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A FRAMEWORK FOR SELF-INSPECTION BUILDINGS BASED ON AUGMENTED REALITY AGENTS

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Abstract. Emergent technologies are being adopted at all the stages of smart building lifecycles. More specifically, mobile, pervasive, and communication technologies are being deployed to achieve a wide range of functions that improve the building performance (including ventilation, air conditioning, heating, lighting, and security) and reduce their related costs. Augmented Reality (AR) has arisen as a promising tool to achieve these goals. However, in spite of the multiple solutions that have integrated AR within smart buildings, several shortcomings are yet to be solved. In addition to the limited user experience and the lack of AR content, current solutions do not provide effective collaborations between construction stakeholders as well as do not include intelligent mechanisms for the management of inspection activities. In order to address some of the smart building challenges, we are proposing in this paper a new framework for intelligent collaborative self-inspection buildings based on the concept of awareness wheel as well as the multi-agent system paradigm.

Keywords: Self-inspection building, augmented reality, agents, competition

1 INTRODUCTION

Recent advances on mobile and ubiquitous technologies have enabled the implementation of solutions offering self-organizing and customized services to their users, wherever they are and whenever they want. These services have been particularly adopted under the wide umbrella of the Smart City paradigm. This paradigm is basically aiming to make citizens' lives easier by deploying the latest IT technologies in order to create more accessible, consumable, coordinated, and smart services [1]. Within this perspective, the construction sector plays a vital role in attaining the expected objectives. We are, indeed, witnessing increasing numbers of smart buildings as well as smart city initiatives build around them [15]. A smart building can be presented as providing an efficient environment via optimized systems, materials, structures, services, and operations. It can also be defined, according to the European Commission, as a building empowered by ubiquitous computing and Internet of Things (IoT) solutions that ultimately aim to locally collect, filter, and generate increasing amounts of data which are further managed globally according to predefined services and business functions [16].

Recent predictions [17] have reported that the global smart building market is expected to have an annual growth rate (CAGR) of 32 %, reaching 43 billion USD by 2022. This growth is being demonstrated at all stages of the building life cycle, including design, construction, and operational phases [15]. It is driven by several factors, such as market and customer, sustainability and resilience, society and workforce, as well as politics and regulation [16]. A study from the United Nations (UN) Environment Programme has reported that buildings at a global level use about 25 % of water, 40 % of energy, and 40 % of resources. They also release 33 % of GHG emissions. The same source has reported that commercial and residential buildings consume around 60 % of the world's electricity [18]. In order to reduce these numbers, considerable efforts are being spent to make buildings smarter for the ultimate goals of saving energy, increasing safety, reducing operation and maintenance costs, as well as reducing environmental impact [19].

Thanks to the recent technological advances (including IoT, Wireless Sensor Networks (WSN), Cloud Computing, Big Data, Artificial Intelligence, etc.), new approaches for obtaining, visualizing, and interacting with services have appeared. To meet new requirements, overcome current and foreseen challenges, and implement sustainable solutions, recent initiatives are focusing on the use of Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) that have emerged as game changing technologies in a wide range of application fields [2], including healthcare (e.g. [3]), military (e.g. [4]), education (e.g. [5]), engineering (e.g. [6]), and manufacturing (e.g. [7]). More specifically, AR provides users with a live view of the real-world environment, which elements are "augmented" by relevant visual information generated by computers [8]. It also allows for new modes of navigation, visualization, and user interaction [9]. In fact, it enables them to immerse into the resulting environment while interacting with its objects and requesting services according to their needs. To implement these functions, numerous AR framework tools are available, including Vuforia, ARKit, ARCore, Kudan, ARToolKit, AR-Media, Maxst, and DroidAR. These frameworks have been investigated by a number of studies (e.g., [51]) from several perspectives, such as tracking methodology, sup-ported platforms, accessibility, and price. In terms of AR hardware, several options are possible. These options could be classified as Smart glasses, Head-mounted gear, Web browser-based AR, and Mobile-based AR. Smart glasses are low-power, light-weight wearables providing first-person views. They include the two products Vuzix Blade and Google Glass. Headsets are constructed to provide users with highly immersive experiences where AR and VR environments are mixed. They include Magic Leap and Microsoft HoloLens. The Web browser-based AR makes use of the available processing capabilities as well as Internet connectivity to overlay AR contents on available online information. Mobile-based AR (or Mobile Augment Reality – MAR) are similar to Web-based AR. However, they focus more on embedding AR content into their current environment on the move. The mobile AR are built on smartphones and tablets. The content is visible on the screens of these devices as holograms. Thanks to the wide use and availability of these devices, mobile AR could be highly accessible to business and users.

