Mitigation of the Spectrum Sensing Data Falsifying Attack in Cognitive Radio Networks

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Road Map

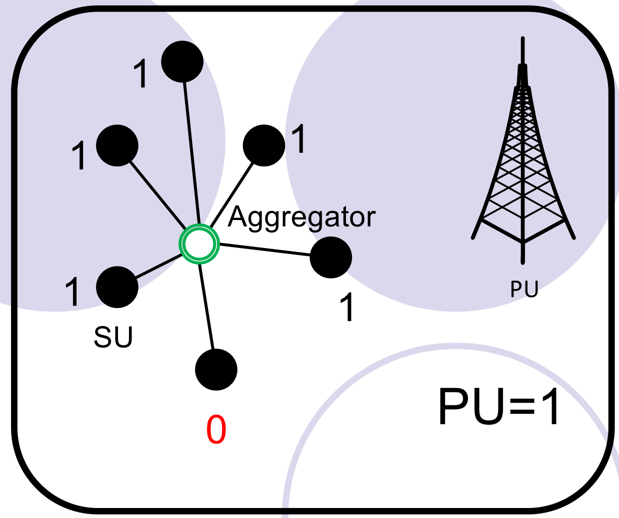
1. Cooperative spectrum sensing
2. Related work
3. Majority voting and existing models
4. Weighted majority voting with confidence
5. Simulation results
6. Extension: two-level majority voting
7. Conclusion

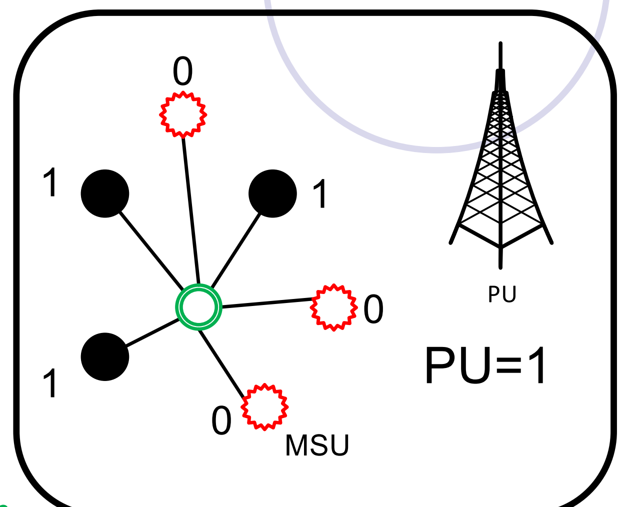
1. Cooperative Spectrum Sensing

- Primary user (PU)
  - Licensed user, high priority
- Secondary user (SU)
  - Send sensing information to aggregator
- Malicious secondary user (MSU)
  - Send opposite sensing information to aggregator
- Aggregator
  - Does majority voting
  - Results are sent back to SUs and MSUs

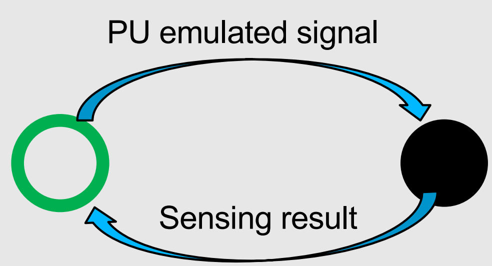
SU's wrong sensing and MSU's result can change aggregator's decision

Solution: reduce weight of MSUs through reputation





2. Previous Work

MSU detection systems	**Limitations**
Linear reputation-based system. SUs send raw sensing information to Aggregator. If a SU agrees with aggregator, reputation increases by "1" or decreases by "1". R. Chen, J. -. Park and K. Bian, "Robust Distributed Spectrum Sensing in Cognitive Radio Networks," IEEE INFOCOM 2008.	• Computation overhead is high for processing raw sensing information. • Linear reputation update mechanisms are not efficient enough.
Active transmission-based system.  T. Bansal, B. Chen, and P. Sinha, "Fastprobe: Malicious user detection in cognitive radio networks through active transmissions," in IEEE INFOCOM 2014.	• PU emulated signals can be detected. • MSU will respond correctly to emulated signal.

