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Construction work cost and duration analysis with the use of agent-based modelling and simulation

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Abstract: Assuming a systemic approach, a construction project can be treated as a complex system composed of many different interlinked elements such as construction works, human agents, equipment, materials and the knowledge needed to perform the said work. The system’s structure can be divided into many mutually connected precision levels. This multilevel decomposition of the system facilitates a bottom-up approach in assessing the performance of a planned project, while starting the analysis at its lowest aggregation levels. The basic level distinguishes three typical units and their attributes: persons, knowledge and construction resources. Unit attributes and their dynamic interactions under changing environmental conditions affect the properties and performance of a given construction work and, as a consequence, the properties and performance of the project. The objective of this article is to analyse the attributes and micro-behaviours of units through bottom-up project assessment, allowing the estimation of its parameters such as completion time and cost. We utilised multiagent modelling that allows for performing micro-simulations in complex systems with adaptive components. The analysis was backed by a case study of road renovation work performed under specific conditions on the grounds of a listed heritage site.

Keywords: system of systems, meta-network, multiagent system, planning a construction project

1 Introduction

Construction projects are complex processes performed within dynamic environments. Recording and analysing this complexity require system-based thinking wherein construction projects are conceptualised as a set of elements (construction works, persons, equipment, materials and knowledge) that remain in specific relationships. In a system-based approach, the complexity of a construction project is first described as its detail complexity, which is time-independent and arises from the system’s structure (the type and number of its elements and the amount of connections between them). Apart from detail complexity, a project is also characterised by dynamic complexity, which evolves over time and is the effect of the system’s operational behaviours, whose cause-and-effect character can be non-linear or even unpredictable [1,2]. One specific property of complex systems (and construction projects as well) is the fact that changes in some elements can cause unforeseen changes in others, while feedback between these elements contributes to the system’s evolution over time [3]. The system’s behaviour and its interaction with the environment lead to emergent properties, such as susceptibility to threats, its adaptive capacity to changing conditions and, as a consequence, the system’s resilience [4]. We can find many system performance assessment tools in the literature that are used on projects similar to construction projects (expressed via, for instance, their completion time and cost), but most of them are based on a top-down approach [5]. This approach does not allow us to detect autonomous micro-behaviours of elements within the system – their interdependent, non-linear and dynamic relationships that change over time – and, as a result, the project’s performance [3,6]. Recently, a concept of an integrated approach to bottom-up construction project performance assessment has appeared – based on systems of systems (SoS) [7]. The system’s abstraction at the basic level and its multilevel aggregation form the...
framework for the effective assessment of construction project performance assessment. One of the tools used to study the micro-behaviours of a system’s elements and their dynamic interactions, which lead to assessing its performance, is agent-based modelling and simulation (ABMS). During the construction of a multiagent model, one identifies active heterogeneous agents with preset attributes. Afterwards, they are placed in a specific environment, defining mutual relations and the rules of their behaviour. Via simulation, dynamic, repeating and often competitive agent interactions and their individual behaviours and adaptation to changing environmental conditions define the behaviour and evolution of the entire system [8,9]. We can find few examples of ABM used to simulate user micro-behaviours during construction work in the literature. We reviewed these concepts and isolated their key limitations. First, we found that these agent micro-behaviour analyses were confined only to a single type of construction work. Second, the number of agents who cooperated and made decisions during this work was very limited. Third, these analyses did not account for the effects of agents learning and forgetting information, nor did they account for impacts caused by adverse events (atmospheric conditions, equipment failures, archaeological discoveries, etc.) which can also affect project efficiency. The objective of our article is to enhance ABM usage potential via the elimination of these limitations, which can allow for more precise modelling and bottom-up analysis of construction projects as systems, which they undoubtedly are.

The first part of the article will describe the approach of the SoS and provide an overview of the general assumptions of ABM micro-simulation. The argument will be backed by an example of assessing the performance of construction work carried out during the renovation of the structural layers of road surfaces present on the grounds of a listed heritage site.

