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Graceful Degradations in Autonomous Systems Through Combinatorial Designs

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PROBLEM STATEMENT

Intelligent Autonomous Systems (IAS) should be highly cognitive and reflexive with dynamic environments.

The learning models should provide incremental guarantees to IAS for learning and adapting in the presence of unknown data / context by supporting progressive enhancements when the environment behaves as expected or graceful degradations when it does not (Figure 1).

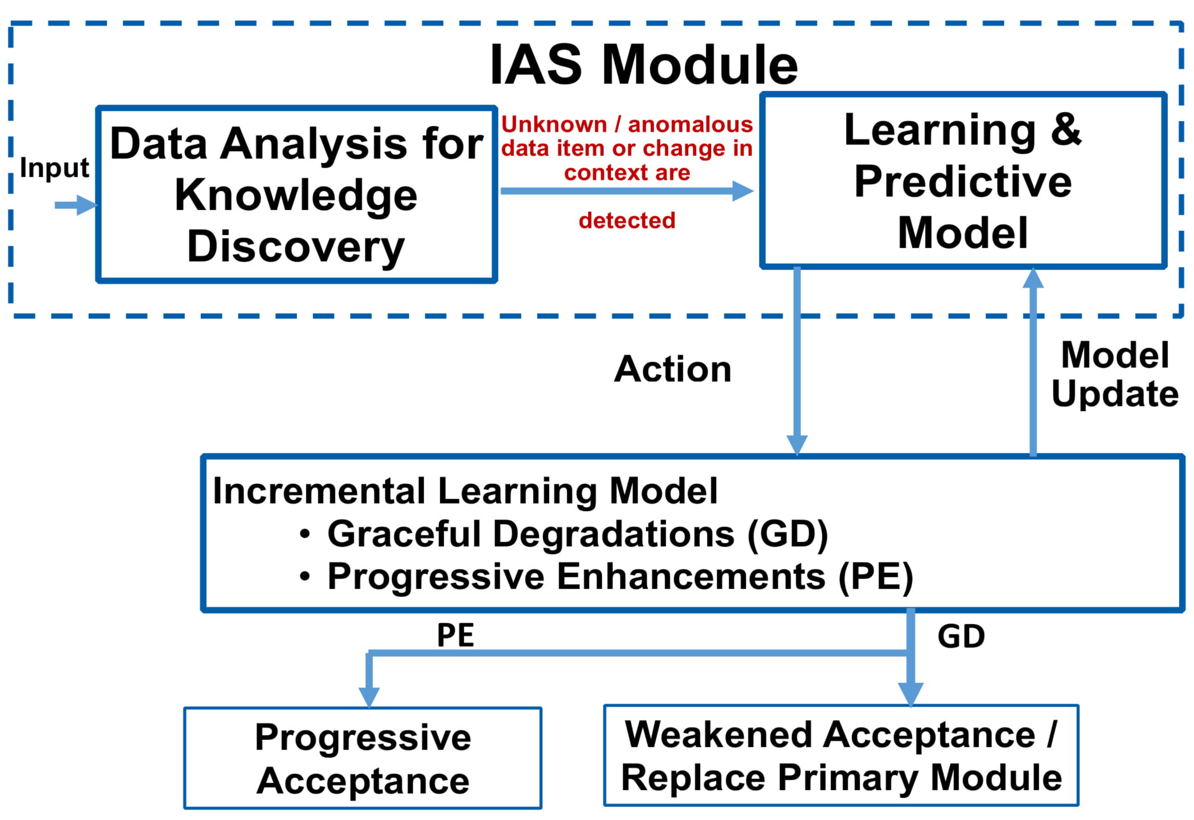

Figure 2. Reflexivity workflow in IAS

In the case of graceful degradations, there are two alternatives:

1. Weaken the acceptance test of data object (operating at a lower capacity) or
2. Replace primary system with a replica or an alternate system that can pass the acceptance test.

