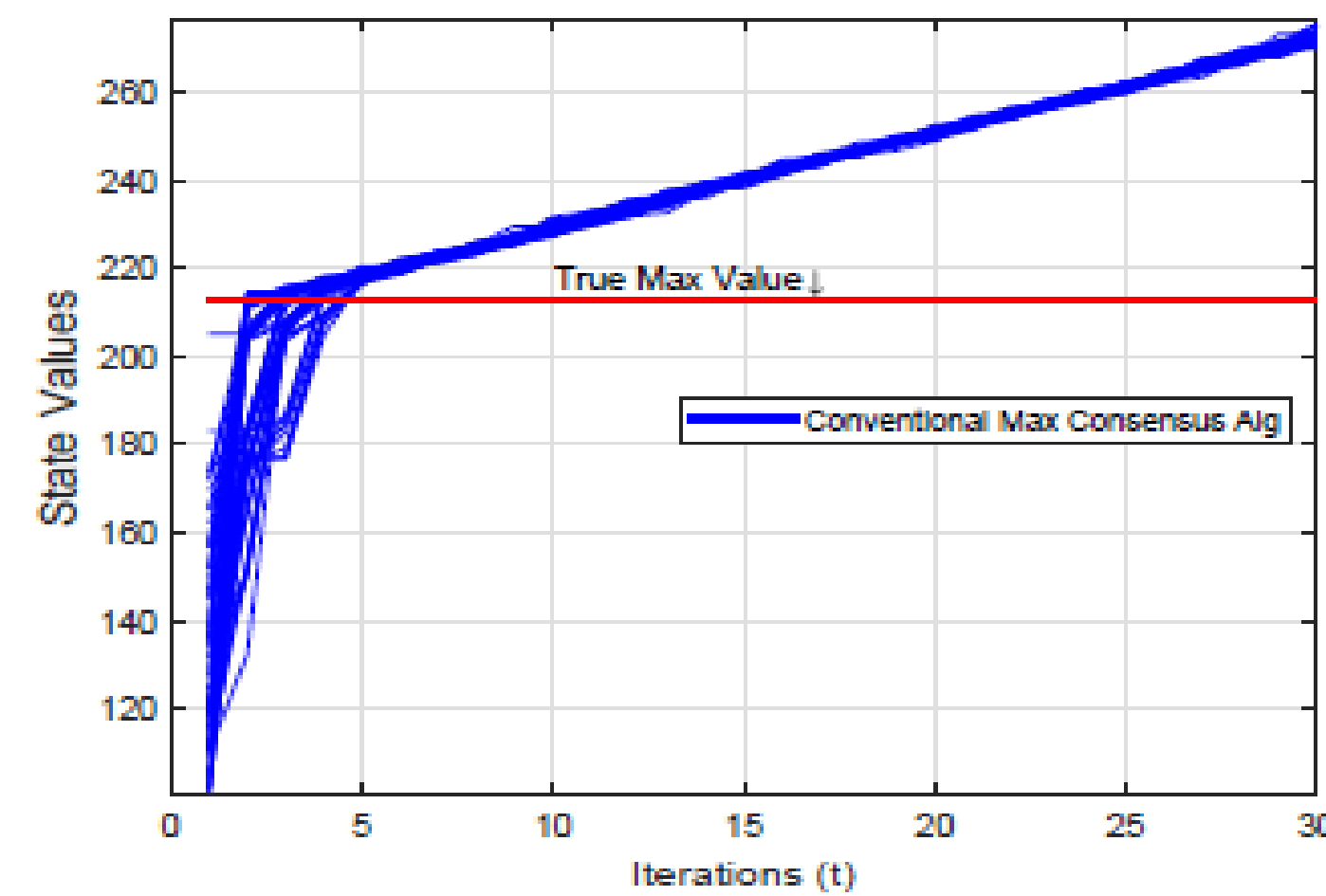


MOTIVATION

- Fully distributed estimation of maximum of initial node state values in the presence of additive noise.
- Due to additive channel noise, the estimate of the maximum at each node has a positive drift at each iteration and this results in nodes diverging from the true max value.
- Derive bounds on growth rate using large deviation theory.
- Design a fast max based 2-run algorithm robust to additive noise, which compensates for the growth rate.