2 SoS

In the traditional approach to assessing construction projects, their performance analysis is typically reactive and disintegrated. The top-down character of this analysis ends at the level of relations between construction projects at most [5]. In this approach to planning construction projects, there is a general belief that a centrally controlled performance of the project should be concordant with its plan and the interactions of entities and construction resources will not have any significant impact on its evolution [10]. This top-down approach does not allow us to explore the dynamic micro-behaviours of the system’s various elements (e.g. people and other resources) at lower abstraction levels (e.g. at the level of a single construction work) – behaviours that directly affect the project’s outcome [11]. In recent years, we have been able to observe the development of a new concept of project management named PM 2.0, whose objective is to provide new tools and methods for effectively assessing the performance of complex projects. As a part of this concept, Zhu and Mostafavi (2014) [7] noted the fact that construction projects demonstrate the properties of SoS and should be conceptualised and analysed as such. The dynamic of these complex systems and the interdependence between them lead to a situation in which changes in one subsystem result in unexpected changes in the remaining subsystems and the feedback between them causes these projects to evolve over time. We can also find several characteristics of SoS in the literature. Scholars like Maier (1998) [12] or Lewis et al. (2008) [13] stressed the operational independence of each subsystem, their decision-making autonomy, spatial distribution, dynamism and their evolutionary character. Pryke et al. [14] also noted the fact that, apart from technical, co-dependent relations within construction projects, social relationships were likewise significant. These relationships arise from interpersonal interactions, including the exchange of information, which considerably highlight the dynamic of complex systems. Emergent properties (e.g. susceptibility to threats, the capacity to adapt to changing conditions and resilience) are an important characteristic of SoS. These properties were defined by Johanson (2006) [15] and are the result of the dynamic behaviours of subsystems and their mutual interdependence, constituting a trait of the entire system.

Figure 1 presents the conceptual structure of the SoS concept, which can be used to develop tools and techniques of assessment of complex construction projects.

The structure of relationships between elements (organisations, tasks and resources) of the sample SoS that can be used to describe a construction project requires selecting proper analysis methods. This selection depends on the chosen system aggregation level. To analyse an SoS at the project level, we can use the so-called system dynamics method. At the process level, discrete event simulation was found to be effective. One of the tools used to perform bottom-up assessments of complex construction projects is the ABMS approach. ABMS allows us to analyse micro-behaviours and micro-interactions between system elements (e.g. people, information and other resources) allowing us to understand their dynamic and, via multilevel aggregation, impacting the properties and performance of the entire project.
For the purposes of an effective bottom-up performance assessment within an SoS, we must consider two types of abstraction of the construction project under analysis [16,18]:

- **Basic-level abstraction** is associated with perceiving construction projects through the prism of separate elements like people, information and resources, whose attributes and interactions with the external and internal environment affect the dynamic properties and ultimately the performance of these projects.
- **Multi-level aggregation** determines effectiveness at higher levels on performance at lower levels.

In light of the above, the assessment of the performance of construction projects conceptualised as SoS requires the adoption of a bottom-up approach for their analysis.

### 3 Theoretical basis for ABMS

The concept of ABMS is a relatively new approach to assessing the behaviour of complex systems [19]. In ref. [20], the authors defined ABMS as a set of agents and an environment that enables their interaction. The primary objective of ABMS is to track the interactions of heterogeneous agents in their artificial environment and understand the processes that display global patterns [21]. In the literature, we can find many definitions of agents and their environment, e.g.:

Macal and North (2009) [20] defined the agent as an active component capable of independent decisions. Epstein and Axtell (1996) [21] defined agents as people within agent-based modules, who possess their own traits and behaviour rules. Meanwhile, Nwana (1996) [22] defined agents within three basic behavioural attribute categories, with each agent possessing at least two (Figure 2).

Autonomy means that the heterogeneous agents possess individual internal states and goals and strive to achieve them. Cooperation with other agents towards achieving specific goals is critical. For agents to be able to cooperate, they must possess the social capacity for interaction. Learning is a key trait of every intelligent being and is based on gaining empirical knowledge and using it to modify one’s behaviour to better adapt to the environment.

The second critical element of ABMS is the environment. Weyns et al. (2007) [23] defined the environment as

![Figure 1: Conceptual representation of an SoS used for analysing construction project efficiency. Source: original work based on refs [16,17].](image-url)
the conditions that surround agents and allow them to function, providing them with the ability to interact and use available resources. Bandini et al. (2009) [24] define the fundamental aspects of the model that are defined by the environment:

- comprehensive modelling of the physical and social placement of the system;
- enabling agents to gather information about their environment and performing actions based on this information;
- creating conditions for agents to interact with non-agent system elements;
- Defining and modelling dynamic changes that occur in non-agent system elements;
- Enforcing adherence to the rules defined in the system.