3. Majority Voting and Existing Models

	SU1	SU2	SU3	SU4
Reputation	r1	r2	r3	r4
Sensing result	s1	s2	s3	s4

$$\hat{r}_i = \frac{r_i}{\sum r_i}$$

$\hat{r}_i$ = normalized reputation

Initial reputation=1

If $\sum s_i \hat{r}_i$ > 0.5
    Aggregator's decision=1
Else
    Aggregator's decision=0

Aggregator makes decision $\longrightarrow$ Update reputation of SUs and MSUs using Reputation Update Function (RUF)

Majority Voting and Existing Models

<u>Linear RUF:</u>

$r_{new} = (\mu)r_{old} + (1-\mu)x$

μ = priority of previous reputation

If SU's result = aggregator's result

$x = 1$

Else

$x = -1$ (or 0, no decrease)

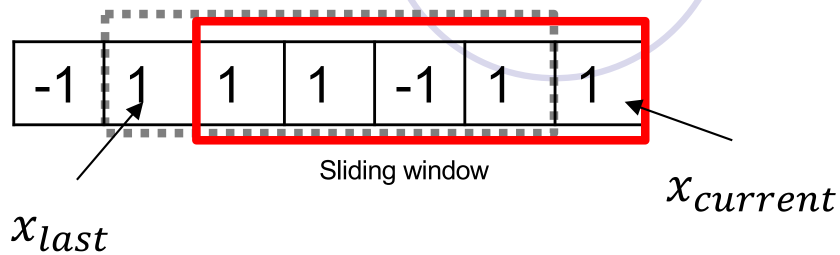
<u>Multiplicative RUF*:</u>

$r_{new} = r_{old}\exp(\eta x)$

η = learning rate: [0, 1]

<u>Multiplicative RUF with sliding window:</u>

$r_{new} = r_{old}\exp(\eta x_{current} - \eta x_{last})$



*S. Arora, E. Hazan, and S. Kale. "The multiplicative weights update method: a meta-algorithm and applications." Theory of Computing 8.1 (2012)

4. Weighted Majority Voting with Confidence

Adaptive Multiplicative RUF

- ρ_t = Normalized confidence
- $r_{new} = r_{old} \times \exp(x\,\eta\,\rho_t)$

Minority: 30

confidence

Majority: 70

$$\rho_t = \frac{|70-30|}{70+30} = 0.4$$

Ground truth

Time	0	100	200	300	400
PU	1	0	0	1	1

Sensing result

SU1	1	1	0	1	1
SU2	1	0	0	1	1
SU3	1	1	0	1	0
MSU1	1	1	1	0	0
MSU2	0	0	0	0	0

Majority voting

A	1	1	0	1	0

False positive

False negative

$\eta = 0.01$

reputation

SU1	1	2.71	7.38	20.08	54.59
SU2	1	2.71	1	2.71	7.38
SU3	1	2.71	7.38	20.08	54.55
MSU1	1	2.71	7.38	2.71	1
MSU2	1	0.36	0.13	0.36	0.13

High variance

A	1	1	0	1	0

Without confidence

ρ	0.6	0.2	0.6	0.2	0.2

reputation

SU1	1	1.82	2.22	4.05	4.95
SU2	1	1.82	1.49	2.71	3.32
SU3	1	1.82	2.22	4.05	4.95
MSU1	1	1.82	2.22	1.22	1
MSU2	1	0.54	0.44	0.81	0.67

