Artificial Emotions for Distributed Cyber-physical Systems Resilience

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Abstract. The concept of system resilience is important and popular in different domains like psychology, psychiatry, sociology, and more recently in cognitive science, biological disciplines, ecology and computer science. The main objective of this paper is to present a research avenue exploring the applicability of knowledge from those domains to solve resilience problems in cyber-physical systems. Emotions have been identified as an important process to cope with unexpected events and is therefore crucial for resilience. Our work is thus aimed at utilizing emotion-like processes in cyber-physical systems to improve their resilience, at individual and collective levels. Furthermore, one of our main assumptions is that the multi-agent paradigm is particularly well suited to embed such emotion-like processes in this type of systems.

Keywords: Artificial Emotions · Multi-agent systems · Cyber-physical systems · Resilience · Distributed Artificial intelligence · Distributed Systems · Human and Social Sciences

1 Introduction

Emotion has a major influence on the ability of humans to adapt to unknown or unusual situations as individuals and as groups. It is therefore, a natural source of inspiration when tackling the problem of distributed complex systems resilience that we consider as the ability of such systems to identify and cope with unexpected situations. As emotions positively have a physiological component, the main application domain of this PhD project[1] will include cyber-physical systems, that is to say systems that are at least partially in direct interaction with the physical world. Resilience concerns the ability to recognize, adapt, and handle unanticipated perturbations that call into question the model of competence, and demand a shift of processes, strategies and coordination [34]. In our work, we aim at including knowledge from psychology and sociology about resilience and emotion in cyber-physical systems utilizing the multi-agent paradigm. This paradigm brings to the existing approaches of resilience a social metaphor for complex systems. In addition, we aim at embedding cognitive science and psychology knowledge about resilience and cognitive functions of emotion in the

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individual systems decision-making mechanisms and in the self-organizing processes of agents groups.

In this paper, we start by presenting a synthesis in the field of resilience in human and social science and present the applicability of these concepts to cyber-physical systems. After that, we will present the multi-agent paradigm our solution will be based on. We will then present artificial emotions and expose the way we plan to use inspiration from human emotion to solve resilience problems. Finally, we conclude this paper by the description of the state of this project.

2 Resilience

Resilience is studied by researchers in a variety of disciplines including psychology, psychiatry, sociology, and more recently cognitive science, biological disciplines, ecology and computer science. Resilience has different definitions in different communities. In ecology, resilience is the ability of an ecosystem or species to recover its normal behaviour after experiencing traumas. In psychology, "resilience is the ability of a person or a group to develop well, to continue to project into the future, despite destabilizing events, difficult living conditions and sometimes severe traumas" [28]. At the level of the individual, traumas destroy the psyche, at the level of the group, traumas destroy the existing bonds between the members of the group [28]. In computer science, resilience is the persistence of supplying services and the availability of features [31].

2.1 Resilience in Human and Social Sciences

In human and social sciences and especially psychology, there are two types of resilience, individual and collective. Individual resilience is the process of, capacity for or outcome of successful adaptation despite challenging or threatening circumstances [23]. Collective resilience is the ability of communities to withstand external shocks to their social infrastructure [3]. Psychological resilience is characterized by the ability to bounce back from negative emotional experiences and by adapting flexibly to the changing demands of stressful experiences, also, the positive emotionality emerges as an important element of psychological resilience [32,15].

The work of Norris *et al.* [26] (see Fig. 1) gives us insight on the applicability of resilience in an artificial system by introducing the robustness, redundancy, and rapidity notions. It explicitly states that resilience depends on its resources to react well and amortize stress. According to Norris *et al.* [26] the keys concepts relating resources and resilience are:

- Resources : Objects, conditions, characteristics, and energies that people value.
- Robustness: resource strength, in combination with a low probability of resource deterioration.
- Redundancy: the extent to which elements are substitutable in the event of disruption or degradation.

– Rapidity : how quickly the resource can be accessed and used (mobilized).

