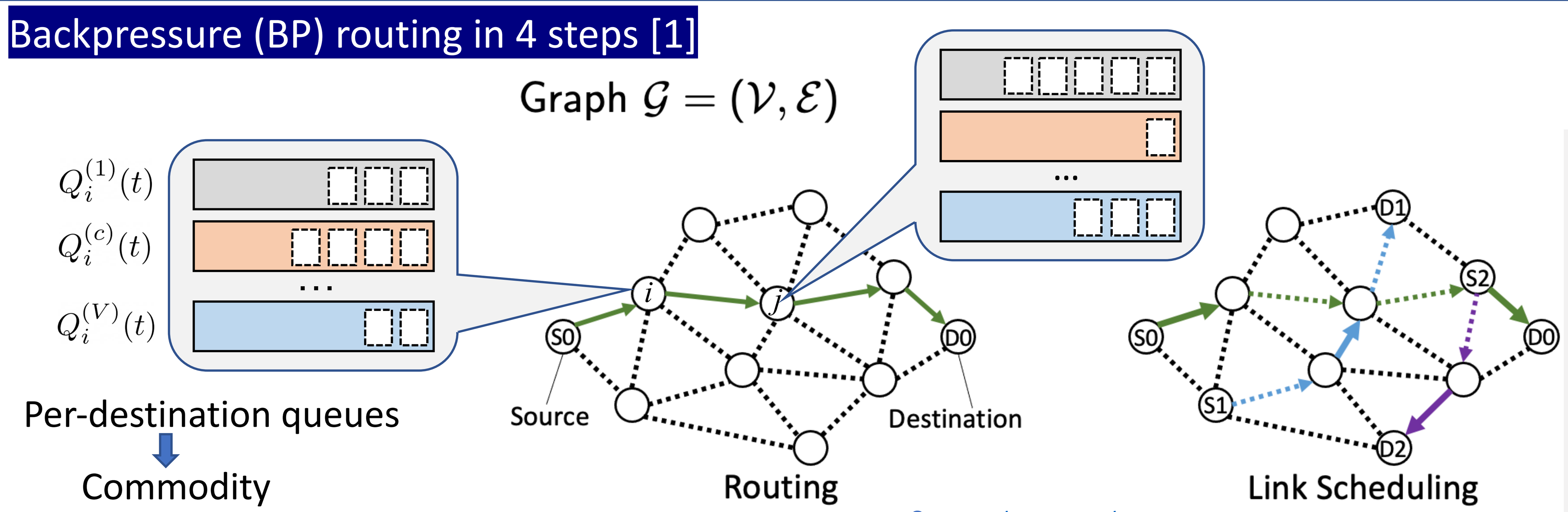
*Rice University, USA; §University of Novi Sad, Serbia; † US Army's DEVCOM Army Research Laboratory, USA

Paper ID: 3944

ICASSP 2023, 4-10 JUNE, RHODES ISLAND, GREECE

Biased Backpressure (BP) Routing for Wireless Multihop Networks

Backpressure (BP) routing in 4 steps [1]



1. Select optimal commodity

$$c_{ij}^*(t)=\underset{c\in\mathcal{V}}{\text{argmax}}\{U_i^{(c)}(t)-U_j^{(c)}(t)\}$$

Modifications here

2. Find link gradient

$$w_{ij}(t)=\max\{U_i^{(c_{ij}^*(t))}(t)-U_j^{(c_{ij}^*(t))}(t),0\}$$

3. MaxWeight scheduling (distributed heuristic)

$$\mathbf{l}^{BP}(t)=\underset{\mathbf{l}(t)\in\{0,1\}^{|\mathcal{E}|}}{\text{argmax}}\ \mathbf{l}(t)^\top\cdot[\mathbf{r}(t)\odot\mathbf{w}(t)]$$

