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# Simulating the behavior of trade crews in construction using agents and building information modeling

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ABSTRACT

Simulation is particularly useful for testing different production control and information flow methods in construction, because field experiments suffer from difficulties with isolating cause and effect. Existing methods such as Discrete Event Simulation are limited in their ability to model the behavior of crews and of individuals who make decisions subject to their perceptions of uncertain conditions. Agent-Based Simulation may offer a better solution because agents can be applied with behavioral models. The aim of this work was to build an experimental tool capable of reflecting the emergent nature of production in construction. This required capturing trade crew behaviors through interviews and encapsulating the behavior in software agents. The system models trades' decision-making and situational awareness while using a Building Information Model to define the physical and the process environment for the simulation. The resulting simulation tool was validated by testing predictable scenarios, which resulted in similar patterns to those found in an actual construction site. It was then applied to explore the emergent outcomes of more complex scenarios.



## 1. Introduction

Research of production control systems in construction is limited by the capabilities of the available research methods. Among research methods used to date are work studies [1,2], action research [3–6] and simulation [7–9]. Both work-studies and action research are performed 'in situ' and thus can only study one control system in one project at a time. They cannot be used to compare or to evaluate the different outcomes that would be obtained if changes were made to the control paradigm or its parameters on a given project; projects cannot be repeated. Given the inherent variability and uncertainty of parameters that influence the outcomes of construction projects – such as material, labor, equipment and information flows [10, p.3, 11] – these methods also suffer from significant drawbacks in terms of isolating cause and effect. It is very difficult to differentiate the effects of any given experimental intervention from the influences of parameters that the researchers cannot control, such as design changes, material shortages, weather effects, unstable subcontractor resource allocations, etc. The Hawthorne effect [12] and the learning curve effect add to the problems of measuring the impact of interventions on site.

For these and other reasons (such as the limitations of research budgets), computer simulations have become the method of choice for comparative research of production systems in construction. Discrete Event Simulation (DES) applications, implemented in languages such as STROBOSCOPE and CYCLONE, have provided general and special purpose frameworks for simulating construction operations and construction management processes [13,14]. Examples abound: Tommelein et al. [9] used DES to illustrate the effect of variable production rates on productivity and cycle times in the 'Parade of Trades' simulation; Brodetskaia et al. [8] used DES to test the impact of production control policies on throughput (TH),on quantities of work in progress (WIP) and cycle time (CT) in high-rise apartment construction; and Bashford et al. [15] demonstrated the relationship between system loading and cycle times for the case of custom house building.

However, due to the nature of DES, these simulations did not model the decision-making behavior of the trade crews nor the effect of movement within a geometrically realistic working environment. Their use has been limited to predetermined events of specific construction processes and general purpose frameworks for developing simulations of construction operations [14,16]. Such research typically uses a "top-down" approach to modeling and understanding the impacts of production control on labor productivity. In a top-down approach, the sequence of events is governed by the availability of crew, materials, information and other preconditions at each time step as events are evaluated, but the subjective behavior of trade crews and their human leaders who function within a certain perception of the construction project reality, is not modeled and does not affect the outcomes [17].

Like many economic systems, building construction projects can be considered to be emergent production processes whose outcomes are the results of the actions of the individual economic agents who

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participate in them [18]. When conditions change unpredictably, such as when a crew arrives at a location and finds that some of the pre-requisite conditions for its work have not matured, agents must make go or no-go decisions at the workface [19]. Thus, given the shortcomings of DES in its ability to represent such systems, and motivated by the understanding that the production control system of construction works leads to dynamic complex behavior that affects work efficiency and productivity, the EPIC (Emergent Production in Construction) approach is proposed. EPIC uses Agent-Base Simulation (ABS) together with Building Information Models (BIM), offering a new method for researching production systems in construction. The goal of this research was to test the feasibility of the EPIC approach by building a suitable simulation capable of evaluating different production control methods in construction.

The following section reviews the literature and builds the argument in favor of using ABS and BIM for simulating construction processes. The subsequent sections present a pilot for using ABS for construction processes, a field study aiming to identify and formulate economic behavior of the trading crew agents, and a review of the simulation prototype. The last sections present validation tests and results of further, more complex scenarios that were used to validate the simulation. Finally, the discussion, conclusions and future work are presented.

## 2. Background

### 2.1. Agent-based vs. Discrete Event Simulation in construction management

In general, when applying a discrete-event simulation to model building construction, the construction crews are represented as "machines" along a "production line", while the work locations are represented as "products" which move along the production line from one construction crew to another. For example, Brodetskaia et al. [8] developed a simulation that examines the impact of production control on productivity and workflow. In this simulation, the products (apartments) were split into sub-products (rooms) which are then processed by the machines (trade crews). Significantly, the "machines" in the simulation that represent the trade crews lack any decision-making mechanism. Their behavior was pre-programmed using probability data that was not context-driven. Tang et al. [20] pointed out that most simulations in construction research model uncertainty within decisions and operations, but do not model the interactions between them, in part due to the narrow selection of research topics and in part due to the limitations of DES tools.

The roots of DES are in operations research and production [21], whereas building construction is performed by independent contractors who are economic agents. Economic agents are decision-making actors who function in contexts that include aspects of economic behavior. Accordingly, each agent makes decisions by solving a well or ill-defined optimization problem [17]. DES models are limited in modeling complex, realistic building construction scenarios and they cannot directly model agents. DES tools do not enable integration of the constructed project as a building information model to simulate the physical environment, and thus dynamic changes to physical aspects such as walking distances and obstacles need to be artificially preprogrammed. Another drawback of DES is that they do not allow experimentation with trade crew behavior that manifests as independent decision-making under uncertainty. Moreover, different contract situational parameters for each participant and the subsequent behavior cannot be modeled.

DES approaches are strongly dependent on pre-construction estimations of production rates and other inputs that can change under varying circumstances during the construction process. Some of these circumstances emerge as interactions among resources. Considering working crews on site as unique entities with varying production rather than an averaged resource, further adds to the adaptive complexity of the simulation [17].

Tang et al.'s Interactive Construction Decision Making Aid (ICDMA) simulation proposed to overcome some of these limitations by introducing a human decision-maker at various points in a simulation in order to apply different strategies to correct the process of a simulated construction project. However, it does not endow trade crews with the ability to think and act independently, but maintains centralized control in the hands of the decision-maker.

Recent thinking suggests that production in construction may be better understood as emergent, dependent on the individual motivations and behaviors of individual crews and workers. According to Laufer [22] construction operations exhibit substantial dynamism and uncertainty, which makes preplanned control systems inadequate. Bertelsen and Koskela [23] charted and analyzed the different management frameworks that address and cope with the inherent complexity and unpredictability within project production systems. Sacks et al. [18] formulated the subcontractor resource allocation behavior, using economic game theoretic approaches. In their work, they emphasized the need to adopt decentralized methods of control in managing projects.

According to Howell [24], lean construction methods tend to shift the focus toward decentralized control, while onsite construction activities at a micro-level seem to show more "organic" control, compared to the much subscribed central and coordinated control. Subsequently, in his work he suggested that the happenings within the construction discipline could be better explained based on the agent-based concept.

Agent-Based Simulation (ABS) is a methodology in which a simulation experiment is constructed around a set of autonomous "agents" that interact with each other and with their underlying environment to mimic the real-world scenario that they imitate [18]. ABS tends to closely describe how systems work in their natural form and it has been used in a variety of fields including social sciences, architecture, biology, ecology, economics, political science and marketing and sales [25, 26]. The agents in ABS sense and stochastically respond to conditions in their surrounding environment, mimicking complex large-scale system behavior. Each agent individually assesses its situation and makes decisions based on a set of rules. Based on their interactions, the agents can make autonomous decisions [26–28]. The ability to study emergent large-scale outcomes by modeling interactions among individual actors is based on the assumption that the system has distributed control rather than central control. This assumption is essential to the applicability of ABS to construction [25].

Siebers et al. [29, p.4.] lists nine features of a domain that make it a good candidate for ABS application. Production in construction has six of these features: individuals that have dynamic relationships, create social networks, cooperate, collude, have geo-spatial aspects to their behaviors, and are engaged in strategic behavior while anticipating other individuals' reactions when making their decisions.

For all of the above reasons, ABS is suitable for simulation of trade crews' workflow on construction sites and of production control, and was selected for implementation of the EPIC system.

### 2.2. Applications of ABS in construction engineering and management

Previous research efforts using ABS in Construction Engineering and Management illustrate that an ABS can mimic the construction environment effectively. Taghados et al. [30] showed how agents (for resource allocation, weather, production units and visualization) could be combined in 'federated' models to simulate different construction project scenarios by using a standardized High Level Architecture.

Sawhney et al. [25] discussed the perception of control and the understanding of construction projects by simulating "what-if" scenarios, and planning for contingencies by performing initial experimentation using Agent-Based Modeling and Simulation (ABMS) either in isolation or in combination with traditional simulation methodologies. Using agents to compose a complex system, alternative setups were applied to evaluate the impact of different production management strategies on the progress of production trade crews and to identify management policies most suited to minimizing cycle time and WIP.

One of the most relevant and advanced models, albeit with some limitations, was built by Watkins et al. [17]. According to Watkins et al. [17], there is some evidence that on-site construction activities exhibit decentralized behavior best described using models which are bottom-up, able to reflect the interactions among individual actors in the construction project. In their research, they used agent-based modeling methods to simulate space congestion on a construction site. Their aim was to explore the impacts of individual interactions on productivity and labor flow, under the assumption that space is a shared resource on a construction site and congestion lowers labor efficiency. The significance of this research lies in the opportunity to minimize congestion due to space conflicts by investigating different starting locations for each individual crew. In their paper, Watkins et al. recommend that future research should extend these simulations in terms of variable productivity of workers and complex task relationships.

The model and simulation presented by Watkins et al. [17] have several limitations. The model assumed that the individual worker agents are independent of each other, whereas this might not be true for all construction trades. Moreover, the graphical environment representation is highly simplified and abstract, limited to a two-dimensional planar grid, as can be seen in Fig. 1.