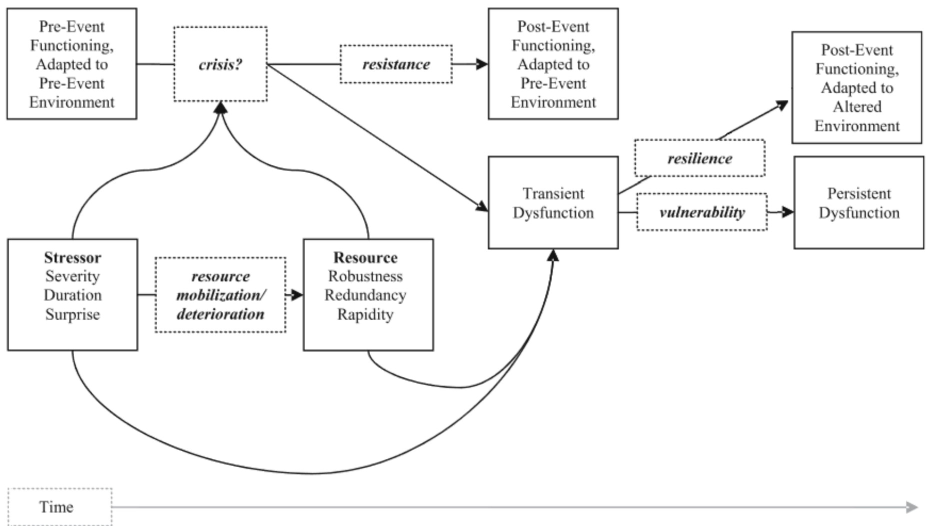

Fig. 1. The model of stress resistance and resilience over time [26].

On the one hand, vulnerability occurs when resources are not sufficiently robust, redundant, or rapid to create resistance or resilience, resulting in persistent dysfunction. The more severe, enduring, and surprising the stressor, the stronger the resources must be to create resistance or resilience. On the other hand, resilience occurs when resources are sufficiently robust, redundant, or rapid to buffer or counteract the effects of the stressor allowing the organization to adapt its functioning to the altered environment. For human individuals and communities, this adaptation manifests in wellness [26].

2.2 Resilience in Cyber-Physical Systems

The 5C architecture presented by Lee *et al.* [18] clearly defines how to build a CPS from the initial data acquisition to the creation of final value through analysis. The detailed architecture of the 5C is described in Fig. 2. As we can see, the configuration level is the one that allows machines to self-configure and self-adapt. According to the definition of resilience we adopted, our contribution to CPSs resilience lies in this configuration level.

Usually, a CPS consists of two main functional components: (i) advanced connectivity that provides real-time data acquisition of the physical world and cyberspace feedback and (ii) intelligent management of data, data analytics and computing capabilities that build cyberspace. However, this requirement is very

