Technical Report

Remote Data Mirroring Experiments
Comparison of Pri-AwaRE with RE-STORM-ARROW

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Version: 0.9

1 Introduction

This report provides the details of the experimental evaluations for the Remote Data Mirroring (RDM) network [1, 2]. Experiments have been performed to compare the Pri-AwaRE approach with the approach of RE-STORM-ARROW [3] which is based on the technique of primitive cognitive network process (P-CNP) [4] and RE-STORM. The approach provides the support of updating initially defined reward values for the technique of RE-STORM [5]. The implementation of RE-STORM-ARROW makes use of the DESPOT POMDP solver [6]. All the experiments have been performed using Lenovo Thinkpad with intel Core i7, 8th Gen processor and 16 GB RAM. Next, the experimental setup and requirements specifications for the experiments are discussed.

2 Experimental Setup

The experimental setup involves the usage of the same initial setup of the RDM network and MR-POMDP++ model as described in Chapter 6 of Thesis. The initial setup for comparisons with the RE-STORM-ARROW [3] considers a different set of Requirements Specifications (R) which have been defined by the experts of RE-STORM [5, 7].

The requirements specifications for the experiments are as follows:

R1: *The probability of satisfaction of Minimization of Cost shall be greater than or equal to 0.70. i.e.* ***P(MC=True)>=0.70****.*

R2: *The probability of satisfaction of Maximization of Reliability shall be greater than or equal to 0.85 i.e.* ***P(MR=True)>=0.85****.*

R3: *The probability of satisfaction of Maximization of Performance shall be greater than or equal to 0.75. i.e.* ***P(MP=True)>=0.75****.*

Next, the experiment results for all the dynamic scenarios S_1 to S_6 of the RDM, presented in Chapter 5, are discussed.

3 Experiments Results

The experiments results for all the scenarios are presented in Figs. 1 to 6. Lets observe, Figs. 1, 2 and 3. Under scenarios S_1 to S_3, the approach of Pri-AwaRE shows better satisfaction levels of NFRs *MC* and *MP* in comparison to the approach of RE-STORM-ARROW. On the other hand, RESTORM-ARROW maintains higher reliability levels compared to Pri-AwaRE under scenarios S_1 and S_3. The reason behind this behavior is that the RE-STORM-ARROW, using P-CNP, supports the update of the initially defined reward values for the RE-STORM approach. This is not the case in the Pri-AwaRE where the autonomous tuning of priorities is provided at runtime with out the update of the initially defined reward values. Furthermore, RE-STORM-ARROW, even supported by the update of reward values, does show poor satisfaction levels of NFRs. For example, under scenario S_5, the approach of Pri-AwaRE shows better satisfaction levels for all the NFRS as compared to RE-STORM-ARROW which shows low the satisfaction levels for *MC* and *MP* at several time steps as shown in Fig. 2. Both the approaches, show comparable results under scenarios S_4 and S_6. Although, the approach of RE-STORM-ARROW supports the update of the initial reward values, this update is not performed autonomously. Instead, it requires external support from P-CNP that causes efficiency problems. Therefore, from the results it can be deduced that the Pri-AwaRE approach offers higher levels of satisfaction of NFRs in comparison to the single-objective technique of RE-STORM-ARROW.