Every heterogeneous agent individually assesses their situation and makes autonomous decisions based on a specific set of rules [25]. However, the capacity of an individual agent to act is limited by their knowledge, the availability of resources, computation capacity and the perspective of the objective. If the analysed system is particularly complex in terms of structure and dynamics, which is distinct for construction projects, one proven way to address this is to create conditions for the cooperation of specific and modular components (agents) that specialise in a given field. The synergetic effect obtained this way will allow the system to behave effectively in solving problems affecting the achievement of the intended goal [26].

In the construction sector, multiagent models have thus far been used in: managing delivery chains [27,28], analysing procurement procedure strategies [29], analysing construction personnel behaviours [30,31], assessing construction site safety [32–34] and analysing mechanised excavation work [35,36].

The latest application of a multiagent approach concerned an SoS-based bottom-up analysis used to assess the performance (duration and cost) of a project which was applied to a case study of tunnelling utilising the New Austrian Tunnelling Method [16]. The article explored the attributes of agents and other system elements, analysed various project variant and assessed their performance. The objective of this article is to further develop this multiagent approach following the SoS concept via introducing a greater project complexity in terms of analysed construction work, introducing a greater number of agents that act while cooperating and accounting for the effects of construction-task-performing agents learning and forgetting, in addition to including the impact of risk factors (weather conditions, equipment failures, archaeological studies, etc.) on the project.

4 Agent-based approach to analyse the performance of a sample project

4.1 Agent-based model assumptions and structure

The example of road surface renovation work under analysis is based on an analogy to the project of the restoration of the outer courtyard and its access roads located at the Royal Castle on Wawel Hill in Krakow, Poland, which was carried out in 2012. The renovation work is associated with replacing the surface of the existing square located in an area that is a listed heritage site. The assumed square surface is 10,000 m². The specificity and character of the renovation work is as follows: the work begins on the first work plot, with a given surface, where workers, applying appropriate equipment, dismantle the existing surface (Figure 3a), the profiling and strengthening/stabilisation of the subbase (Figure 3b).
and an assessment of the soil strength (Figure 3c). Initial studies performed during the design phase reported that the probability of encountering good soil strength was 0.1, average strength had a probability rate of 0.3 and poor strength had a probability rate of 0.6, as the area largely features soil of anthropogenic origin. Based on the soil strength studies, the designer selects the strengthening method (which varies in terms of cost and performance time) (Figure 3d) based on empirical data (Table 1) and a specific approach to risk (Table 2) [16]. Afterwards, the workers on the first plot apply the selected soil strengthening method and verify it. When the desired soil strength parameters are not detected, the site manager makes the decision to perform repairs. If the repairs do not produce expected results, the site manager informs the designer of the need to change the soil strengthening method to a better alternative, which is associated with the additional costs of replacing the previous soil strengthening solutions. The site manager (depending on how the situation develops and on their degree of risk aversion), upon finishing the

### Table 1: Probability of soil strengthening variant’s effectiveness depending on soil type (empirical data – an analogy to the project of the restoration of the outer courtyard and its access routes at the Royal Castle at Wawel Hill)

| Soil type                        | Variant 1                                                                 | Variant 2                                                                 | Variant 3                                                                 |
|----------------------------------|---------------------------------------------------------------------------|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| Improved subbase from            | Reinforcement with geogrid with a tensile strength of 150 kN/m +          | Cellular geogrid with a height of 2 m × 0.2 m filled with mechanically    |
| mechanically stabilised          | mechanically stabilised crushed aggregate 0/31.5 in two 0.2 m layers      | stabilised crushed aggregate 0/31.5                                      |
| crushed aggregate 0/31.5         |                                                                           |                                                                           |
| Good (secondary modulus above 70 MPa) | 0.5                                                                      | 1                                                                         | 1                                                                         |
| Average (secondary modulus above 35 MPa but below 70 MPa) | 0.25                                                                     | 0.75                                                                     | 1                                                                         |
| Poor (secondary modulus up to 35 MPa) | 0                                                                        | 0.25                                                                     | 1                                                                         |

*Post-stabilisation soil strength requirements (secondary modulus = 120 MPa) for KR3 per PN-S-02205:1998.*
proper soil strengthening task, makes the decision concerning the area size of the next plot (Table 3). After completing soil strengthening tasks for the entire square, the workers begin to construct the base course from lean concrete (Figure 3e) and then proceed to lay the wearing course from previously recovered stone materials (Figure 3f). The information about the workload and the cost of performing each task, including those associated with technological variants of soil strengthening, were estimated as average values that occur under normal construction conditions.

