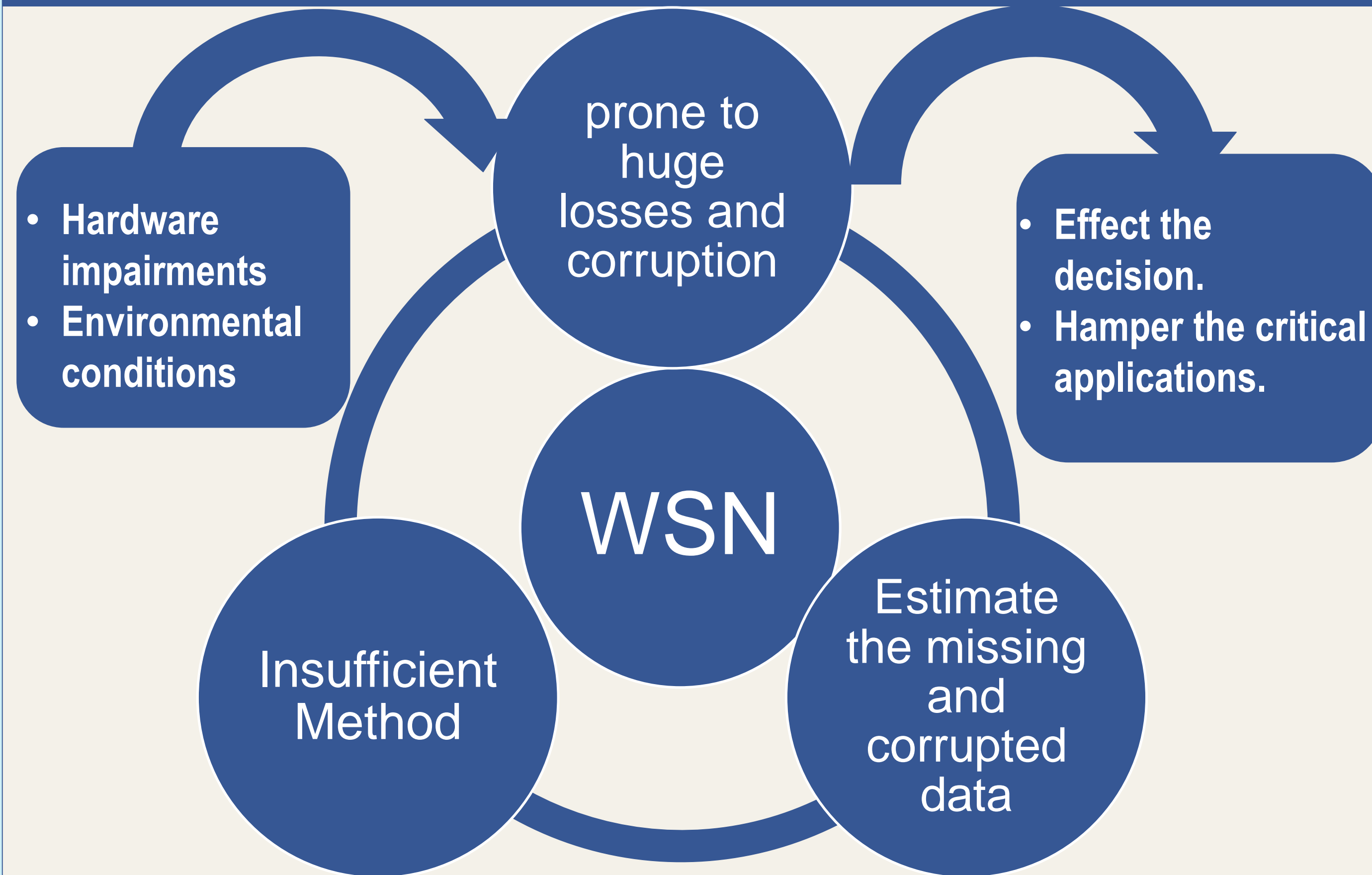


## Motivation



## Conventional Methods of Matrix completion

### SVT: Singular value thresholding [1]

$$\min_{\mathbf{X}} \|\mathbf{X}\|_* + \lambda_1 \|\mathbf{Y} - \mathbf{B} \bullet \mathbf{X}\|_F^2$$