POTENTIAL APPLICATIONS

- Distributed computation of extremes is necessary in : resource management, network area estimation, node counting, node clustering, message routing and distributed detection and tracking.

CONVENTIONAL MAX CONSENSUS

- Each node updates their state value by the maximum of the received measurements. In the presence of additive noise the update equation is given by,

$$x_i(t+1) = \max(x_i(t), \max_{j \in N_i}(x_j(t) + v_{ij}(t)))$$

UPPER BOUND ON GROWTH RATE

- Upper bound for general additive noise distribution is given by ,

$$\lambda \leq \inf \left\{ x : \sup_{0 \leq \beta \leq 1} \left[H(\beta) + \beta \log(\rho) - \beta I(x/\beta) \right] \right\}$$

- Upper bound for additive Gaussian noise :

$$\lambda \leq \sup_{0 \leq \beta \leq 1} \sqrt{2\beta(H(\beta) + \beta \log(\rho))}$$

- Alternate upper bound is obtained by solving : $I(x) = \log(\rho + 1)$
- Alternate upper bound for Gaussian noise : $\lambda \leq \sqrt{2 \log(\rho + 1)}$.

ROBUST MAX CONSENSUS ALGORITHM

- A two run algorithm is proposed to compensate the positive drift of the node state values (growth rate)
- First run : Initialize all nodes to zero and run the natural max consensus algorithm. After t iteration estimate the growth rate locally.
- Second run : With the knowledge of the local growth rate, run the max consensus algorithm on true state values. During each node update, subtract by the locally estimated growth rate.

$$x_i(t+1) = \max(x_i(t), \max_{j \in N_i}(x_j(t) + v_{ij}(t)) - \lambda_i)$$

First run ::

Input: iterations = t , # of nodes = N

Initialization

Initialize all nodes to zero, $x_i(0) = 0$

repeat until : t iterations

for $\{i = 1 : N\}$

$x_i(t) = \max(x_i(t), \max_{j \in N_i}(x_j(t-1) + v_{ij}(t-1)))$

end : for

end : repeat

growth rate estimate : $\hat{\lambda}_i = \frac{x_i(t)}{t}$

Second run ::