Tah [31] presents an exploration of different supply chain networks for construction using the "ZEUS agent building toolkit". Tah [31] identifies the potential benefits of the agent-based approach, and according to his conclusions, the emerging new techniques of ABS should be brought together. However, the developed model was not supplemented with case studies of the represented procurement methods, typical product structures, and their relevant supply chains. The example is mentioned as "illustrative only, and it is not conclusive in any sense". Kim and Kim's ABS model [32] of construction equipment traffic flow is another example of a construction application of ABS that does not model the professionals involved nor the complex behavior of agents as actors.

The examples above show that ABS methods have been used for pilot research in construction management. However, there are some important limitations of the work to date: (a) they use highly simplified virtual environments to represent construction sites. The use of highly simplified virtual environments represented as a planar grid could not

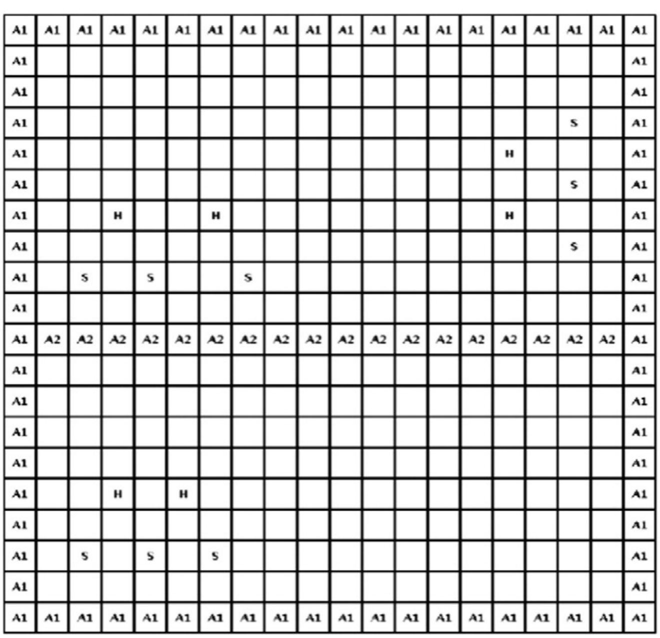

**Fig. 1.** Planar grid representing agent environment. Each agent occupies one square of a $20 \times 20$ grid and interacts with the neighboring agents based on a set of simple rules [17].

support decision making according to complex environmental cues; (b) they were not calibrated to real systems and did not correlate with observed behavior.

Thus, it appears worthwhile to explore and to develop a simulation for studying and improving production control in construction processes that accounts for individuals' decision-making. In order to overcome the limitations of existing research models, simulations must be situated in realistic virtual environments. This may be done by designing the environment using a Building Information Model that describes both the process and the product. Moreover, unlike previous attempts, ABS of construction operations should faithfully model emergent outcomes given any set of constraints applied to the agents. This could be achieved by capturing a sufficiently wide range of trade crew behaviors based directly on data from the field and establishing the model based on the procedural knowledge acquired through field interviews and observations.

## 3. Objective and methodology

The main objective was to develop an agent-based simulation model for studying production control policies in construction processes. The tool was required to account for individuals' decision-making processes, subject to a) different initial conditions of payment, material supply regimes, and behavioral characteristics, and b) their acquisition of knowledge as the project progresses. The underlying motivation is to facilitate research of production systems in construction using a bottom-up approach that considers how the motivations and policies of individual crews and subcontractors develop as they self-organize subject to the conditions and limitations of the project and the contract.

The simulation was required to exhibit the interdependence of individual workers and crews as they interact with each other and share resources. The goal was to build a robust and valid model by capturing a sufficiently wide range of trade crew behaviors based directly on data from the field so that the simulation could faithfully model emergent outcomes given any set of constraints applied to the agents. Unlike the few existing research models, the simulation aimed to reflect a realistic virtual environment modeled using BIM, where the model stores not only geometry but also production process information, allowing experimentation with acquisition of information from the environment. The use of BIM also allows future experimental setups that can incorporate real buildings. Finally, the use of gaming technology allows future experimental setups that can incorporate human subjects as avatars.

The research adopted a Design Science methodology [33]. It began with definition of the technological capabilities of existing simulation methods and the requirements for the new approach (EPIC). An initial pilot simulation was developed to test the use of ABS to simulate construction processes. The next step was to realize an artifact – the EPIC simulation. Knowledge of construction work processes and behavior parameters was acquired through field interviews and observations of site superintendents and trade crew leaders and expressed as rules and utility functions to be used in the simulation. The artifact was validated by simulating relatively predictable scenarios, and finally, it was used to simulate unpredictable, complex and comparable scenarios as a test of its feasibility. The goal was not to imitate real scenarios in real construction projects, but to isolate cause and effect in each scenario, in order identify the correlation between the different initial conditions and the resulting outcomes.

## 4. Pilot: Agent-Based Simulation of the LEAPCON™ game

A pilot test was conducted by compiling an Agent-Based simulation of the LEAPCON™ Lean Apartment construction game [34] using the STARLOGO TNG tool for multi-agent simulations [35]. The goal was to test the basic feasibility of ABS for modeling a production system in a

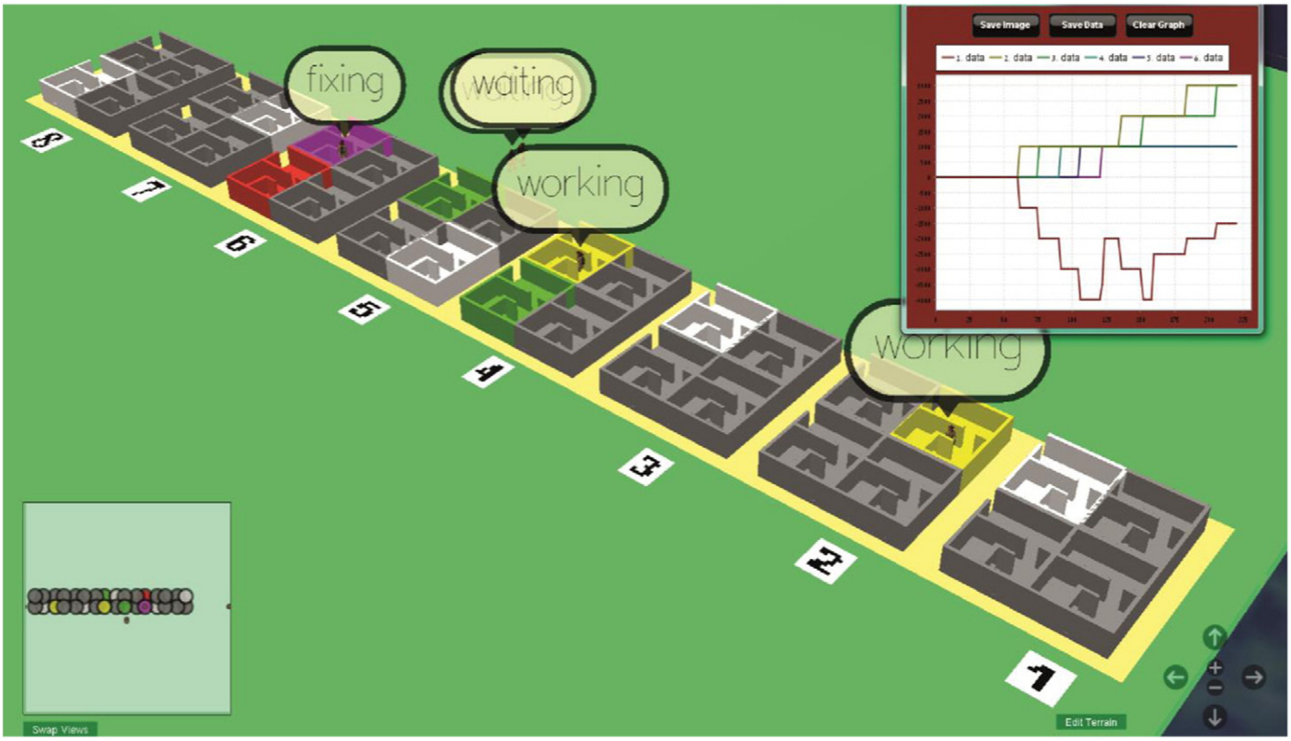


**Fig. 2.** The environment simulated in the LEAPCON™ Agent-Based Simulation with a cash-flow chart generated in real-time. The environment has four apartments on each of eight floors.

construction setting that incorporated independent decision making by the production agents.

The LEAPCON™ management game demonstrates the potential impact of production control policy on apartment construction subject to customization. The game simulates construction of an eight-story building with four apartments on each floor. It was originally developed in order to test the impact of Lean management concepts, which were proposed in response to the significant waste identified in the conventional approach to scheduling and managing construction projects. It was subsequently found to be a useful educational tool for introducing project managers, site engineers, supervisors, senior management, and students at all levels to some of the basic concepts of lean construction: single-piece vs. batch flow, pull vs. push scheduling and control, and multi-skilling vs. task specialization [36].

The LEAPCON™ game is implemented as a live simulation. Participants are assigned the roles of project manager, a client change manager, a quality controller, a tower crane operator, and four specialty subcontractors. The overall task is to carry out the interior finishing works for all 32 apartments in as short a time as possible. Execution of the finishing works is simulated using assembly of small building models using LEGO® bricks. The finishing works are subjected to a dynamic flow of information, in which changes to designs of particular apartment are delivered during the construction activity. Each successfully delivered apartment earns the subcontractor $1500.

The limitations of the live simulation (such as the learning curve effect and the limited possible execution sample) led Sacks et al. [34] to implement a DES of the game. The simulation was implemented using STROBOSCOPE [13]. The DES reinforced the findings of the live simulation. The demonstrative clarity of the lean model simulation, both live and computerized, makes it a powerful tool for education and research. However, the DES modeling technique imposed some significant limitations. The simulation describes the flow of the apartments along the different trades' activities, which are fixed. Consequently, work methods cannot be changed nor assigned to different crews, the number of subcontractors could not be modified, and there is no way to model a situation where two subcontractors work on an apartment simultaneously.

