

AN AGENT-BASED APPROACH FOR MODELING THE EFFECT OF LEARNING CURVE ON LABOR PRODUCTIVITY

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The labor-intensive nature of construction projects requires proper management and efficient utilization of labor resources. Improvement of labor productivity can enhance project performance and thereby lead to substantial time and cost savings. Several studies focused on identifying the effect of different factors on labor productivity, whereby the learning curve factor proved of paramount importance. Although previous research efforts developed models to represent the learning curve effect using traditional simulation approaches such as System Dynamics (SD) and Discrete Event Simulation (DES), none of these studies used Agent-Based Modeling (ABM) techniques. This study takes the initial steps and presents work targeted at analyzing the effect of learning on labor productivity using ABM. Based on ABM, a construction site can be modeled as an active environment in which agents interact with each other and their surroundings thereby creating an adaptive environment open for learning and improvement. The solution to the problem is described in details using a simulation model developed in AnyLogic 7 (Educational Version). The components of the proposed model have been created and preliminary results highlighted the potential of using the agent-based modeling paradigm to simulate the effect of learning on labor productivity in the construction industry.

Keywords: Construction, Management, Simulation, Modeling, Proficiency, ABM.

1 INTRODUCTION AND PERTINENT LITERATURE

Among many factors that impact construction labor productivity (Gunduz 2004, Hanna *et al.* 2005, Lee 2007, Singh 2010, Hinze 2011, Hafez *et al.* 2014), the learning curve has long been proven to be of paramount importance (Wright 1936). The learning curve theory states that, under a repetitive process, whenever the production quantity of a product doubles, the unit required for production drops by a certain percentage of the previous unit referred to as the learning rate (Jarkas 2010). Many models have been developed to illustrate this learning curve phenomenon and show, for example, the relationship between the cycle number and the time per cycle. These models include: (1) The Straight-Line Model (Wright's Log-Linear Model) (2) The Stanford "B" Model (3) The Exponential Model (4) The De Jong's Model; and (5) The Cubic Power Model (The S-Curve Model) (Thomas *et al.* 1990, Hijazi *et al.* 1992, Naresh and Jahren 1998, Chen *et al.* 2009, Taylor *et al.* 2009, Jarkas, 2010, Shehata and El-Gohary 2012, Pellegrino *et al.* 2012, Panas and Pantouvakis 2014). On the other hand, using

simulation for modeling the learning curve phenomenon has gained more and more attention over the last years. The most popular simulation techniques adopted were Discrete-Event Simulation (DES) (Hijazi *et al.* 1992, Lutz *et al.* 1994, Panas and Pantouvakis 2014) and System dynamics (SD) (Nasirzadeh and Nojedehi 2013). However, none of the previous studies used Agent-Based Modeling (ABM) to model the effect of learning on labor productivity. ABM can be defined as a computer simulation technique allowing the examination of how system patterns develop from the behaviors of individual agents. ABM creates virtual agents that have the ability to interact with each other and their environment and accordingly make autonomous decisions (Awwad *et al.* 2014). ABM was used to model the effect of congestion (Watkins *et al.* 2009, Marzouk and Ali 2013) and safety (Marzouk and Ali 2013) on labor productivity but the effect of learning development was not modeled. As a matter of fact, it was stated in prior ABM efforts that the limitation was the exclusion of the learning curve effect (Watkins *et al.* 2009). The objective of this paper is thereby to analyze the effect of learning on labor productivity by making use of the ABM paradigm and developing a model that incorporates different learning curve techniques into the simulation.

2 METHODOLOGY

2.1 Construction Process Description

In order to best illustrate the learning curve effect, a process of repetitive nature must be selected. Typically, high-rise buildings projects incorporate many tasks of this nature whereby the floors are almost identical and learning can be witnessed. For that reason, a case study of a multi-story building (50 stories) in the region of Beirut, Lebanon was adopted. The building consists mainly of a core wall, slabs and exterior walls. Only activities related to the structural construction, in particular erecting forms, installing steel rebars, and pouring concrete were modeled. Based on the RS Means Building Construction Cost Data book (RS Means Building Construction Cost Data 2014), the daily outputs of the aforementioned activities together with respective crews are shown in Table 1 for a slab and a wall. The corresponding volumes of concrete and steel needed are calculated and summarized in Table 2.

Table 1. Productivity rates and crews.