We used the UML standard to describe agent interrelationships and actions. The specificity of construction projects assumes a discrete time (date) when an agent makes a decision or takes an action. This decision/action is based on a ruleset that depends on experience collected during previous projects, risk approach and the current situation at the construction site. In addition, agents do not have their own goals and are not equipped with the function of assessing their own actions. Despite agents being autonomous, they are heavily restricted by the specificity of construction. Therefore, we found presenting the model in a UML standard justified (as opposed to using an agent-based standard).

Figures 4 and 5 present two types of diagrams: a class diagram and a sequence diagram of the agent-based model as per the OMG UML standard [37, 38].

The model also accounts for the ability of the workers who perform the tasks on successive work plots to learn and forget skills. Learning and forgetting is the object of many types of work in construction. The learning and forgetting mechanism was applied in the study of the construction of underwater caissons [39], applying roof insulation [40] or finishing work on a multistorey residential building [41].

The proposed approach utilised the learning and forgetting mechanism introduced by Nembhard and Uzumeri (2000) [42], which can be used to determine worker effectiveness.

In order to do so, one needs to employ the following formulas:

\[
Y_x = k \left( \frac{xR^a_x + p}{xR^a_x + p + r} \right),
\]

\[
R_x = \frac{\sum_{i}^{x}(t_i - t_0)}{x(t_f - t_0)},
\]

where \( k \) is the asymptotic value limit of \( y \), \( x \) is the amount of accumulated work done, \( p \) is the previous experience in the same unit as \( x \), \( r \) is the amount of work required to achieve a performance value of \( \frac{1}{2} \), \( a \) is the forgetting coefficient and \( R_x \) is the relation of time that has passed since the first unit \( t_0 \) to the time that has passed since the last unit produced \( x \).

The parameters were set so that worker performance could vary between 70 and 130%: \( k = 260, r = 225 \) and \( a = 0.3 \). The value of parameter \( p \) depends on the worker experience based on which the following was assumed: \( p = 260 \) (70% performance), averagely qualified workers \( p = 780 \) (100% performance) and highly qualified workers \( p = 26,000 \) (130% performance).

A performance of 130% meant that the average cost and duration of a task was lowered by 30%. Thereby,

\[
y_{\text{Laf}} = 2 - \frac{y_x}{260}, \quad k_{\text{Laf}} = y_{\text{Laf}} \cdot k \quad \text{and} \quad t_{\text{Laf}} = y_{\text{Laf}} \cdot t\text{,}
\]

where \( y_{\text{Laf}} \) and \( t_{\text{Laf}} \) denote the time and duration of a task after accounting for the curve of learning and forgetting, while \( y_{\text{Laf}} \) denotes the performance coefficient. Workers learn

| Table 2: Three approaches towards risk were analysed for the designer who performs the selection of the soil strengthening variant based on the empirical data depending on soil strength analysis, original work based on ref. [36] |
|---|
| Soil type | Designer choice |
| | Risk approach (conservative/normal/risk-taker) |
| | Variant 1 | Variant 2 | Variant 3 |
| Poor | 0/0/0.1 | 0/0/0.3 | 1/1/0.6 |
| Average | 0/0/0.4 | 0.6/1/0.6 | 0.4/0/0 |
| Good | 0.6/1/1 | 0.3/0/0 | 0.1/0/0 |

| Table 3: Three types of risk approach displayed by the site manager depending on the successful strengthening of the soil; the site manager’s decision can result in: increasing, decreasing or maintaining the previous area of the subsequent work plot |
|---|
| Risk approach | Successfully reaching the required soil strength after stabilisation |
| | The first time (after repairs) | The second time (after repairs) | The stabilisation had to be dismantled and a more effective variant had to be used |
| Conservative | Increase | Increase | Decrease |
| Normal | Increase | Maintain | Decrease |
| Risk-taker | Increase | Increase | Decrease |
and forget every task performed according to a given technology independently.

It should also be noted that the project is exposed to various random adverse effects that can negatively affect its performance. Based on the specificity of the project, we limited ourselves to accounting for four typical risk factors in the model. Based on an analogy to the previously mentioned project at Wawel Castle, we assumed that these factors materialised with an estimated probability of 0.5 in the case of archaeological discoveries, 0.3 in the case of the occurrence of adverse atmospheric conditions, 0.05 in the case of construction equipment failure and 0.1 in the case of construction material delivery delays. It was also assumed that the materialisation of any of these risk factors under specific project conditions will result in extending its duration by 1 working day each time. In the case of archaeological discoveries, this assumption can be justified if it occurs in the form of an intervention (under mandatory conservation guidelines, taking the form of securing any relics without further study).