### LMaFit: Low rank matrix fitting [2] = Matrix factorization with dynamically updated rank

$$\min_{\mathbf{X}, \mathbf{U}, \mathbf{V}} \lambda_2 (\|\mathbf{U}\|_F^2 + \|\mathbf{V}^T\|_F^2) + \lambda_3 \|\mathbf{Y} - \mathbf{B} \bullet \mathbf{X}\|_F^2$$

$\mathbf{U} \in \mathbb{R}^{n \times r}$   
 $\mathbf{V} \in \mathbb{R}^{t \times r}$

### RPCA: Robust principal component analysis [3]

$$\min_{\mathbf{X}, \mathbf{L}, \mathbf{S}} \lambda_4 (\|\mathbf{L}\|_* + \|\mathbf{S}\|_1) + \lambda_5 \|\mathbf{Y} - \mathbf{B} \bullet \mathbf{X}\|_F^2$$

### Data loss reconstruction in WSN [4]

$$\min_{\mathbf{X}, \mathbf{U}, \mathbf{V}} \lambda_6 (\|\mathbf{U}\|_F^2 + \|\mathbf{V}^T\|_F^2 + \|\mathbf{H}\mathbf{U}\mathbf{V}^T\|_F^2 + \|\mathbf{U}\mathbf{V}^T\mathbf{T}\|_F^2) + \lambda_7 \|\mathbf{Y} - \mathbf{B} \bullet \mathbf{X}\|_F^2$$

$\mathbf{X} \in \mathbb{R}^{n \times t}$  is unknown WSN matrix, with  $n$  sensor nodes and  $t$  timestamps  
 $\mathbf{Y} \in \mathbb{R}^{n \times t}$  is known incomplete and noisy WSN matrix  
 $B(i, j) = \begin{cases} 0 & \text{if } Y(i, j) = 0 \\ 1 & \text{Otherwise} \end{cases}$

## Proposed: TS-MC Algorithm

### First Stage

#### Method-1

$$\min_{\hat{\mathbf{X}}} \|\mathbf{Y} - \mathbf{B} \bullet \mathbf{X}\|_F^2 + \lambda_{p1} \|\mathbf{D}_1 \hat{\mathbf{X}} \mathbf{D}_2\|_1$$

$\mathbf{D}_1 \in \mathbb{C}^{n \times n}$ ,  $\mathbf{D}_2 \in \mathbb{C}^{t \times t}$  are the DCT matrices.

#### Method-2

Matrix completion problem formulated as Compressive sensing problem.

$$\mathbf{y} = \Phi \mathbf{X}(:, i) = \Phi \mathbf{x} = \Phi (\mathbf{D}_2 \otimes \mathbf{D}_1^T) \mathbf{s} = \Phi \Psi^{-1} \mathbf{s}$$

$$\mu(\Phi, \Psi^{-1}) = \sqrt{nt} \max_{i,j} \frac{|\langle \Phi_i, \Psi_j^{-1} \rangle|}{\|\Phi_i\|_2 \|\Psi_j^{-1}\|_2} = \sqrt{2}$$

$$\mu(\Phi, \Psi^{-1}) \in [1, \sqrt{nt}]$$

$$\hat{\mathbf{s}} = \min_{\mathbf{s}} \|\mathbf{y} - \mathbf{A}\mathbf{s}\|_2^2 + \lambda_c \|\mathbf{s}\|_1, \quad \hat{\mathbf{x}} = \Psi^{-1} \hat{\mathbf{s}}$$

• WSN data varies slowly/ smoothly in both spatial and temporal domain.

• DCT acts as a KL type basis for large class of smooth signals, hence may act as the best sparsifying basis for WSN signal in both spatial and temporal domain.

### Second Stage

Compute rank of the data from First stage

$$\min_{\mathbf{U}, \mathbf{V}} \|\hat{\mathbf{X}} - \mathbf{U}\mathbf{V}\|_F^2 + \mu \|\mathbf{U}\|_F^2 + \mu \|\mathbf{V}\|_F^2$$