Task	Task Type	Daily Output	Crew	Number of Crews
Single Slab	Erect slab forms	470 S.F.[44 m ²]	1 Forman, 4 Carpenters	4
	Install steel rebars	2.9 Ton [2.6 Ton]	4 Rodmen	3
	Place concrete	160 C.Y. [122 m ³]	1 Forman, 5 Laborers	1
Single Wall	Install steel rebars	4 Ton [3.6]	4 Rodmen	3
	Erect Forms	280 S.F. [26 m ²]	1 Forman, 4 Carpenters	4
	Place concrete	95 C.Y. [73 m ³]	1 Forman, 5 Laborers	1

Table 2. Materials takeoff.

Task	Concrete (m ³)	Steel (T)	Area (m ²)
Single Wall	117	23	778
Single Slab	196	39	982

2.2 Agent-Based Model Development

The agent-based model is composed of agents whose behavior is defined by state-charts. State-charts define an agent's different states connected through a logical flow. In the case of the proposed model, five agent types were included, *Steel Crews*, *Formwork Crews*, *Concrete Crews*, *Slabs and Walls*, which can be divided into two categories; the crews and the constructed entities. All crews are assumed to have a similar behavior and state-charts and the same applies to constructed entities (Fig.1). To that end, only one of each was explained.

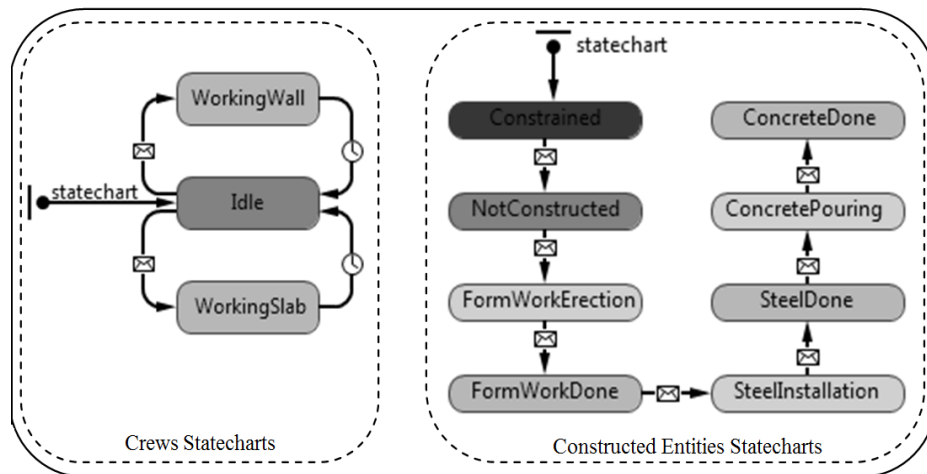


Figure 1. Statecharts of agents.

As shown in Fig. 1, the slab agent has eight states. The first one named *Constrained* is the initial state of every slab or wall whereby construction cannot begin due to predecessors or dependencies. The transition from *Constrained* to *NotConstructed* is triggered by the message “unconstrained”, which is sent in the following three instances, (1) On start-up, the floor slab directly moves from *Constrained* to the state *NotConstructed* since it has no predecessors; (2) Each time a slab is constructed, the wall above becomes unconstrained; (3) Each time a wall is built, the slab above becomes unconstrained. More specifically, when a slab moves to the *NotConstructed* state, it sends “move to slab” message to the *Formwork Crew* agent. This allows the crew to move from its initial state *Idle* to the state *WorkingSlab* and accordingly, a message is sent to the slab to move from *NotConstructed* to *FormWorkErection* (Fig.1). The formwork crew becomes idle again once formwork erection is complete. As such, one of the most important transitions in the model happens when the crew moves from the working state to the idle state. In fact, this transition of type timeout represents the duration it takes to complete a certain task. In order to model the learning curve phenomenon, the timeout duration was assumed to vary each time the crew goes through its specific transition. In other words, using each of the aforementioned learning curve models (i.e., Straight-Line, Stanford “B”, Exponential, De Jong, and Cubic Power) and assuming an 80% learning rate, the timeout duration was computed in such a way it is gradually decreasing with each task repetition. Once this specified

time elapses, the crew moves back to the state *Idle* and the slab moves to the state *FormWorkDone*. The same process is repeated for other concrete activities related to slabs and the entire process is repeated for walls. The state-charts keep interacting until the whole building is completed. In addition to these charts, variables and functions were incorporated in the simulation model to represent factors affecting learning rate. These include shared worker experience, psychological effects and work interruptions.