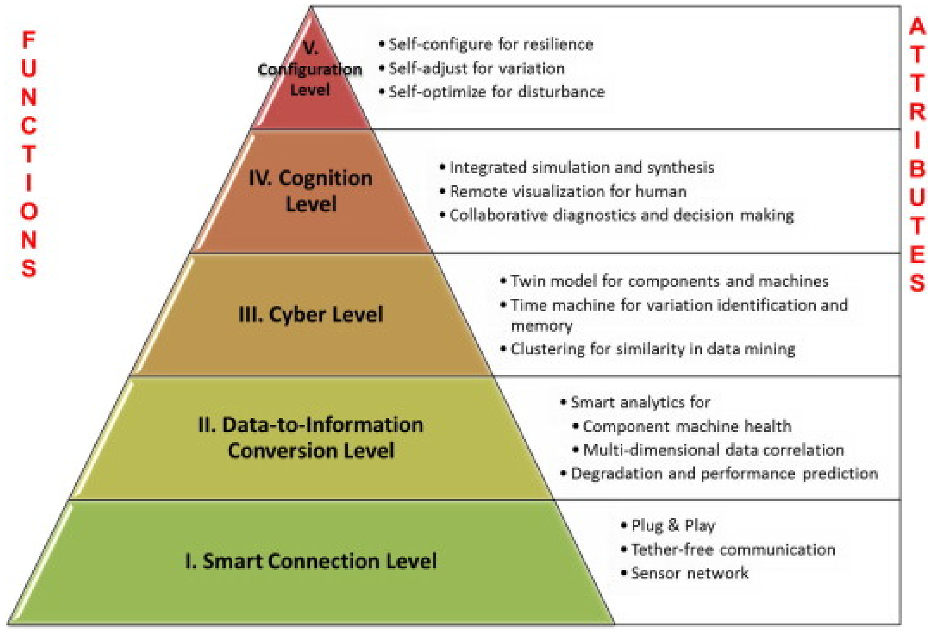

Fig. 2. 5C architecture for the implementation of a cyber-physical system [18].

abstract and not specific enough for the implementation in general. The total integration of the 5 levels within a CPS is currently rarely achieved, and it is not always justified according to the type of application [18].

Linkov and Kott [20] define cyber-resilience as the ability of a system to recover or regenerate its performance after a malfunction (or attack) has degraded it (see Fig. 3). In this graph, we can see the four stages of the event management cycle that a system needs to maintain to be resilient according to the National Academy of Sciences (NAS) [1,19] which are:

1. **Plan/Prepare**: lay the foundation to keep services available and assets functioning during a disruptive event (malfunction or attack).
2. **Absorb**: maintain most critical asset function and service availability while repelling or isolating the disruption.
3. **Recover**: restore all asset function and service availability to their pre-event functionality.
4. **Adapt**: using knowledge from the event, alter protocol, configuration of the system, learning process, or other aspects to become more resilient.

2.3 Traditional resilience approaches problems

In general, resilience approaches can be divided into two broad categories: *qualitative* and *quantitative*.

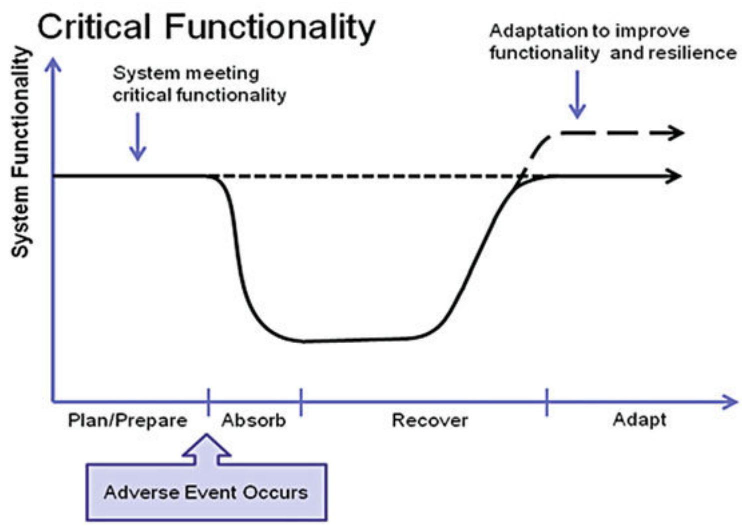

Fig. 3. Notional resilience profile, plotting a systems critical functionality over time [20].

- The qualitative category, which includes methods that evaluate the resilience of a system without a numeric descriptor, contains two sub-categories:
  - Conceptual frameworks that offer best practices.
  - Semi-quantitative indices that provide expert assessments of different qualitative aspects of resilience.
- Quantitative methods include two sub-categories:
  - General resilience approaches that provide domain-independent measures for quantifying resilience across applications.
  - Structural modelling approaches that model representations specific to the components of the resilience components.

Linkov and Kott [20] classify existing work dealing with resilience into two other main categories: metric-based and model-based approaches. Metric-based approaches use measurements of the individual properties of system components or functions to assess overall system performance. Model-based approaches use system configuration modelling and scenario analysis to determine the overall performance of the system (see Fig. 4). Agent based approach and multi-agent systems are considered as model-based approaches to address resilience.