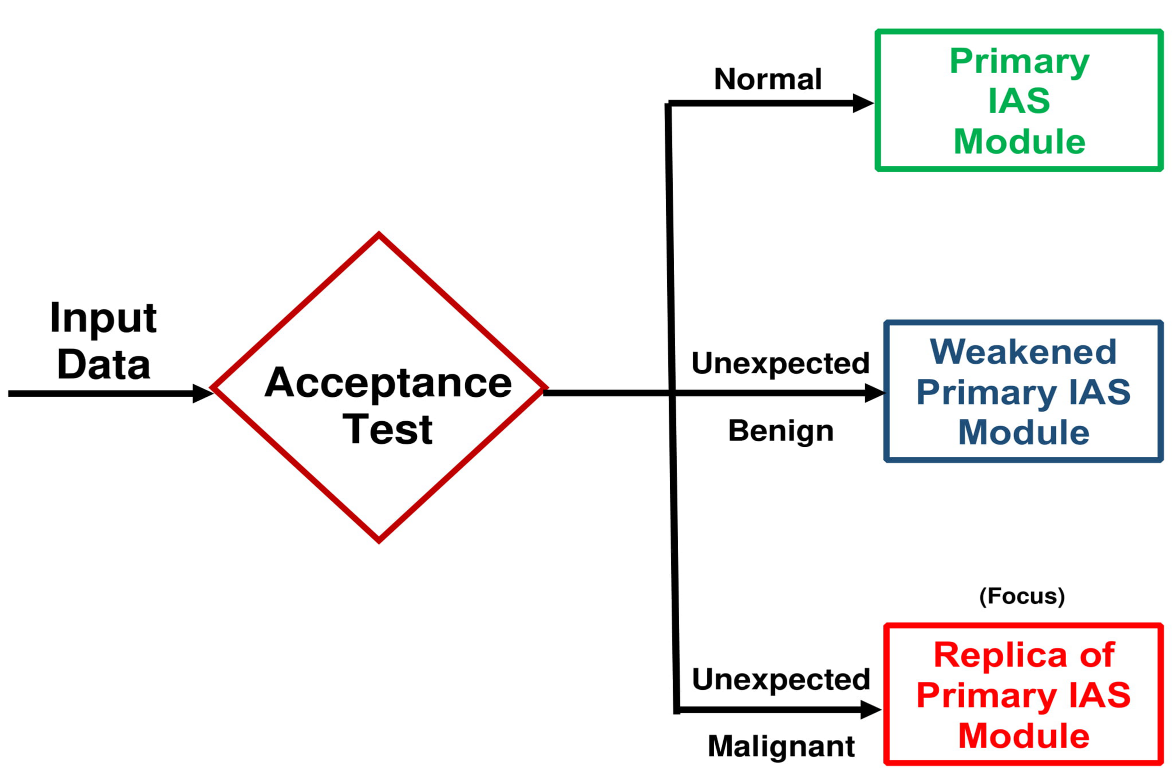

Figure 2. Graceful Degradations in IAS

Graceful degradations in IAS through replica replacement (Figure 2) must take place while

- Underlying critical processes continue to progress without interruption,
- Replication cost is at its minimum.