Input: # of nodes = N , Initial state : $x_i(0)$

repeat until : convergence

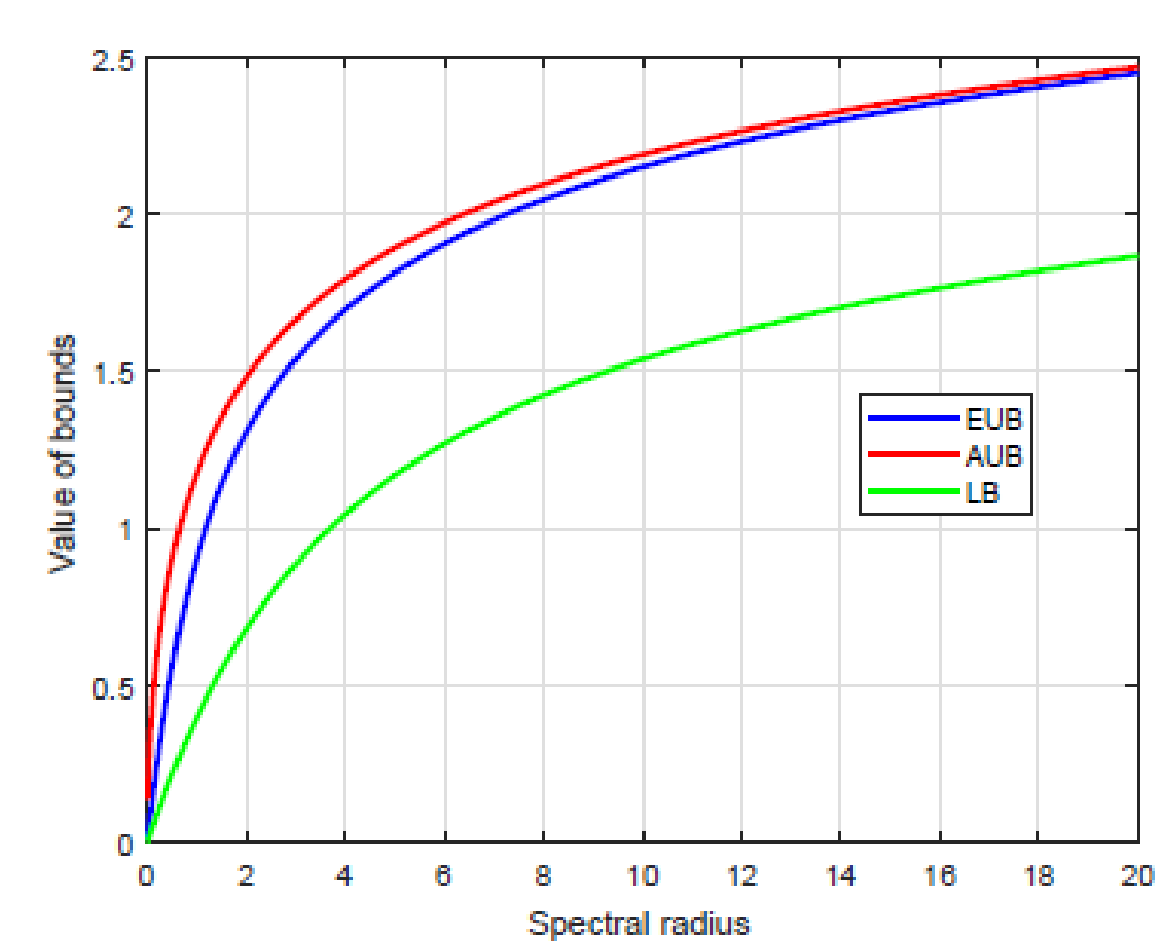
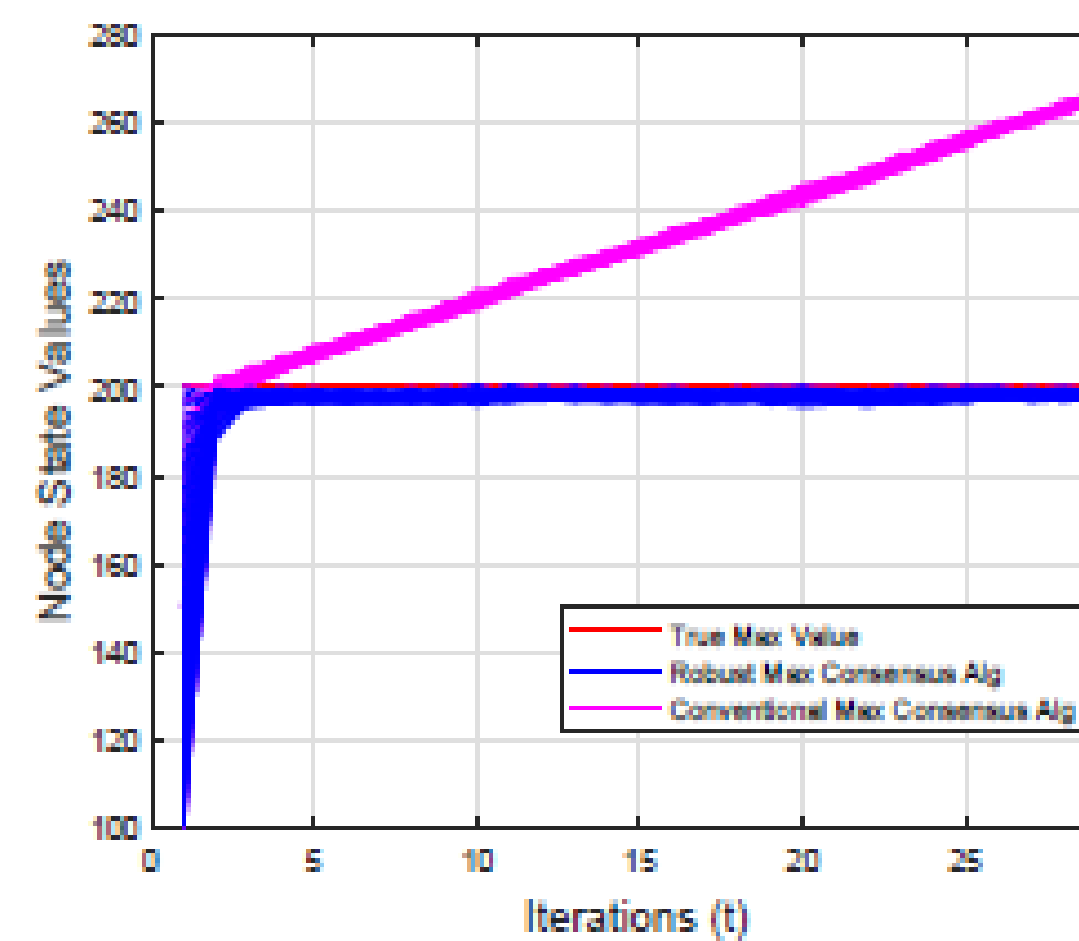