In the specific field of construction, MAR systems are being used to deliver, visualize, and interact with the available information about buildings in innovative manners contributing, therefore, to the implementation of intelligent Building Management Systems (BMS) [11]. BIM may refer here to a 3D model that stores all the data related to a given building digitally [23]. It may also refer to the process of producing digital building models that will be used by construction stakeholders (e.g., architects, engineers, and construction professionals) to carry out effective construction operations (e.g., planning, design, maintenance, etc.) throughout the building entire life [24]. With the use of MAR, construction companies are becoming capable of engaging in real time all the stakeholders, reporting and clarifying construction progress, reducing the time that operators and inspectors have to spend in high-hazard areas, improving asset-management, optimizing the use of data throughout the construction projects' life cycles, and sharing knowledge [16]. In addition, MAR is particularly enabling the Simultaneous Localization And Mapping (SLAM) technique that allows for working in real time without the need for any GPS [12]. These performances, which have been demonstrated in smart building through several works (e.g., [47, 49]), are mainly attributed to the capability of AR-related techniques in enabling the collection of unambiguous, high-resolution, and full-field measurements of construction structures (e.g., [42, 43, 44, 45, 46]).

In spite of the high interest in using AR technologies in the construction sector, there are still challenges that need to be addressed. These challenges include the limited tracking accuracy (which is not enough yet to correctly overlay the BIM in the AR environment [12]), the shortage in appropriate support of mobility, as well as the lack of effective collaboration between stakeholders. Other challenges also include the limited user experience (due to technological limitations), partial/unavailability of content, high cost, reluctance to embrace AR by business and consumers, lack of investment, and lack of supportive regulations [52]. In order to address some of these challenges in the construction sector, we are proposing in this paper a new framework for an intelligent self-inspection of buildings and construction sites. The framework includes collaborative agents that compete for the attraction of inspection services. Our contributions in this paper include:

1. A new Framework for self-inspection buildings based on the concept of awareness wheel; and
2. An intelligent Social Competition based on collaborative inspection of buildings.

In the reminder of the paper, Section 2 outlines the current literature on the use of AR technologies for the inspection of buildings and construction sites. Section 3 sheds light on our new solution called Framework for Intelligent Collaborative Self-Inspection Buildings – FICSIB. It also explains our approach for the intelligent collaboration between agents as well as our competition solution for resource inspection. In addition, it highlights how inspection tasks are going to be assigned intelligently in a distributed way by following a distributed constraint satisfaction problem formulation. Section 4 outlines a proof of concept of the core intelligent part of our solution. Section 5 highlights some challenges and opportunities related to our solution. Section 6 concludes the paper.

2 RELATED WORK

Thanks to the adoption of recent technologies, the smart building field is being transformed to meet new requirements and implement sustainable solutions. These transformations represent huge business opportunities. They also represent challenges, particularly when it comes to matters related to data collection, sharing, and processing as well as adaptability to the environment, compliance of the buildings with the city ecosystem, and operation control [20, 21, 22]. In order to implement the transformations above, several key technologies are being adopted (see Figure 1). In this regard, a wide range of data acquisition devices (e.g., sensors, drones) are being used in order to collect data of interest anytime, anywhere. As several stakeholders are commonly involved in the design and the creation of a smart building, numerous emergent communication and tracking tools are being adopted to facilitate the sharing of data, particularly within the concept of BIM [11, 33]. As such, BIM is being used as an effective collaboration platform by construction stakeholders [25, 26], where the quality of design/construction can be jointly improved [27], redundant reworks are reduced [28], and costs are optimized [29, 30]. In order to meet these goals, several technologies are being used throughout the construction lifecycle. Among these technologies, XR techniques (i.e. virtual reality, augmented reality, and mixed reality) are being particularly deployed to implement collaborative actions between construction teams/stakeholders. Big data analytics techniques are also being increasingly used to handle the huge amounts of data generated with in-situ sensing devices.

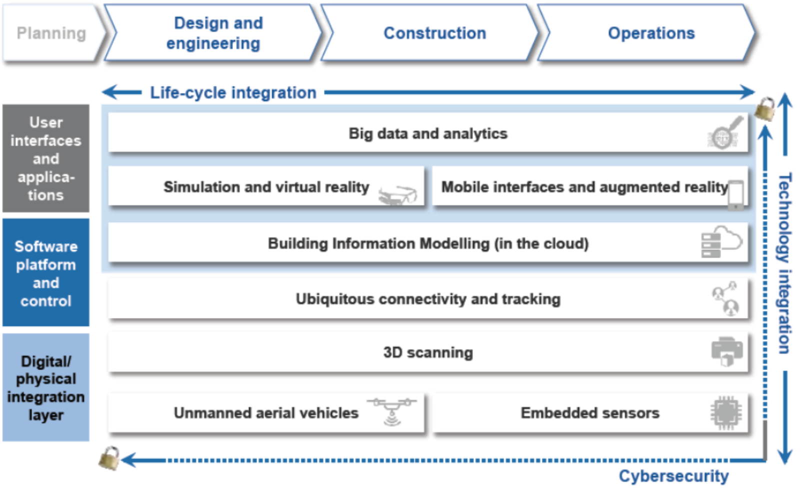

Figure 1. Digital technologies applied in the construction value chain (Source: Press reports, World Economic Forum, The Boston Consulting Group, see [16])