### 4.1. Agent-Based Simulation (ABS) of the LEAPCON™ management game

The STARLOGO TNG tool provides visual block based scripting and a 3D visual context (Fig. 2). The simulation was calibrated using motivation and production rate data collected rigorously in field observations of LEAPCON players by Sacks et al. [34]. Agents were created for each of the independent specialty subcontractors, the client representative and the quality controller, and for the 32 apartments considered. Unlike the DES, the ABS allowed each agent's behavior to be modeled separately, and the number of subcontractor agents could be increased or decreased dynamically.

Moreover, the agents' decisions due to interactions with other agents and with environmental cues could be applied and modified. In the simulation, each of the subcontractors chooses whether to work, wait, or rework (fix), according to the maturity of the work packages. The status that resulted from their decisions was visualized using color-coding which can also be seen in Fig. 2.

### 4.2. Validation

The simulation results showed good correlation with existing observed field data and with the results of the existing DES for comparable situations). The results were compared using measures of Work In Progress (WIP), Cycle Time (CT), cash flow and operational efficiency. Table 1 shows the calculated measures for the simulated scenario of

**Table 1**
Comparison of the different results of the real game, the DES and the ABS.

| Measured parameter | | Live game | DES | ABS | | |
|---|---|---|---|---|---|---|
| | | | | 3 agents | 4 agents | 5 agents |
| Replications | | 11 | 1000 | 1000 | 1000 | 1000 |
| WIP (units) | Average | 2 | 5.2 | 2.7 | 2.3 | 3.7 |
| | σ | 1.1 | 0.9 | 0.6 | 2.4 | 1.3 |
| TH (units/min) | Average | 1.98 | 2.7 | 2.22 | 2.76 | 3.06 |
| | σ | 0.282 | 0.18 | 0.384 | 0.444 | 0.528 |
| Cash flow ($) | Average | 6316 | 5000 | 1519 | 7639 | 5189 |
| | σ | 1645 | 1535 | 2911 | 4191 | 3572 |

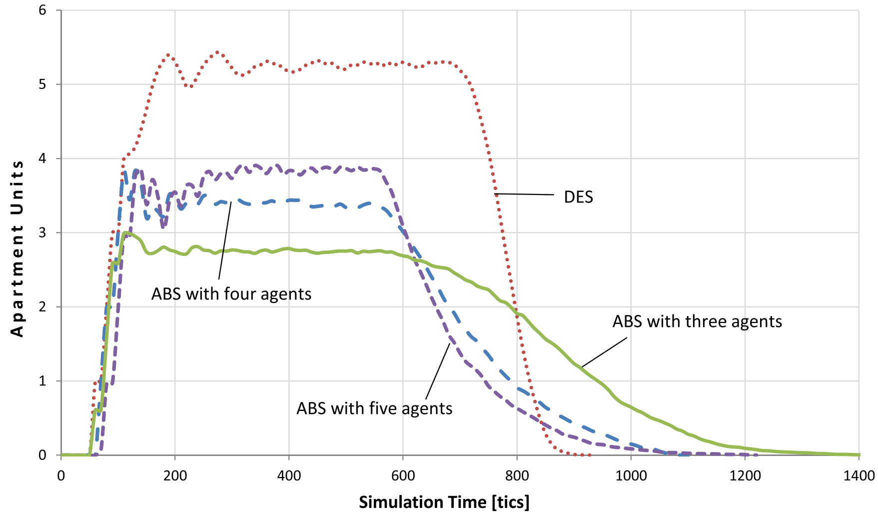


**Fig. 3.** WIP over time for the DES and the ABS.

the time limited game at its stopping point (11 min) for the case of the lean construction round of single piece flow with pull scheduling, work restructuring and multi skilling. The results of both the DES and the ABS are averaged over 1000 simulation runs, while the live game's results were taken from eleven runs with different teams. The DES was programmed with four subcontractors as for the live game, whereas the ABS provided the option to vary the number of subcontractors.

The results of the ABS with four agents show reasonable similarity with the results of the live game and the DES. Whereas the live game results could be measured only at the end of play, the DES and ABS results are recorded continuously throughout the simulation durations until all work is complete. Thus superior comparisons can be made using the continuous cash flow and WIP results, as shown in Figs. 3 and 4. As can be seen, the agent-based system has faithfully replicated the behavior of the LEAPCON™ game as simulated by the DES. Yet the ABS is capable of providing deeper insights into people's behavior due to the ability to program individual agent behaviors. As such, the pilot study confirmed that ABS is a valid approach for modeling a construction production system.

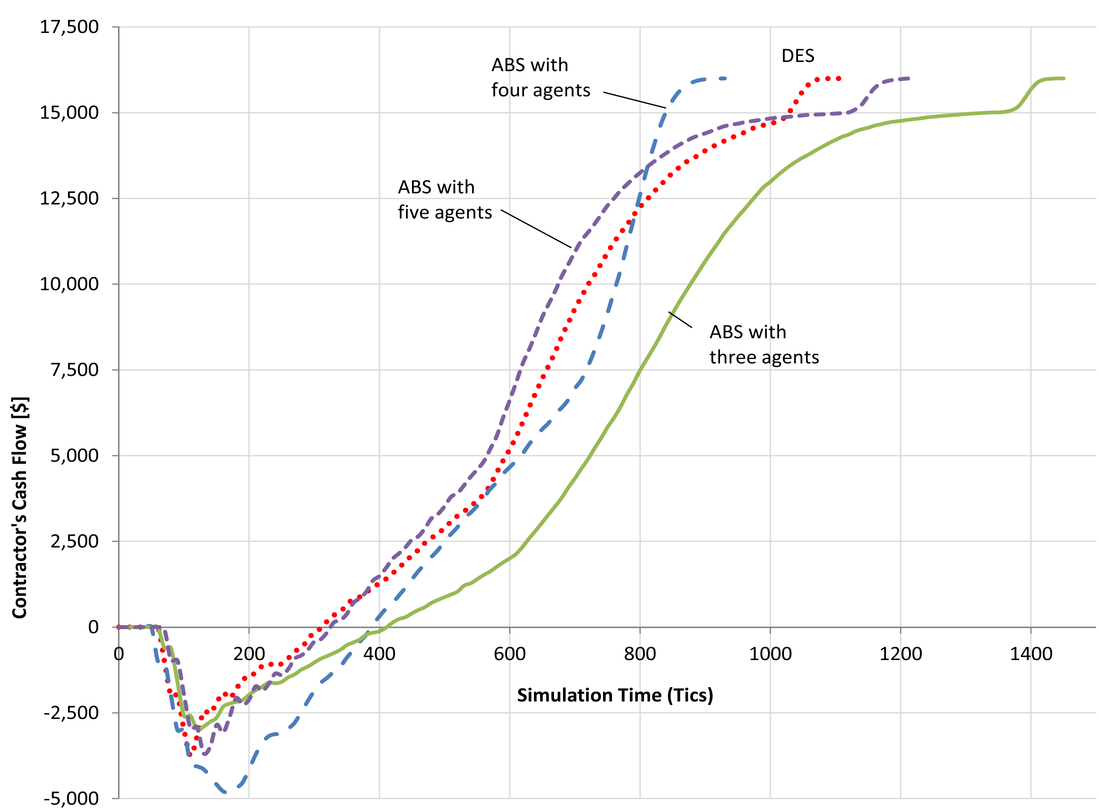


**Fig. 4.** Cash flow over time for the DES and the ABS.

**Table 2**
The different construction projects and the corresponding interviewees.

| Construction project | A | B | C | D |
|---|---|---|---|---|
| Type | Offices | Residential | Residential | Residential |
| Number of buildings in the project | 2 | 20 | 30 | 1 |
| Height of the buildings(in floors) | 11 | 8–21 | 16 | 22 |
| Number of apartments per floor | Open space | 4 | 4 | 3 |
| Number of buildings in which finishing works were being performed at the time of the interviews | 2 | 2 | 8 | 1 |
| Number of superintendents interviewed | 2 | – | 1 | 1 |
| Number of subcontractor managers interviewed | – | – | 1 | – |
| Number of trade crew leaders interviewed | 3 | 3 | 2 | – |

**Table 3**
Annotation (following Sacks and Harel [18]).

| Parameter | Definition |
|---|---|
| $I_i$ | Net income from work package *i* during any period *T* |
| $W_i$ | Actual work performed on work package *i* during any period *T* |
| $U_i$ | Unit price for the works at work package *i* |
| $C_{M_i}$ | Unit cost of the materials for the works at work package *i* |
| $k$ | Ratio of resources supplied to resources demanded |
| $W_{Di}$ | Work promised/demanded by general contractor for work package *i* in period *T* |
| $W_{Pi}$ | Quantity of work planned in work package *i* in period *T* |
| $W_{Ai}$ | Work actually made available in period *T* |
| $\frac{W_{Ai}}{W_{Di}}$ | Project manager's reliability |
| $C_{Si}$ | Cost/unit of time for one unit of resources allocated by the subcontractor to work package *i*, assumed constant over period *T* |
| $C_{Oi}$ | The management overhead cost for work package *i* over period *T* |
| $\bar{r}$ | Averaged work rate (units/time) for a single unit of resource *R* |
| $S_d$ | Resource units as demanded by the superintendent |
| $b$ | Averaged waste factor for materials that remain unused |
| $q$ | Boolean parameter that indicates whether the subcontractors brings his own materials to the construction site. |
| $T_{i,j}$ | Transfer time from work package *i* to work package *j* |
| $\mathrm{r}(\mathrm{S},\mathrm{k}_{\mathrm{m}_i}\mathrm{W}_i)$ | Work rate function (units/time) for a single unit of resource *R*, which varies over time |
| $k_{m_i}$ | Maturity factor of work package *i* |

## 5. Field study and behavior modeling

The purpose of the field study was to establish the factors that influence decision-makers behavior and considerations in determining the flow of work on site. The rules and utility functions described in the following section (Section 6) were based on knowledge of construction work processes and behavior parameters acquired through field interviews and observations of site superintendents and trade crew leaders acquired in the field study. This knowledge was used both to formulate the simulation's algorithms as well as to produce initial input for evaluating the simulations. This step was pursued in collaboration with a construction company.