Low variance

A	1	1	0	1	1

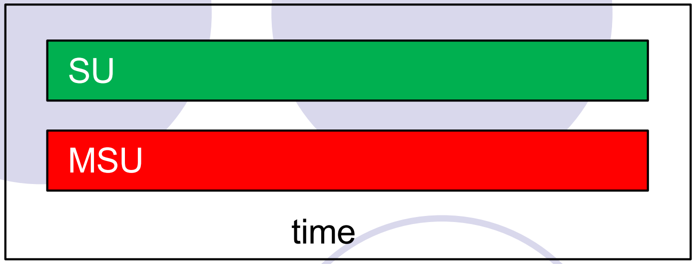
With confidence

5. Simulation

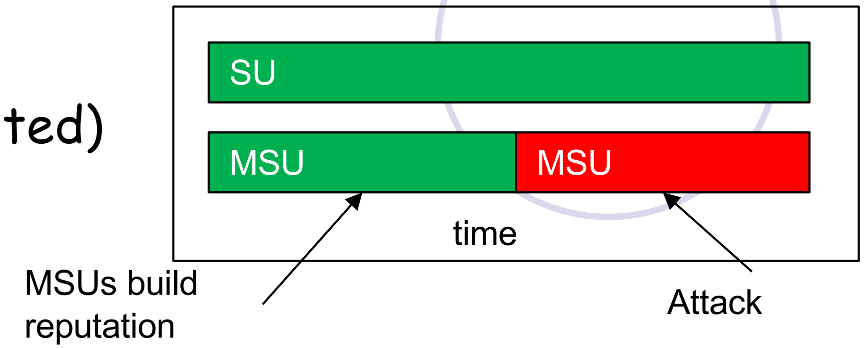
Settings and datasets

- Number of SUs: 10-50
- SU error rate: 0-0.3 (randomly selected)
- Number of MSUs: 7-50
- MSU error rate: 0.7-1 (randomly selected)
- Initial reputation: 1
- Sensing records of 100,000 timeslots.

