Assessing the Impact of Smart Initial Response Strategies on the Resilience of Complex Systems

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ABSTRACT: The initial response and especially the identification of the damage in a complex engineered system is critical for its performance maintenance. Simultaneously, smart technology enhances the features of preparedness and automation that promote the systems' response processes. The purpose of this research is to investigate the impacts of different smart initial response strategies on the system's resilience, under specific disruptive events of increasing magnitude and complexity. The response strategies were examined with an agent-based modeling approach and the relevant simulations' outcomes were comparatively analyzed. The findings demonstrate that as the smart features increase, the system's initial response becomes more effective in the performance maintenance. Particularly, the effectiveness of the smarter approaches is more evident during disturbances of greater severity. The results also suggest that the nature of a disruptive event can affect the performance of the response strategies. The research provides a methodological approach for the resilience assessment of the initial response and practically supports the design and the deployment of smart solutions into existing systems.

1. INTRODUCTION

All types of systems from either the ecological, the technical, or the social context, experience disturbances, which first create an effect to their performance and then, thanks to the property of resilience, they adjust to overcome the adversities (Barker et al. 2017; Ferreira and Bellini 2018; Xiao et al. 2020). System resilience is broadly characterized by the discrete stages of absorption, response, and recovery (Kallaos et al. 2014), however recently, the research focuses more on the aspects of prevention that can determine decisively the system's adaptive and restorative capacities (Adini et al. 2017; Shakou et al. 2019). Borrowing from the context of disaster resilience, the initial response is considered as a set of processes that link the damage anticipation, to the damage identification, and to the initiation of recovery, that eventually determines the system's reaction to the disruption (Blackman et al. 2017; Goldschmidt and Kumar 2016).

At the same time, monitoring, sensing, and early warning are enhanced with the advances in the field of the smart technology that offer an increased potential to the systems' capacity for prevention (Habibzadeh et al. 2018; Sheikh et al. 2021). So far, the contribution of these smart technical solutions is identified and estimated only in specific engineered systems and exclusively for certain applications. Albeit, the concept of smartness is not limited to the technological applications, but it is entwined with the systemic attributes of connectivity, efficiency, adaptivity, and sustainability (Parks and Rohracher 2019; Tzioutziou and Xenidis 2021). To this end, the aim of this research is to investigate the effectiveness of diverse initial response strategies of different levels of smartness, by exploring their impacts on a system's resilience, under specific conditions of disturbance.

The paper is structured as follows. Section 2 describes the research methodology and

essentially the development of the models and the diverse analysis scenarios. Section 3 presents the findings and the impacts of the initial response strategies on system resilience, while Section 4 concludes the research.

2. METHODOLOGY

The entire methodological approach of system resilience assessment is based on agent-based modeling which captures very efficiently the system dynamics and the emergent adaptive behaviors (Railsback and Grimm 2012) and therefore, provides expository evidence for the system's resilience (ten Broeke et al. 2016).

This research comprises two (2) discrete and consecutive methodological steps: first, the development of agent- based models with their respective response strategies and second, the development and analysis of the various disturbance scenarios and their respective simulations' results. All these are presented analytically in the subsections 2.1 and 2.2.

2.1. Development of models and strategies

The configuration of the base model aims to simulate a complex infrastructure system (e.g., an urban transportation system) by featuring a relatively small number of components. The model consists of two discrete subsystems that are designed as networks of undirected links between nodes in specific locations, to be easily identified. For the example of the transportation network, each different network represents a subsystem, while the nodes are the stations and the links are the flows. Figure 1 illustrates the networks' topology.

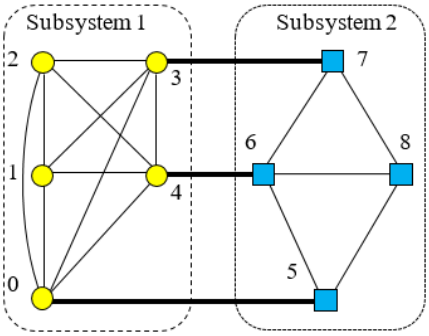

Figure 1: Structure of the examined system.