GRACEFUL DEGRADATIONS

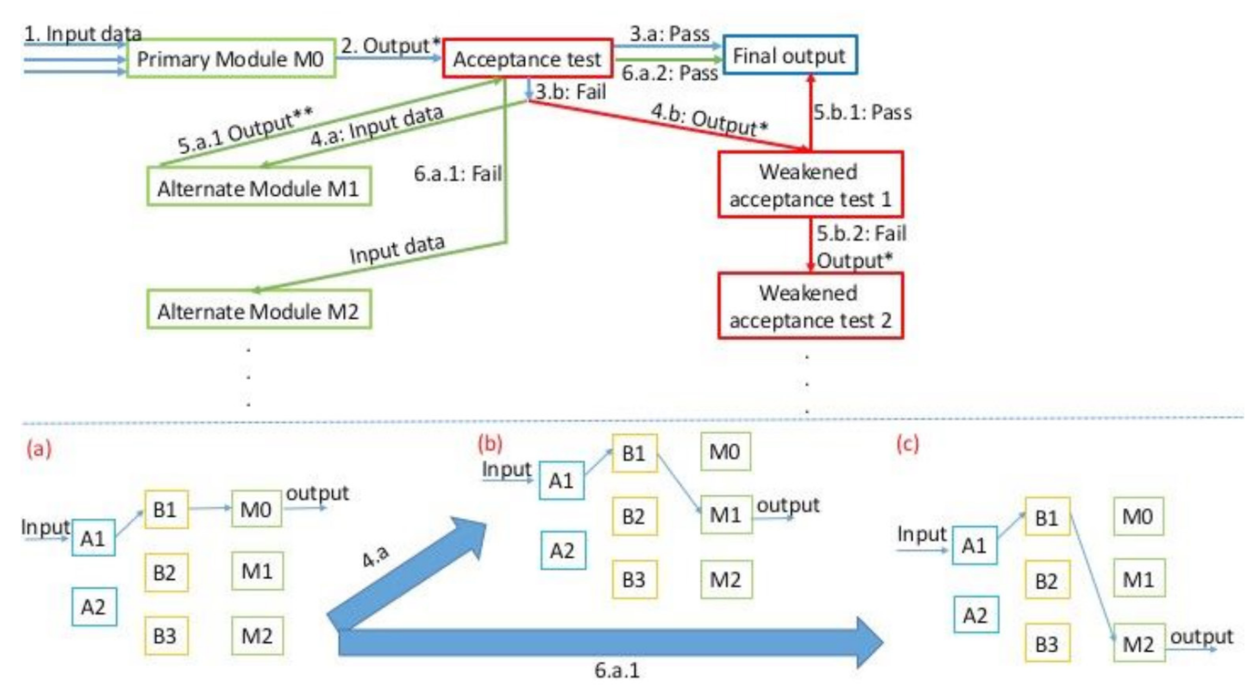

Figure 3. Dynamic Adaptation based Recovery Block Scheme

Generic adaptations of replicas for graceful degradations are not efficient with unaccounted number of replicas. Figure 3 shows a generic scheme for graceful degradations but the replica cost is not controlled.

COMBINATORIAL BLOCK DESIGN

We provide an efficient solution through a combinatorial mathematical model: balanced block design for replica replacement in IAS [1].

The combinatorial model is defined as follows: A distributed environment with

- Set of **A** systems
- Split into **M** distributed blocks
- Each block has **R**-subsets of N systems
- Each system appears exactly in **C** subsets
- Each pair of systems appears in **O** subsets.
- Each replicas get updates every **F** interval

It is a balanced *MACROF*-configuration. We use N = 7 M = 7 R = 3 C = 3 Z = 1 as our base setting since it represents one of the balanced incomplete block design of combinatorial mathematics. Figure 4 illustrates the design.

$$DAB_1 = \{S_1, S_5, S_7\}, DAB_2 = \{S_1, S_2, S_7\}, DAB_3 = \{S_2, S_3, S_7\},$$
$$DAB_4 = \{S_1, S_3, S_4\}, DAB_5 = \{S_2, S_4, S_5\}, DAB_6 = \{S_3, S_5, S_6\},$$
$$DAB_7 = \{S_4, S_6, S_7\}$$