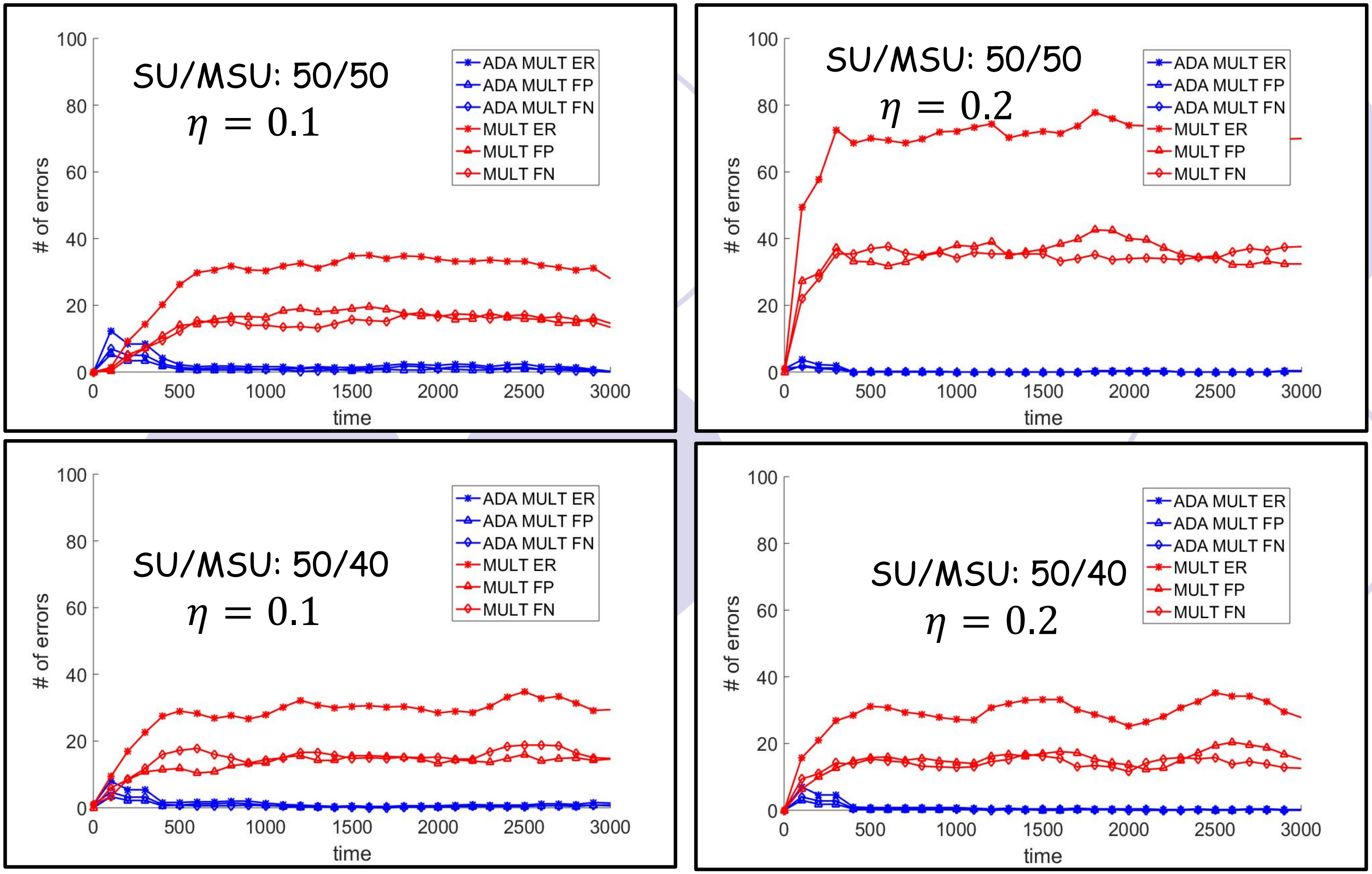
Dataset type 1



Dataset type 2



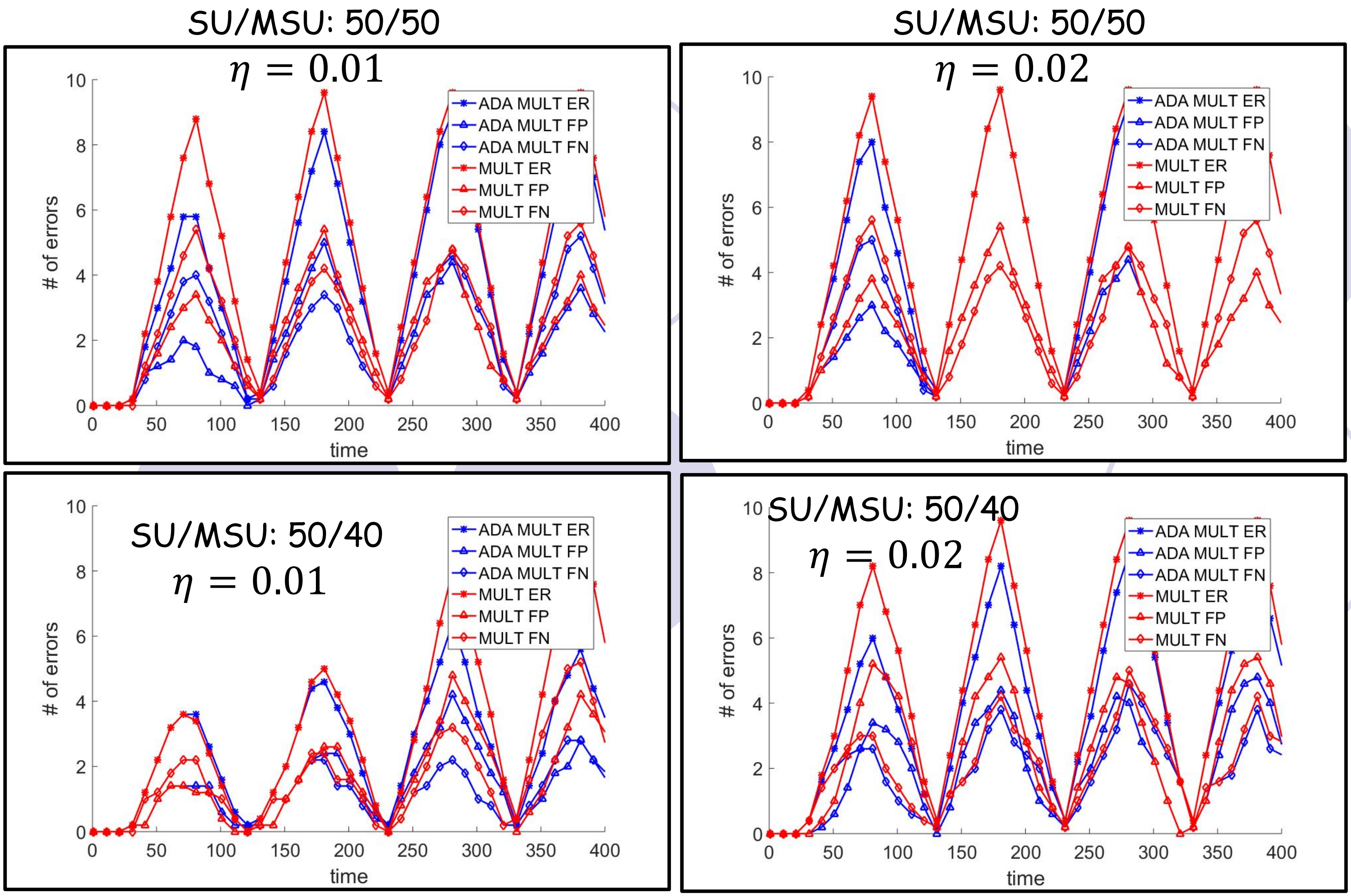
Multiplicative vs. Adaptive Multiplicative RUF



Dataset type 1 Used for simulation.