In order to reach the expected benefits from the technologies applied in the construction value chain, it is important to identify and inspect the right features to ultimately make sure that sustainability, cost effectiveness, and security are maintained. Numerous automated decision tools have, therefore, been used. These tools have proven to allow for an overall accuracy of about 88.5 % when compared to manual approaches [34]. Furthermore, in addition to deploying dedicated human-machine interfaces (e.g., [35, 36]), a number of researchers (e.g., [37, 38, 39, 40, 41]) have investigated the use of smartphones mainly to enhance the ease of use of technologies by inspectors. AR-related techniques have additionally been considered to enable collecting unambiguous, high-resolution, and full-field measurements of construction structures (e.g., [42, 43, 44, 45, 46]). For instance, thanks to its computer-generated holograms superimposed on the real world, AR can allow the inspectors to minimize inspection inconsistencies and provide highly accurate measurements of a structure's geometry [47]. These capabilities are particularly helping in the assessment and improvement of building performance, which reflects how well buildings achieve with respect to several criteria, like energy, safety, occupants' comforts, and control systems [48]. In this regard, a wide range of Building Performance Models – BPMs (e.g., [46]) have been proposed to explore, foresee, and recognize the performance of buildings and make decisions accordingly.

The contributions of using AR-based solutions for smart buildings have been demonstrated through several works (e.g., [47, 49]). More precisely, the authors in [49] have proposed an approach where the inspector collaborates with a solution combining AR with semi-supervised deep learning mechanisms for an improved visual inspection. The authors in [47] have proposed an AR tool that quantitatively assesses and documents the irregular geometries of sidewalks. They have also proposed to use an AR headset to perform a structural inspection of concrete structures. In addition, they have proposed a software development framework for the creation of robust, modular applications that carry out structural inspections based on AR technologies. These achievements have been reached within the context of the project Intuitive Self-Inspection Techniques using Augmented Reality (INSITER) [50]. This project ultimately aims to create a software tool to help construction workers in executing their inspection processes, while reducing major errors and cost over-heads. To this end, it emphasizes the concept of building self-inspection, which could be defined as the process of monitoring the quality of construction work to make sure that the predefined specifications are executed as per the prior design [50]. Furthermore, the authors in [54] have proposed a global platform that highlights the requirements and recommendations related to the execution of any AR studies in construction sites. In [55], the authors have presented a mobile AR app to demonstrate virtual construction components in outdoor and indoor spaces. In [56], the authors have used a mobile AR app to identify and decrease errors in construction sites. In [57], the authors have proposed an app that illustrates construction projects in actual environments. The authors in [58] have introduced a mobile AR app to provide users with intuitive information about construction sites. The authors in [59] have created a mobile AR app that allows users to identify buildings under construction within a given area of interest as well as to obtain information on how these buildings will look like once their constructions are completed. Finally, the authors in [60] have outlined an AR app in the construction of tunneling sites.

3 INTELLIGENT COLLABORATIVE BUILDING INSPECTION

Based on our thorough literature review, we argue that new approaches are still needed to improve the inspection of buildings, particularly with the use of emerging sensing, computing, and communication technologies. In this regard, we are focusing in this paper on the concept of self-inspection building. More precisely, we are proposing a new intelligent approach where the management of inspection operations is promoted and executed collaboratively between several physical components (e.g., inspectors, building facilities, etc.) as well as virtual components (i.e. software agents). In order to give more details, we explain in what follows the fundamentals ideas, architecture, and operations of our innovative solution.

3.1 The FICSIB Architecture

We are proposing in this paper a new architecture called Framework for Intelligent Collaborative Self-Inspection Buildings – FICSIB. It is motivated by the concept of building self-inspection (see [50]). It is also based on the concept of awareness wheel [61]] (see Figure 2) where:

1. Sensory data refer to the information/observations acquired through the physical senses of an individual. The mind immediately processes this information by carrying out comparisons with previous experiences.
2. Thoughts refer to the exiting norms, assumptions, beliefs, interpretations, expectations, assessments, opinions, and judgments.
3. Feelings represent the physiological responses to the thoughts. They will result into pleasant or unpleasant sensations that can be described as happiness, frustration, fear, sadness, anger, joy, guilt, excitement, etc.
4. Wants refer to the desire, aspirations, expectations, goals, and intentions that an individual has for him/herself.
5. Actions represent the behaviours, the activities, and the accomplishments. They also represent the future plans.