4. Assign link capacity to optimal commodities

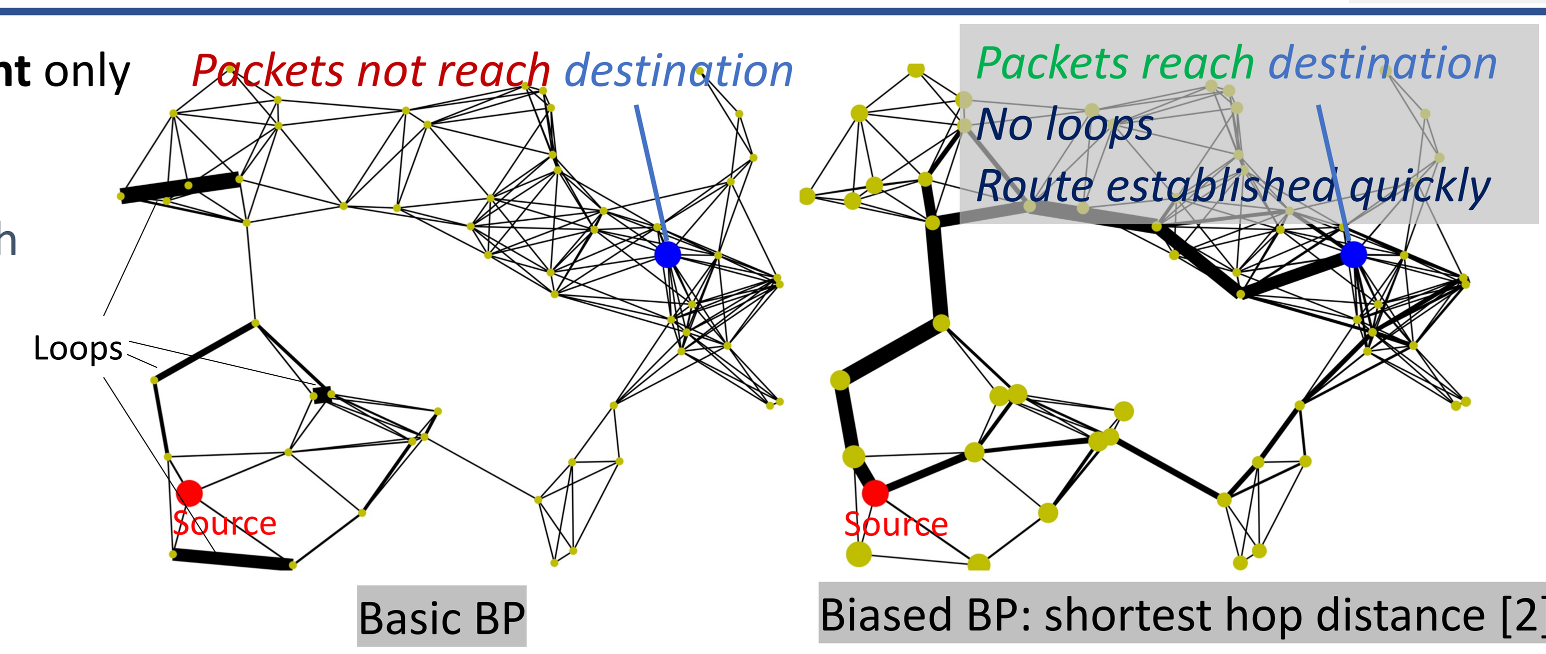
$$\mu_{ij}^{(c)}(t)=\begin{cases}r_{ij}(t), & \text{if } c=c_{ij}^*, w_{ij}>0\\ 0, & \text{otherwise}\end{cases}$$

Basic BP driven by **congestion gradient** only

$$U_i^{(c)}(t)=Q_i^{(c)}(t)$$

Queue length

- ✓Distributed Routing
- ✓Congestion prevention
- ✓Throughput optimality
- ✗Poor latency performance
  - ✗Slow start
  - ✗Loop
  - ✗Last-packet problem



Basic v.s. biased BP: route visualization for simulations of 500 steps

Biased BP adds **distance gradient**

$$U_i^{(c)}(t)=Q_i^{(c)}(t)+B_i^{(c)}$$

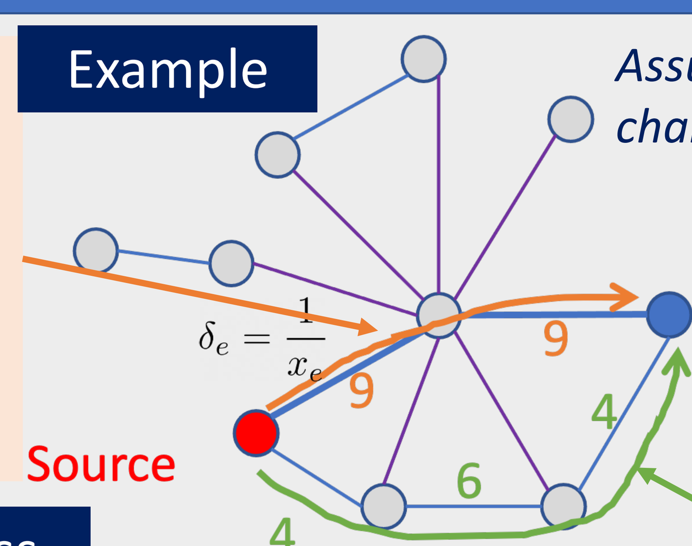
Queue length; shortest path bias (e.g., hop counts from i to c)