We find that the main approaches addressing the issue of resilience are centralized or based on redundancy [11]. This project aims to provide the subsystems constituting a CPS with a form of decision-making autonomy, allowing the CPS to detect abnormal situations and then adapt its behaviour to these situations. To do so, our approach utilize the *multi-agent paradigm*.

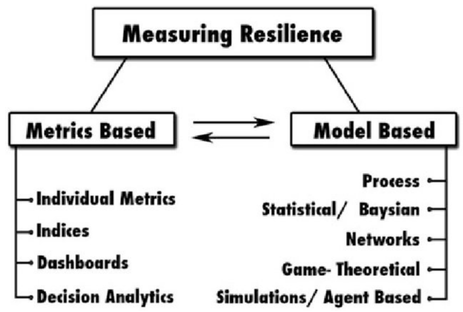

Fig. 4. Metric-based and model-based approaches for resilience assessment [20].

3 Multi-agent systems and resilience

In this section, we are going to present multi-agent systems, self-organization and the advantages of using a multi-agent approach for cyber-physical systems resilience.

3.1 Multi-agent system (MAS)

An agent is a real (physical) or virtual entity, located in an environment, able to perceive and act upon it, which can communicate with other agents, an agent is responsive, proactive, social, autonomous and can also have the ability to learn [8,33]. According to Demazeau, a multi-agent system is a system composed of: a set of agents, an environment, a set of relationships and interactions between agents and a set of organizations of agents [6].

According to Ferber [8] MAS main characteristics are:

- Each agent has its own role.
- No global control.
- The data and the decisions are decentralized.
- The operations are asynchronous.

The notion of *organization* plays a fundamental role within MASs and can be defined as:

- a mean of logically organizing agents,
- a default communication network, and
- an agent, role, or competence search media.

In addition, its reification provides an entry point into the system for visualizing and improving agent interactions through its dynamic evolution. Organization is needed to structure the interactions that occur between different system entities (agents) [24]. MASs can be provided with a self-organization process making them able to adapt to changes in the environment. Self-organization is an endogenous, bottom-up, process concerning systems in which only information is manipulated by agents which may be unaware of the state of the organization in its entirety [7,13]. Self-organization is achieved by modifying the organization; either by directly changing the configuration of the system (topology, neighborhoods, and influences) or through the system's environment by using local interactions and influences, avoiding using predefined models.

3.2 Multi-agent approach for resilience

Multi-agent systems offer us a decentralized solution to solve the "single point of failure" problem which is intrinsic in centralized solutions. Moreover, with a multi-agent approach we can avoid the redundancy/replication of a lot of software and hardware components of the cyber-physical system [8]. Multi-agent system can maintain its functioning in case communication loss, decrease of data volumes to be transmitted and scaling using the autonomy of its agents. In addition, adopting the multi-agent paradigm and self-organization is breaking with traditional approaches of resilience by the fact that it makes a use of a social metaphor for complex systems. Adding to that, this paradigm allows us to use cognitive science and psychology to reproduce the cognitive functions of emotions, both in the decision-making mechanism of the individual and in the process of the self-organization of the group.

4 Artificial emotions and CPSs

In this section, we are going to present artificial emotions, emotions theories (computational models) and the use of artificial emotions in our project.

4.1 Artificial emotions

According to Frijda [9], emotional phenomena are: non-operationalized behaviours, non-instrumental behavioural traits, physiological changes, and evaluative experiences, related to the subject, all caused by external or mental events, and primarily by the meaning of such events. In computer science, artificial emotions are a set of pre-programmed or non-scheduled processes running within a machine, facilitating decision-making and enabling the system to adapt to the environment. This artificial emotion is the fruit of the program's input-output as well as its own internal activity, and is often the object of a collaboration with a cognitive structure, by means of which the system deals with the problems introduced by its environment. In addition, it is part of a programming logic more or less explicit, but still in the field of computable [21]. In the literature, a panoply of emotion models and computational models are offered but for an artificial system, certain constraints are always present (performance, reliability, durability, integration...) for this reason the choice of an emotion model and a computational model requires a deep analysis to have the best choice for a cyber-physical system (see Fig. 5).