In our proposed framework (Figure 3), the Sensory Layer is responsible for acquiring data from the building environment and carrying out the subsequent data preprocessing and storage activities. The Thought Layer is responsible of revising the current data building and intelligently generating knowledge from the data acquired via the sensory layer. This knowledge will then be used by the collaborative self-inspection function of the Feeling Layer to identify the potential deficiencies in the building where additional investigations would be required. The collaboration is reflected by the use of AR-based tools that the self-aware building will deploy to communicate with its facilities (e.g., sensors, pipelines, etc.) as well as with the appropriate stakeholders (e.g., site worker). The goals as well as the priority of inspections of the self-aware building will be updated in the Wants Layer, based on the self-inspection. An option generation function will then be executed in order to identify the possible actions that can be executed in order to carry out the necessary inspections. These potential actions will be explored thoroughly using the collaborative plan generation function in the Actions Layer. This function will, indeed, coordinate the efforts of the different facilities of the building as well as the construction stakeholders and generate an action plan for the inspection activities.

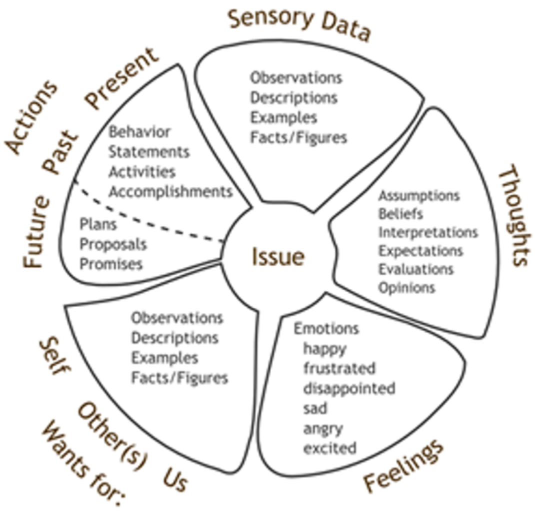

Figure 2. Sensory wheel

A follow up on the plan execution will be accomplished with the collaborative execution function. The results of this execution as well as its impact on the building environment will be fed to the predictive inspection function that will identify any future inspection needs. The outputs of this function will be sent to the Thought Layer. In order to optimize the operations of several functions of our architecture, we are relying on machine learning tools. The use of these tools will ultimately improve the self-awareness of the building as well as its capability of predicting future inspection activities.

3.2 System Model

In order to showcase the operations of our framework, we assume in this paper that any given building or construction site is formulated as $C = F \cup R$, where $F = f_1, f_2, \dots, f_n$ is the set of facilities and $R = r_1, r_2, \dots, r_m$ is the set of resources. Resources include the construction stakeholders as well as any data collection devices (e.g., IoT device, drone, etc.). Facilities include different construction elements/components, such as doors, lights, pipes, etc. We assume that the inspections will concern individual facilities. We denote them as $I = i_1, i_2, \dots, i_p$, where every inspection is represented as a vector $i_i = \langle ref, r_u, t, type, f_j, loc, s_k \rangle$, including a reference (i.e. ref) for the inspection, the resource doing the inspection (i.e. r_u), the time of its execution (i.e. t), its type (i.e. manual or self-inspection), the facility that was inspected (i.e. f_j), the location of the facility (i.e. loc), and the class of the risk identified by the inspection (i.e. s_k). We assume that the set of risks are represented with $S = s_1, s_2, \dots, s_q$. S could, for example, be critical,

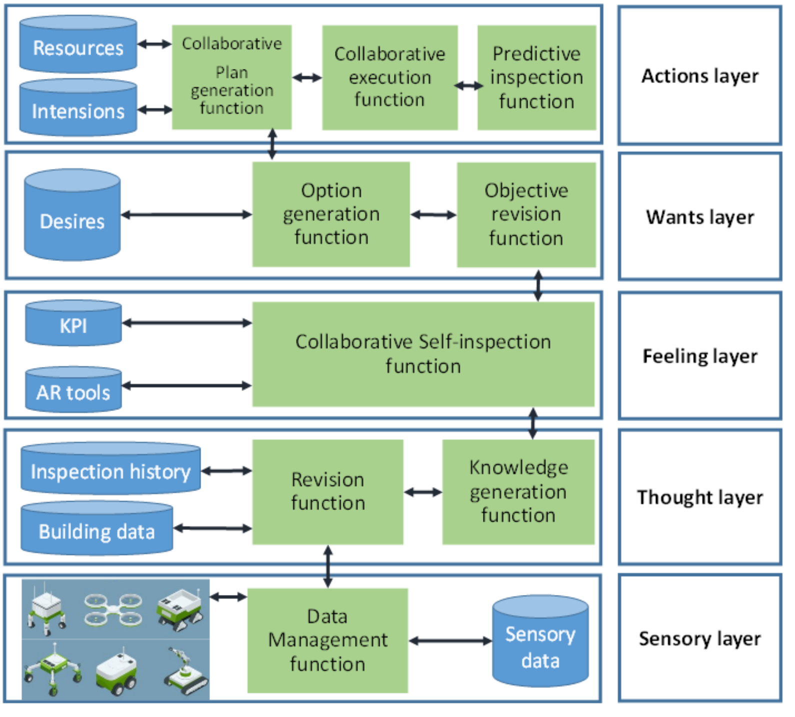

Figure 3. Proposed framework for intelligent collaborative building inspection

major, moderate, minor, or cosmetic. We finally assume that every risk would generate an impact on neighboring facilities. We denote the types of impact as $E = e_1, e_2, \ldots, e_u$.