Figure 1: Satisfaction of NFRs over Time under Scenario S_1

Figure 2: Satisfaction of NFRs over Time under Scenario S_2

Figure 3: Satisfaction of NFRs over Time under Scenario S_3

Figure 4: Satisfaction of NFRs over Time under Scenario S_4

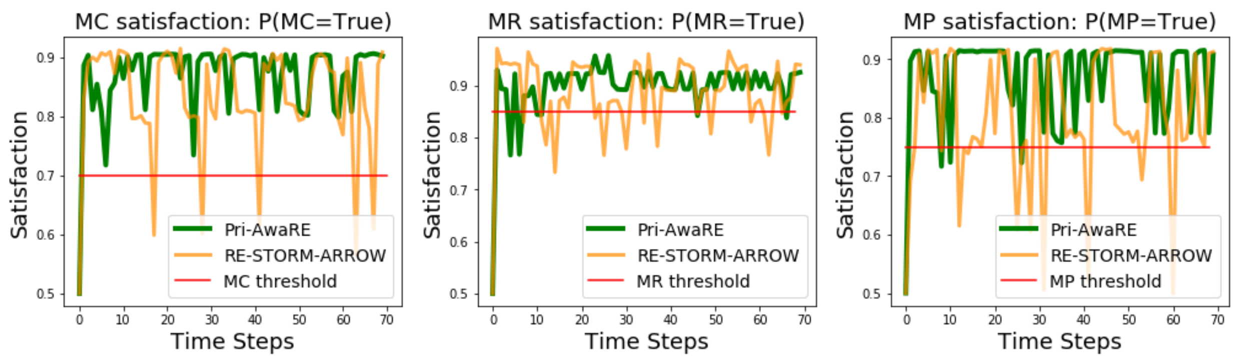

Figure 5: Satisfaction of NFRs over Time under Scenario S_5

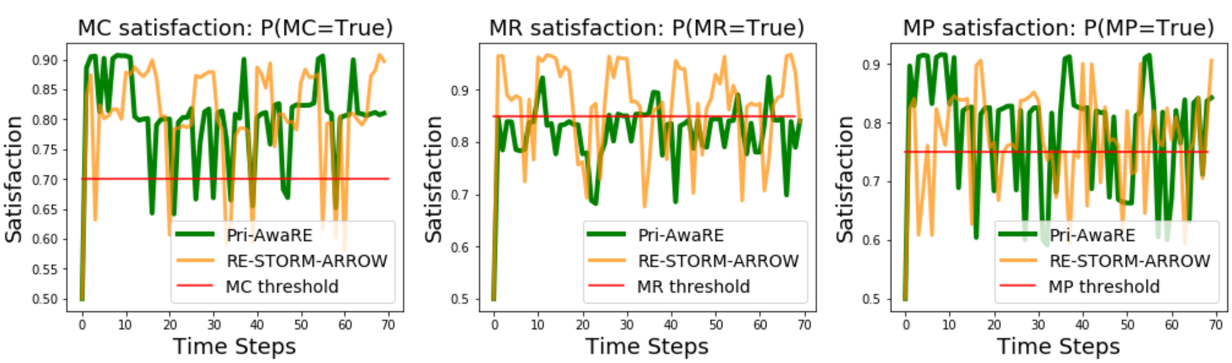

Figure 6: Satisfaction of NFRs over Time under Scenario S_6

3.1 Summary of Findings

In summary, the experiment results show that Pri-AwaRE shows compliance with the requirements specification for the NFRs on average under almost all of the scenarios as presented in Fig. 7. The results show a confidence level of 95 percent. The confidence intervals along with the standard error for average satisfaction levels of NFRs for all the dynamic scenarios are presented in Table 1. The average satisfaction levels for MC and MP are above the satisfaction thresholds under all the scenarios and therefore, maintain the threshold requirements of $P(MC = True) >= 0.70$ and $P(MP = True) >= 0.75$. For example, under scenario S_1, the average satisfaction level for MC is 0.8439 with a standard error of 0.0088 and for MP the average satisfaction level is 0.8301 having a standard error of 0.0105 which shows compliance with the required thresholds for satisfaction of both MC and MP respectively. The experiment results also show satisfaction of the threshold requirements for the MR with the average satisfaction being above the threshold of 0.85 under most of the scenarios. For example, under scenarios S_1, S_2, S_4 and S_5, the average satisfaction levels of MR are 0.8727, 0.9016,0.8555 and 0.8965 respectively, and therefore satisfies the requirement of $P(MR = True) >= 0.85$. The Pri-AwaRE approach also shows comparable results with respect to RE-STORM-ARROW under other scenarios as well. The exception lies in case of S_3 and S_6, where the average satisfaction for MR is 0.8155 and 0.8171 with confidence intervals of 0.7999 - 0.8311 and 0.8025 - 0.8317 respectively. However, the average satisfaction level for MR is below the threshold, it is closer to the required satisfaction level. Moreover, these satisfaction values for MR under the dynamic scenarios of S_3 and S_6 are considered to be usual. As under such circumstances, the preference is given to support the satisfaction of the MC and MP more than MR. To sum up, it can be concluded from the results that Pri-AwaRE offers statistically sound results in terms of satisfaction of the requirements. Furthermore, under all the scenarios, the Pri-AwaRE approach shows comparable and sometimes even better satisfaction levels for NFRs in comparison to the technique of RE-STORM-ARROW.