As shown in Figure 1, Subsystem 1 comprises five (5) nodes (yellow-colored circles), which are fully interconnected via the subsystem's links. Similarly, Subsystem 2 comprises four (4) nodes (cyan-colored squares), where only the closest neighbors are interconnected via the respective links. The two subsystems are partially interconnected via three (3) trans-system links, which are presented with thick lines in Figure 1.

The performance estimation method applied in this research is a simplified and more generic approach of the agent-based model about socio-ecological disturbances by Baggio and Hillis (2018). To investigate the model's resilience, it is essential to set a measure of performance; therefore, the connectedness between the nodes is used as such. More specifically, the number of links connected to each node determine the node's performance. For the neighbors of the same subsystem, a single directed link between two nodes would get the performance value of 1. However, given that the links are undirected and can function in both directions they would get the value of 2. For the neighbors of different subsystems, the performance value is estimated as the total number of links of the end node's subsystem divided by the total number of the trans-system links and then, added to the respective quotient calculated for the opposite end node. For example, for the nodes 0, 3, and 4 of Subsystem 1 the performance equivalent is 4 + 4 + 4 = 12, while for the nodes 5, 6, and 7 of Subsystem 2 is 2 + 3 + 2 = 7. For the trans-system links of Figure 1, the performance value would be 12/3 + 7/3 = 6.333 for the subsystems 1 and 2, respectively. It should be noted that this performance estimation refers to all the three (3) trans-system links, whereas the performance of each trans-system link is estimated at 6.333 / 3 = 2.111. Finally, all discrete performance values are summed and transformed to percentage, in order to yield the integrated performance value that could easily reflect the changes during the diverse states of the entire system.

This generic model includes the aspect of time in the form of procedural steps, also known as ticks. In all the different versions of the developed agent-based model the disturbance occurred at the same tick, while the last tick of all the recovery procedures was recorded as the 'recovery tick'.

All the events of damage and recovery for the evaluation of the system's resilience are associated with the networks' connectedness. Specifically, the disturbance is simulated as a collapse of specific links, according to the respective scenarios, while the recovery describes the system's actions to restore the damages and to regain its original performance level.

Regarding the system's recovery and particularly the stage of initial response, four (4) different versions of the base model are developed in the programming environment of NetLogo version 6.2. (Wilensky 1999). Each one of the examined strategies describes a different approach to identify the disturbed elements, characterized by increasing levels of preparedness, automation and overall smartness, as presented in more detail in the following subsections.

2.1.1. Strategy 1

Strategy 1 features a very simplistic way to inspect the two subsystems' performance by checking the nodes' connectedness in a consecutive order, as shown in the flowchart of Figure 2.

The inspection starts with the first node of Subsystem 1 to identify any missing links in a single procedural step. If no missing links are found, the inspection starts again for the second node of the same subsystem. Conversely, if the agents identified a missing link, they would identify the inspected node as 'disturbed' and store this information as output, required for the phase of recovery. When all the nodes of both subsystems are checked and all the disturbed nodes are successfully identified one by one, the inspection procedure ends, first in Subsystem 1 and then in Subsystem 2, and finally, the respective recovery procedures begin.

The inspection procedure is executed for every node based on the inspection list, where each subsystem's nodes are ordered by their identification number.

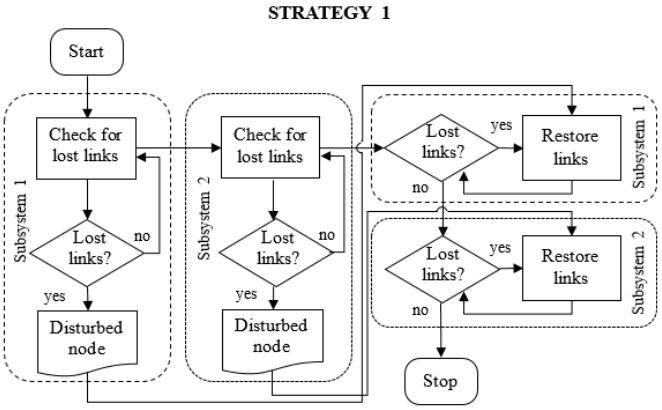

Figure 2: Flowchart of Strategy 1.