False positive (FP), False negative (FN), Error (ER), Adaptive multiplicative (ADA MULT), Multiplicative (MULT)

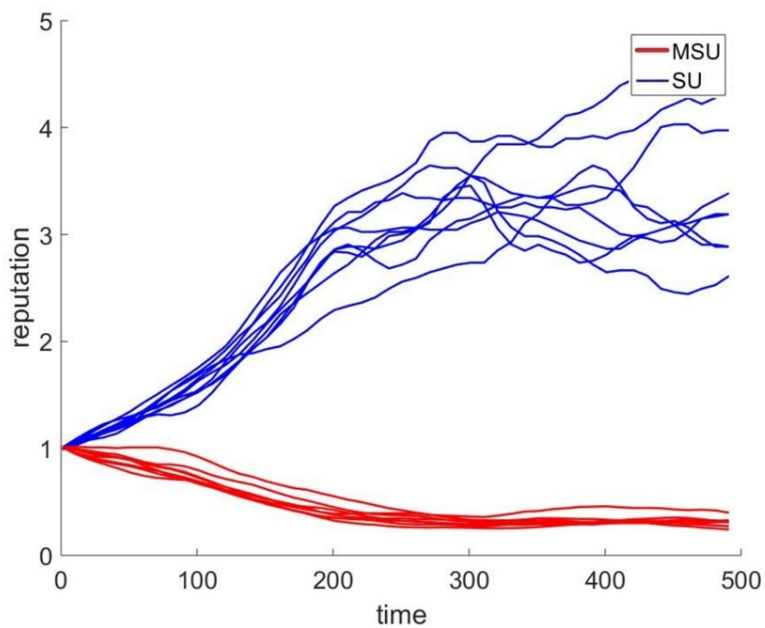
Multiplicative vs. Adaptive Multiplicative RUF