Table 1: Confidence Intervals for Average Satisfaction Levels of NFRs

Scenario	**NFR**	**Sat$_{AVG}$**	**Confidence Interval**	**Standard Error**
S_1	**MC**	**0.8439**	**0.8264 - 0.8615**	**0.0088**
	MR	**0.8727**	**0.8511 - 0.8942**	**0.0108**
	MP	**0.8301**	**0.8092 - 0.8512**	**0.0105**
S_2	MC	0.8755	0.861 - 0.8899	0.0072
	MR	0.9016	0.8889 - 0.9142	0.0063
	MP	0.8858	0.8711 - 0.9006	0.0074
S_3	MC	0.8773	0.8628 - 0.8918	0.0073
	MR	0.8155	0.7999 - 0.8311	0.0078
	MP	0.8827	0.8675 - 0.8979	0.0076
S_4	MC	0.8098	0.7917 - 0.8279	0.0091
	MR	0.8555	0.8347 - 0.8762	0.0104
	MP	0.7902	0.766 - 0.8144	0.0121
S_5	MC	0.8693	0.8543 - 0.8843	0.0075
	MR	0.8965	0.8826 - 0.9104	0.0069
	MP	0.8693	0.8514 - 0.8873	0.0089
S_6	MC	0.8007	0.7822 - 0.8192	0.0093
	MR	0.8171	0.8025 - 0.8317	0.0073
	MP	0.7871	0.76305 - 0.8111	0.012

*Sat$_{AVG}$ represents the average satisfaction level of NFR

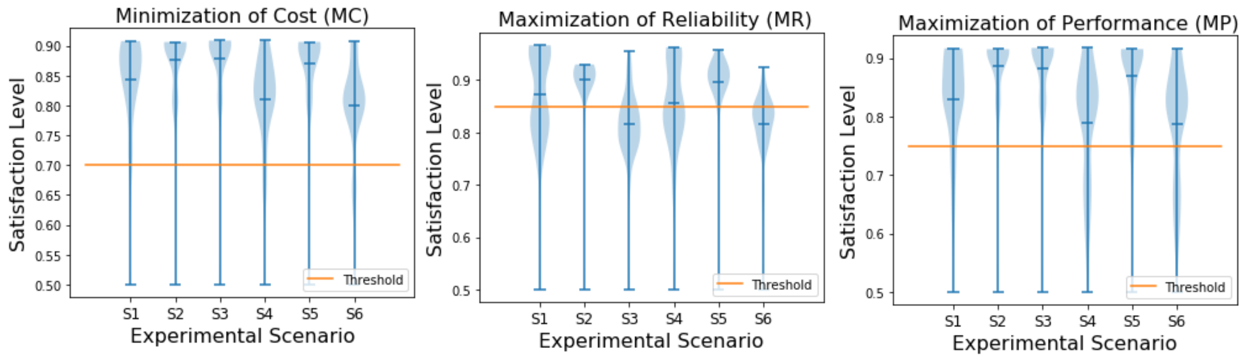

Figure 7: Average Satisfaction of NFRs using Pri-AwaRE

References

[1] K. Keeton, C. Santos, D. Beyer, J. Chase, and J. Wilkes, "Designing for Disasters," Mar. 2004.

[2] H. Samin, L. H. G. Paucar, N. Bencomo, C. M. C. Hurtado, and E. M. Fredericks, "Rdmsim: an exemplar for evaluation and comparison of decision-making techniques for self-adaptation," in *2021 International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS)*. IEEE, 2021, pp. 238–244.

[3] L. H. G. Paucar, N. Bencomo, and K. K. F. Yuen, "ARRoW: automatic runtime reappraisal of weights for self-adaptation," in *Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing - SAC '19*. Limassol, Cyprus: ACM Press, 2019, pp. 1584–1591.

[4] K. K. F. Yuen, "The Primitive Cognitive Network Process in healthcare and medical decision making: Comparisons with the Analytic Hierarchy Process," *Applied Soft Computing*, vol. 14, pp. 109–119, Jan. 2014.

[5] L. H. G. Paucar and N. Bencomo, "RE-STORM: mapping the decision-making problem and non-functional requirements trade-off to partially observable markov decision processes," in *Proceedings of the 13th International Conference on Software Engineering for Adaptive and Self-Managing Systems - SEAMS '18*. Gothenburg, Sweden: ACM Press, 2018, pp. 19–25.

[6] A. Somani, N. Ye, D. Hsu, and W. S. Lee, "DESPOT: Online POMDP Planning with Regularization," in *Advances in Neural Information Processing Systems 26*, C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2013, pp. 1772–1780.

[7] L. H. Garcia Paucar and N. Bencomo, "Knowledge Base K Models to Support Trade-Offs for Self-Adaptation using Markov Processes," in *2019 IEEE 13th International Conference on Self-Adaptive and Self-Organizing Systems (SASO)*, Jun. 2019, pp. 11–16, iSSN: 1949-3681, 1949-3673.