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Computing and Optimizing the Index of Resilience of Networks and Information Systems

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Abstract. The paper addresses the concept of resilience as a two joint processes and focuses especially on the recovery phase. The treatment uses the frame of the resilience index previously introduced. The main contributions are the results on resilience index properties and optimization and the application of graph measures in the calculation of the recovery phase for resilience definition. The resilience index computation is exemplified for information systems.

Keywords: resilience, recovery process, optimization, hazard, information system, communication network.

1. Introduction

The interest in resilience and the term itself migrated from psychology, where human resilience to stress and adverse conditions was first introduced decades ago [1] toward ecological [2], [3], social and technical systems [4]. The interest for defining and studying resilience has increased significantly during the recent years [5], [6], [7], [8], [9], [10]. While many articles deal with qualitative and integrative aspects of resilience, with the management for resilience [11], and with the qualitative connections difference between resilience, adaptation, and vulnerability, see for example [12], [13], this study addresses details of the quantitative representations of the resilience. In what may be the first general metric (formal) definition of system resilience equally applicable to social, economic, and technical systems, [14] has introduced the resilience index as the logarithm of the product of two probabilities: the probability of a hazard that may produce the failure of the system and the one of recovery in a specified time, where the time is standing for the duration after which the system is unrecoverable at its original state. The resilience index was further investigated in [15]. The purpose of this article is to discuss the properties of the recently introduced index of resilience and its optimization.

Because the terminology varies in the literature [16], the following meanings are specified: *System* is any technical, economic, or social system; communication networks, companies, human communities such as cities or countries are system; the notions of *system operation* and of *normal operation* are assumed predefined or agreed upon; *hazard* is any natural or human-produced process that affects systems and degrade their operation; *fault* is any physical or structural degradation of the system that degrades its operation; *recovery* is any process that restores normal operation; *risk* is defined in accordance to its economic meaning as the predicted average loss or *a posteriori* loss of value, where the value is determined according to a specified measure, e.g., economic, monetary, structural, or based on life quality. The notion of maximal allowed time of recovery tries to incorporate numerous pieces of anecdotal evidence that point to the permanent impairment of systems or even their dissolution when the recovery process is not achieved under some threshold of time.

The paper is organized as follows. Section 2 discusses the computation of the resilience index under several cases. Section 3 deals with optimization issues. The fourth Section applies the resilience concept to networks by specifying a meaning for the recovery process. The last section derives conclusions, shows limits of the paper, traces unsolved problems, and proposes research topics for the future.

Throughout the paper, H denotes a hazard, F denotes faults (improper operation or no-operation), T_r denotes a maximal time allowed for the recovery process, $\bigvee$ denotes logical or as well as occurrence of either one of the conditions related by $\bigvee$, p denotes a probability, and R denotes the resilience index.

2. Resilience index and its properties

The evaluation of the resilience is a type of performance evaluation. The resilience index is meant to be a key performance indicator (KPI), together with other KPIs. In this respect, one should not fall in the trap of choosing a simple to compute or immediately measurable system parameter in defining a resilience measure.

Resilience refers to two distinct processes: the production of a fault or degradation of operation at large, due to a hazard event, and the recovery process. A system is resilient when its recovery duration is less than a specified term, T_r, beyond which the further degradation of the system can no more be stopped or reversed. For a specified fault, there is a probability of recovery before the specified time limit, $p(t < T_r)$. The resilience index is defined as [14] $R = -ln(p_{non-op}(t < T_r))$, where p_{non-op} is the probability of non-operation of the system at a minimal satisfactory level as effect of a hazard for a time larger than a maximal time, T_r, before complete recovery to the initial level of operation or even salvage of the system is no more possible. The above general definition can be detailed taking into account the two dichotomous processes involved: the occurrence of a fault stopping the normal operation, respectively the recovery process. The fault is produced by a hazard H having a probability $p(H)$, which produces the fault F with the conditional probability $p(H, F) = p(F|H)$.