- ✓Distributed Routing
- ✓Path finding
- ✓Throughput optimality
- ✓Better latency performance
  - ✓ ~~Slow start~~
  - ✓ ~~Loop~~
  - ✓ ~~Last-packet problem~~

Improve "*Shortest Hop Counts*" with "Conflict-aware shortest distance"

Shortest hop count bias promotes the orange route, of which both links have 8 conflicting neighbors, thus less likely being scheduled (link duty cycle = 1/9)

Example



Shortest path bias based on link duty cycle promotes the green route, of which links have fewer conflicting neighbors, thus more likely to be scheduled (higher link duty cycle)

Conflict-awareness

Link duty cycle $\quad 0<x_e\leq 1 \quad e\in\mathcal{E}$

How likely a link is scheduled under current network topology and traffics

Per hop distance $\quad \delta_e=\dfrac{1}{x_e}$

Per hop distance with link rate $\quad \delta_e=\dfrac{\bar{r}}{x_e r_e}$

Link duty cycle estimated by an L-layer graph convolutional neural network (GCNN) $\quad \mathbf{x}=\Psi_{\mathcal{G}^c}(\mathbf{1};\boldsymbol{\omega})$

Fully distributed execution of GCNN $\quad \mathbf{X}_{e*}^l=\sigma_l\left(\mathbf{X}_{e*}^{l-1}\boldsymbol{\Theta}_0^l+\left[\mathbf{X}_{e*}^{l-1}-\sum_{u\in\mathcal{N}_{\mathcal{G}^c}(e)}\frac{\mathbf{X}_{u*}^{l-1}}{\sqrt{d(e)d(u)}}\right]\boldsymbol{\Theta}_1^l\right)$

Cost: Additional Distributed Complexity

GCNN	$\mathcal{O}(L)$	Constant
Single source shortest path (SSSP)	$\mathcal{O}(V)$	Linear
All pairs shortest path (APSP)		weighted graph

Note: GCNN and APSP algorithms only need to be ran once a while, when network topology changes.

Training of GCNN

Episode iteration

1. Draw a random network instance

$$(\mathcal{G}(k),\mathcal{G}^c(k),\mathcal{F}(k),\mathbf{A}(k),\mathbf{R}(k))\sim\Omega$$

(*Connectivity graph, Conflict graph, Flows, Packet arrivals, Link rates*)

2. Find delay-aware shortest path bias with GCNN and APSP

Per-link distance $\quad \mathbf{x}(k)=\Psi_{\mathcal{G}^c(k)}(\mathbf{1};\boldsymbol{\omega})$

Shortest path bias $\quad \mathcal{B}(k)$

3. Run routing simulation for T steps, collect empirical schedules

Empirical schedule $\quad \mathbf{s}^k(t)\in\{0,1\}^{|\mathcal{E}|}$

4. After simulation, update GCNN with mean-square-error loss

$$\ell(\boldsymbol{\omega})=\mathbb{E}_\Omega\left[MSE(\mathbf{x}(k),\mathbb{E}_t(\mathbf{s}^k(t)))\right]$$