In this case, all nodes' inspections, namely nine (9) checks for both subsystems, must be completed before the restoration of Subsystem 1 starts. Obviously, Strategy 1 simulates a system that responds reactively with no preparedness, which relies on gradual steps and on damage-naïve agents (i.e., agents that do not realize the loss in their connections).

2.1.2. Strategy 2

Strategy 2 (Figure 3) reflects an initial response that combines the damage identification and the restoration processes in a single procedural step.

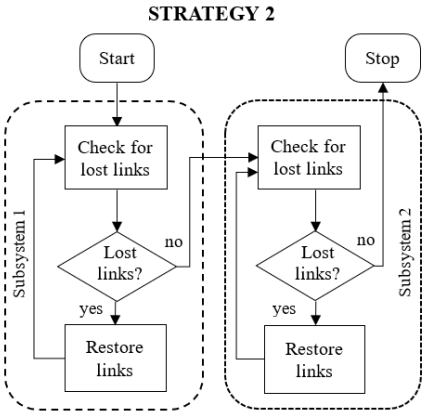

Figure 3: Flowchart of Strategy 2.

According to the flowchart of Figure 3, each subsystem's node is inspected, ordered by identification number and if a missing link is found, it is directly restored. Conversely, if all the node's links remain intact, the inspection ends, and the inspection of the following node starts at the next tick. For instance, in Subsystem 1, if a lost link is found during a node's inspection, the connection is immediately restored and then the inspection procedure is resumed for the remaining nodes. In this way, the subsystem can recover after any of the first five (5) inspections. This response procedure occurs consecutively for the two subsystems.

Strategy 2 allows the system's nodes to respond more timely to the disturbance, compared to Strategy 1, by eliminating the step between the identification and the restoration of the damage. Essentially, Strategy 2 represents a reactive response with multiple gradual steps similar to Strategy 1, however, this time the agents are prepared to initiate the recovery process directly after they detect it, demonstrating a level of autonomy of their recovery actions.

2.1.3. Strategy 3

Strategy 3 was based on the procedures of Strategy 2, but with a significant change in their execution order, as shown in the flowchart of Figure 4.

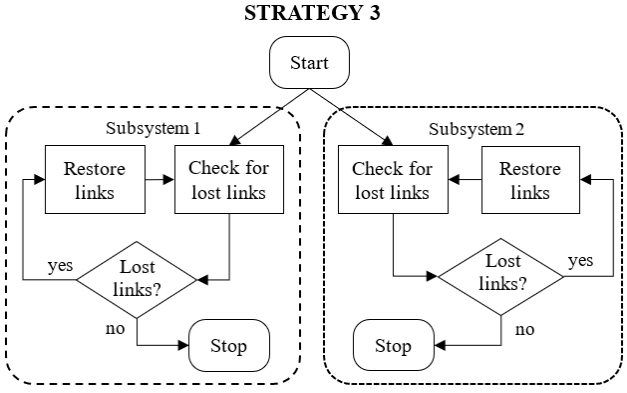

Figure 4: Flowchart of Strategy 3.

In particular, in Strategy 3 the two subsystems start their initial response actions simultaneously after the disruptive event occurs. Both Subsystems 1 and 2 initiate the inspection process for their nodes and if a missing link is found, it is directly recovered. Consequently, both subsystems can recover after any of the five (5) inspections. This approach of parallel instead of consecutive responses could significantly reduce the time to recovery and therefore, maintain the overall system performance at higher levels. Even though Strategy 3 delineates a reactive approach, the two subsystems are qualified to identify and restore their damages independently, whereas the individual agents remain unprepared and damage-naïve.