A specified hazard has, in a geographical place, a probability of occurrence, $p(H)$. The hazard, when materialized, produces a fault with some probability $p(H, F)$. The probability of a fault F induced by a hazard H is then $p(F) = p(H)p(H, F)$. Assuming the hazard and fault occurrence instantaneous, the resilience index becomes

$$R = -log(P(H)) - log(p(H, F)) - log(p(t_r > T_r)) \quad (1)$$

Notice that it is easy to convert the resilience index as defined in [14] in an index with values in the range $[0, 1]$, using $R^* = 1 - \frac{1}{1+R}$; this yields the definition of the normalized resilience, R_n,

$$R_n = 1 + \frac{1}{1 - log(p_{non-op}) - log(t_{rec} > T_r)}. \quad (2)$$

In this paper we use only resilience according to (1).

Resilience computation may be seen as keen to the computation of the Value At Risk (VaR) in finance [17] and of conditional VaR (CVaR) [18], where the risk regards the complete loss of the entire system value. While the computation of R is based on probabilities, R is deterministic. However, when the probabilities are not well known, and a second-order probability distribution is implied, or a description based on fuzzy sets, taking into account aspects related to continuity [19] and possibility of adaptation [20], or a second order fuzzy set, R becomes a stochastic or fuzzy variable and its estimator is needed. Notice that in this case the convolution of the probabilities of the processes are involved. In this paper we limit the discussion to the probabilistic case. The computation of the resilience index will be exemplified in this paper for information systems and communication networks, which are known to have poorly performed during severe disasters in the last two decades, moreover to be prone to numerous security threats [21], [22]. The issue of the vulnerability and resilience of networks and information systems is amply dealt in the literature, see for example [5]. Notice that in many cases, standards establish the maximal time of non-operation that we use in the resilience computation. In case of datacenters, the TIA-942 Data Centre Standards [23] specifies four tiers, the highest level (Tier 4) requiring '99.995% availability and annual downtime of (less than) 0.4 hours'. In comparison, the lowest level (Tier I - Basic) requires '99.671% availability and annual downtime of 28.8 hours' [23].

There are several intuitive requirements that the resilience should satisfy, among others, it should be monotonically decreasing in the probability of catastrophes and in the duration of recovery. Subsequently, we assume that the recovery time for any fault is lower or equal than the recovery from that fault and any other fault(s) superposed, $t_r(F_1) \leq t_r(F_1 \bigvee F_2)\ \forall F_2$ (monotony of the recovery in the number of faults, in a deterministic setting), respectively we assume the following natural property of the recovery process in the probabilistic setting: $p(t_r > T_r, F_1 \bigvee F_2) \geq p(t_r > T_r, F_1)$; the condition $F_1 \bigvee F_2$ means the occurrence of both F_1 and F_2. Because the resilience index is defined based on the logarithm of the product of two variables, $R = -log(u \cdot v)$ and the variables represent probabilities, R inherits all the properties of the logarithm with respect with the variables. This leads to the following desirable properties of the resilience index, consistent with the intuitively required properties:

Proposition. The resilience index defined by (1) has the properties:

1. Non-negative: $R \in [0, \infty)$ because $\forall u = p_1,\ v = p_2,\ 0 \leq u \cdot v \leq 1$. $R = 0 \Longleftrightarrow p(t_r > T_r) = 1 \& p(H) \cdot p(F|H) = 1$;

2. Continuity in the three variables, that is, probabilities in (1);

3. Symmetry of the processes; denoting $R((p(H)p(F|H)), p(t > T_r)) = = R(p_A, p_B)$, $R(p_A, p_B) = R(p_B, p_A)$;

4. Rule of the strongest link $R(p_A, p_B) \geq R(1, p_B)$ and applying symmetry, $R(p_A, p_B) \geq R(p_A, 1)$ (insures achievable resilience, in the sense that one can improve resilience strengthening any of the aspects);

5. Monotony in the hazard variable: for two hazards that produce the same failure with different probabilities, (assuming that only one type of failure can be produced) $\forall H_1, H_2 :\ p(H_1) > p(H_2),\ R(H_1) \leq R(H_2)$;