$$\hat{\mathbf{X}} = \mathbf{U}\mathbf{V}$$

Proposed TS-MC-1: Method-1 + Second stage

Proposed TS-MC-2: Method-2 + Second stage

## Simulation Results

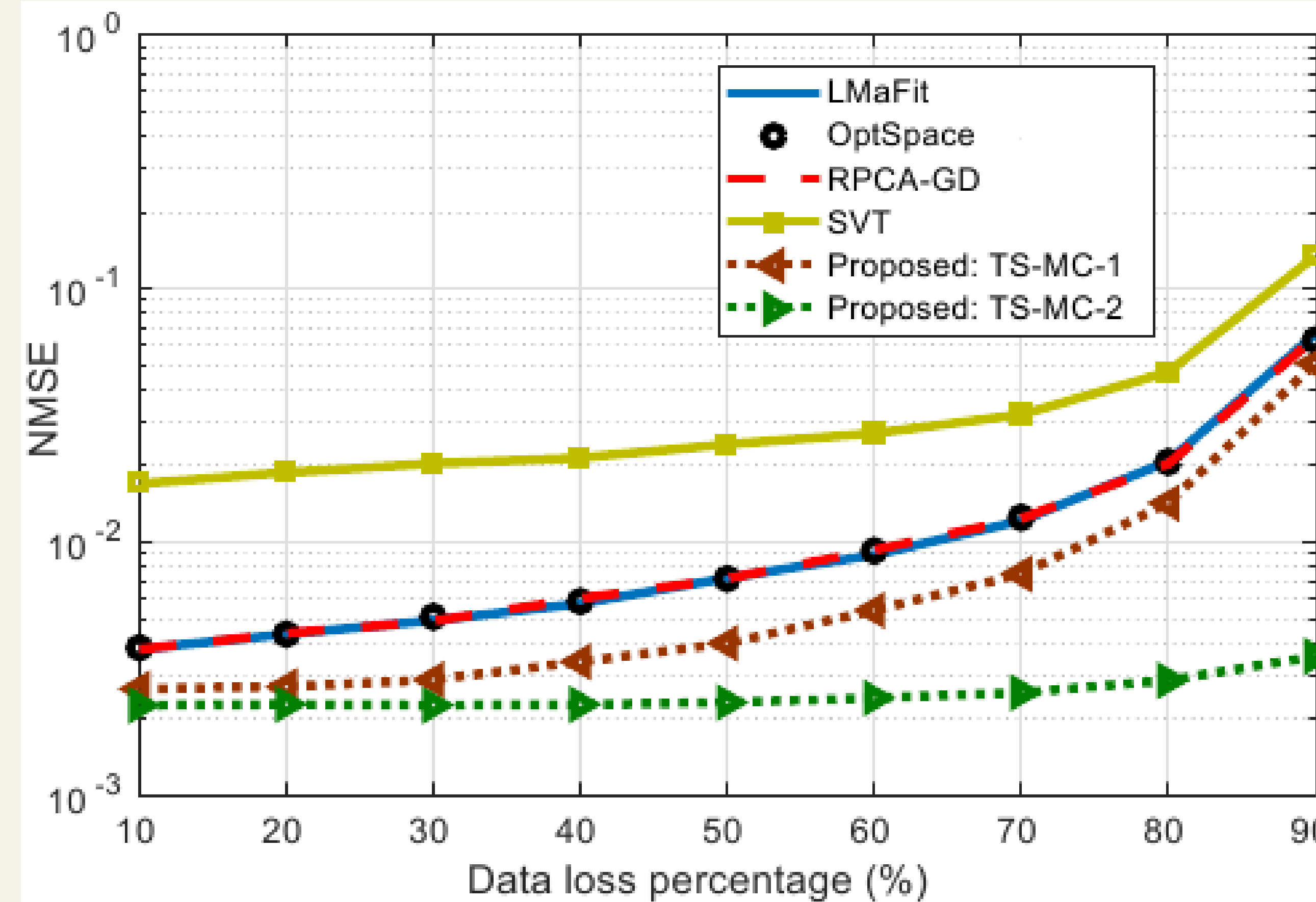


Fig. 1 NMSE against data loss percentage at SNR = 10 dB for humidity dataset taken from Intel lab [6].