2.1.4. Strategy 4

Strategy 4 presents a completely different approach, graphically presented in Figure 5. Each node is assigned to check its own connections throughout the run and reports its own status. If any missing link is identified, the node is identified as a 'disturbed node'. This check runs for all nodes of the subsystem simultaneously and all the disturbed nodes are automatically recognized. The final step of the procedure is to restore the links between the disturbed nodes of each subsystem.

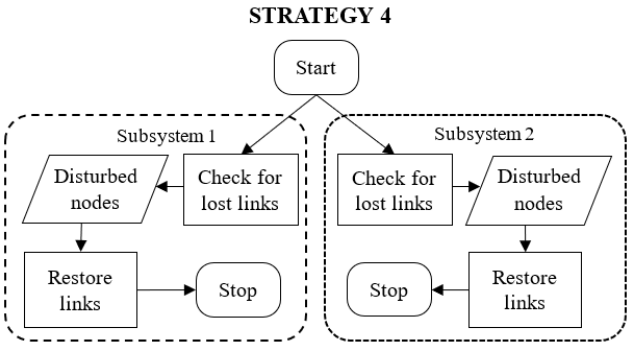

Figure 5: Flowchart of Strategy 4.

The main difference of this approach is that the entire procedure of the inspection and the restoration is completed in a single step in a linear automated way, without any repetitive loops of checks. In Strategy 4, which could be described as the smartest approach, the agents become damage-aware and the subsystems demonstrate the highest level of preparedness and automation.

2.2. Development and analysis of scenarios

Three (3) different disruptive scenarios were developed to test each one of the examined initial response strategies and the corresponding models. Each disruptive scenario was executed for each one of the four (4) examined strategy models, yielding 12 analysis scenarios. Under these analysis scenarios, a randomly located disturbance occurred in order to initiate the system's initial response and recovery processes and evaluate its resilience in terms of performance levels and recovery time. For accuracy, each analysis scenario ran for 20 repetitions. All the required repetitive simulations were executed by the NetLogo's BehaviorSpace tool (Wilensky 1999).

The results of the simulations were analyzed separately and comparatively. Except for the differential comparisons, a sensitivity analysis was employed, as the most appropriate method to evaluate the results of agent-based simulations (Railsback and Grimm 2012). In particular, a sensitivity analysis was used to estimate the differences between the four (4) response strategies results, using Strategy 1 as the base case scenario. All the relevant analyses were implemented for both the performance levels and the recovery time in Microsoft Excel 2013.

The developed disruptive scenarios represented three (3) discrete events disturbing the system's performance in an increasing magnitude and complexity, as shown in Table 1.

Table 1: The disruptive scenarios and their corresponding disturbances to the subsystem and to the entire system, respectively.

Disruptive event	*Disturbance in each subsystem*		*Disturbance in entire system*	
	links	*nodes*	*links*	*nodes*
Simple	*1*	*2*	*2*	*4*
Cascading	*2*	*3*	*4*	*6*
Complex	*1*	*2*	*3*	*4-6*

The scenarios and the respective disturbances are described in more detail in the subsections 2.2.1-2.2.3.

2.2.1. Simple disruptive event

The first disruptive scenario represents the simplest case of disturbance with the minimum damage to the system. It features the loss of an individual link in each one of the two examined subsystems. The missing links of both subsystems were set randomly by the NetLogo algorithm at each run of the model. In this case, the losses can be considered as independent events that affect only specific nodes of the network.

2.2.2. Cascading disruptive event

The second disruption describes a more complex kind of disturbance that causes a more severe damage to the system due to the interdependent events of loss. This scenario simulates a cascading event with the simultaneous loss of two (2) links, which are connected to the same node of the subsystem. In this scenario, the node that would lose the two links, as well as the affected neighboring nodes were randomly selected at each run of the simulation.