6. Monotony in the number of hazards. For two hazards, H_1, H_2, $R(H_1, H_2) \leq R(H_1)\ \forall H_2$, because $p(H_2) \geq 0$, $p(H_2, F) \geq$ for all faults F;

7. Monotony in the recovery time variable: $R(H, T_{r1}) \leq R(H, T_{r2}) \forall T_{r2}, T_{r2} :$ $\int p(t > T_{r2})dt > \int p(t > T_{r1})dt$;

8. Monotony in the failure variable: adding a new failure, all other conditions being the same, decreases the resilience index value;

9. If two hazards H_1, H_2 lead to the same single failure, with recovery probability $p_r(F; t < T_r)$ from that failure, then

   $R(H_1 \bigvee H_2) = -[log(p_1+p_2-p_1p_2)+log(p(t > T_r))] \geq -[log(p_1)+log(p_2)+$

$$+log(p(t > T_r))] = max(R_1, R_2) + R_1/log(p(t > T_r)) \leq R_1 + R_2;$$

10. Assume, without loss of generality, that $1 > p_1 > p_2 > \cdots > p_n$; then, a rough range of the resilience index is $R_{min} < R < R_{max}$ where $R_{min} = -(ln(n)+ln(p_1)+ln(p_{non-r})$ and $R_{max} = -(ln(n)+ln(p_n)+ln(p_{non-r}))$.

11. When $(p_2 + \cdots + p_n)/p_1 \ll 1$, a good approximation is $R \approx -ln(p_{f0}) - ln(p_1) - (\frac{p_2}{p_1} + \cdots + \frac{p_n}{p_1}) - ln(p_{non-r}(t < T_r))$.

Remark. When several causes (hazards) may occur, potentially producing one or several faults $F_1, F_2, ..., F_n$, each involving a recovery time distribution $p_(F_k)(t_r > T_r)$, then, assuming that the faults are solved in parallel (independently), the recovery time smaller than T_{rmax} is achieved with the probability

$$p = \Pi_k \int_{t \geq T_{rmax}}^{\infty} p_{F_k}(t)dt. \quad (3)$$

However, if tasks of solving the faults are not independent, for example because teams have to be switched from one task to another (typical limitations of human resources), the above is an optimistic lower limit.

When the intervals of the probabilities involved in R are given, $[log(p_{1m}) + log(p_{1M})]$, $[log(p_{2m}), log(p_{2M})]$, the interval of R can be computed as $R_{min} = log(p_{1m}) + log(p_{2m})$, and similarly for the maximal value $R_{max} = log(p_{1M} + log(p_{2M})$. When the intervals are due to small errors ϵ_1, ϵ_2 in the estimations, $p_1 = p_{10} \pm \epsilon_1, p_2 = p_{20} \pm \epsilon_2$, using the approximation of the logarithms $log(a + x) \approx log(a) - x/a$, one obtains $R \approx R_0 + \epsilon_1/p_1 \cdot log(p_2) + \epsilon_2/p_2 \cdot log(p_1)$.

Example. Assume that only two major faults may occur, namely the loss of power supply due to a major destruction on the site of a datacenter, and the destruction of equipment (e.g, in a communication center, or on a manufacturing line.) Assume uniform distributions of recovery in time during the intervals [0, 100] hours for the power supply and [20, 1000] hours for the second. Assume the allowed maximal time of recovery before loosing key customers (or paying too high fees to customers for losses and interests) is 140 hours. Then, as the tasks are independent, and as the first is solved before the time limit, only the solving of the second task counts in the resilience computation. Therefore, the probability of not recovery in due time is $(1000-140)/(1000-20) \approx 0.88$. Thus, the probability of non-recovery is almost equal to that of the disaster, which is unacceptable. That communication facility must be made redundant.