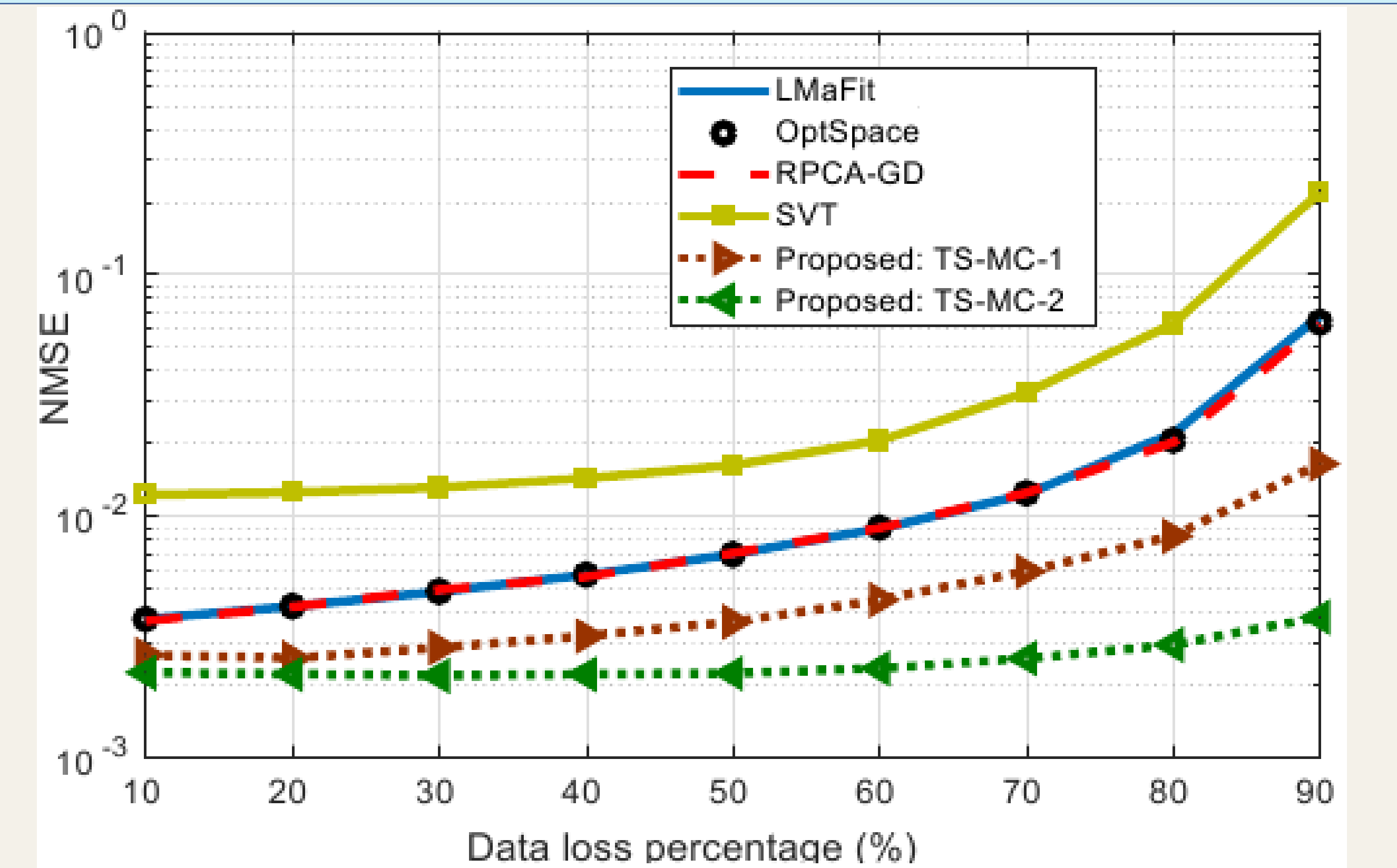


Fig. 2 NMSE against data loss percentage at SNR = 10 dB for temperature dataset taken from Intel lab [6].