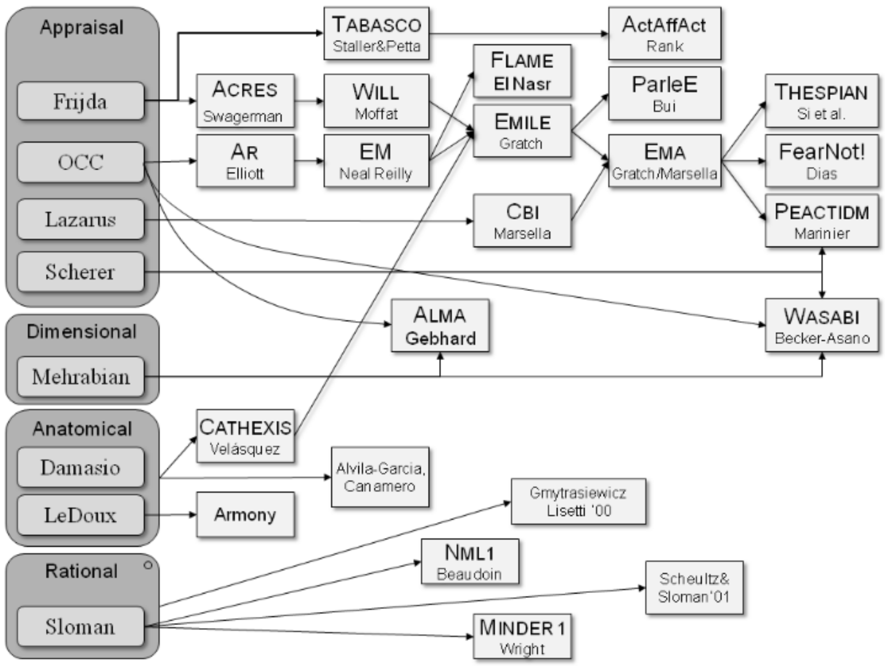

Fig. 5. A history of computational models of emotion [22].

Appraisal theory is one of the main psychological perspectives on emotion and arguably the most fruitful source for the design of symbolic AI systems. In this theory, emotion is argued to arise from patterns of individual judgment concerning the relationship between events and an individuals beliefs, desires and intentions, sometimes referred to as the person-environment relationship [16]. These judgments, formalized through reference to devices such as situational meaning structures or appraisal variables [10], characterize aspects of the personal significance of events. Patterns of appraisal are associated with specific physiological and behavioral reactions. Computational appraisal models have been applied to a variety of uses including contributions to psychology and AI. For example, several authors have argued that appraisal processes would be required by any intelligent agent that must operate in real-time, ill-structured, multi-agent environments (e.g., Staller and Petta [30]).

Dimensional theories of emotion argue that emotion and other affective phenomena should be conceptualized, not as discrete entities but as points in a continuous (typically two or three) dimensional space [25]. It is not surprising that these theories relegate the term emotion to a cognitive label attributed, retrospectively, to some perceived body state. Computational dimensional models are most often used for animated character behavior generation, perhaps because it translates emotion into a small number of continuous dimensions that can be readily mapped to continuous features of behavior such as the spatial extent of a gesture. For example, PAD model of Mehrabian and Russell [25] where these dimensions correspond to pleasure (a measure of valence), arousal (indicating the level of affective activation) and dominance (a measure of power or control).

Anatomic theories stem from an attempt to reconstruct the neural links and processes that underlie organisms emotional reactions [17]. Unlike appraisal theories, such models tend to emphasize sub-symbolic processes. Unlike dimensional theories, anatomic approaches tend to view emotions as different, discrete neural circuits and emphasize processes or systems associated with these circuits. Computational models inspired by the anatomic tradition often focus on low-level perceptual-motor tasks and encode a two-process view of emotion that support for a fast, automatic, undifferentiated emotional response and a slower, more differentiated response that relies on higher-level reasoning processes (e.g., Armony *et al.* [4]).