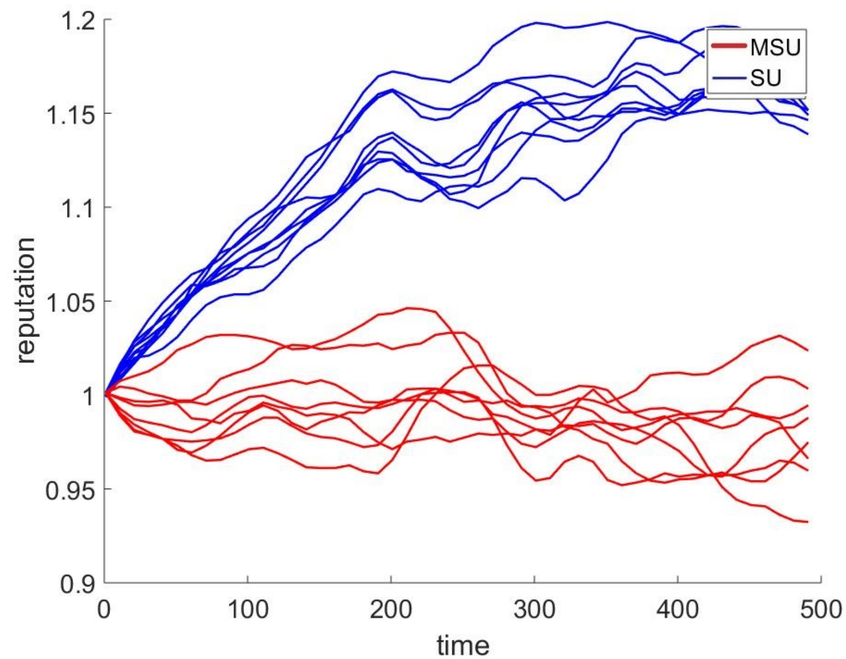
Dataset type 2 Used for simulation.

False positive (FP), False negative (FN), Error (ER), Adaptive multiplicative (ADA MULT), Multiplicative (MULT)