Thirteen superintendents and trade crew leaders from four high-rise residential tower projects (for details, see Table 2) were interviewed with the aid of a guiding questionnaire. Each interview took from 40 to 60 min, and was recorded, transcribed, analyzed and decoded. In addition to questions exploring decision-making under various circumstances, the questionnaires included tables for production control parameter values (production rates, supply quantities, supply frequency, probabilities of events being delayed, labor assignments and crew sizes, incomes, expenses, working hours, etc.). Both the superintendents and the crew leaders were asked about the following subjects:

- Decision-making and motivations.
- Transition between team's different activities.
- Possible common scenarios on construction site.
- Interaction with other workers and information exchange.
- Materials supply parameters (supply amounts, schedule and certainty).
- Workers parameters (team size, salaries, condition).
- Reliability of the project manager and subcontractor's strategy.

Moreover, the superintendents were asked about their time distribution and movement patterns in the construction site.

One of the main objectives of the field survey was to identify the behavioral states[1] that trade crew leaders assume and the conditions under which they shift their crews from one state to another. The conditions for changing state depend on the information comprising utility factors for each state, combined with the certainty regarding the accuracy of the information, as described in detail below.

Seven basic assumptions describing behavior were formulated from analysis of the field study data. In the following sub-sections, the first paragraphs describe these behaviors, and the latter paragraphs describe the way in which the behavior was implemented in the EPIC simulation model.

[1] The term ‘state’ is used here rather than the term ‘activity’, which is more common in the literature on BTs. The reason is that in construction the term ‘activity’ refers to the different construction activities, e.g. flooring, plastering. Note that the use of the term states does not imply to the use of the Finite State Machine (FSM) method.

**Table 4**
Selection of behavior states as a function of expected utility and the certainty of the utility.

| | High utility | Low utility |
|---|---|---|
| High certainty | Work | Wait/abandon |
| Low certainty | Gather info | Gather info |

### 5.1. Economic utility function

#### 5.1.1. Observed behavior

One of the most obvious aspects of behavior observed was that when making decisions trade crew leaders consider their employer's perceived profitability or economic utility. The subcontractor's net utility from any action considered includes the expected payment for the specific work package, reduced by the expenses for labor, materials, and transition from the current action (the cost of moving the crew, which is a non-value adding activity). The decision to move a crew from one task to another will be positively influenced when the expected utility of the new task outweighs that of any other candidate task.

#### 5.1.2. Implementation

The economic utility model developed by Sacks & Harel [18] was adopted to describe the subcontractors' economic utility as perceived by the crew leader. The model, derived originally for an economic game theory model used to research the behavior of subcontractors in allocating resources to projects, was modified to add consideration of the task maturity, certainty, and transition costs. Eq. (1) is the original economic utility function [18]. It computes the subcontractor's utility in terms of income $I_i$ when an amount of work $W_i$ is made available (these and the other parameters are defined in Table 3).

$$U_{SUB} = I_i = W_i(U_i - C_{M_i}) - b(W_{Pi} - W_i)C_{M_i} - k\frac{W_{Pi}}{\overline{\mathrm{r}}}C_{S_i} - C_{O_i} \tag{1}$$

Eq. (1): Subcontractor's economic utility function [18].

Eq. (2) is the new utility function, expanded to consider the perceived degree of maturity of the work available and the cost of transferring a crew to a new task. It too assumes that the subcontractor is remunerated for each work package according to the quantity of work actually performed, as is the case for unit price contracts. The terms on the right-hand side of the equation represent income for work performed, where $k_{m_i}W_i$ is the current amount of mature work in work package $i$ (commonly an apartment in high-rise residential construction), $U_i$ is the unit price for the works, $k\frac{W_D}{W_P}\frac{C_{S_i}}{\mathrm{r}(\mathrm{S},\mathrm{k}_{\mathrm{m_i}}\mathrm{W_i})}$ is the cost of materials (actually consumed plus excess), $q_iC_{M_i}(1+b)(\frac{W_D}{W_P})$ is the resource costs and fixed overheads, and $C_{S_i}S*T_{i,j}$ is the cost embodied in transferring workers between work locations.

$$U_{SUB} = I_i = k_{m_i}W_i\left[U_i - k\frac{W_{D_i}}{W_{P_i}}\frac{C_{S_i}}{\mathrm{r}(\mathrm{S},\mathrm{k}_{\mathrm{m_i}}\mathrm{W_i})} - q_iC_{M_i}(1+b)\left(\frac{W_{D_i}}{W_{p_i}}\right)\right] - C_{S_i}S*T_{i,j} \tag{2}$$

Eq. (2): Economic utility function incorporated in the current simulation model.

### 5.2. Maturity factors

#### 5.2.1. Observed behavior

Two of the key factors that influence task selection decisions, as observed in the field study, are (a) the status of the set of minimal requirements for the execution of any given work package, and (b) the priority assigned to differentiate among those work packages that are considered to be mature (ready). According to the trade crew leaders, the maturity of a work package was observed to increase whenever clear design information and sufficient materials and equipment were available, the workspace was clear, and prerequisite work was complete.

#### 5.2.2. Implementation

This was implemented in the simulation by computing an overall task maturity factor ($Km_i$) as the multiplication of the percent confidence that each of three factors would be available or complete at the time a new task was due to start: materials, updated design information and pre-requisite work.

### 5.3. Perceived maturity

#### 5.3.1. Observed behavior

The interviewees reported that the actual maturity of the pending works and the scope and size of the work packages in real time was occasionally different from the superintendents' and/or the trade crew leaders' perceptions during resource allocation. In other words, there was a gap between actual maturity and perceived maturity. A possible outcome in such situations may be resource allocation to a work package with low maturity. This can have a detrimental effect on workflow and efficiency, and in some cases, general contractors are forced to compensate subcontractors.

#### 5.3.2. Implementation

Accordingly, the implemented simulation provides a separate ‘information matrix’ for each agent, so that each agent's perception of the state of maturity for any work package can be stored independently from the actual state of the work package. The cells of the matrix contain the work package status data for all work locations for all task types. The operator of the simulation (the researcher) can set different modes for updating the information matrix for each agent. For example, the agent may gather information when meeting another agent whose data has a higher degree of confidence, by visiting a location and observing the actual status of work, or from a simulated project IT system.

### *5.4. Working prior to receiving design information*

#### *5.4.1. Observed behavior*

As has been reported often in the literature (e.g. [37]), interviewees reported that crews were often sent to perform work where design information was still incomplete or missing, usually in an attempt to meet target milestones in preset construction plans, and that this commonly caused re-entrant flow and re-work. Whenever newer and changed design information is received, crews are required to return to presumed complete work locations in order to fix, add to, or demolish the work that was previously carried out.

#### *5.4.2. Implementation*

Accordingly, the simulated crew leader agents may perform work without plans (i.e. when the perception of information maturity is less than 100%). When new design information is received in course of the simulation, a percentage of rework is assessed and added to the economic utility of the relevant work packages if any part those packages had already been performed.

### *5.5. Leaving small work packages for later completion*

#### *5.5.1. Observed behavior*

Crew leaders tend to leave small or difficult work packages, or parts of work packages, for completion as late as possible. Similarly, crews often prefer to start a new task with a high rate of income (such as tiling the main areas of an apartment) rather than completing more delicate work with low income rates (such as the finishing touches). The same applies to returning to complete small amounts of work remaining from a previous work package or as rework as a result of design changes. In terms of economic utility, there are certain situations and conditions under which completion of work packages is not worthwhile.

#### *5.5.2. Implementation*

To simulate this possibility, the crew leader agents were programmed with a preference threshold. The threshold expresses the amount of difference in utility for which the crew leader will obey the construction plan or the superintendent's instructions in cases where their employer's expected utility from some given work package exceeds the utility of any of the planned work packages. The choice is made as follows, expressed in pseudo code:

```
FOR EACH work package available for execution for a given crew;
    COMPUTE expected utility;
    IF the work package is part of the superintendent’s construction plan,
    THEN expected utility = expected utility + preference threshold
  ENDIF
NEXT work package;
SELECT the work package with the highest expected utility for execution by the crew.
```

In this way, the trade crew leader will instruct the crew to disregard the plan and perform tasks out of planned sequence when it is sufficiently worthwhile for them, as observed in the field study.