2.2.3. Complex disruptive event

The final disruptive scenario is to simulate the most complex and extended damage, by building onto the first scenario of the simple event. Specifically, while the events in the subsystems are identical to the simple disruptive scenario, one of the three (3) trans-system links is additionally lost. In this case, as shown in Table 1, in the entire system there were totally three (3) lost links, while the affected nodes would vary between four (4) and six (6), depending on the randomly selected locations of the disconnected links. The loss of the interconnecting link was considered as an independent event, randomly selected by the algorithm, regardless of the disruptive events that occurred in the discrete subsystems.

3. IMPACTS OF THE INITIAL RESPONSE STRATEGIES

The first findings of the simulations, which are presented in Figure 6 provide a general picture of the effectiveness of each initial response strategy to the system's resilience in terms of performance maintenance and time to recovery, under the

different disruption scenarios. These results suggest that the smarter the initial response process, the more effective for the maintenance of the system's performance levels and principally for the system's time to recovery. Particularly, according to Figure 6a, the maintenance of the performance level is improved gradually and steadily from the first to the fourth strategy, as the responses become more automated.

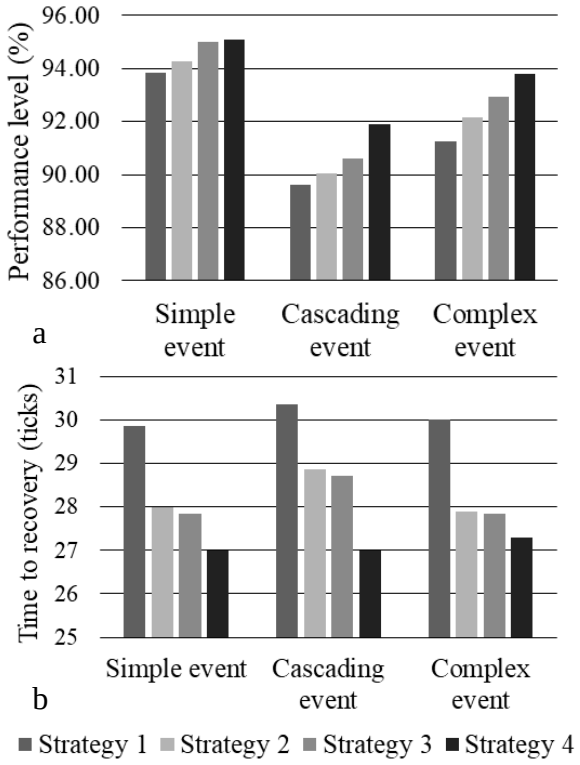

Figure 6: Simulations' average results for a) performance levels and b) ticks to recovery of each strategy, respectively, under the different disruption scenarios.

According to the graph of Figure 6b, the time to recovery is reduced as the response strategies get smarter, but with a different trend, compared to the performance ratios. In fact, the decrease is significant between the first and the second strategy, it is almost unnoticeable between Strategy 2 and 3, and it becomes notable again between the last two strategies. These findings also highlight that the strategies' effectiveness in terms of both performance maintenance and recovery time is affected by the conditions of the disturbance.

Apart from the general trend, it is necessary to examine analytically the simulations' results and their variances for the given response strategies in respect with performance scores and recovery duration. These results are presented in Table 2. To facilitate the comparison, the outcomes of the relevant sensitivity analysis, i.e., the percentage differences between the results of the different strategies and Strategy 1 are also presented.

Table 2: Data table of simulations' average results, variances and differences in performance levels and time to recovery, under the different disruptive scenarios.

Impacts examined per disruption		*Initial Response Strategies*			
		1	*2*	*3*	*4*
Simple event	*Performance level (%)*	*93.86*	*94.27*	*95.00*	*95.09*
	Variance	*0.094*	*0.125*	*0.068*	*0.036*
	Difference (%)	-	*0.44*	*1.22*	*1.31*
	Time to recovery (ticks)	*29.85*	*28.00*	*27.85*	*27.00*
	Variance	*1.292*	*1.053*	*0.661*	*0.000*
	Difference (%)	-	*-6.20*	*-6.70*	*-9.55*
Cascading event	*Performance level (%)*	*89.62*	*90.05*	*90.59*	*91.92*
	Variance	*0.221*	*0.119*	*0.317*	*0.037*
	Difference (%)	-	*0.48*	*1.08*	*2.56*
	Time to recovery (ticks)	*30.35*	*28.85*	*28.70*	*27.00*
	Variance	*0.661*	*.0555*	*0.432*	*0.000*
	Difference (%)	-	*-4.94*	*-5.44*	*-11.04*
Complex event	*Performance level (%)*	*91.23*	*92.16*	*92.95*	*93.78*
	Variance	*0.155*	*0.197*	*0.229*	*0.045*
	Difference (%)	-	*1.02*	*1.88*	*2.79*
	Time to recovery (ticks)	*30.00*	*27.90*	*27.85*	*27.30*