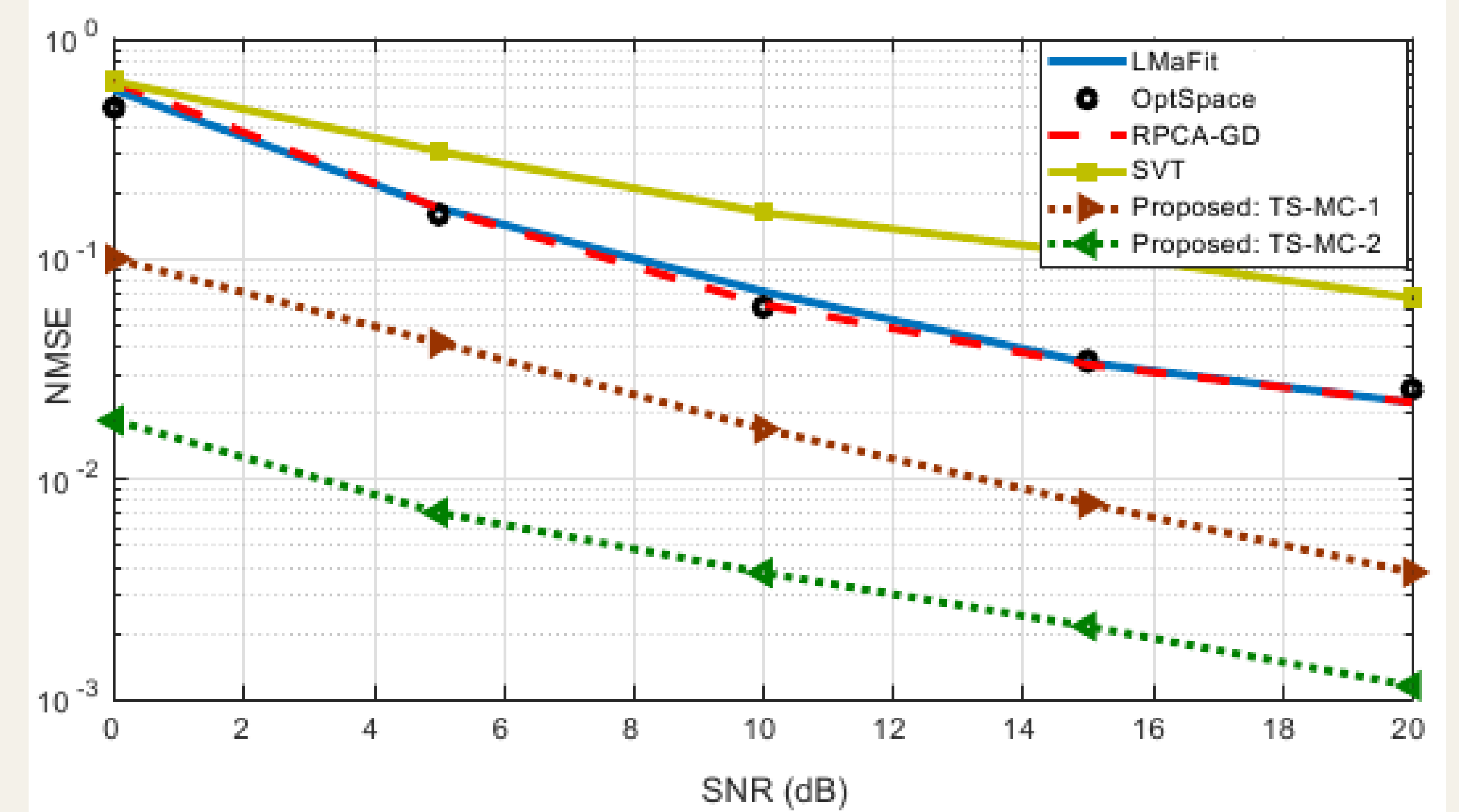


Fig. 3 NMSE against SNR (dB) at 90% data loss for temperature dataset taken from Intel lab [6].

## Future Work

- The proposed TS-MC algorithm will be verified for various other data sets like biology data and recommender system.
- This algorithm will also be used for channel estimation in millimeter wave Massive MIMO system.

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## References

- [1] Jian-Feng Cai, Emmanuel J Candès, and Zuowei Shen, "A singular value thresholding algorithm for matrix completion," SIAM Journal on Optimization, vol. 20, no. 4, pp. 1956–1982, 2010.
- [2] Zaiwen Wen, Wotao Yin, and Yin Zhang, "Solving a low-rank factorization model for matrix completion by a nonlinear successive over-relaxation algorithm," Mathematical Programming Computation, vol. 4, no. 4, pp. 333–361, Dec 2012.
- [3] Emmanuel J. Candès, Xiaodong Li, Yi Ma, and John Wright, "Robust principal component analysis?," J. ACM, vol. 58, no. 3, pp. 11:1–11:37, June 2011.
- [4] L. Kong, M. Xia, X. Y. Liu, M. Y. Wu, and X. Liu, "Data loss and reconstruction in sensor networks," in 2013 Proceedings IEEE INFOCOM, April 2013, pp. 1654–1662.
- [5] Anubha Gupta, Shiv Dutt Joshi, and Pushpendra Singh, "On the approximate discrete KLT of fractional brownian motion and applications," Journal of the Franklin Institute, 2018.
- [6] "Intel lab data," <http://db.csail.mit.edu/labdata/labdata.html>, 2004.