3.3 Agentification of Self-Inspection Building

In order to implement our self-inspection building concept, we are using the paradigm of Multi-Agent System (MAS) to endow the different components of our solution with intelligence and autonomy. A MAS consists of a group of interacting software agents. These agents may have several behaviours and social skills, including communication, interaction, collaboration, coordination, and negotiation. In a MAS, agents can operate autonomously and intelligently as well as reason, learn, and adapt themselves to meet their individual objectives. They will use their skills in order to collectively achieve common goals, which are beyond their individual capabilities. MAS are particularly suitable to modeling and solving complex problems which are characterized by open, dynamic, and uncertain environments.

Element	Set	Description
Construction	C = F ∪ R	The construction site includes facilities and resources
Facilities	$F = \{f_1, f_2, \dots, f_n\}$	Facilities could be lights, doors, etc.
Resources	$R = \{r_1, r_2, \dots, r_m\}$	Set of inspection resources
Risks	$S = \{s_1, s_2, \dots, s_q\}$	Risks may have several levels, like critical, major, moderate, minor, or cosmetic
Inspections	$I = \{i_1, i_2, \dots, i_p\}$ where $i_i = < \text{ref}, , r_u, \text{t}, \text{type}, f_j, \text{loc}, s_k >$	Set of inspections. Each inspection has a reference and a time, concerns a facility f_j, has a location, and identifies a risk of class s_k
Impact	$E = \{e_1, e_2, \dots, e_u\}$	Set of impact types

Table 1. System model

The MAS architecture of our solution is depicted in Figure 4. It includes static agents (e.g., for the different resources and facilities of the building) as well as mobile agents that will be created on-demand (e.g., by the agent assigned to a given inspection) and then migrate to neighboring facilities and/or resources to promote the defect detected and attract the necessary resources to solve risks detected. Our idea is to allow competition between agents to solve ongoing and/or foreseen defects. The competition will give priority to defects according to their impact and based on the availability of the inspection resources.

For every inspection that detects a problem that would need an intervention, a dedicated agent (called Inspection Agent – IA) is created. The IA will assess the problem (based on the observations reported by the owner of the inspection, the available data, as well as the data obtained from other resources) and classify its risk (as per the set of risks S).

The impact on neighboring and/or dependent facilities is then evaluated (as per the set of impact E). One or more Augmented Reality Agents (ARAs) will then be created accordingly. Every ARA will start by bagging the necessary AR tools before migrating to the appropriate locations (i.e. neighbor facility) that would be affected by the problem detected. For instance, as AR is mainly about visualization, we assume here that several AR objects are available for the ARA agent to reflect the risk of the defect, its impact, and its urgency.

The ARA agent has the mission to raise awareness about the current and expected impact of the defect, notify any neighboring resources about new updates on the ongoing situation, collect new information to improve the management of the inspection, and attract actions to solve the defect. To meet this end, we are proposing to endow the ARAs with social behaviours where the impacted facilities

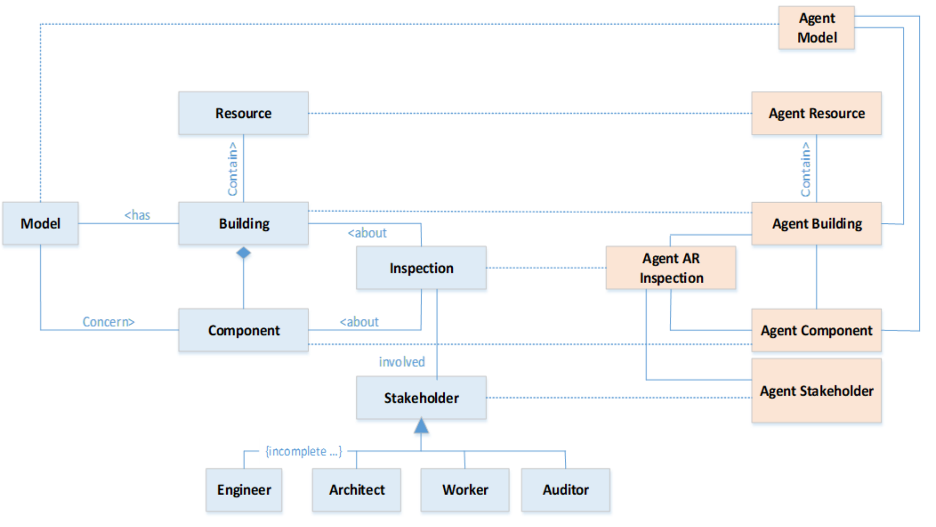

Figure 4. Multi-agent system architecture for building inspection

(receiving the ARAs) would individually promote the ARAs and, consequently, promote the actions needed to solve the defect being managed by the agent IA. More specifically, based on the estimated value of the impact of the defect (or defects) on the neighboring facility y where it will migrate, the ARA agent (which is initially located on the facility x) will calculate its related attractiveness for y (i.e. $\beta_{(\overrightarrow{xy}}(t))$ at t as follows:

$$\beta_{(\overrightarrow{xy}}(t) = (w_x - w_y) \times \sum impact(defect_j, y) \tag{1}$$

where w_x denote the weight (or importance) of facility x, w_y denote the weight of facility y, and $\sum impact(defect_j, y)$ denote the sum of expected impact of all the current defects detected in facility x on facility y.

If the attractiveness above is higher than a predefined threshold that reflects whether the defect (or defects) are serious (and thus must be solved), the facility y will calculate the value of its promotion $\Pi_{(\overrightarrow{yx}}(t)$ at t for the facility x as follows:

$$\Pi_{(\overrightarrow{yx}}(t) = \frac{1}{\log(\beta_{(\overrightarrow{xy}}(t)}. \tag{2}$$

All the individual promotion values will be sent to the IA agent to collectively contribute to the attractiveness of the facility x (i.e. (i.e. $\beta_x(t)$)) that needs to be checked/repaired.

$$\beta_x(t) = \sum \Pi_{(\overrightarrow{nx}(t)} \tag{3}$$

where $\Pi_{(\overrightarrow{nx}(t)}$ denote the promotion of the neighbouring facility n for the facility x. The operation of the ARAs agents can, therefore, be regarded as a competition whereby they contest to attract solutions for the resolution of the ongoing construction problems.

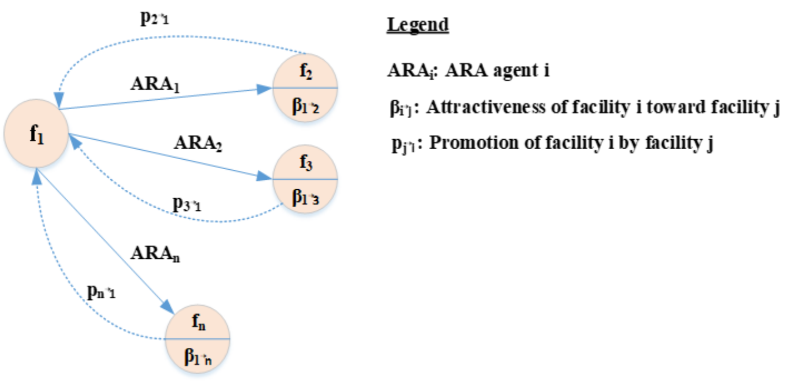

Figure 5. Attraction and promotion in the social model of ARA agents

3.4 Distributed Intelligent Inspection

The competition of the ARA agents is mainly aiming to promote the needs for interventions as well as attracting inspection resources. The output of this competition will serve as ground information for inspectors to plan their actions. More specifically, the inspectors must intervene in a way to check/repair defects while satisfying specific related constraints (e.g., urgency/impact of defects, locations of the defects, etc.). The interventions must not be necessarily centrally coordinated. For this reason, we model in this paper the intervention process as a Distributed Constraint Satisfaction Problem (DCSP). A constraint satisfaction problem (CSP) is a problem where the solution is requested to be within some conditions or limitations (also called constraints). It can be defined with the following elements:

- A finite set of variables $X = \{X_1, X_2, \ldots, X_n\}$.
- For each variable X_i, a finite set Di of possible values (also known as domain). The domains of all the variables is denoted $D = \{D_1, D_2, \ldots, D_n\}$. The values are not necessarily a set of consecutive integers. They do not also need to be numeric.
- A finite set of constraints $C = \{C_1, C_2, \ldots, C_n\}$ that restrict the values that the variables can take at the same time. Constraints are commonly symbolized by an expression including the concerned variables (e.g., $X_i < X_j < X_k$ for $i < j < k$; $X_i \neq X_j$; $2Xi - 3X_j = 0$).

Within the context of our current paper, CSP will be needed in order to ensure that the available inspectors will be intervening efficiently on the building/construction resources where ongoing problems are happening or ongoing alerts are fired. In this case, we define the CSP as follows:

- Variables: $X = \{I_1, I_2, \ldots, I_n\}$ is the set of available inspectors.
- Variables: $D = \{R_1, R_2, \ldots, R_n\}$ is the set of domains, where R_i refers to the set of resources that the inspector I_i can be assigned to (for example: An inspector cannot be assigned to a given resource since he/she does not have specific required skills or due to travel time to reach the resource).
- Constraints:
  - $\forall (rp, rq) \in R_i$ where $p < q$, $f(rp) \leq f(rq)$ (in other words, the attractiveness of the resource rp is less than the attractiveness of the resource rq. This attractiveness is calculated as described in Section 3.3).
  - Two inspectors cannot be assigned to the same resource at the same time. In other words, $\forall (Ip, Iq), g(Ip) = rp \neq g(Iq) = rq$, where g is an assignment function.