Rational approaches typically reside in the field of artificial intelligence and view emotion as window through which one can gain insight into adaptive behavior. Within this rational approaches, cognition is conceived as a collection of symbolic processes that serve specific cognitive functions and are subject to certain architectural constraints on how they interoperate. Emotion, within this view, is simply another, although often overlooked, set of processes and constraints that have adaptive value. Models of this sort are most naturally directed towards the goal of improving theories of machine intelligence [22].

4.2 Artificial emotions for CPSs

Emotions have inspired many studies on human-machine interaction and especially on the detection and expression of natural emotions [5]. Other work on artificial emotions aim to reproduce in artificial systems the stereotyped behaviors that are associated to make virtual agent behaviors more realistic [29,2].

It should be noted that our work is clearly distinct from these themes because it does not deal with the interaction with humans or simulation of natural emotions but to reproduce their functions [27]. In existing approaches of artificial emotions, emotions are elicited by an analysis of symbolic events related to the system's goals or include a lot of knowledge from the system's designer about situations the system might encounter. These initial assumptions of existing work limits intrinsically the resilience of the resulting systems. Furthermore, these characteristics are hardly applicable to CPSs since 1) they are embedded in the physical world and can't trigger emotions from symbolic data about the situation and 2) the distributed and open nature of CPSs make it impossible for their designers to foresee all possible situations.

Our aim is to design processes that replicate some functions of emotions while avoiding to depend upon such assumptions. Therefore, the functions of emotion we chose to replicate in artificial systems to improve their resilience are: detecting abnormal situations and updating social organizations in response to these abnormal situations. These functions are directly related to the "Absorb" and "Adapt" phases of the resilience profile depicted in Fig. 3.

5 State of the project

In this project, we adopted an experimental approach made of different hypotheses, and currently we are working on an emotional agent model for testing their validity.

From the state of the art of artificial emotions, resilience and multi-agent systems, we are designing an individual, decentralized mechanism for detecting abnormal situations using a process inspired by the triggering of an emotional episode. The mechanism will be used in the "Absorb" phase of the resilience profile and integrated in our agent model. Another mechanism will be designed, a process of adapting the individual behaviour of subsystems to improve the resilience of the CPS (the "Adapt" phase of the resilience profile). Using the multi-agent paradigm, we design a collective process for detecting abnormal situations using the information built by the individual detection mechanism. This collective process is initiated by the behaviour adopted when an abnormal situation is detected individually. The adaptation of individual behaviour impacts on the social organization of the group of agents carrying out the control of the CPS, which will trigger a self-organization in order to collectively adapt to the abnormal situation.

The mechanisms proposed in this project are generic, not specific to the tasks of the system. For validating our hypotheses, we have chosen a case of application, a building's thermal regulation system (CPS_{trb}), consisting of a set of heaters, air conditioners, thermal sensors, thermostats, light sensors, fans and automatic rolling shutters. The resilience in this system is that CPS_{trb} continues to ensure the temperatures chosen by users in case of problems. Before defining the resilience for our CPS_{trb}, we have described the main features, sensors, actuators of this system as well as the potential problems it may encounter. In this context, we are interested in problems like: connectivity breakdown, a node failure, increasing workload issue and adding or removing a node to/from CPS_{trb}. This cyber-physical system is agentified using DIAMOND method [12]. In this method, there are four phases to move from global characterization to the specification of local behaviours:

- **Situation phase** : define the general context of the multi-agent system, i.e. the environment, the agents with their main capacities and their contexts.
- **Individual phase** : define agents from an internal point of view (independent of social relationships).
- **Social phase** : describe the interaction and organization from an external point of view.
- **Integration phase** : to integrate social influences into agents behaviours.

The proposed processes and multi-agent system will be simulated using MASH[2] [14], a hybrid hardware software simulation platform, in order to quantify experimentally the resilience improvements they bring.

[2] MASH (MultiAgent Software/Hardware simulator)

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