3 RESULTS AND CONCLUSION

The proposed ABM model was run using each of the aforementioned methods (i.e. Straight-Line, Stanford “B”, Exponential, De Jong, and Cubic Power). Fig.2 depicts the respective learning curves (time vs. floor number) for the slabs formwork activities under each method. On the other hand, Fig. 3 portrays the duration of all concrete activities under each method.

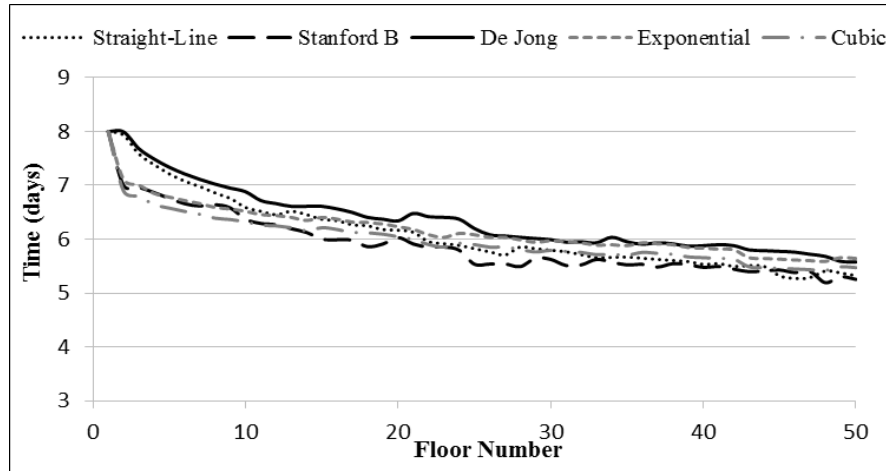


Figure 2. Learning curves for slabs formwork activities.

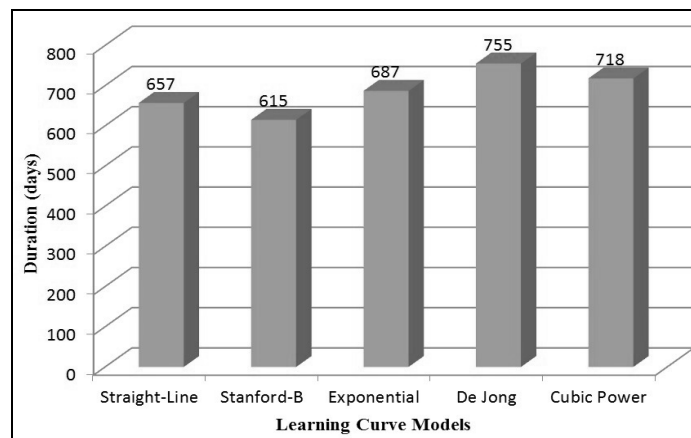


Figure 3. Total Duration of slabs and walls concrete activities (days).

Based on the results in Fig.2, the influence of learning under all five methods was clear in the first 18 floors then started to vanish. For instance, using the Straight-Line model, the estimated time at the beginning was 8 days/floor dropping to 3.2 days/floor when reaching the 18th floor. If the effect of learning and interaction was not considered, the 8 days/floor requirement would be constant and the formwork activities duration would be greater. The absence of learning development would thereby lead to an overall duration greater than 1000 days. Fig. 3 shows that the duration of all concrete activities, when the learning effect is taken into consideration, varies between 615 and 755 days whereby the Stanford-B model led to the shortest duration.

It can be concluded that ABM is a reliable technique that allows modeling the interaction of agents and the quick generation of different learning curves and activities overall durations. The proposed approach is flexible and user-friendly in that the user can try various scenarios with different learning rates and test different learning curve methods.

Future work will include additional factors affecting the learning curve such as the change in crew size, unforeseen conditions such as bad weather and accidents, etc. These factors will be added to the current simulation model and their effect on learning curve and thereby productivity will also be assessed. Moreover, the proposed agent-based model will be verified and validated by visualizing processes in 3D and graphically depicting variables and parameters as the model is running.

Acknowledgments

The presented work has been supported by AUB's University Research Board (URB). The authors gratefully acknowledge URB support. Any opinions, findings, conclusions, and recommendations expressed by the authors in this paper do not necessarily reflect the views of URB.

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