The presented model was implemented in the Python programming language using the Mesa library, which is used to model agent-based systems. We can share the program if needed. The model was subjected to internal validation, extreme condition testing and the tracking technique, which confirmed its validity [16].

4.2 Agent-based model analysis

A block diagram of the simulation algorithm featured in our method has been presented in Figure 6. For the method to function correctly, the following starting data must be available:

- the various risk approaches displayed by the designer (expressed in percentages of reinforcement choices depending on base type),
- the various risk approaches displayed by the site manager (expressed in the manner of site size choice by the site manager, depending on success or failure in applying reinforcement at the previous site),
- various types of crew experience (expressed via learning curve parameters – described in detail further in the article),
- soil reinforcement methods and their parameters, expressed as a method effectiveness percentage depending on soil category.

The user should also determine $n$, the number of simulations. For each parameter set (for the designer,
site manager and workers), $n$ simulations shall be performed. Every simulation follows the sequence diagram presented in Figure 5. Simulation time and cost shall be aggregated for the given agent parameters. The output shall be the mean construction time and cost for each agent parameter set.

### 4.3 Results

Three hundred simulations for each of the 27 different parameter sets (three types of designer risk aversion, three types of site manager risk aversion and three types of worker experience) were performed for the project, which amounted to a total of 8,100 simulations. Tables 4–7 present the results that were obtained. Each table shows the result divided by designer and site manager risk aversions and worker experience (divided by semicolons). Table 4 presents the average cost of completing the project (in thousands of euros). Table 5 presents the standard deviation of cost (in thousands of euros). Table 6 presents the average project completion time and Table 7 presents the standard deviation for project completion time.

Figures 7 and 8 present selected probability distributions and the distribution function for project completion cost and duration assuming the following agent attributes: designer with normal risk aversion, site manager with normal risk aversion and averagely qualified workers.
Figure 9 presents a selected distribution of the relationship between the project's completion time and cost, assuming the following agent attributes: a designer with a normal risk approach, a site manager with a normal risk approach, divided by the various worker experience ratings.

The results concerning the learning and forgetting of skills by workers who perform tasks on subsequent
work plots are presented in Figure 10, which also shows a sample performance coefficient \( Y_{x, \text{ref}} \) dependency over project time in reference to soil strengthening as per variant 3 by workers with little experience. The lower the value of \( Y_{x, \text{ref}} \), the lower the cost and completion time of the task. When the value of \( Y_{x, \text{ref}} \) decreases, this means that worker performance increases when they perform the soil strengthening task as per variant 3.

Table 8 presents the percentage share of the average cost of each work within the overall cost of the entire project, while Table 9 presents an analogous share in respect to project completion time.

Table 10 presents the average frequency of selecting a given soil strengthening variant by the designer in respect to their risk approach, and Table 11 presents the average frequency of selecting plot size depending on the site manager’s risk approach.
5 Discussion

Enhancing construction project modelling and analysis relative to refs [16,17], as performed through a bottom-up assessment of their effectiveness by accounting for a greater number of decision-making agents, the effects of learning and forgetting, as well as the impact of risk factors, allows for a better assessment of a given situation. In addition, focusing on a greater number of construction work types included in a given sequence allows for effective integration and a transition from multiagent simulation to a discrete event simulation, which is often used in project analysis at the process level.

The graph (Figure 9) demonstrates that under these assumptions, the project would be completed quickly and cheaply by experienced workers, analogously, using

Figure 7: Probability distribution and distribution function for project completion time.

Figure 8: Probability distribution and distribution function for project completion cost.
workers with little experience would result in the project having the longest completion time and the highest cost. In cases where the soil strengthening variant is changed (by the designer’s decision) or there is a pause in the work (as the result of adverse risk factors), workers’ effectiveness and skills associated with variant 3 deteriorate – which is the result of the forgetting mechanism. Successive project days have been marked on the horizontal axis. The effect of learning and forgetting on workers in respect to soil strengthening variant 3 began after 104 days after the project started, as it was the first time when the designer decided to apply this solution (Figure 10). Based on Tables 8 and 9, it can be observed that work associated with soil strengthening forms the greatest share of both project cost and time, which confirms that the detailed analysis of this type of work is critical in assessing project performance. In one case (assuming high worker experience), the percentage share