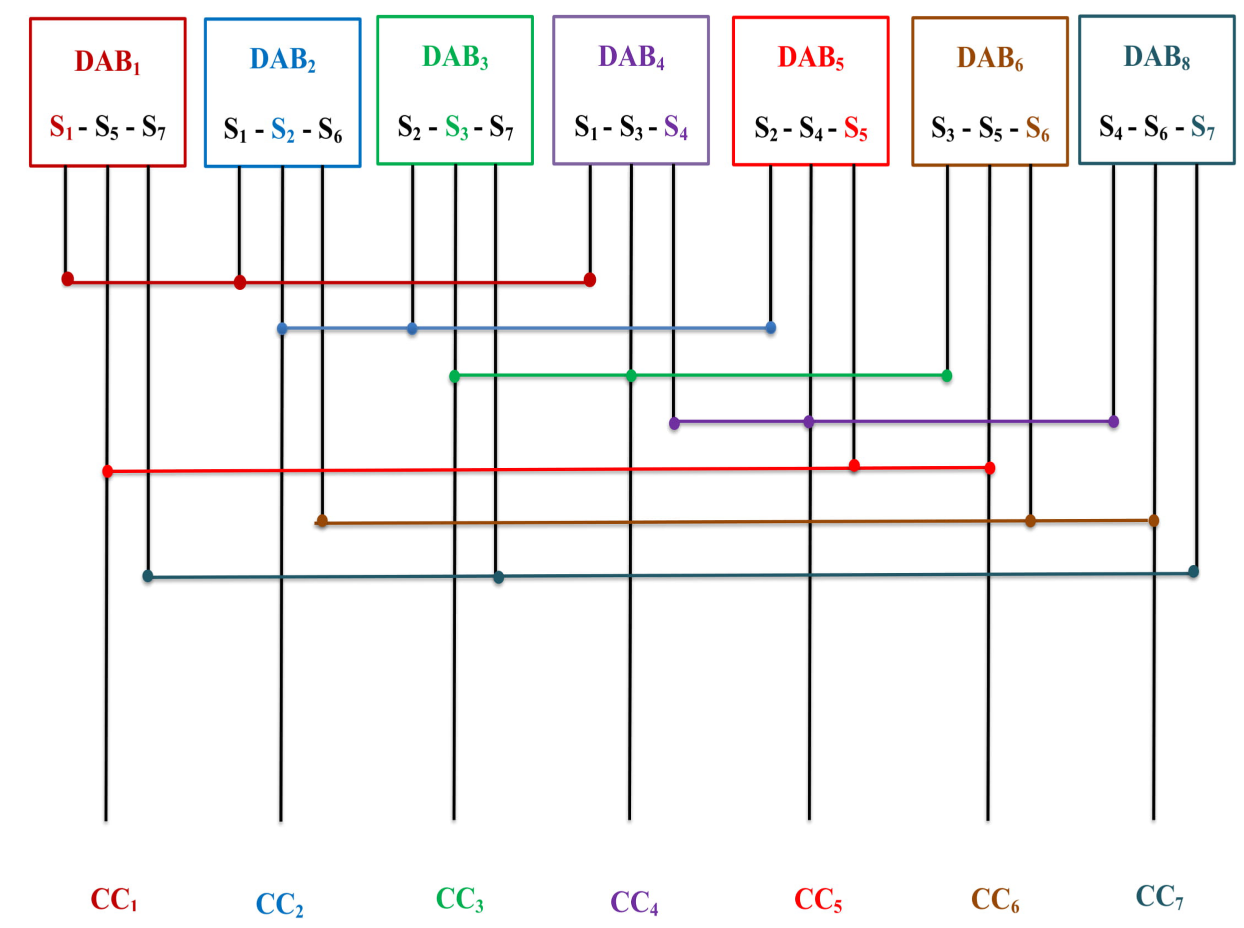

Figure 4. MACROF System Design with Distributed Autonomous Blocks (DAB), Communication Channels (CCs), and Systems (S)

The replicas are connected and F is set by Bayesian learning. Given data item D and context C,

$$P(C_j \mid D_i) = P(D_i)\, C_j / P(C_j)$$

$$F = t_{P(Cj+1 \mid Di+1)} - t_{P(Cj \mid Di)}$$

RESULTS

Design is implemented through a simulator [2].