Based on the description above, we depict in Figure 6 a typical example of a constraint graph related to our case study. In this figure, a given resource rp is linked to another resource rq if both resources are neighbors and a defect on one resource would impact the other one. In this case, the weight of an edge has the format $\langle Arq, Arq \rangle$ where Arp and Arq represent the current attractiveness of the resource rp and rq, respectively.

A DCSP is a CSP where the variables and the constraints are distributed among autonomous entities. In the current paper, these entities are represented by intelligent software agents, each of which is assigned to a given inspector. These agents can rely on the commonly used backtracking algorithm in order to come up with an assignment for inspections. Backtracking can be synchronous (i.e., a preorder is defined to coordinate the actions of the agents) or asynchronous (i.e., agents can operate concurrently). We are opting here for the asynchronous approach. As several works (e.g. [63, 64]) have proposed algorithms supporting this approach, we will rely on the widely used ADOPT algorithm (see [65]).

4 PROOF OF CONCEPT

To demonstrate the performance of the proposed solution, we developed a prototype for the intelligent core that manages the social interactions between the ARA agents. The prototype was developed using the GAMA platform, based on the recommendations presented in [62]. We illustrate in Figure 7 the simulation environment. In the 3D representations (Figure 7 a) and Figure 7 b)), the blue squares represent the inspection resources and the other spheres represent the defects (the color and the size increase with the severity of the defect). Figure 7 c) is a 2D illustration of the simulation environment.

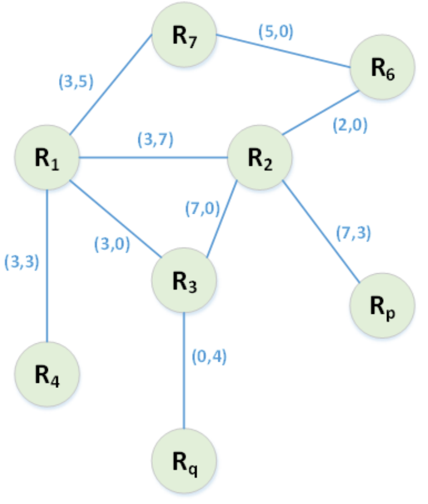

Figure 6. Constraint graph

For a better assessment of this performance, we compared the results of the proposed FICSIB framework with two other approaches: Random inspection and Priority-Based inspection. In the former approach, inspection tasks are done randomly, i.e. the inspection resource is checking the facilities during his/her navigation in the construction site (or building). In the latter approach, inspection resources plan their tasks by selecting the facilities to inspect based on their priorities. These facilities must fall within the awareness range of the inspection resources.

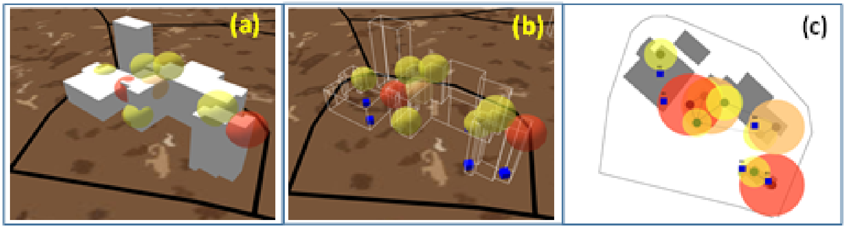

Figure 7. Simulation environment

Our simulations for the Random approach (Figures 8 a), 8 b) and 8 c)) are showing that the resources were capable of handling the defects in several locations (the color of the defect is turning green). However, it happened that some defects were not addressed on time and, therefore, degenerated into high severity problems (Figure 8 c)). The simulations of the Priority-Based approach (8 d), 8 e) and 8 f)) are showing a better performance. Indeed, the inspectors were capable of addressing the defects which are falling within their awareness range. Nevertheless, the approach may not take into consideration the priority of defects correctly. Indeed, part of the severity of these defects are reflected by their impact on their neighbors, which is not seen to the inspector. Consequently, some defects were not considered as of high priority and, therefore, worsened for some time before being addressed by the inspectors. This issue was solved in the simulations reflecting our proposed FICSIB solution. We can, indeed, see (8 g), 8 h) and 8 i)) that the defects were addressed on time. It is important to mention that the results obtained (Figure 8) basically depend on the initial configurations of the simulations. Indeed, in these configurations, which are randomly generated, defects vary in numbers, severity, and occurring time.