Multiplicative vs. Adaptive Multiplicative RUF



Multiplicative

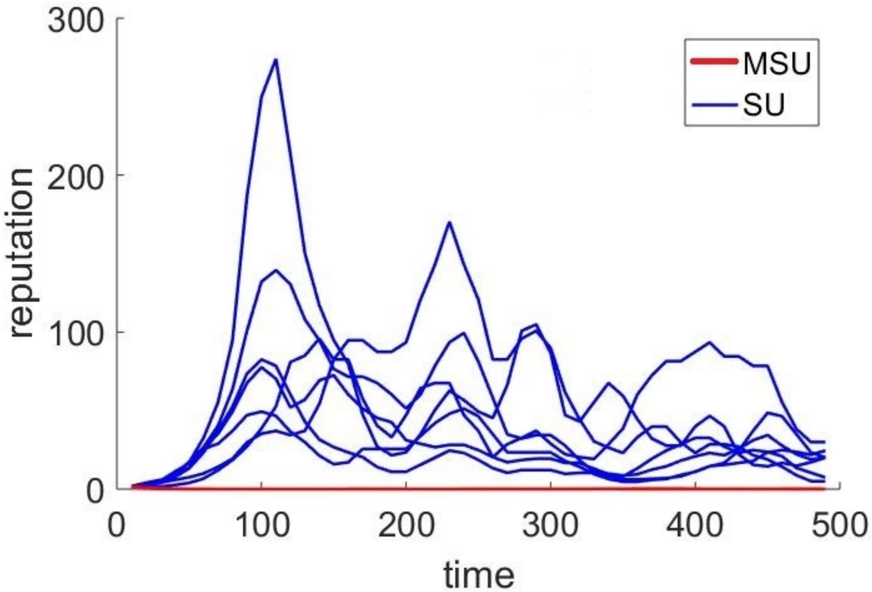


Adaptive multiplicative

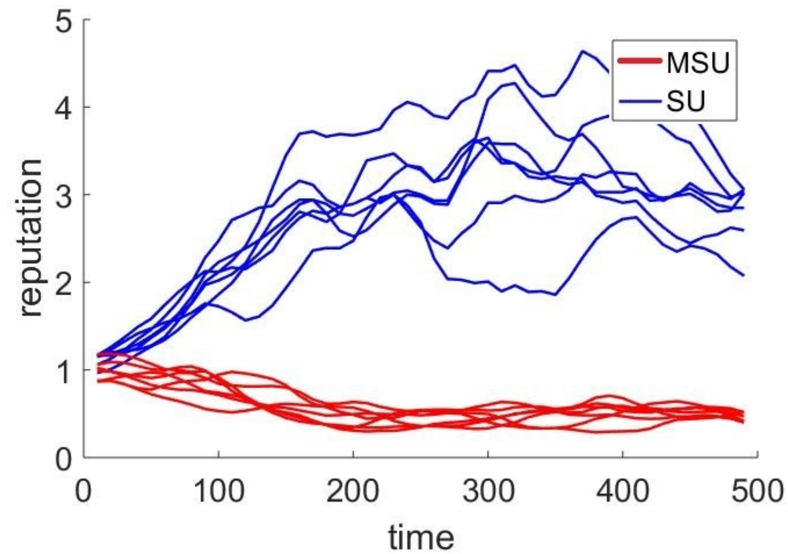
Dataset type 1 with $\eta = 0.01$

- Both work fine.
- High variation of reputation in multiplicative RUF may leads to more errors.

Multiplicative vs. Adaptive Multiplicative RUF



Multiplicative



Adaptive multiplicative

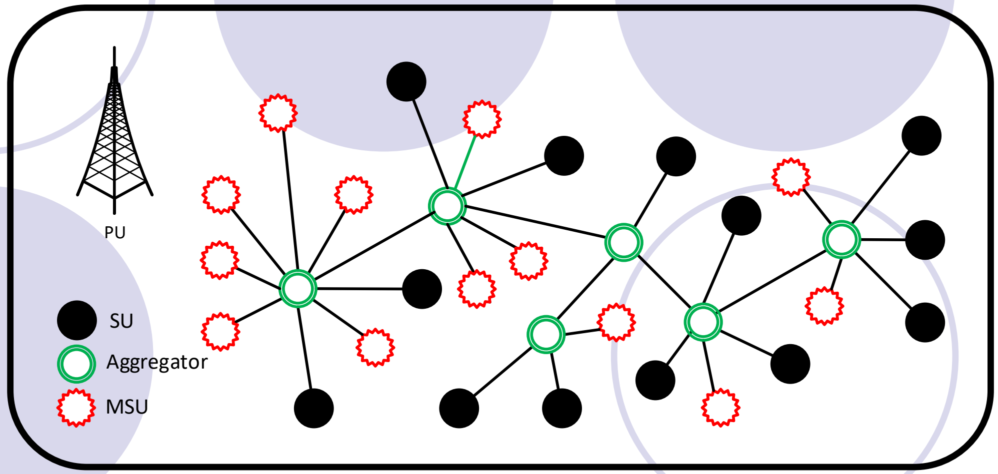
Dataset type 2 with $\eta = 0.01$

- High variation of reputation in multiplicative RUF leads to more errors.

6. Extension: Two-Level Majority Voting

A simple illustration

- 13 MSUs (clustered)
- 13 SUs
- 2 wrong aggregators
- 4 correct aggregators.