3. Resilience index calculation and cost-aware optimization

In this section, we assume that hazards are modeled by a Poisson process, $p(M, n \leq 1, T_0, \tau) = 1-e^{-T_0/\tau}$ [16], where T_0 is a specified period of time during which that type of event is expected, M is the magnitude of the event, n is the times the event occurs during T_0, and τ is the average recurrence period of the event (empirically determined, for example counting the number of earthquakes during a long enough time). The duration T_0 varies depending on the field; in earthquake geological surveys, taking into account an average duration of a building of 50 years, one draws maps as: 'The mapped hazard refers to an estimate of the probability of exceeding a certain amount of ground shaking, or ground motion, in 50 years' [25]. It is usual to consider the annual probability of events of magnitude larger or equal to a specified value, M, defined as [26] $p_a = 1/T_0$. Then, $p(t) = 1 - e^{-p_a \cdot t} \approx 1/T_0$ [26]. A similar approximation is used for floods [26]. The values of T_0 are well-known for various types of major hazards, such as earthquakes and floods [26], [27]. For example, for Bucharest, for magnitudes $M_1 = [6.5 - 7.5]$ (Richter), the frequency is about 1/25 years (consistent with [27], while for $M_2 = [7.5 - 8.2]$ the frequency is about 1 /200 years.

There are little data on the relationship between the reduction of the average recovery time and the cost of improvement. The article [28], in line with previous studies, suggests that the cost of improvement of the quality in terms of decrease of the probability of deficient operation, p_d, is proportional to the logarithm of the reduced probability, p_{d1}, with respect to the initial probability of deficient operation, p_{d0}, $C(p_d) = b{\cdot}log(\frac{p_{d0}}{p_{d1}})$. Consider an event of magnitude M, with the probability of the event (the hazard) $p(H,M)$ and the conditional probability of producing a specified fault F denoted by $p(H,M,F) = p(F|H,M)$. Next, consider that the resilience constraints require a specified maximal tolerable probability p_{dM} of the fault. Then, the cost of reducing the fault probability from $p(H,M) \cdot p(H,M,F)$, to p_{dM} is

$$C(p_d) = b \cdot log(\frac{p(H,M) \cdot p(H,M,F)}{p_{dM}}). \tag{4}$$

This cost may help making a decision between two possibilities: the increase of the resilience of a single datacenter on a given site, up to the minimal acceptable value, or to build two datacenters at places far enough for they have a negligible chance to be hit by the same disaster. Assuming that the cost (before the increase of quality) is C_0, the decision is simply made by determining if the inequality $2C_0 \leq C_0 + C(p_d) + C_{staff}$, where C_{staff} is the cost of extra personnel for the life period of the datacenters.

4. Resilience definition incorporating graph measures for networks

In the previous sections we have seen that analyzing the resilience requires a definition of recovery. The in-depth knowledge about the underlying system and its efficiency is fundamental for adequate decision making especially if we consider the availability and allocation of resources. In [14] and [15], the resilience of systems was analyzed via a two stage-process which is based on a probability model. If we would like to clarify the meaning of recovery and minimize the cost and therefore optimize the whole process we might ask for additional measures.

In classic network theory, see for example [29], the flow-weighted efficiency measure is typical; in [30], it was introduced and demonstrated on a physical network - the underground network of Munich, Germany. The proposed measure calculates the flow-weighted efficiency in a subway network by compiling the shortest route between every pair of stations [30] and the according bottleneck flow of the trains. Results show [30] that the flow-weighted efficiency is significantly varying over schedules; it is highest on the densest schedule and lowest when the least trains are operating. By means of such an analysis it is possible to optimize the quality management of such systems. This was described in detail in [30]. Such an approach can be taken as basis for an extension of the probability approach which enables the minimization of the underlying costs.

Subsequently, the Munich subway network is considered as network example, closely following and using ideas from [24], [30] and applying well-known elements from graph theory. The subway network information could be formally encoded in two different ways. The first option is by two weighted adjacency matrices, one matrix for the length distances between stations and the second matrix for the train flow between stations. In a first step, using the description and notations from [30], the network (for example, Munich subway) is represented by a directed and weighted graph $G = (V, E)$, with the set of nodes (stations) $V = \{v_i, i = 1, 2, ..., N\}$ and $E = \{(v_i, v_j), v_i, v_j \in V\}$ the set of edges. The weight (cost) of a directed edge, $(v_i, v_j) \in E$, is given by their weights $w_{ij} \geq 0$. The weighted adjacency matrix $A = [a_{ij}]$ is defined by $[a_{ij}] = w_{ij}$, for $(v_i, v_j) \in E$ and $[a_{ij}] = 0$ else; in case of a transportation network, $[a_{ij}]$ stand for the length of the physical (geographical) distances (in km) between every pair of stations. The weighted adjacency matrix $U = \{u_{ij}\}$ encodes the train flow between every pair of stations [30], with $u_{ij} \leq 0$ denoting the flow (number of trains per hour) from i to j; for (v_i, v_j) not in E, $u_{ij} = 0$. The second option is by weighted edges list(s). In [30], the first option was chosen. In this contribution, we propose to extend this option via a certain probability approach.