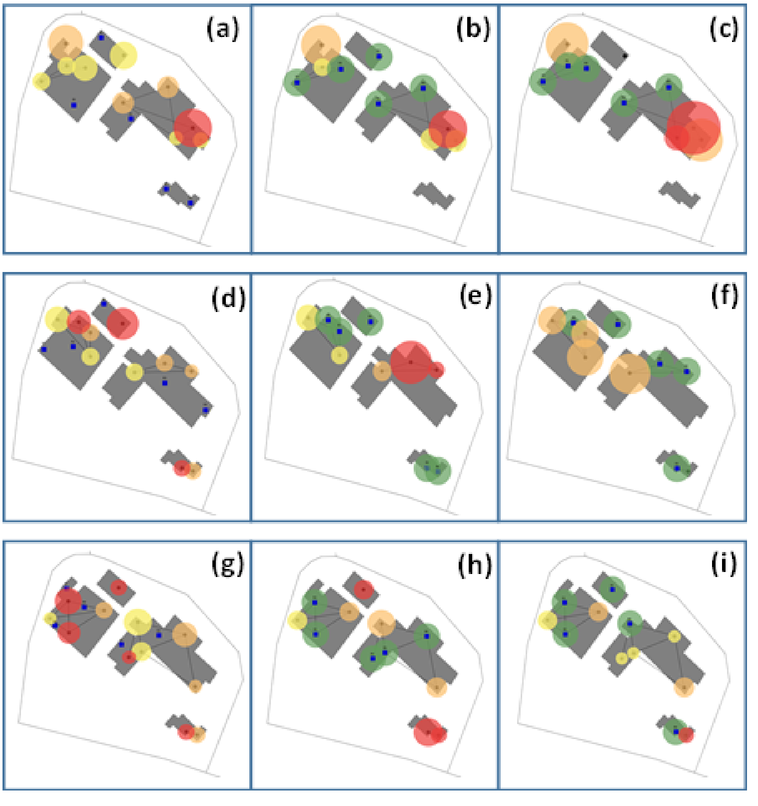

Figure 8. Simulation results

5 CHALLENGES AND OPPORTUNITIES

Our current implementation is providing satisfactory results. However, several challenges should be addressed in order to extend this implementation. Some of these challenges could be summarized as follows:

Support of AR capabilities. Our prototype does not yet allow ARA agents to carry out AR elements during their promotions of defects. These elements are particularly important in order to visually reflect the course of the competition. They will also be used by the inspectors in order to prioritize their interventions. Our current works are focusing on creating appropriate AR elements and making them available for use by the ARA agents.

Integrating the DCSP approach. As highlighted in Section 3.4, the management of inspection interventions will be carried out by following the ADOPT algorithm. Our current prototype does not yet integrate the implementation of this algorithm. We will address this issue from a MAS perspective. Consultations with some field experts will be necessary in order to endow agents with appropriate decision-making approaches to solve defects in buildings/construction sites.

Testing the prototype. Our work must be tested in a real-world scenario with field experts. This step is crucial in order to validate the simulation results.

Furthermore, we argue that several opportunities could be offered by our solution once its implementation is achieved. Some of these opportunities could be summarized as follows:

New proactive approach to inspecting buildings and construction sites. Our solution is mainly aiming to create a platform where inspection and maintenance operations are autonomously discovered by building facilities. These facilities will follow a proactive approach to attract inspectors by running a competitive solution. Random as well as late inspection operations could, therefore, be reduced.

Dynamic visualization of defects. By using AR elements, the ARA agents will dynamically change the visualization of the ongoing situation in the building/construction site. This visualization will reflect the impact of current/foreseen defects. Therefore, our solution would propose an attractive real-time, dynamic deficiency dashboard for inspectors to better plan their actions.

Optimizing inspection operations via big data analytics. A thorough investigation of data collected from/about the buildings/construction sites as well as inspections would reduce operation costs. Indeed, by using big data analytics mechanisms and machine learning tools, we can predict which facilities would need inspection as well as when this inspection would be needed. The inspection resources could, therefore, be assigned to defects on-time. The impact of these defect could also be reduced.

6 CONCLUSION

We addressed in this paper the issue of inspecting buildings and construction sites. We proposed an approach where the elements of a given building become proactive in the identification of defects and the attraction of inspection resources. More specifically, we proposed a new framework for self-inspection that relies on the concept of awareness wheel as well as on multi-agent systems for the assessment and the promotion of problems. Our approach is following a social approach whereby software agents compete to ultimately implement inspection tasks based on the severity of defects as well as their impact on the building resources. The agents are expected to use Augmented Reality (AR) objects during their promotions of ongoing defects as well as during their competition for the inspection resources.

Our current prototype is showing promising results in terms of the intelligent core of our solution. Nevertheless, it still needs to be extended with AR capabilities as well as with the appropriate mechanisms to manage the inspection resources. In addition, the algorithm for distributed constraint satisfaction problem needs to be integrated into the prototype. These issues are going to be addressed in our future works.

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