	Variance	*0.632*	*0.937*	*0.766*	*0.221*
	Difference (%)	*-*	*-7.00*	*-7.17*	*-9.00*

Starting with Strategy 1, the most simplified and repetitive process and the least smart one, it is evident that it is the slowest and least effective response in terms of performance maintenance under every disturbance. It is characterized by the lowest performance ratios and the highest time to recovery in every analysis scenario. It is interesting that Strategy 1 demonstrates high variances in the recovery times with a particularly high value of 1.292 at the first disruption scenario; however, this condition changes in the next two scenarios. In fact, despite the severity of the events, Strategy 1 yields more consistent outcomes in the recovery duration, compared to the smarter strategies.

Strategy 2 ranks third in the overall effectiveness, regarding both the performance and the response duration, with high variances, especially during the simple event. According to the evidence of Table 2, the most notable impacts are observed in the recovery ticks especially in the complex event, rather than in the system's performance levels. Strategy 2 offers an average improvement of 0.64% in performance levels and an average decrease of 6.05% in the time to recovery, compared to Strategy 1.

Strategy 3 is identified as the second most effective response, for all the examined events. It provides improved outcomes particularly in the performance ratios, compared to both Strategy 1 and Strategy 2. During the simple event, Strategy 3 delivers increased performance scores, as well as reduced response durations of low variance. In the next two events, Strategy 3 improves the performance maintenance from Strategies 1 and 2, however, it yields similar recovery times with Strategy 2. This fact highlights the similarities between Strategies 2 and 3, which seem to be more effective compared to the base response in the complex event, but less effective in the cascading event.

Finally, Strategy 4 is clearly recognized as the most effective response strategy, which delivers the most significant improvements to the system's response and recovery, under any circumstances. As presented in Table 2, Strategy 4 yields significantly more effective and highly consistent results, both in the performance maintenance and the recovery duration. Paradoxically, this response strategy yields better results when facing more severe events. In the cascading event, Strategy 4 leads to increased performance ratio, but most importantly, it yields the greatest reduction observed in recovery time at -11.04% from Strategy 1. Likewise, during the complex event, this strategy demonstrates the greatest increase of performance ratio at 2.79% from Strategy 1.

Conclusively, the findings regarding the examined strategies' effectiveness revealed that the most naïve and repetitive response, namely Strategy 1 is the least effective strategy, whilst the smartest response of Strategy 4 is clearly the most effective one in every disruption scenario with respect to performance rates and recovery time. Strategies 2 and 3 that represent the medium levels of automation, offer increasing positive impacts to the system's performance levels and almost identical but significant reductions in the system's time to recovery.

4. CONCLUSIONS

The presented research aims to investigate the impacts of smart initial response strategies on a system's resilience, under different disruptive events. The experiments' findings demonstrate that as the level of preparedness and automation in the response process increases, the strategies are more effective in the maintenance of a system's performance and the promotion of its resilience. It is observed that as the disruptions of the examined system get more severe, the differences between the responses effectiveness become more evident, especially with respect to the reduction of the recovery time.

The research provides a better understanding of the impacts of smartness to the initial response processes and to the system's resilience. The results of this research can practically support the data-informed design of initial response strategies

and offer an effective integration of smart technology procedures and tools into existing complex systems.

5. ACKNOWLEDGEMENT

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