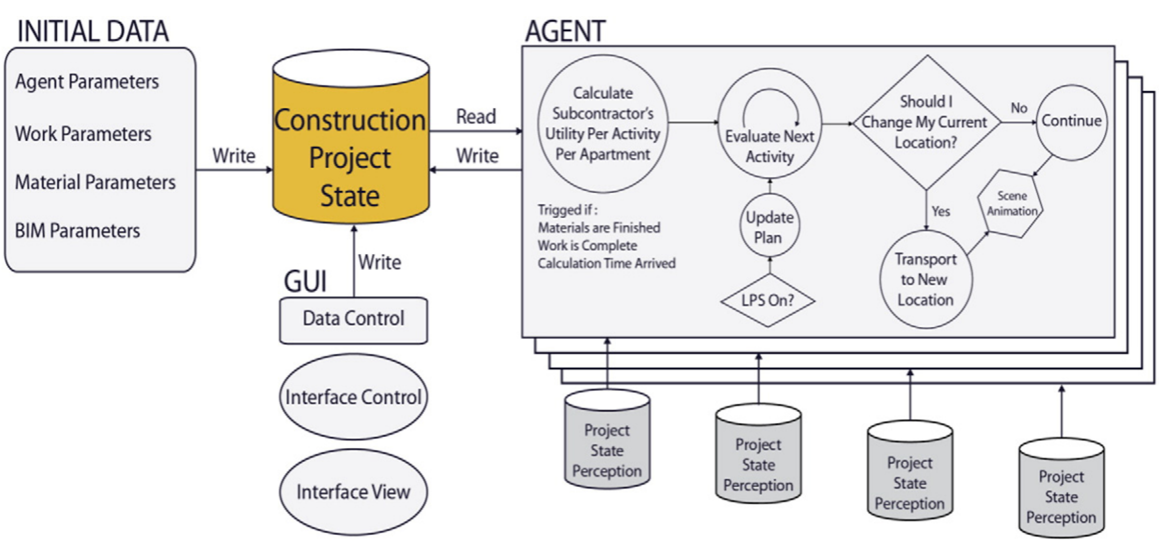


**Fig. 5.** The system architecture of the simulator showing the agent's decision-making mechanism.

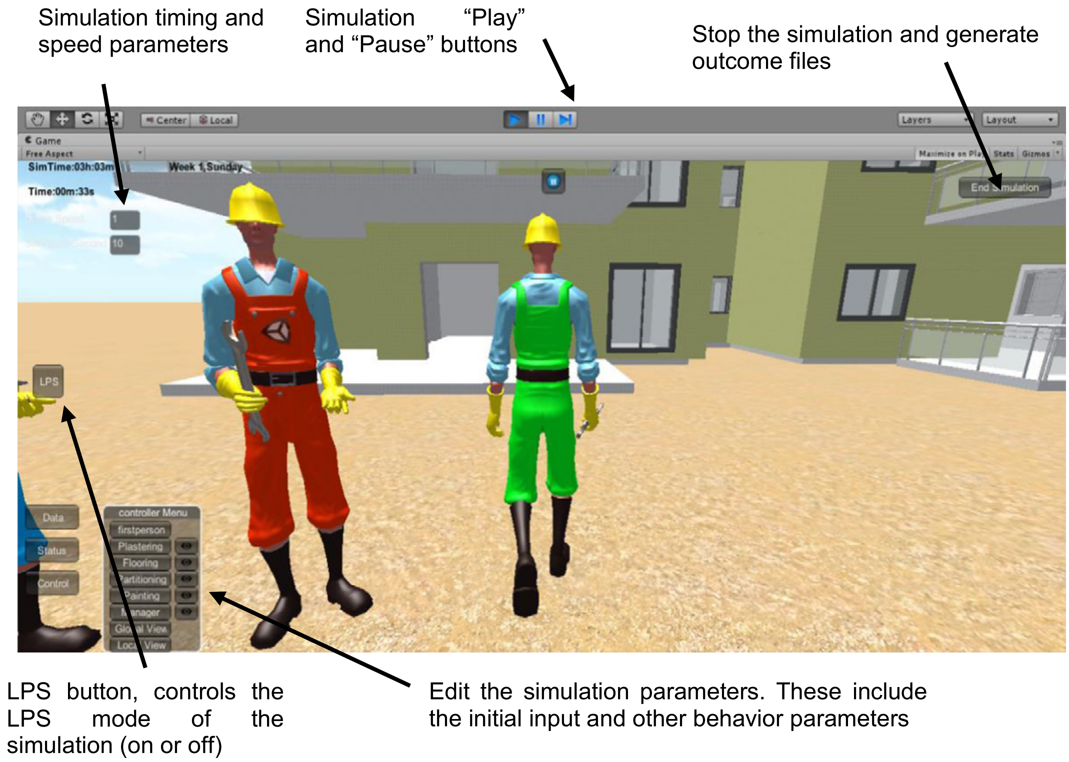


**Fig. 6.** Visualization of agents in the EPIC simulator prototype and Graphical User Interface (GUI) of the initial screen.

## *5.6. Influence of utility and certainty on changes between behavioral states*

### *5.6.1. Observed behavior*

The field study revealed four basic states of behavior for trade crews: working, waiting, gathering information, and abandoning the construction site. When a crew reaches a point in time at which its leader makes a conscious decision concerning their next action, selection of the next state is governed by the utility and the certainty of the available work packages. The outcome of the decision can be expressed as shown in Table 4. Where a work package is available with high utility and the perception of certainty of that utility is also high, the crew will be assigned to work

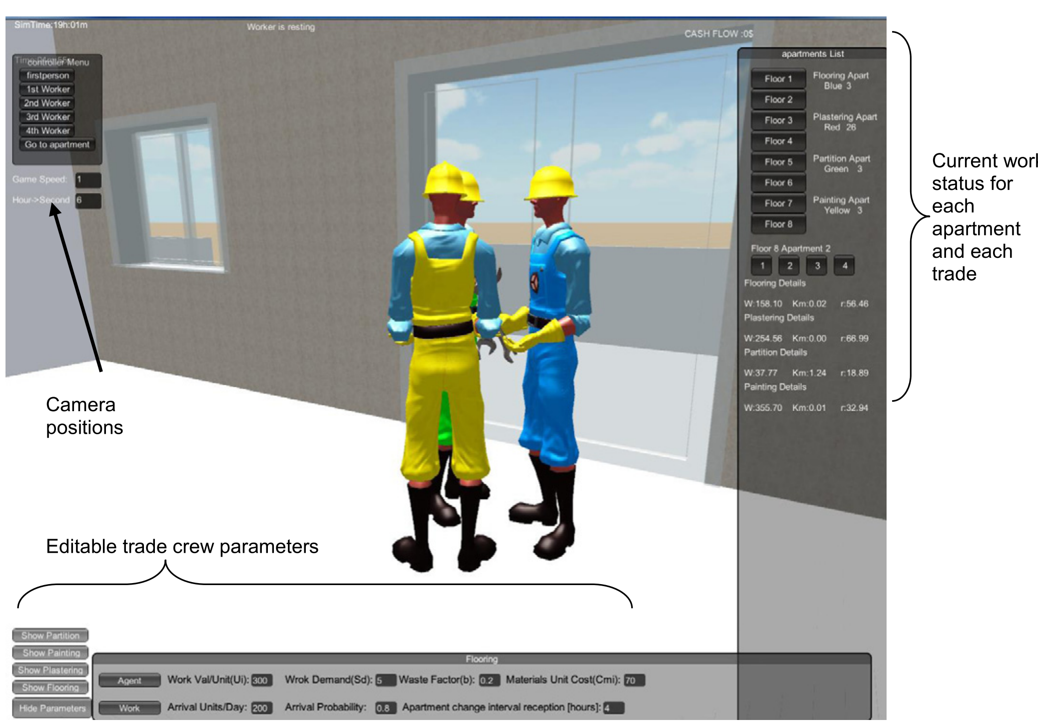


**Fig. 7.** Visualization of agents in the EPIC simulator prototype and the GUI during a simulation run.

on that work package. When all of the available work packages have low utility with high certainty, the crew will either wait on site (if the utility is expected to increase, such as in the case where materials are expected to arrive) or abandon the site and move to a different project. Alternatively, where certainty is low, the next action will likely be to wait and to gather more information before making a decision.

### 5.6.2. Implementation

This behavior was implemented using Behavior Trees (BT), an artificial intelligence technique for modeling decision making that is used in commercial games [38]. From the interviews with the crew leaders, the following BT routine was formulated to simulate the behavior of the trade crew leader agents. Each branch of the tree is performed in sequence:

a. Sensory system (sight of other objects and agents): When the agent physically meets the superintendent agent, project status information is copied from the superintendent's to the agent's information matrix. Similarly, the task status of locations that the agent visits is copied from the reality matrix to the agent's matrix, simulating the agent's observation of its surroundings.
b. Perform work in the chosen location: The agent will enter the working state if all the conditions are met: materials, labor and information are available and some amount of work remains to be completed. This state ends when the current work amount is completed, when a precondition fails (e.g. materials run out) or at the end of each working day.
c. Select where to work: When the working state ends, the agent will evaluation all available work packages to determine the best available. If the best work package has high certainty, the agent will move to that location and begin work.
d. Gather information regarding the maturity of the different work packages: If work selection fails and the certainty of the utility of all available work packages is low, then the agent will try to gather information by physically going to the working locations to collect information, by checking with the superintendent, or by collecting information from other agents. These are implemented using the sensory system - by copying actual status data to the agent's matrix.
e. Wait in the construction site: Where gathering information fails to yield a work package with high utility and high certainty, (i.e. certainty toward low utility is high for all available work packages), then the agent will wait. Waiting will continue until a preset time threshold is reached.
f. Abandon the construction site: Finally, the agent will choose to abandon the construction site if no new viable work has been identified within a preset time. Abandoning the site may also occur if a more profitable project becomes available to the subcontractor (although this has not been implemented as yet).

## 5.7. Superintendent behavior

### 5.7.1. Observed behavior

From the point of view of production control, the superintendent's role on site is to plan in the short term, to monitor the work status, and to communicate production plans and status to the other agents.