Test Results: 100 random network instances

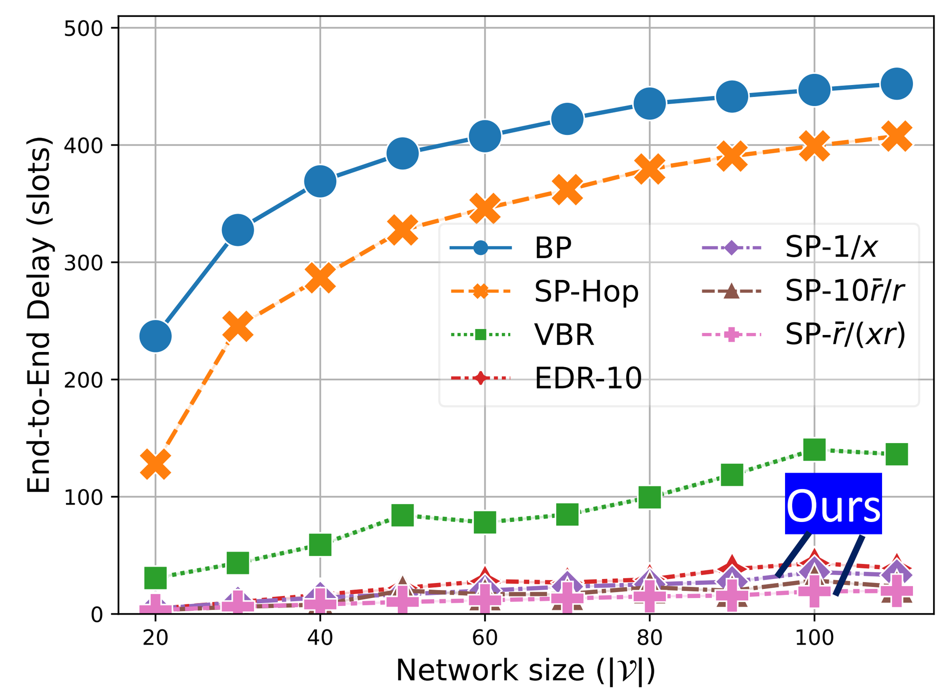


Fig. 1 End-to-end delay under **interface conflict model** *(e.g., mmWave/THz wireless backhaul networks)*

2D point process
- Nodes on random locations
- A link between two nodes if their distance is within 1
- Conflict relationship based on interface or physical distance models

Flow traffic & link rate
- Poisson arrivals
- Uniformly random avg link rate
- Zero-mean normal fluctuation on link rate

Simulation length
- T=1000
- *Delay of undelivered packets as (1000 – birth time)*

Benchmark Basic BP and shortest path-aware biased BP

Algorithms	Per-hop distance
BP (basic) [1]	$\delta_e=0$
SP-Hop [2]	$\delta_e=1$
EDR-10 [4]	$\delta_e=10$
VBR [3]:	virtual queue BP
SP-$1/x$	$\delta_e=1/x_e$
SP-$\bar{r}/(xr)$	$\delta_e=\bar{r}/(x_e r_e)$
SP-$10\bar{r}/r$	$\delta_e=\bar{r}/(0.1r_e)$

Highlights of link duty cycle-based biased BP
- Outperform others on end-to-end delay
  - Under same access of information (avg link rate)
  - Can adapt to conflict density
- Maintain high delivery rate across traffic loads

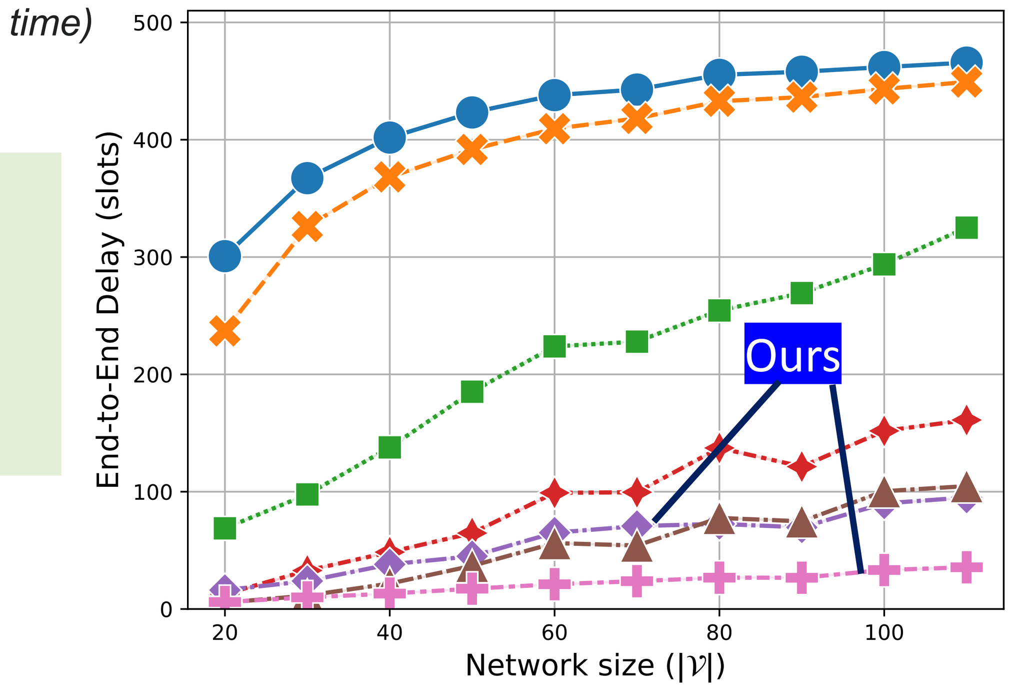


Fig. 2 End-to-end delay under **unit-disk conflict model** *(e.g., wireless ad-hoc/sensor networks)*