![Figure 9: Cost–time dependency for a designer with a normal risk approach and a site manager with a normal risk approach, divided by worker experience rating.](image)

![Figure 10: Performance coefficient value $y_{x_{\text{dif}}}$ for workers with little experience in respect to soil strengthening variant 3.](image)
in terms of both time and cost was higher and pertained to laying the wearing course. Based on Table 10, it can be observed that a conservative designer is highly inclined to choose the third soil strengthening variant, which is the most expensive and the most time-consuming. A risk-taking designer is more prone to select the first variant, which is the cheapest, but its performance is not high. However, when analysing the results of average project completion time and costs, the risk taken by the designer paid off in this case. The site manager behaved as expected, i.e. the greater his risk aversion, the more often they chose a small-sized plot (Table 11). As risk aversion lowered, they were observed to choose larger plots more often. The difference in the frequency of selecting each plot size was not substantial. In the future, the authors should investigate possible revisions to the rules of the site manager’s behaviour when selecting plot size, so that the impact of their decision on project cost and completion time would be greater.

It should be noted that the presented model has its limitations. First, the project completion time listed in the model takes on an absolute form (denoted as a working form) and does not account for pauses arising from the work schedule. The introduction of the schedule into the model, while accounting for the effect of the learning and forgetting mechanism, could significantly magnify the latter, which will be explored in further research. The second limitation is the small number of risk factors that we accounted for in the analysis. In future studies, the collection of these factors will be expanded based on project specificity. As we presented a calculation experiment based on a hypothetical case of a renovation of a

### Table 10: Average frequency of selecting each soil strengthening variant over the course of the project by designer risk approach

| Designer risk approach | Soil strengthening variants | Variant 1 | Variant 2 | Variant 3 |
|------------------------|----------------------------|-----------|-----------|-----------|
| Conservative           |                            | 0.96      | 3.38      | 11.57     |
| Normal                 |                            | 1.53      | 4.52      | 9.15      |
| Risk-taker             |                            | 3.33      | 4.33      | 4.29      |
| All                    |                            | 1.94      | 4.08      | 8.33      |

### Table 11: Average frequency of selecting each working plot size over the course of the project by designer risk aversion

| Site manager risk approach | 200 m² plot | 400 m² plot | 600 m² plot |
|---------------------------|-------------|-------------|-------------|
| Conservative              | 1.26        | 2.20        | 10.66       |
| Normal                    | 0.31        | 0.79        | 11.93       |
| Risk-taker                | 0.28        | 0.48        | 12.14       |
| All                       | 0.62        | 1.16        | 11.58       |
historical road surface, similar studies on actual construction project cases should be performed in the future, as it could allow for an effective verification of our findings.

6 Conclusion

Assuming a system-based approach, construction projects can be treated as complex systems composed of many different interlinked elements like construction works, people, equipment, materials and knowledge. The concept of SoS that has recently been introduced into the literature [7] allows for multilevel modelling of the dependency structure of such projects and the multilevel aggregation of their performance (e.g. in the context of the time and cost of their completion). The preferred bottom-up approach to the analysis of the aforementioned project performance starts with assessing the attributes and micro-behaviours of its individual elements defined at the so-called basic level of the aforementioned multilevel structure. For the purposes of performing such a bottom-up analysis, we focused on ABMS of construction projects, which has rarely been used until now and that allows one to account for the micro-behaviours of the aforementioned system elements and their dynamic interactions. As a consequence, this carries over to the assessment of the performance of the entire project. The objective of this article was to develop the agent-based approach in accordance with the concept of SoS [16]. For this purpose, we accounted for a greater complexity of the analysed project by: analysing not one, but several types of work, introducing a greater number of cooperating agents within tasks, accounting for the effects of learning and forgetting on agents who perform individual construction works and the impact of adverse events (weather conditions, equipment failure, archaeological discoveries, etc.) on the project. We based the model and its analysis on a sample project associated with carrying out renovation work in the road construction sector. One important aspect that needs to be investigated in the future is the problem of formulating reliable and precise assumptions for the model and input data for its analysis, which pertain to, among others, defining risk aversion for each agent and the rules for their possible behaviours, empirical data concerning the qualification and performance of production means or concerning risk factors and their materialisation probability. When developing ABMS and its application in the construction sector, one should also note the potential of machine learning, which would allow for more reliable modelling, understanding and optimisation of agent micro-behaviours (smart agents) for the purposes of maximising project performance.

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