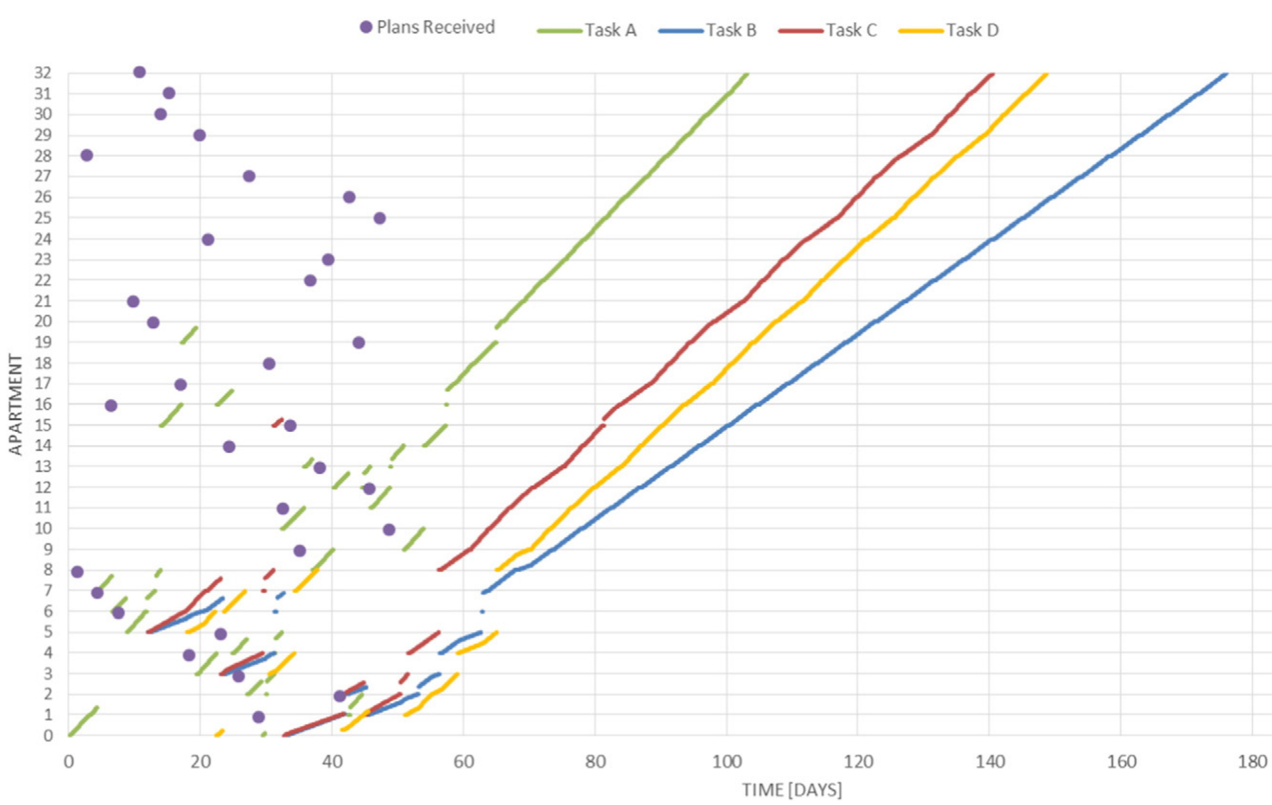


**Fig. 8.** Flowline chart of scenario #6. The dots represent the arrival of new design information.

**Table 5**
The different scenario features modeled by the simulation tool.

| Parameter | Values | Expected outcomes |
|---|---|---|
| The threshold amount of work units for which the agent chooses next apartment in plan over the highest utility apartment. | Zero to high | When the value is set below the common work package content, size, crew agents will tend to follow the construction plan sequence as communicated by the superintendent. When higher, crew agents will prefer their subcontractor's economic utility to the project utility; tasks with high perceived utility will be performed out of planned sequence, modeling local optimization. |
| Timing for evaluation of the next task to be performed. | Fixed time (at the start of each week/shift); periodically | If a fixed time is set, agents will not abandon work unless it is finished, the materials are finished, or the fixed time has passed. If a periodic time is set, agents may abandon a work location at any time if there is justification according to their perception of utility. |
| Stability of the materials supply (arrival probability per arrival date) | ≈0.5 to 1.0 | If set low, significant waiting will occur due to material shortages. An intermediate value will cause some waiting time due to materials shortages. If set to 1.0, materials will always be available and there will be no waiting time due to materials shortages. |
| Rate at which client design changes for locations are made and delivered | One per time period (typically one day to two weeks) | The slower the rate, the more significant will be the waiting time and rework due to lack of design information if the agent follows the work plan. |
| Work planning method | Traditional (LPS Off) or | Agents work according to plan and the re-work rate will be high if materials or information flows become unstable. |
| | Lean (LPS On) | The re-work rate will be lower, but this depends on the planning frequency. |
| Work planning frequency (when LPS is on) | Time period (weekly, daily) | If the time period is relatively short, agents will follow the plan which will correspond to the work packages' maturity levels and the re-work will be low. However, if the material deliveries are unstable and/or if the design information delivery cycle is faster than the planning period, rework will still occur. |
| Information communication mode | Full | The information regarding the actual maturity state is made available to the agents at all times, and they make decisions accordingly. |
| | Restricted | The agents collect information and may have only partial (or false) information to make decisions with. |

*5.7.2. Implementation*

The superintendent agent's behavior tree begins with his sense of vision, implemented as a proximity check to objects and agents and resulting in information updates). The next action is to walk through the building project, visiting all active work locations, observing the production status (materials, work accomplished, etc.) and communicating with other leader agents. In these events, status information is copied from the other agents' information matrices for any cell where the agent's certainty is greater than that of the superintendent, or information is copied from the reality matrix when a status is observed first hand.

## 6. EPIC simulator prototype implementation

Fig. 5 shows the system architecture of the developed simulator, including the decision-making mechanism. The initial data includes parameters regarding the materials, the agents' work behavior and priorities, and the BIM. The construction project state changes over time, according to the different conditions and the agents' decisions. The chosen tool, Unity 3D, provides a 3D real time rendering environment, allowing high quality visualization of the simulation progress [39].

System parameters can be modified throughout the simulation using the Graphical User Interface (GUI). The GUI enables editing of the initial production data and control of the visual interface (simulation speed, camera views) and reports simulation status (production measurements for agents and for work packages). The agents' progress through the building project over time in accordance with their decision-making mechanism, which is based upon their perceived project state.

At each appropriate event during the simulation, the agents evaluate the required amount of work in each location, its utility and its certainty, using the data in the BIM and in their individual information matrix (state perception). They then decide whether to change state according to their behavior tree, i.e. whether to continue existing work, start new work, gather information, or wait.

The BIM model was prepared in Revit and imported into Unity using a workflow developed by Dalton et al. [40]. The BIM contains information about the product (geometry, work quantities, etc.) and the simulation parameters. These include the initial input and other behavior parameters process (the 'actual status' information). The simulation tool prototype developed for validation of the EPIC approach

**Table 6**
Predictable production control scenarios.

| # | Description | Project duration (days) | Average trade crews' time distribution (%) | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Wait | Transport | Setup | Work with design information | Work without design information | Rework |
| 1 | Plan-driven agents and materials are supplied according to plan. | 161 | 0 | 3 | 3 | 90 | 3 | 1 |
| 2 | Plan-driven agents and new design information supplied at a high rate. | 165 | 4 | 5 | 3 | 82 | 5 | 1 |
| 3 | Plan-driven agents with unstable material supply. | 185 | 11 | 4 | 4 | 81 | 0 | 0 |
| 4 | Economic utility-driven agents. | 156 | 2 | 5 | 5 | 86 | 2 | 0 |
| 5 | Plan-driven agents and new design information supplied at an intermediate rate. | 200 | 1 | 5 | 3 | 80 | 7 | 4 |
| 6 | Plan-driven agents and new design information supplied at an intermediate rate, with weekly LPS. | 178 | 2 | 4 | 3 | 90 | 1 | 0 |
| 7 | Economic utility-driven agents and new design information supplied at an intermediate rate, with weekly LPS. | 169 | 7 | 7 | 5 | 81 | 0 | 0 |

**Table 7**
Complex production control scenarios.

| # | Description | Project duration (days) | Average trade crews' time distribution (%) | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Wait | Transport | Setup | Work with design information | Work without design information | Rework |
| 8 | Economic utility driven agents with unstable material supply | 232 | 29 | 4 | 5 | 62 | 0 | 0 |
| 9 | Agents with different motivations and low rate of new design information arrival | 218 | 16 | 5 | 4 | 46 | 20 | 9 |
| 10 | Agents with different motivations and low levels of new design information, with weekly LPS | 211 | 23 | 8 | 5 | 54 | 7 | 3 |
| 11 | Agents with different motivations and low levels of new design information, non-transparent project state | 224 | 12 | 5 | 2 | 50 | 24 | 7 |

incorporates four finishing trade crew leader agents and one agent to represent the superintendent.

Figs. 6 and 7 show the visualized mode of the simulation. The agents can be seen moving through the project and interacting with one another and with the BIM model. Fig. 6 shows the GUI of the simulation's initial screen, including the different controls. Fig. 7 shows the GUI of the simulation interface during a simulation run. The user can control the current camera position, review the current work status for any apartment, and edit the agents' behavioral parameters.

### 6.1. Modeling state perceptions – agent's information matrix

Each agent has its own matrix containing the information it 'knows' about the project state. The matrix contains three pairs of values for every work package in every location: the maturity of material delivery and the confidence level (certainty) of the material maturity; maturity and confidence level for design information; quantity of work remaining and its confidence level. All of the maturity and confidence levels range from 0 to 1. Each agent also stores the current construction plan, represented as a sequential list of locations in which tasks are to be completed.

As agents move through the building to pursue their work or to attend meetings, they meet other agents. When they meet, they exchange and update their information. The information transferred only describes the physical state of the work; they do not give each other directives or instructions. The meeting events occur when any two agents are physically present in the same space (a corridor or an apartment). The ability to test for this condition of physical proximity is a feature of the Unity 3D modeling software, which uses the BIM model geometry and Boolean solid operators to test for collisions with a threshold offset distance.