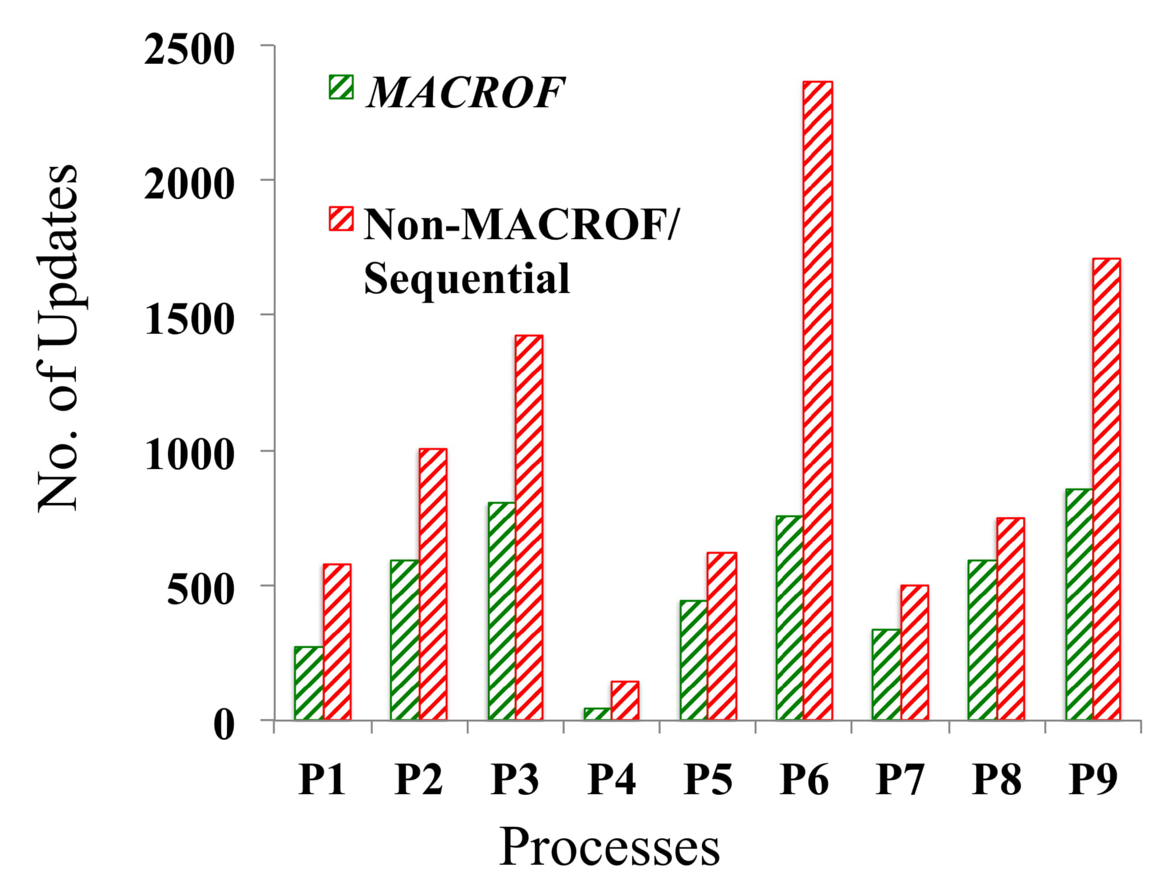

Figure 3. Updates needed for MACROF compared to a sequential non-MACROF

ACKNOWLEDGMENTS

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REFERENCES

[1] G. Mani, B. Bhargava, B. Shivakumar, J. Kobes "Incremental Learning Through Graceful Degradations in Autonomous Systems", IEEE ICCC, June 2018 (In Submission).

[2] "MACROF Simulator," : https://goo.gl/pgVHdk

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