Following [30] and taking from there definitions, the classic average efficiency measure of a graph $EAvg(G)$ is defined as [30] $EAvg(G) = \frac{1}{N(N-1)} \cdot \Sigma_{i \neq j \in V(G)} \frac{1}{d_{ij}}$ where d_{ij} is the shortest route length between each pair of vertices in the graph G. The shortest route calculation takes the weighted adjacency matrix A as input. This was the approach in [30]. The efficiency measure of a vertex $v_i \in V(G)$ in the graph G, $EV_G(i)$ is defined as [30]: $EV_G(i) \frac{1}{N-1} \cdot \Sigma l_{d_{i,j}} j \in V(G)$. The computation of the efficiency measures $EAvg(G)$ and $EV_G(i)$ are involved only [30] the distance values from the matrix A . Using one of the typical threshold Θ values used in engineering, 90% of the normal value, or $\Theta = -3dB$ (50%) of the normal value, the recovery time can be defined as the time of recovering the threshold value of the efficiency the system (network) had before the event (disaster) has occurred.

In [24], [30], a new efficiency measure was proposed, named *flow-weighted average efficiency measure*. Such an approach might support the determination of the optimal value of the resilience index. In further studies we are able to analyze the relationship of an resilience measure and restricted resources. Several scenarios might be developed for definite models of recovery processes. Advanced decision support tools could be adapted and integrated in a reachback architecture. Via such an architecture, serviceability might be increased and stabilized: Risk and resilience will represent the two different perspectives within a closed reachback architecture (see also [31]). Now, applying the concept of resilience to networks endowed with a measure of efficiency, for example average flow on its edges, or average distance between nodes, is straightforward:

Definition. Being given a network measure, a network is absolutely resilient if the time for recovering the threshold Θ level of the initial (before event) value of the measure is smaller than the time of survivability, T_r; that is,

$$max_t t(AvFlow(t) \leq \Theta \cdot AvFlow(0)) < T_r. \tag{5}$$

Instead of using the average measure, one may require that the minimum over all edges of the ratio (flow at time t)/(flow at initial time) is larger than the threshold; similarly for nodes (in-flow + outflow per node), $min_{t,e \in E}(flow(e,t)/(flow(e,0)) > \Theta \; \forall t \geq T_r$. When an edge or a node is critical, the above concept is applied to that node or edge.

In [30] a vulnerability measure was introduced for networks, describing the serviceability of the network. In [24], [30], the manner the network is affected was analyzed for the case of one isolated node. It would be interesting to apply the above considerations also to social networks (SNs) for determining their reliability in reporting on major events, in line with [32], in the various contexts described in [33].

5. Conclusions

The paper detailed the analysis of the resilience index and shown a set of properties of this index, which are deriving largely from the properties of the logarithm function and are similar to several properties of the entropy, while conforming to the properties required by intuition of the notion of resilience measure. Next, using Poisson models accepted in the literature for hazards, and models for quality as a function of paid cost for it, the issue of the optimization of the resilience under costs constraints was addressed. Finally, the definition of level of recovery for communication and transportation networks, as used in the resilience index definition, was reconsidered from the point of view of graph metrics. Further studies should address in more detail the optimization of the resilience and the decision making process based on the costs of improvements and on various measures of recovery.

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Supplementary material: Several annexes with examples of resilience computations will be available soon at `http://iit.academiaromana-is.ro/sps/index.html`

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