The communication is effected by copying data between pairs of corresponding cells in the agents' information matrices in the direction of increasing certainty. When a status is observed at first hand (by visiting

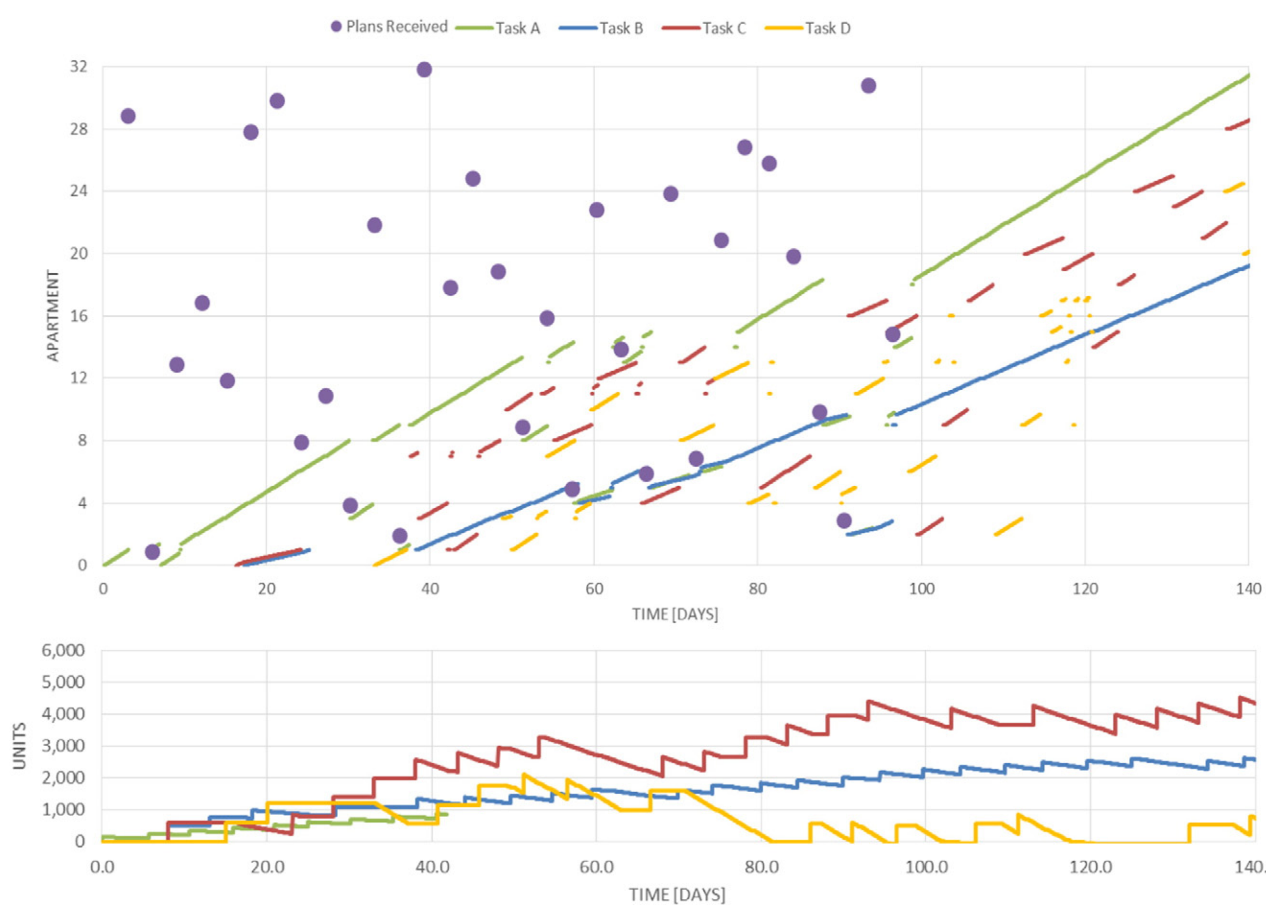


**Fig. 9.** Flowline chart of scenario #11 (above) and the stocks of materials (below).

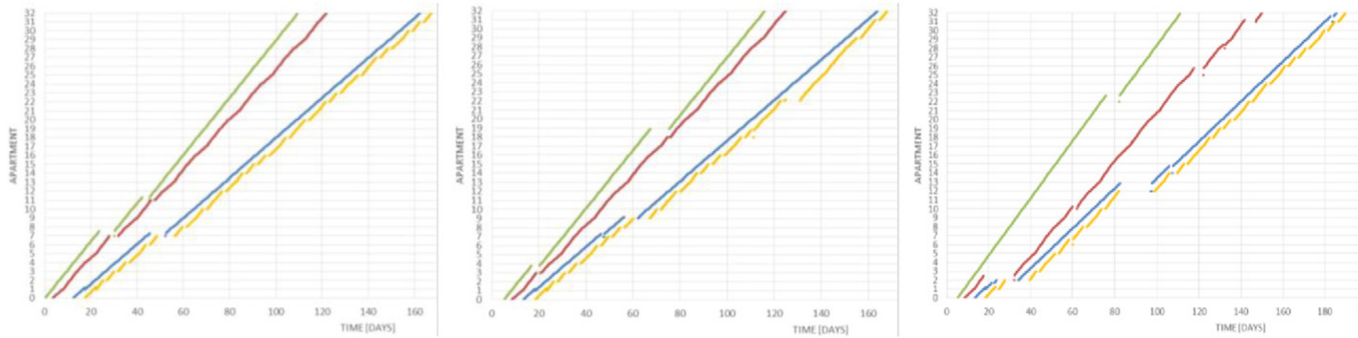


**Fig. 10.** Flow line trends for typical runs of scenario #3. The flowlines show the progress of the four trades (A–D). The axes are as defined in Fig. 8.

the location), the certainty values for that location's maturity factors are set to one, representing complete confidence. As time progresses, the confidence value decays, representing growing uncertainty.

Similarly, planning meetings, such as a Last Planner System (LPS) weekly work-planning meeting can be simulated. An updated construction plan can be set at any given time by sorting all the pending tasks in the superintendent's information matrix according to their maturity values and adding or removing tasks from the work plan according to their maturity in terms of previous work and their remaining time to completion. The meeting event itself is simulated by copying the updated construction plan from the superintendent to all of the other agents.

### 6.2. Simulation control parameters

The system architecture not only allows researchers to set up any given building with any number of work packages and trade crews, it also enables setting of different production control parameters that can be used collectively to establish the control protocols that need to be tested. Not only can different combinations of values be set, but they can also be changed during the simulation. For example, one might want to explore the effect of changing the frequency of planning meetings at some point during a project. The control parameters are detailed in Table 5.

## 7. Validation

The EPIC simulation model was tested and validated in three steps: a) simulation of seven standard scenarios with known conditions that result in predictable outcomes, b) testing four further scenarios, for which the results could not be predicted, and c). internal validation of statistical difference among the sets of results from multiple runs of each scenario.

The following sections present the different scenarios that were tested. Each scenario represents a particular set of conditions pertaining to production management on a construction site with 32 apartments on eight floors, with four trade crew agents and a superintendent agent. The scenarios vary in the following respects: trade crew agents' adherence or non-adherence to the construction plan; rate of delivery of design changes; stable or unstable material supply; and the use of weekly LPS meetings.

### 7.1. Predictable scenarios

Table 6 summarizes the seven predictable scenarios, providing details of the initial conditions set for each scenario and the average results for the time distribution of all four trade crew agents in each scenario.

In all of the first seven scenarios, the results of the simulation runs were as expected. Consider for example the fifth and sixth scenarios. In both cases the agents' behavior is ‘plan-driven’ (i.e. they adhere to plan even in situations where they have alternative work packages with greater economic utility) and the delivery rate for new design information is set to be intermediate. The only difference between them is that scenario #6 includes Last Planner System for production control (implemented in the simulation by updating the plan itself once a week – mature work is scheduled, and work that is not ready is postponed by evaluating the maturity of each work package). Accordingly, in scenario #6 the agents execute the work according to an updated work plan. As a result, the amount of rework and re-entrant to previous work locations is lower than in scenario #5, as predicted.

In each case, the expected phenomenon was observed, with regard to the impacts of agents' economic behavior (expressed as respect or disregard for the construction plan), the flow of design information,

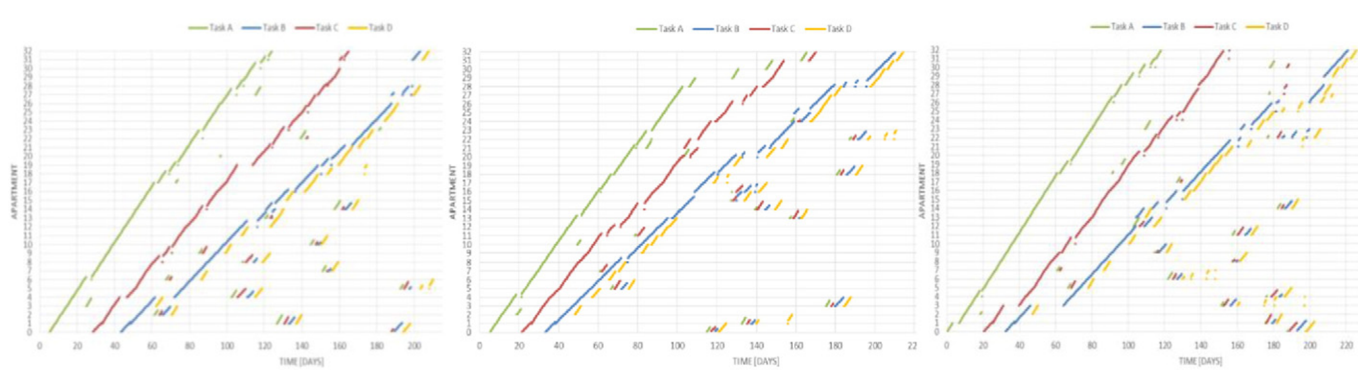


**Fig. 11.** Flow line trends for typical runs of scenario #9. The flowlines show the progress of the four trades (A–D). The axes are as defined in Fig. 8.

**Table 8**
Project duration in working days for eight runs of scenarios #3 and #9.

| Runs | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Average | Std. dev. |
|---|---|---|---|---|---|---|---|---|---|---|
| Scenario #3 | 188 | 215 | 189 | 223 | 200 | 167 | 178 | 167 | 190.0 | 19.4 |
| Scenario #9 | 225 | 214 | 230 | 223 | 228 | 217 | 225 | 237 | 224.9 | 6.8 |

the stability of material supplies and the planning regime. For example, where agents were set to follow the work plan, despite missing design information, the result was high amounts of rework. Scenarios that incorporated the LPS resulted in more effective production performance in terms of resource allocation and time distribution of the different activities where agents adhered to the periodically updated plan. At the same time, LPS did not have much effect on economic-utility driven agents that did not follow the plan. In general, agents that organize their workflow according to economic utility generated lower amounts of re-work and re-entrant flow, while having greater amounts of transition time from work package to work package due to their preference of work packages with high maturity even if those work packages were distant from the agents' current locations.

### 7.2. Complex scenarios

Table 7 summarizes the four complex scenarios. Three of them (#9–#11) introduce a new parameter: by default, the status of the work in the project is not known to the trade crews or the superintendent. They therefore make decisions at times based on incorrect perceptions of the state of the project. They do however update their status information when they visit a location or when they interact with any other agent whose information is more reliable than their own, whether in a planning meeting or in passing.