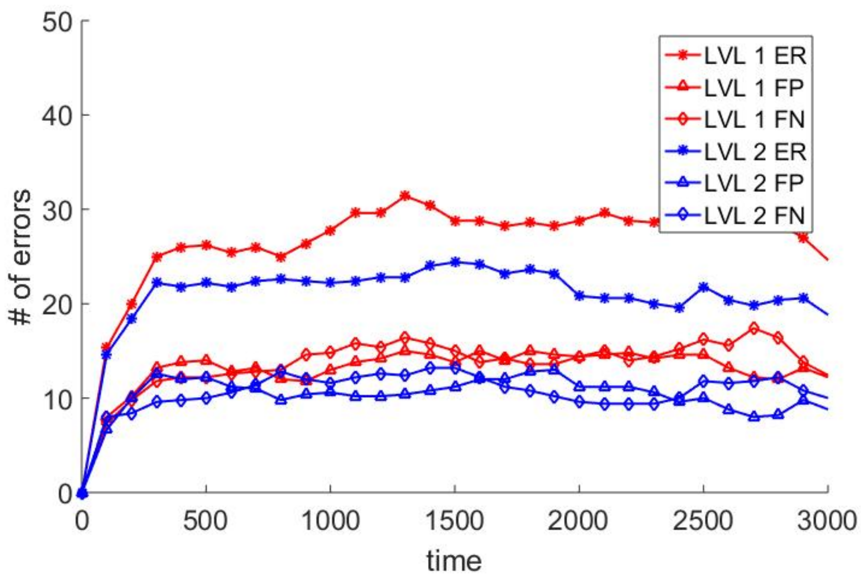


MSUs may win in one-level voting

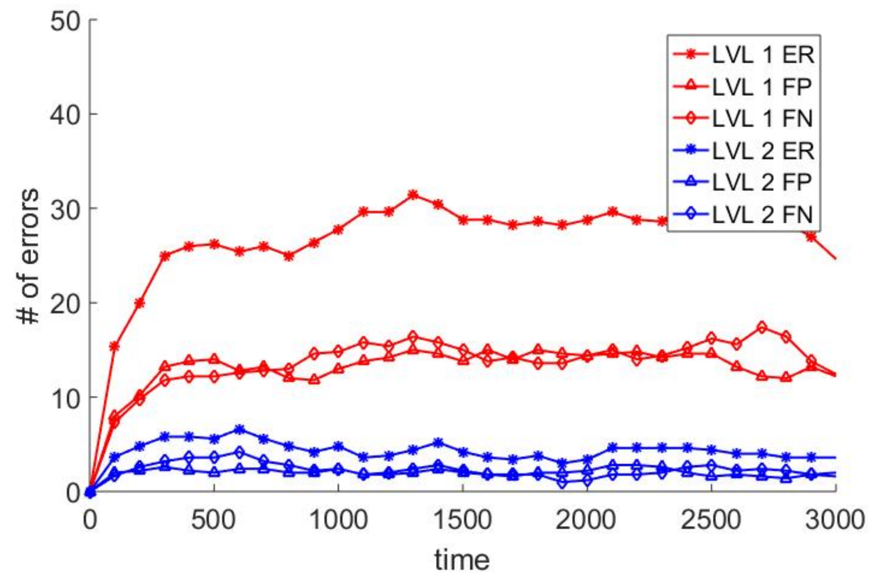
MSUs cannot win in two-level voting

Connected dominating set based distributed aggregator selection process

Two-Level vs. One-Level Voting



MSUs are sparse (uniform).



MSUs are clustered.

False positive (FP), False negative (FN), Error (ER), Level 1 (LVL 1), and Level 2 (LVL 2)

Dataset type 2 with $\eta = 0.01$

SU/MSU: 50/40

80% MSU: clustered

20% MSU and all SU: uniformly distributed

- Two-level voting works better when MSUs are clustered

7. Summary

- Adaptive multiplicative RUF using confidence
- Adaptive multiplicative RUF works better than other RUFs
- Two-level voting produces less errors than one-level voting