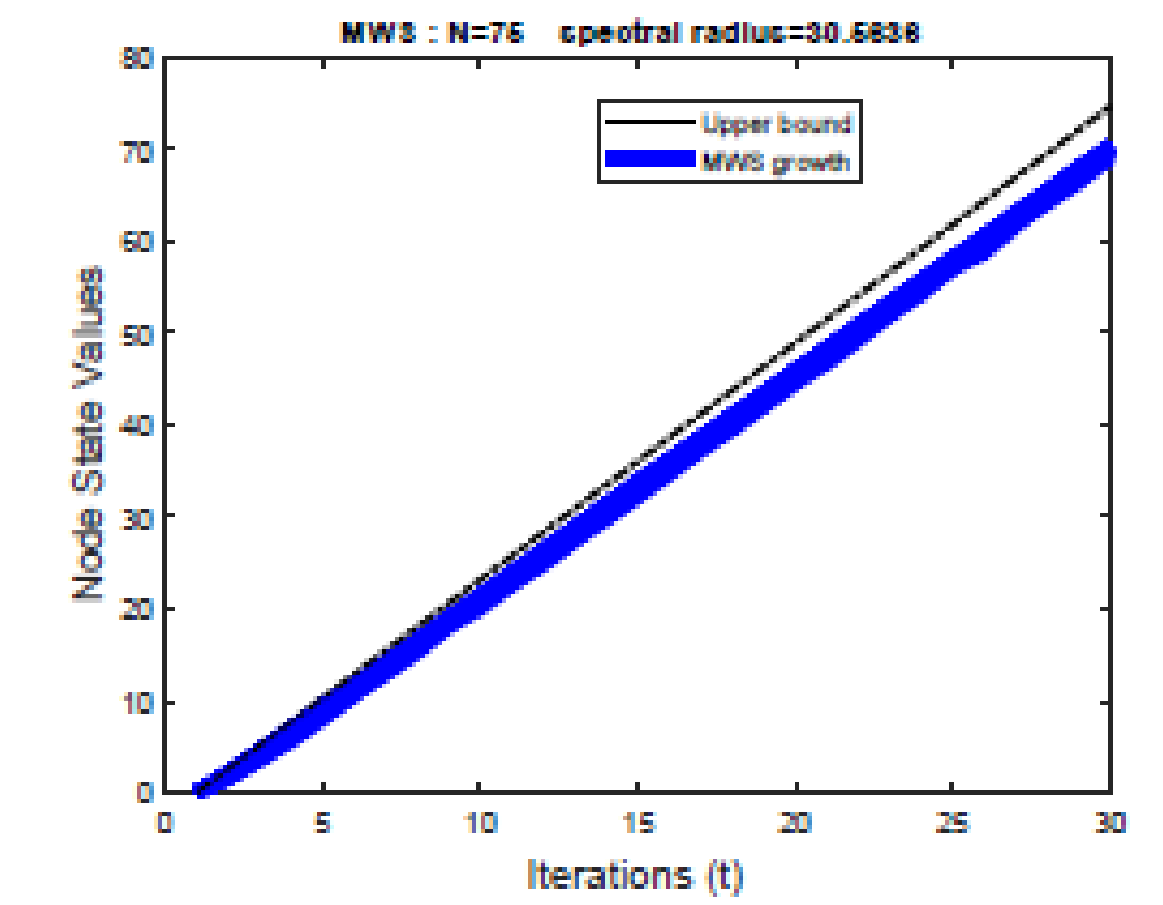
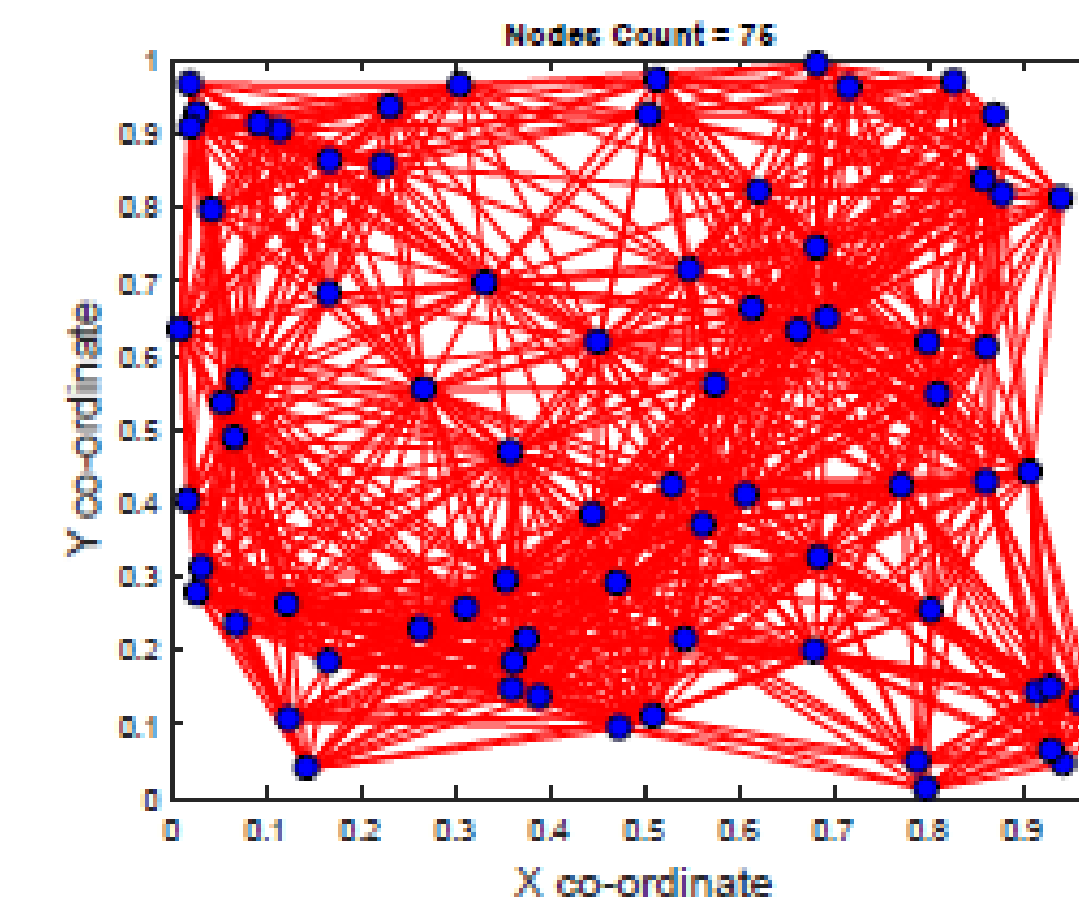
for $\{i = 1 : N\}$

$x_i(t) = \max(x_i(t), \max_{j \in N_i}(x_j(t-1) + v_{ij}(t-1)) - \hat{\lambda}_i)$

end : for

end : repeat

SIMULATION RESULTS



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