Scenario #11 is a good example of the variation that can be introduced into the starting conditions for a simulation. In this scenario, the trade crew agents do not know the actual maturity of the work packages unless they encounter the superintendent agent or physically observe the status in each apartment. Of the four trade crew agents, A and B are plan-driven, whereas agents C and D are economic utility driven.

Accordingly, the flowline in Fig. 9 exhibits less movement between apartments of agents A and B compared to agents C and D. Agents A and B have more rework added as new design information arrives. The main interesting result of scenario #11 is the interaction between the agents as they transfer information. A detailed examination of the results shows that trade crews C and D reallocate their resources, moving from location to location, as they gather work package status information during physical meetings with the superintendent agent, who walks up through the building at fixed intervals. The superintendent is better informed than the trade crew agents because he/she observes the work status while walking through the building.

Adjustment of the values of model parameters was also tested. For example, the model allows modification of the cost of transition from location to location within the site (this is a parameter of the subcontractor agent's economic utility function). Raising the transition fee gives rise to preference for work in close proximity, minimizing movement within the site. This was increased and decreased and observed to produce the expected results.

### 7.3. Internal validity of the model

In order to examine the statistical integrity of the simulation tool, eight scenarios were chosen for comparison and each was run multiple times. The simulation model used random seeds, and as can be seen in Fig. 10 and in Fig. 11, independent simulation runs with the same input data produced similar outputs in terms of the calculated outputs and the workflow patterns. On the other hand, the workflow patterns of the different scenarios are quite different to one another. As expected, the results obtained for each scenario clearly reflect the initial conditions and uniquely describe the project workflow that resulted, while at the same time each scenario exhibited variation in its specific results due to the emergent nature of the simulation. The data in Table 8, for example, show the distribution of project durations for eight runs each of scenarios #3 and #9.

Tables 9 and 10 show the trade crew agents' total time distribution through the different runs for each of these scenarios. Due to the simulated late delivery of design changes to the construction site in scenario #9, agents sometime work with incorrect design information. As a result, the total number of work hours differs from one simulation run to another, depending on the amount of accumulated rework. In contrast, in scenario #3 the total number of working hours remained constant throughout the different runs due to the absence of rework. Moreover, the results clearly show the waste of hours in scenario #9 in comparison with scenario #3, which manifests in hours spent

**Table 9**
Agents' total time distribution for eight runs of scenario #3 (h).

| Runs | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Average | Std. dev. |
|---|---|---|---|---|---|---|---|---|---|---|
| Waiting | 291 | 629 | 814 | 1055 | 977 | 352 | 586 | 362 | 633 | 274 |
| Transporting | 189 | 190 | 263 | 228 | 206 | 240 | 249 | 234 | 225 | 26 |
| Working | 3519 | 3519 | 3520 | 3520 | 3512 | 3519 | 3520 | 3520 | 3519 | 3 |
| Setup | 135 | 142 | 185 | 211 | 212 | 146 | 145 | 156 | 166 | 30 |
| Working without plans | 17 | – | – | 16 | – | 20 | 2 | – | 7 | 8 |
| Rework | – | – | – | – | – | – | – | – | – | – |
| Total labor hours | 4151 | 4480 | 4781 | 5030 | 4906 | 4276 | 4502 | 4272 | 4549 | 323 |

**Table 10**
Agents' total time distribution for eight runs of scenario #9 (h).

| Runs | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Average | Std. Dev. |
|---|---|---|---|---|---|---|---|---|---|---|
| Waiting | 671 | 1029 | 1231 | 887 | 1028 | 1088 | 983 | 1269 | 1023 | 190 |
| Transporting | 258 | 349 | 342 | 321 | 352 | 391 | 345 | 327 | 335 | 38 |
| Working | 3494 | 3465 | 3360 | 3233 | 3454 | 3526 | 3435 | 3505 | 3434 | 96 |
| Setup | 148 | 248 | 249 | 221 | 228 | 260 | 224 | 230 | 226 | 35 |
| Working without plans | 645 | 1361 | 2295 | 1437 | 1361 | 1520 | 1307 | 1389 | 1414 | 447 |
| Rework | 223 | 536 | 706 | 544 | 614 | 756 | 582 | 598 | 570 | 160 |
| Total labor hours | 5437 | 6987 | 8183 | 6643 | 7036 | 7540 | 6875 | 7318 | 7003 | 791 |

waiting, working with incorrect or missing design information and rework.

### 7.4. Summary

The predictable scenarios all produced results that conformed to expectations based on production control theory, particularly with regard to the relationship between variability and productivity. The complex scenarios produced results that were indeed unpredictable and varied, such as those for scenario #9 illustrated in Fig. 11, Tables 8 and 10, and for scenario #11 as shown in Fig. 9. Finally, the internal validation tests showed that sets of repeated simulations were sufficiently different to one another to allow association of the resulting patterns with the configuration of the input parameters for each case.

## 8. Discussion

EPIC simulates the flow of trade crews using a bottom-up approach and modeling technique that reflects behavioral aspects. Unlike the approach of most building construction simulations that use DES, the locations (apartments in this case) were not modeled as independent products that flow through the production system. Instead, the superintendent and the trade crew leaders were modeled as agents who operate within a physical building.

The distributed control based modeling approach exposes different modes of function on construction sites that other modeling approaches do not. In particular, distributed control based modeling exposes the fluidity of labor allocations and the emergent and unpredictable patterns of movement of crews on site that result from human decision making under uncertainty. The results are subject to the perceptions of decision-makers and not necessarily to the objective reality of the project's state, so that the availability or unavailability of information concerning current project status has strong effect.

Different social relationships and different production control methods have great impact on the workflow on construction site [41]. ABS enables testing the impacts of behaviors, relationships and control methods, whereas these aspects cannot be modeled naturally in DES systems. DES can simulate uncertainty, but only uncertainty of physical systems that can be implemented as probability distributions for a predetermined set of possible outcomes. Such simulations are not suitable for modeling people's intentions or motivations and the outcomes of their decisions.

An aspect of construction management that can be researched using ABS systems like EPIC is the limitations of command and control systems. The difficulty managers experience in enforcing plans cannot be illustrated by simulation systems that ignore the autonomy of crews by making the assumption that crews are simply obedient an axiom of the simulation, as is common practice using DES.

Among the current limitations of the EPIC tool is that it neglects potential improvement of production rates due to learning. In experiments with people, the learning curve effect is often an obstacle to interpretation of the results. Thus although a learning effect could be modeled in the simulation, its absence provides a constancy of working rates that allows reliable and valid comparison of the results obtained in different scenarios under different production control policies.

A second limitation is that the composition of work crews remains fixed throughout. Crews cannot be split to work simultaneously in different locations as they can in building construction. This too could be addressed by modeling individual workers as agents, but that requires a greater level of detail in modeling than has been applied in EPIC. Furthermore, the production rate data used as input are specific to the local industry context in which they were collected, and cannot be assumed accurate for any other locale. Finally, due to restrictions on research scope, the observed behavior of crews temporarily abandoning the construction site when all available work packages have low maturity and/or utility with high certainty was not implemented.

For these reasons, the EPIC model cannot be used to predict the outcomes of any given particular construction project, nor could the simulated project be validated against an actual project. Calibrating simulations to real project outcomes is very difficult given the wide variety of parameters that affect the outcomes of construction projects. Therefore, using simulation of this kind to predict specific outcomes accurately for a specific project is only possible for highly controlled or predictable situations. As researchers, we turn to simulation precisely because it allows us to compare outcomes across scenarios whose input variables and contexts are under our control, rather than comparing real projects subject to differing control strategies, in which we cannot reliably isolate the impact of the strategies we are studying. All of the experiments described above were conducted on an idealized project with a limited set of work packages that involved only four activity types.

## 9. Conclusion

The primary focus of the research was to implement a tool, based on the EPIC model, capable of simulating the behavior of trade crews in the interior and building systems works in construction of buildings. The tool is intended for exploration of the emergent patterns of production that result from the interactions of trade crews and their decisions. Unlike earlier ABS simulations in construction, the building is realistically represented using BIM. The EPIC model has a graphical user interface for experimentation with different "what-if" scenarios with emergent, unpredictable outcomes.

The behavioral model was based on prior knowledge and on interviews with 13 superintendents and trade crew leaders. The agent-based implementation applied the behaviors using behavior trees and an information matrix for each agent.

The system was validated through modeling of seven scenarios with predictable outcomes. The results of pairs of scenarios in which only one parameter of the production control system was changed were compared to check whether the change produced the expected results. The flow behavior on the project level corresponds to the main principles and to the crews' behaviors as observed in the case studies. The ability of the model to simulate emergent outcomes was tested using four further scenarios with a variety values for different parameters. Each one involved a range of behaviors. The results reflect the spectrum of the actual features and problems of construction work, such as interactions among trade crews, variability of resource supply chains and dependence on product and process information, causing waste, unstable work plans and re-entrant flow. The validation showed the simulation model to be applicable and useful for prognosis of the possible flow progress and production control scenarios in the context of production control research.

Future research using the EPIC tool may add value for the investigation and exploration of the relationship between a) process information flow in construction sites and b) task maturity perception by on site labor, and the resulting impact on workflow. Moreover, experiments that challenge the notion of command and control may be addressed; the effects of distributed control and self-organization compared to centralized control on site can be investigated.

To conclude, the contribution of this research lies in the development and testing of the ABS and demonstration of its utility for testing the potential of different modes of production control policies on a construction site. The results underline the importance of the individual trades' allocation of available production resources to the different activities. The importance of information flow policies and the effects of different motivations and preferences can be shown.

Lean construction and BIM research has revealed the potential of novel ways to organize production on site that exploit the benefits of pull flow and thorough yet flexible planning. The EPIC simulation platform is uniquely capable of testing the impact of these ideas because it models the complex, emergent patterns of production behavior that result from the interaction of the subcontracting teams and suppliers that perform construction work on and off site. In particular, the influence of each participants' knowledge, context and motivations on their day-to-day decisions about resource allocation and work sequence can be modeled, which represents a significant advantage over DES models.

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