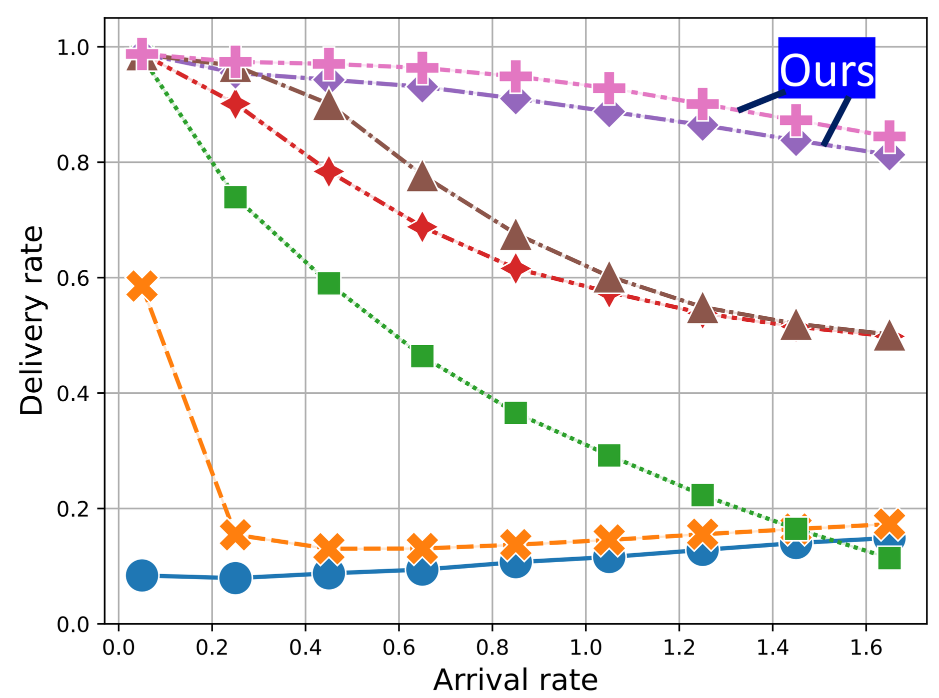


Fig. 3 Delivery rate under unit-disk conflict model, 100 nodes

- Longer end-to-end delay
  - Larger networks (longer distance)
  - Higher conflict density (lower network capacity)
- Average conflict degree
  - Interface-conflict model: 12.4
  - Unit-disk conflict model: 34.6

Conclusion & Future work

- Use shortest path bias to improve delay performance of back-pressure routing
  - Delay/conflict-aware shortest path bias based on link duty cycle
  - Link duty cycle predicted by Graph Convolutional Neural Networks (GCNN)
- Key advantages of biased backpressure routing
  - Fully distributed execution
  - Low overhead (low complexity & reusable bias)
- Future work: apply to other routing schemes, improve training method

References

[1] L. Tassiulas, "Stability properties of constrained queueing systems and scheduling policies for maximum throughput in multihop radio networks," IEEE Trans. on Automatic Control, vol. 31, no. 12, 1992.
[2] M. Neely, E. Modiano, and C. Rohrs, "Dynamic power allocation and routing for time-varying wireless networks," IEEE J. Sel. Areas Commun., vol. 23, no. 1, pp. 89–103, 2005
[3] Z. Jiao, B. Zhang, W. Gong, and H. Mouftah, "A virtual queue-based back-pressure scheduling algorithm for wireless sensor networks," EURASIP J. on Wireless Commun. and Netw., vol. 2015, no. 1, pp. 1–9, 2015.
[4] Y. Cui, E. M. Yeh, and R. Liu, "Enhancing the delay performance of dynamic backpressure algorithms," IEEE/ACM Trans. Netw., vol. 24, no. 2, pp. 954–967, 2016.